Gender Inequality Across UK Labour Markets

by

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Abstract

This thesis presents empirical evidence on the magnitude, spatial variation, and drivers of gender inequality across UK labour markets, with a focus on policy implications.

Using secure data from the 2022 Annual Survey of Hours and Earnings, the first empirical Chapter identifies substantial spatial variation in the Gender Pay Gap across areas within Britain. Oaxaca-Blinder decompositions reveal that while spatial differences in the allocation of employees partly explain this variation, most gaps remain unexplained, varying on the basis of local labour market characteristics, including industrial composition and unemployment rates.

The second empirical Chapter explores the Gender Gap in Commuting using pooled data from the Quarterly Labour Force Survey for 2022-2023. A Two-Stage Least Squares regression with an instrumental variable approach, alongside an Oaxaca-Blinder decomposition, estimates that gender differences in commute time account for 10.1% of the raw Gender Pay Gap, highlighting the importance of spatial constraints and non-wage amenities in shaping gender gaps, even amidst increased home and hybrid working.

The third empirical Chapter provides the first quantitative evaluation of the Childcare Offer for Wales on parental labour market outcomes using secure data from the Annual Population Survey. A Sharp Regression Discontinuity Design and Difference-in-Differences approach find no significant impact on parental employment rates or hours worked, offering timely insights as England expands childcare subsidies and concerns grow over the financial sustainability of devolved provision.

The thesis makes three contributions. First, it documents the scale of intra-regional and -local variation in the Gender Pay Gap and the role of local labour market characteristics. Second, it provides contemporary evidence on commuting patterns, showing how spatial factors shape gender disparities in wages. Third, it delivers the first quantitative evaluation of the Childcare Offer for Wales, addressing a policy-relevant evidence gap. Overall, the thesis emphasises the value of spatial analysis for understanding gender inequality and the need for improved data to evaluate policies, particularly in devolved contexts where data constraints present challenges.

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This research is mostly based on secure data accessed through the Secure Data Service. The UK Data Service agrees that the results are non-disclosive, and cannot be used to identify a person or organisation. The use of these data does not imply the endorsement of the data owner or the UK Data Service at the UK Data Archive in relation to the interpretation of analysis of the data. This work uses research datasets which may not exactly produce National Statistics aggregates.

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Contents

List of Tables

List of Figures

List of Abbreviations

Acronym	Full Term
APS	Annual Population Survey
ASHE	Annual Survey of Hours and Earnings
BHPS	British Household Panel Survey
CGG	Gender Gap in Commuting
CS	Callaway and Sant'Anna
DiD	Difference-in-Differences
GPG	Gender Pay Gap
HRH	Household Responsibility Hypothesis
IMD	Index of Multiple Deprivation
ITT	Intention To Treat
IV	Instrumental variable
JMP	Juhn Murphy Pierce decomposition
LAU	Local Administrative Units
LSOA	Lower layer Super Output Area
NES	National Earnings Survey
NMW	National Minimum Wage
NUTS	Nomenclature of Territorial Units for Statistics
OB	Oaxaca-Blinder
OECD	Organisation for Economic Co-operation and Development
Offer	Childcare Offer for Wales
OLS	Ordinary Least Squares
ONS	Office for National Statistics
PSED	Public Sector Equality Duty
QLFS	Quarterly Labour Force Survey
RDD	Regression Discontinuity Design
SDS	Secure Data Service
SIC	Standard Industry Classification
SOC	Standard Occupational Classification
WERS	Workplace Employment Relations Study
2SLS	Two Stage Least Squares

Chapter 1

Introduction

Gender gaps in labour market outcomes remain persistent features across economies. On average, women earn lower wages, have lower employment rates, work fewer hours than men, and tend to be over-represented in lower-paying occupations and sectors (e.g., Blau and Kahn 2017; Goldin 2014; Razzu 2014; Fortin 2005).[1] The UK labour market is no exception. Although gender gaps have narrowed over the past decade, progress has been slow relative to other OECD countries, and gender inequality in the UK labour market remains pronounced (Qamar, 2024). In 2022, the UK's median Gender Pay Gap (hereinafter, GPG) - defined as the average difference in earnings between women and men - was 14.0%, higher than both the EU (9.1%) and OECD (11.4%) averages, placing the UK alongside countries such as the United States and Germany (OECD, 2024). While the gender gap in employment rates is relatively modest in comparison, the high prevalence of part-time work among women significantly contributes to overall gender inequality in the UK labour market (Francis-Devine and Hutton, 2024).[2] These gender gaps persist despite relatively strong equality legislation, such as the Equality Act (2010), and political commitments to 'end the gender pay gap in a generation' (David Cameron, October 2015).

Beyond its prevalence, gender gaps in the labour market exhibit substantial spatial variation. Across OECD countries, the GPG ranges from as low as 1.2% in Belgium to 31.1% in Korea (OECD, 2023).[3] This international variation has been widely studied, with comparative research identifying national wage structures, gender differences in characteristics, labour market penalties associated with having children, and discrimination as key drivers of gender inequality in the labour market (Blau and Kahn,

[1] While closely linked, gender gaps and gender inequality are conceptually distinct: gender gaps quantify observed differences in labour market outcomes, whereas gender inequality represents the structural, institutional, and social factors partially driving these differences.

[2] In April 2024, the GPG in the UK was 13.1% for all employees and 7.0% for full-time employees. Among part-time employees, the GPG was -3.0%, reflecting the higher proportion of women in part-time roles (39% of female employees compared to 15% of male employees) (ONS, 2024b).

[3] The low GPG in Belgium can be partially attributed to the exclusion of certain sectors where pay gaps tend to be wider, such as agriculture, mining, real estate, and professional, technical, and scientific activities (OECD, 2023).

1992; Blau and Kahn, 1996b; Kleven et al., 2019; Kleven et al., 2018; Bertrand et al., 2015; Kabeer, 2021). However, cross-country comparisons present challenges related to data harmonisation, institutional heterogeneity, and cultural differences, making it difficult to disentangle the key drivers of gender inequality. Despite these challenges, relatively little attention has been paid to the spatial variation in gender inequality within countries. This is particularly striking given that within-country variation - observed within a shared institutional, economic, and policy context - can be as large as those observed between countries (Schäfer and Gottschall, 2015). Moreover, local economic structures, industrial composition, and agglomeration economies have been shown to influence wages and employment patterns (Combes and Gobillon, 2015; Card et al., 2025; Moretti, 2011; Bacolod, 2017), and these effects may differ for men and women. By shifting the focus from international comparisons to the spatial variation of gender gap and gender inequality within a single country, this thesis aims to build a comprehensive body of evidence on the magnitude, spatial variation, and drivers of gender inequality across labour markets in the UK, with a particular emphasis on policy implications.

The UK provides an interesting case study for analysing spatial variation in gender gaps and gender inequality. Official statistics indicate substantial spatial variation: for example, the GPG is consistently higher in all regions of England compared to Scotland, Wales, and Northern Ireland. This marks a significant divergence from the situation in April 1997, when gender gaps in labour market outcomes were more uniform across the UK (ONS, 2022b). Consequently, regional inequalities have been a longstanding concern for successive UK governments, receiving renewed attention under the 'levelling up' agenda (2019–2022), which explicitly recognised geography as a key dimension of labour market inequality. Furthermore, while the UK has undergone a process of devolution, it retains a largely uniform institutional and policy framework, reducing some of the complexities associated with cross-country comparisons. Nonetheless, devolution and decentralisation have introduced important spatial policy differences that may shape gender inequality.[4] These policy divergences provide an opportunity to assess the extent to which spatial variation in gender inequality can be mitigated through policy interventions.

To build a comprehensive body of evidence on the magnitude, spatial variation, and drivers of gender inequality across labour markets in the UK, the thesis consists of three empirical Chapters, each employing secondary data and established econometric methods. The first empirical Chapter quantifies the spatial variation in the GPG across regions and localities within Britain, identifying key drivers and examining their spatial heterogeneity.[5] The second Chapter explores the Gender Gap in Commuting

[4]The UK's devolution process has transferred varying degrees of power from Westminster to separate governance structures in Scotland, Wales, and Northern Ireland. For example, tax-raising powers are devolved to Scotland and Wales but remain reserved in Northern Ireland. England, by contrast, does not have a devolved government, though certain policy powers have been transferred to city regions through mayoral devolution deals. See Table A.2, Appendix A for details on what is devolved in each UK nation.

[5]Due to data constraints, this analysis is limited to Britain (i.e., England, Scotland, and Wales), rather than

(hereinafter, CGG) and its potential role as an underexplored driver of the mean GPG in the UK. The third Chapter evaluates the impact of the Childcare Offer for Wales (hereinafter, the Offer) - a devolved policy - on parental labour market outcomes, in the context of an expansion of childcare subsidies in England and broader policy concerns regarding the effectiveness of early childcare education and care provision in Wales.[6]

Each empirical Chapter uses cross-sectional microeconomic data in the UK, specifically the Annual Survey of Hours and Earnings (hereinafter, ASHE), the Quarterly Labour Force Survey (hereinafter, QLFS) and the Annual Population Survey (hereinafter, APS). The selection of these data is motivated by their respective strengths in addressing the research questions of each Chapter, although their combined use enhances the comprehensiveness and robustness of the analysis. While all three data provide coverage of wages, employment patterns, and demographic characteristics, each offers unique advantages. For example, the ASHE offers comprehensive and reliable wage data, making it particularly well-suited for examining the spatial variation in the GPG. In contrast, the QLFS provides richer information on labour market participation and individual employment characteristics. The APS, with its large sample size due to sample boosts, facilitates analysis at smaller geographical levels.[7] The use of multiple data strengthens the research by enabling a more comprehensive exploration of gender inequality in the UK labour market across different dimensions. The analysis primarily focuses on the 'post-pandemic' labour market, a period characterised by significant shifts in labour market dynamics, gender inequality, and spatial patterns of work (Blundell et al., 2022). However, the evaluation of the Offer focuses on the period leading up to the pandemic, reflecting the timing of its implementation and before any pandemic-induced labour market changes.

The first empirical Chapter (Chapter 3) provides evidence of the magnitude and determinants of spatial variation in the mean GPG across areas within Britain at both the regional and local levels. Using secure data from the ASHE in 2022, as the first post-pandemic year unaffected by furlough,[8] the analysis applies the Oaxaca-Blinder (hereinafter, OB) decomposition methodology (Oaxaca, 1973; Blinder, 1973) to quantify the extent to which the GPG across the 11 NUTS 1 regions and 160 (out of 168) NUTS 3 localities can be explained by gender differences in observable characteristics, and the extent that remains unexplained. This approach extends recent studies conducted in Germany (Fuchs et al., 2021) and Spain (Murillo Huertas et al., 2017) to the UK, where evidence of spatial variation remains mixed. Existing research suggests that the GPG is smaller in urban areas (Phimister, 2005), yet particularly pronounced in London

the entire UK, which includes Northern Ireland.

[6]These policy concerns relate to the sustainability and awareness of systems. See Thomas (2024) for an overview.

[7]The first and third Chapters utilise secure versions of the ASHE and APS, respectively, accessed via the UK Data Service's Secure Data Service (hereinafter, SDS), while the second Chapter utilises End User License data from the QLFS (discussed further in Section 2.2.4).

[8]Furlough refers to a temporary leave of absence from work. During the COVID-19 pandemic, the UK government introduced the Coronavirus Job Retention Scheme, which provided government grants to cover a significant proportion of wages for employees unable to work due to the coronavirus restrictions.

(Stewart, 2014), and that it is lower in Northern Ireland relative to the rest of the UK (Jones and Kaya, 2022b). Recognising the limitations inherent in the ASHE and the potential influence of broader contextual factor, the Chapter further explores how the unexplained portion of the GPG varies on the basis of local labour market characteristics, such as industrial composition, unemployment rates, and rurality. This spatial analysis lays the foundation for the subsequent empirical Chapters by highlighting the role of the spatial allocation of employees, economic structures, and local labour market conditions in shaping gender inequality.

The second empirical Chapter (Chapter 4) extends the spatial analysis of gender inequality in the labour market by focusing on the CGG and its role as a potential driver of the mean GPG in the UK. While traditional explanations of the GPG primarily emphasise wage determinants and pay structures, a substantial portion of the gap remains unexplained, leading to growing recognition of the role of non-wage amenities (Goldin, 2014). Among these, commuting (until recently) has received comparatively little attention, despite its potential impact on gendered labour market outcomes, particularly if women trade higher wages for shorter commutes (Mas and Pallais, 2017; Wiswall and Zafar, 2018; Goldin, 2014). Existing studies estimate that commuting explains between 10–25% of the raw GPG (Caldwell and Danieli, 2024; Gutierrez, 2018; Le Barbanchon et al., 2021; Ekberg and Widegren, 2019; Farré et al., 2023), though research has been constrained by data limitations and methodological challenges, particularly concerning endogeneity arising from reverse causality, omitted variable bias, and simultaneity (Manning, 2003). Using pooled data from the QLFS for the fourth quarters of 2022 and 2023, this Chapter applies the OB decomposition methodology to analyse both the CGG and GPG, assessing the extent to which gendered commuting patterns contribute to wage differences. To address endogeneity concerns, the analysis also employs a Two-Stage Least Squares (hereinafter, 2SLS) regression, using average commute times within one-digit Standard Industrial Classification (hereinafter, SIC) sectors as an instrumental variable for self-reported commute time. As a result, the analysis contributes UK evidence to the international research on commuting as a driver of the GPG and provides new evidence on gender inequality in the 'post-pandemic' labour market. In doing so, the analysis complements the first empirical Chapter by further developing the evidence of how local economic conditions, spatial factors, and individual labour market choices interact to influence the spatial variation of gender inequality.

While the first two empirical chapters of the thesis are concerned with understanding drivers of gender gaps across labour markets in the UK, the third empirical Chapter (Chapter 5) shifts focus to the role of policy in mitigating gender inequality. Specifically, it evaluates the impact of the Offer - a devolved policy providing up to 30 hours of free childcare per week for working parents of three- and four-year olds - on parental employment rates, given that time out of the labour market is a major determinant of the child wage penalty and long-term gender gaps (Bertrand et al., 2010; Kleven et al., 2018; Kleven et al., 2019; Schober, 2013). The evaluation of the Offer uses secure data from the person and household APS and employs two identification strategies. The first approach applies a sharp Regression Discontinuity Design (hereinafter, RDD), exploiting the Offer's age-based eligibility criteria to estimate its impact in the first full year of implementation (March 2019-March 2020, i.e., post-trial period). The second approach adopts a Difference-in-Difference (hereinafter, DiD) framework, exploiting the phased geographical rollout of the Offer across Welsh wards during the trial period (January 2016 - March 2019). This analysis builds upon international evidence suggesting that well-designed childcare policies and subsidies can significantly enhance labour market participation and employment, though effects vary by demographic factors such as gender, family composition, and educational background (e.g., Berlinski et al. 2011; Havnes and Mogstad 2011a; Lundin et al. 2008; Bauernschuster and Schlotter 2015. Furthermore, it directly builds on prior research on a similar, though less generous, childcare policy in England, which found positive employment effects only for mothers whose youngest child was eligible (Brewer et al., 2022). Given this and the potential variations in the benefits of participating in childcare, the Chapter examines the heterogeneity of the Offer's impact across different parental subgroups. By evaluating both the overall impact of the Offer on employment rates and its spatial rollout, this Chapter aligns with the broader themes of the thesis, emphasising the role of policy in addressing spatial variation in gender inequality across labour markets.

The thesis makes several contributions to the academic literature on gender inequality in the labour market. First, it provides evidence on the magnitude and spatial variation of the GPG across regions and localities in the UK. This analysis builds on cross-country comparisons (Kaya, 2023), complements prior research on subnational disparities (Fuchs et al., 2021; Murillo Huertas et al., 2017), and extends investigations into the smaller GPG observed in Northern Ireland relative to the rest of the UK (Jones and Kaya, 2022b). It also contributes to the literature on the evolution of the GPG in the UK by examining the persistence of its unexplained component at a regional and local level (Jones et al., 2018; Jones and Kaya, 2022b). Second, this thesis contributes to the growing literature on non-wage amenities as drivers of gender inequality in the labour market (Goldin, 2014). Specifically, it contributes to the literature that examines gendered commuting patterns as a potential significant driver of the GPG, which has until recently been overlooked. In doing so, it addresses previous data and methodological limitations related to endogeneity. By integrating contemporary UK evidence, this study extends recent international research that highlights commuting as a key determinant of the GPG (Caldwell and Danieli, 2024; Gutierrez, 2018; Le Barbanchon et al., 2021; Ekberg and Widegren, 2019; Farré et al., 2023). Third, the research contributes to the debate on gender inequality in the post-COVID-19 era by analysing the role of commuting in explaining the GPG in the context of pandemic-induced shifts towards home and hybrid work arrangements. Specifically, it provides UK-specific evidence to complement the emerging international literature, which suggests that despite these changes, a substantial CGG persists (Le Barbanchon et al., 2021; Meekes and Hassink, 2022; Farré et al., 2023). Fourth, the thesis fills an important gap in the literature by evaluating the impact of a devolved childcare policy - the Offer - on parental labour market outcomes. This analysis complements annual qualitative assessments of the Offer (Glover et al., 2018; Glyn et al., 2019; Glyn et al., 2021; Glyn et al., 2022; Harries et al., 2023) and extends previous research on the effects of England's similar, though less generous, childcare policy (Brewer et al., 2022). While existing research has primarily focused on the regional impact of national policies (e.g. Robinson 2005), this research demonstrates how devolved policies can influence gender gaps in employment.

Methodologically, this thesis advances econometric approaches in gender inequality research, particularly in addressing endogeneity concerns that arise in the analysis of commuting and wages. Given the longstanding difficulty in identifying suitable instruments for commuting (Manning, 2003), the thesis employs a causal technique of instrumenting self-reported commute time with average commute times within industry sectors. This addresses endogeneity concerns in estimating the relationship between commuting and wages, complementing existing studies that have employed alternative strategies, such as fixed-effects models, sample restrictions, quasi-experimental designs, job duration models, and other instrumental variables (Manning, 2003; Gutiérrez-i-Puigarnau et al., 2016; Van Ommeren et al., 2000; Isacsson and Swärdh, 2007; Mulalic et al., 2014; Caldwell and Danieli, 2024; Gutierrez, 2018; Le Barbanchon et al., 2021; Ekberg and Widegren, 2019; Farré et al., 2023), Additionally, this thesis extends the application of the OB decomposition to the CGG, contributing evidence to the debate over whether household responsibilities or labour market structures drive the CGG. Further, the application of a staggered DiD approach in evaluating the impact of the Offer represents a methodological innovation in the study of devolved policies. By exploiting the phased geographical rollout of the Offer, this thesis strengthens causal inference in assessing its impact on parental labour supply, contributing to the broader methodological literature on policy evaluation.

The findings of this thesis have significant policy implications. Chapter 3 demonstrates that areas with low GPGs may not necessarily reflect genuine gender equality but may instead reflect the spatial distribution of workers and industries. This highlights the need for policymakers to look beyond national headline figures and adopt targeted interventions to address structural labour market inequalities, including industrial policies that promote gender equality in high-paying industries. Chapter 4 emphasises the importance of mitigating spatial mobility constraints, reflected by commuting times. Potential policy responses could include improvements in public transport infrastructure, measures to alleviate gendered household responsibilities, and initiatives to encourage flexible working arrangements. Chapter 5 provides the first empirical evidence on the impact of the Offer, complementing existing qualitative assessments by the Welsh Government and offering timely insights as England expands its childcare subsidies to all children under five from September 2025. While no equivalent expansion is currently planned in Wales, the funding mechanism via the Barnett formula presents an opportunity for similar initiatives. The findings suggest that the Welsh Government should consider lessons from England and evaluate whether expanding the Offer would be preferable to its current strategy of expanding the Flying Start scheme. Recent evidence indicates that many low-income families do not meet the work requirements to qualify for the Offer, and only 23% of local authorities currently provide sufficient childcare to meet demand (Joseph Rowntree Foundation, 2020). Together, these raise critical questions about the aims of the Offer, its long-term sustainability, and its ability to address gender inequality across labour markets in the UK.

Collectively the empirical Chapters in this thesis provide a comprehensive analysis of gender inequality across UK labour markets, exploring the spatial variation of gender gaps, the role of commuting patterns, and the potential impact of policy. The thesis is structured as follows: Chapter 2 provides an overview of the institutional and policy context surrounding gender inequality in the UK, alongside a review of the academic literature on the drivers of national GPGs from both cross-country and UK evidence. This is followed by the three empirical chapters discussed above (Chapter 3, 4, 5). Each empirical Chapter follows a consistent structure, beginning with a brief motivation, a literature review to situate the research, a discussion of the data and methodology, presentation of empirical results, and a discussion of the findings. The final Chapter, Chapter 6, synthesises the key findings of each empirical Chapter, detailing their contribution the academic literature, econometric methodologies, and policy debates. It also identifies overarching themes, discusses the main limitations of the analysis, and proposes directions for future research.

Chapter 2

Background Literature Review

2.1 Introduction

This Chapter provides a comprehensive review of the literature on gender inequality in the labour market, laying the foundation for the thesis' three empirical Chapters. Section 2.2 introduces key concepts and their measurements in labour market inequality research, along with an overview of geographical areas and recent challenges around data collection in the UK. Section 2.3 reviews the UK's legislative framework and policies aimed at addressing gender inequality. Section 2.4 explores theoretical approaches on the persistence of gender inequality in the labour market. Section 2.5 reviews quantitative methodologies commonly employed in economic analyses of labour market inequality, with a particular focus on those employed in this research. Section 2.6 presents international and UK empirical evidence on the drivers of the GPG and its spatial variation. Section 2.7 concludes.

2.2 Concepts, Areas, and Data

2.2.1 The Gender Pay Gap

The GPG refers to the difference in average earnings between women and men, typically expressed as a percentage of men's earnings. While conceptually distinct, it is widely used as an indicator of gender inequality in the labour market, reflecting structural barriers, including gender differences in access to economic opportunities and occupational segregation, as well as potential discrimination (Blau and Kahn, 2017). The GPG is also shaped by societal factors, including cultural norms around work and caregiving, as well as individual preferences.

Accurate measurement of the GPG is essential, given the increasing societal, political, and academic focus on gender gaps and inequality in the labour market, with estimates often informing policies aimed at reducing these gender gaps. However, GPG estimates can vary considerably depending on the methodology and data employed. In the UK, the official measure of the GPG is derived from the ASHE by the ONS, which defines the GPG as the difference between women's and men's average hourly earnings, excluding overtime, expressed as a proportion of men's average hourly earnings, excluding overtime:

$$GPG = \frac{\overline{W}^M - \overline{W}^F}{\overline{W}^M} \tag{2.1}$$

where W indicates hourly earnings excluding overtime, the bar denotes the average value, and the superscripts M and F refer to men and women, respectively. Based on this definition, the ONS estimated the median GPG for all employees at 14.9% in April 2022, indicating that women earned, on average, 85.1p for every £1 earned by men. A negative GPG, by contrast, would indicate that women, on average, earn more than men. In the same period, the median GPG was 8.3% for full-time employees and -2.8% for part-time employees.

This definition reflects methodological considerations aimed at minimising distortions arising from gender differences in working patterns. The use of hourly earnings, rather than weekly or annual earnings, ensures that differences in working hours do not artificially inflate the GPG. Without this adjustment, the GPG would be larger, as women are more likely to work part-time. Similarly, excluding overtime accounts for men's greater likelihood of working overtime hours. The ONS favours the GPG measure for full-time employees, as it reduces distortions associated with women's higher prevalence in part-time employment, which typically offer lower hourly wages.[1] Consequently, the GPG for all employees, which includes both full-time and part-time employees, tends to be larger than the GPG for full-time employees, as it captures both women's greater likelihood of part-time employment and broader labour market disparities (Antonie et al., 2020).

The ONS primarily reports the median GPG, as it is less sensitive to extreme value and provides a more representative measure of typical earnings. However, the mean GPG remains widely used in empirical research as it measures disparities across the entire earnings distribution, including at the upper end. While the mean GPG provides a broader picture of overall wage inequality, the median focuses on central wage differences, avoiding distortion from outliers. This distinction is relevant given that men's wage distributions often have longer upper tails (Anderson et al., 2001). Consistent with the UK empirical literature, this thesis primarily focuses on the mean hourly GPG, explicitly noting and justifying alternative measures.

[1] Direct comparisons of hourly earnings between women and men in part-time employment can be less precise due to the relatively small proportion of men working part-time. In practice, comparisons often involve the mean hourly earnings of women in part-time roles relative to all men or to men in full-time employment, thereby blending the GPG for part-time work with broader disparities between full-time and part-time employment.

Equation 2.1 represents the raw or unadjusted GPG, which measures the average wage difference between women and men without accounting for differences in individual or work-related characteristics. As such, it captures both structural labour market factors and potential discrimination. In contrast, the adjusted GPG accounts for observable factors influencing earnings, such as education, work experience, industry, and occupation. By isolating the residual or unexplained portion of the GPG after controlling for these characteristics, the adjusted GPG is often considered a more precise measure of gender pay inequality, reflecting the extent to which discrimination or unmeasured factors contribute to the GPG (further discussed in Section 2.5.2).

Although the raw GPG does not fully reflect gender pay inequality, it remains the primary measure reported by international organisations such as the OECD and the EU (e.g., Figure 2.1). This is because it facilitates cross-country comparisons and remains unaffected by gender differences in observable characteristics that may themselves reflect gendered norms and structural inequalities (Rubery et al., 2005).[2] However, while the adjusted GPG provides a more refined estimate of gender pay inequality, it may still underestimate discrimination, as it does not account for gender inequality in access to opportunities, career progression, or other broader structural biases (ibid.).

The choice of methodology and data significantly influences GPG estimates, sometimes leading to inconsistent or non-comparable results. This variation underscores the need for transparency in measurement approaches and a comprehensive understanding of methodological considerations.

2.2.2 Labour Market Discrimination

Labour market discrimination refers to the unequal treatment of individuals based on characteristics such as gender, race, or ethnicity, rather than differences in productivity or qualifications.[3] In this context, these characteristics are assigned an economic value in the labour market despite their lack of relevance to individual productivity (Arrow, 1973). Gender-based labour market discrimination can manifest in various forms, disadvantaging women relative to men in hiring, wages, promotions, and career progression. While the GPG captures overall earning differences between women and men, discrimination specifically refers to cases where these differences result from unequal treatment rather than voluntary choices, occupational sorting, or other non-discriminatory factors. As such, discrimination is more directly aligned with gender inequality than with statistical gender gaps.

Labour market discrimination can be direct and indirect, distinctions that align more

[2] While the EU's Directorate General for Employment advocates for the adjusted GPG as a more insightful measure for gender inequality, the raw GPG remains prevalent in policy discussions due to methodological challenges in defining appropriate adjustment variables.

[3] Discrimination extends beyond the labour market to various domains, including education, housing, and broader economic opportunities (Yinger, 1995).

closely with the legislative framework than with economic theory. Direct discrimination involves explicit differential treatment of equally qualified women and men, such as offering lower wages to women for identical roles. In contrast, indirect discrimination arises from seemingly neutral policies or practices that disproportionately disadvantage women, such as rigid promotion criteria or a lack of flexible working arrangements (Altonji and Blank, 1999). These mechanisms not only constrain individual opportunities but may also create a feedback loop in which the anticipation of discrimination influences labour market behaviour (Mincer and Polachek, 1974). Additionally, societal and cultural norms reinforce discriminatory practices, as gendered assumptions about caregiving responsibilities or perceived career commitment frequently shape the behaviour of employers.

Several theoretical frameworks explain the persistence of labour market discrimination. Taste-based discrimination (Becker, 1957) suggests that some employers, co-workers, or customers may exhibit a preference, or 'taste', for working with men over women, leading to wage penalties or exclusionary hiring practices. In contrast, statistical discrimination (Arrow, 1973) suggests that employers use gender as an indicator for unobservable productivity-related characteristics, such as job commitment or career continuity, even in the absence of explicit bias. These models, among others, provide the foundation for empirical research on discrimination, further discussed in Section 2.4.2.

The measurement of discrimination is a core theme in empirical labour economics, with various methodologies employed (discussed further in Section 2.5). The adjusted GPG, which accounts for observable characteristics, is often used as a proxy for discrimination and other unmeasured factors. Decomposition methods, such as the OB decomposition, decompose the raw GPG into an explained component (attributable to observable differences in worker or job characteristics) and an unexplained component, often interpreted as an upper-bound estimate of discrimination, despite well-established limitations (Neumark 2018, see discussion in Section 2.5.2). While these methods provide valuable insights, they face methodological challenges, including the selection of appropriate explanatory variables and the risk of omitted variable bias. These methods may also underestimate discrimination if systemic gender norms influence observable characteristics.

2.2.3 Geographical Areas in the UK

The analysis of gender inequality across UK labour markets requires a clear understanding of geographical areas. While all microeconomic data inherently relate to place and space, the categorisation of geographical areas in the UK lacks standardisation, with varying boundaries and hierarchical structures across different classification systems. The thesis adopts the comprehensive framework of the ONS, which uses a system of nine-digit codes to uniquely identify geographic areas, facilitating consistent spatial analysis. Table 2.1 summarises the number of geographical units at each level of three main classification systems used in the thesis: (i) Eurostat territorial units, (ii) administrative divisions, and (iii) Census statistical geographies. Counts are provided for each UK nation, illustrating the hierarchical nature of these classifications.

Table 2.1: Number of geographical units in the UK, by level of statistical and administrative geography.

		England	Northern Ireland	Scotland	Wales
Eurostat	NUTS 1	9	1	1	1
	NUTS 2	23	1	4	2
	NUTS 3	132	5	23	12
Admin.	Local Authorities	326	26	32	22
	Electoral wards	7,669	582	353	852
Census Statistical Geographies	Middle-layer Super Output Areas	6,856	-	-	408
	Lower-layer Super Output Areas	33,755	-	-	1,917
	Output Areas	171,372	4,537	46,351	10,036

Note: (i) Local authorities are referred to as Unitary authorities in Wales, Council Areas in Scotland and District Council Areas in Northern Ireland. In England, they are formed from London Boroughs (33), Metropolitan Districts (36), Non-Metropolitan districts (201) and Unitary Authorities (56). (ii) The 139 NUTS 3 regions can be further broken down into 451 LAU 1 Areas, which can be broken into 10,332 LAU 2 Areas. (iii) In Northern Ireland, Output Areas are referred to as Small Areas.

Source: Author's compilation.

The thesis employs official administrative geographical areas to define spatial units of analysis. However, the scope varies across empirical Chapters due to data constraints. Chapter 3 focuses on Britain (comprising England, Scotland, and Wales), while Chapter 4 extends the analysis to the UK, incorporating Northern Ireland. The devolved governance structures in Wales, Scotland, and Northern Ireland introduce further complexities, as each nation has distinct administrative divisions and policymaking powers. While key labour market policies — such as the national minimum wage and welfare system — remain reserved at Westminster, policies related to education, skills training, and equal opportunities are devolved to varying degrees across the UK nations (see Section 2.3 and Table A.2, Appendix A). For instance, although some aspects of equal opportunities policy (e.g., those related to public bodies in Wales) are devolved, primary equality legislation (e.g., the Equality Act 2010) applies across Britain but not in Northern Ireland, which has its own equality legislative framework.

At the broadest level, the UK is divided into three hierarchical administrative levels under the Nomenclature of Territorial Units for Statistics (hereinafter, NUTS) classification, which is further divided into two levels of Local Administrative Units (hereinafter, LAU). Throughout the thesis, 'regional' refers to NUTS 1 regions and 'local' refers to NUTS 3 regions within Britain. In England and Wales, NUTS 3 regions are further divided into Middle-layer Super Output Areas and Lower-layer Super Output Areas (hereinafter, LSOA), containing approximately 1,500 individuals. In Scotland, the equivalent geographical units are Intermediate Zones and Data Zones. The smallest geographical unit used for statistical purposes is the Output Area, which encompasses between 40 and 250 households.

An alternative approach to classifying UK geographical areas is through administrative divisions, which include local authorities, further subdivided into electoral wards. These units are central to policy implementation and local governance. Chapter 5, for example, exploits the phased geographical rollout of the Offer across Welsh wards.

2.2.4 Recent Challenges around Data Collection in the UK

Microeconomic data in the UK are collected through official surveys, administrative records, and longitudinal studies. These data capture detailed information on individual and household economic behaviour, including employment, earnings, and education, serving as the basis for evidence-based policy-making and empirical research on labour markets, income inequality, and policy evaluation. The thesis examines gender inequality across UK labour markets using three microeconomic datasets: the ASHE, the QLFS, and the APS. Each data offer distinct advantages, as discussed in each empirical Chapter, enabling complementary analytical analyses.[4]

The Covid-19 pandemic significantly disrupted data collection and quality across all three datasets. The ASHE experienced reduced sample sizes in 2020 and 2021, with its coverage further affected by the inclusion of furloughed employees under the Coronavirus Job Retention Scheme, necessitating ONS weighting adjustments. Similarly, the QLFS transitioned from face-to-face to telephone interviews, altering the sample composition (e.g., fewer workers) and exacerbating longstanding response rate challenges. These issues became more pronounced after the temporary pandemic-related response rate boost was removed in July 2023. Between June-August 2013 and June-August 2023, the QLFS response rate declined from 47.9% to 14.6%, reducing the sample size in Britain from 78,994 to 36,526 over this period (Francis-Devine, 2023). This decline increases the risk of non-representative samples, reducing the reliability of estimates for employment, unemployment, and economic inactivity rates.

Concerns about data reliability prompted the Resolution Foundation, the Financial Times, and the Institute for Employment Studies to question the suitability of QLFS data for labour market analysis. In response, the ONS temporarily suspended the publication of QLFS data between October 2023 and January 2024. When the ONS resumed publication resumed in February 2024, the figures were reclassified as 'official statistics in development' rather than 'official statistics'.

To address these issues, the ONS reintroduced face-to-face interviews from October 2023 and boosted the sample from January 2024 onwards, improving data reliability. They

[4]The first and third empirical Chapters utilise secure versions of the ASHE and APS, respectively, accessed via the UK Data Service's Secure Data Service (hereinafter, SDS). Given the confidential and potentially disclosive nature of the data, access required ethical approval, full ONS accreditation for each member of the PhD team, strict adherence to statistical disclosure controls to ensure individual anonymity, and independent verification of all outputs through a dual-checking process. Separate SDS applications were submitted and approved for these two empirical Chapters. Chapter 4 utilises End User License QLFS data, as the primary source of national labour market statistics in the UK.

also reweighted QLFS data from December 2024 using updated population figures from January-March 2019 onwards, creating a discontinuity in the data for periods before and after this quarter. To further address these data challenges, the ONS plans to introduce the Transformed Labour Force Survey, which will replace the QLFS as the primary source of labour market data by 2027 (although this has already been delayed several times). The new survey aims to improve data collection through in-home interviews, model-based estimation techniques, and prioritisation of under-represented groups (ONS, 2023e). It will also employ an online-first approach, supplemented by telephone and in-person interviews in low response areas. These methodological improvements should facilitate more granular data analysis and produce more robust estimates of labour market trends.

Given these challenges, the thesis adopts a cautious approach when interpreting data from 2020 and 2021, acknowledging potential biases introduced by pandemic-related disruptions. By using multiple datasets, the empirical analysis seeks to provide a robust and reliable assessment of gender inequality across UK labour markets.

2.3 Background and Legislation

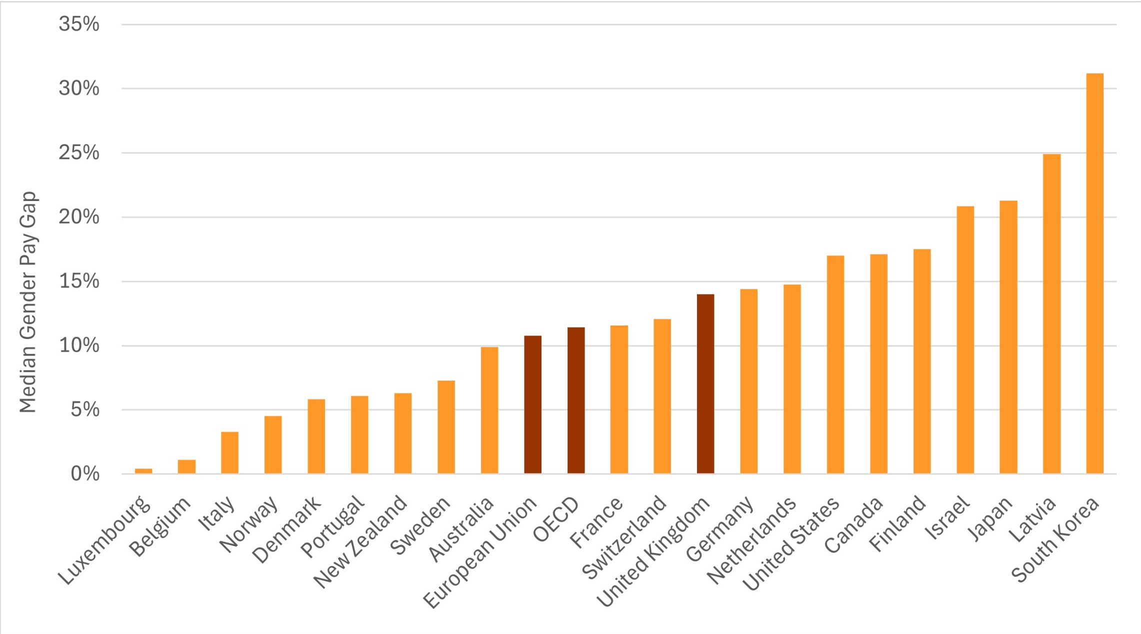
The international variation in the GPG is both substantial and well-documented. Figure 2.1 presents the median raw GPG for full-time employees across selected OECD countries in 2022 (OECD, 2024). While direct cross-country comparisons are constrained by differences in data collection methods and reporting standards (as outlined in Figure 2.1), the use of the median GPG provides a more reliable basis for cross-country comparisons than the mean GPG (see Section 2.2 for a detailed discussion of GPG measures).

In 2022, the median raw GPG for full-time employees across OECD countries was estimated at 11.43%, reflecting a modest decline from 14% in 2010. Certain countries, including Luxembourg, Belgium, Denmark, and Sweden consistently report relatively low median GPGs (below 10%), whereas others, including South Korea, Japan, and Israel, report persistently high median GPGs (above 20%) (OECD, 2024). These variations reflect differences in national economic structures, labour market policies, and broader social factors, identified as drivers of the GPG by international research (Section 2.6.1).

Historically, the UK has had a relatively large GPG compared to other EU and OECD countries (Figure 2.1). In 2022, the median GPG for full-time employees in the UK was estimated at 14.0%, exceeding both the EU27 and OECD averages.[5] This estimate is considerably higher than the ONS estimate of 7.5% for full-time employees in 2022, likely reflecting methodological differences: the OECD uses gross weekly earnings and the ONS relies on gross hourly earnings (see discussion in Section 2.2).

[5]Data for 2023 suggest a decline in the UK's median GPG for full-time employees to 13.3% (OECD, 2024).

Figure 2.1: Median GPG for Full-Time Employees in Selected OECD Countries in 2022



Notes: (i) Estimates are for 2022. (ii) Figures are derived from national surveys, including the Australian Weekly Earnings Survey, Belgian Structure of Earnings Survey, Canadian Labour Force Survey, Danish Structure of Earnings Survey, Finnish Income Distribution Survey, German Socio-Economic Panel, Israeli Integrated Household Survey, Japanese Enterprise Survey, New Zealand Income Survey, Norwegian Census of Employees, South Korean Enterprise Survey, Statistics Sweden, Swiss Enquête suisse sur la structure des salaires, the UK's Annual Survey of Hours and Earnings, the US Current Population Survey, and the European Union Structure of Earnings Survey for France, Italy, Latvia, Luxembourg, the Netherlands, Portugal, Spain and Switzerland. (iii) The GPG estimates represent the difference between the median earnings of men and women relative to the median earnings of men. Estimates generally refer to raw gross earnings of full-time wage and salary workers. (iv) Methodological variations exist across countries: for instance, estimates for France, Germany, Iceland, Israel, Italy, Japan, the Netherlands, Spain, and Sweden are based on gross monthly earnings; for Australia, Canada, the UK, and the US, they are based on gross weekly earnings; and for Belgium, they include bonuses for night or weekend work.

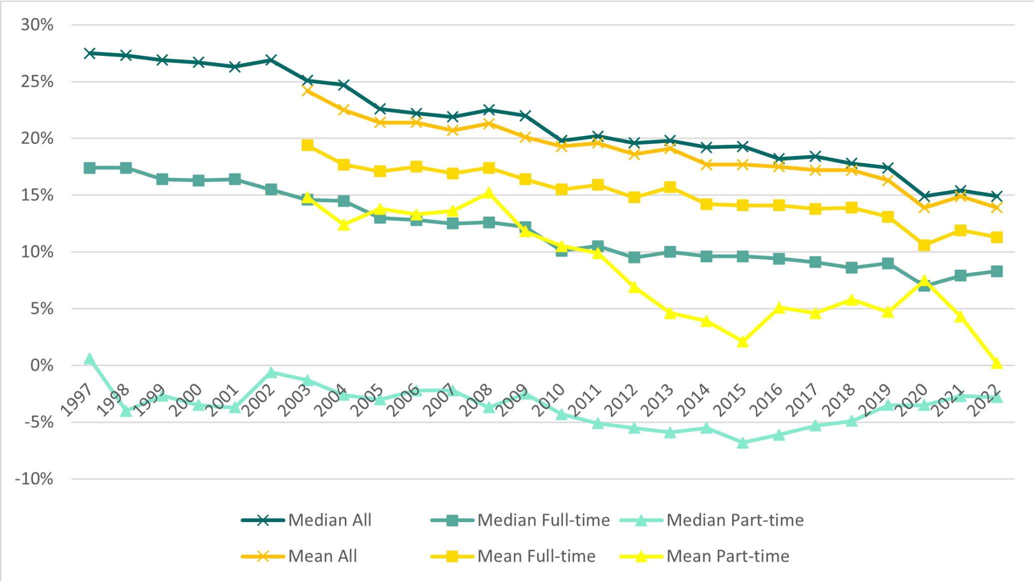
Source: Data collated by OECD (2024) from national surveys as detailed above.

Despite these methodological differences, both international and national estimates indicate a gradual decline in the UK's GPG since 1997. Figure 2.2 presents the evolution of ONS estimates for the mean and median GPG for all employees, as well as for full-time and part-time employees, from 1997-2022. The observed differences between mean and median GPG estimates can be attributed to the disproportionate impact of highly paid individuals on the mean (Section 2.2.1). Over the past decade, the GPG for all employees, as well as for full-time employees, has declined by approximately a quarter, with current levels representing nearly half of those reported in 1975 (ONS, 2023d).[6]

The long-run decline in the UK's GPG across all measures can be attributed to a series of legislative attempts and policy reforms aimed at addressing gender gaps in wages and

[6] GPG estimates for 2020 and 2021 should be interpreted with caution due to the impact of the COVID-19 pandemic. Disruptions in wages, working hours, and data collection during this period likely influenced reported figures (Section 2.2.4).

Figure 2.2: Estimated Median and Mean Hourly GPG for All, Full-Time and Part-Time Employees in the UK from 1997-2022



Notes: (i) Estimates are collated by the ONS from the New Earnings Survey (pre-2004) and the ASHE (post-2004). (ii) Discontinuities occurred in the New Earnings Survey in 2004 and in the ASHE in 2006 and 2011. (iii) The GPG is defined as the difference between the mean or median hourly earnings (excluding overtime) of men and women as a proportion of men's earnings. (iv) Mean estimates are derived by summing the earnings of all individuals in a sample and dividing by the number of observations. Given the skewed nature of earnings distributions, the mean can be disproportionately influenced by a small number of high-paying jobs (Section 2.2). Estimated mean GPGs were not released under End User Licence pre-2003. (v) The median is the earnings value below which 50% of jobs fall. The ONS prefers the median as a measure of average earnings, as it is less affected by a outliers and provides a more accurate representation of typical earnings (Section 2.2). (vi) Full-time employment is defined as working more than 30 hours per week (or 25 or more for the teaching profession). (vii) Measures of pay are based on adult rates and are unaffected by absence unless furloughed in 2020 or 2021. (viii) Estimates of annual changes in the GPG are not adjusted to account for changes in the composition of the labour market during that period.

Source: Original data from the ASHE and NES, collated and analysed by the ONS (ONS, 2023d).

other labour market outcomes (Table A.1, Appendix A). The principle of 'equal pay for equal work' was first enshrined in international law through the International Labour Organisation's Equal Remuneration Convention (1951) and subsequently incorporated into the Treaty of Rome (1957), which established the European Economic Community. Reflecting these international commitments, the UK formally introduced this principle into domestic law through the Equal Pay Act 1970.

The Equal Pay Act was designed to 'prevent discrimination, as regards terms and conditions of employment, between men and women' (UK Government, 1970, Chapter 41). It introduced a contractual mechanism that automatically aligned women's employment contracts with those of their male counterparts performing comparable work. However, the Act's initial scope was limited, as claims were restricted to a two-year retrospective period. In response to a directive of the European Economic Community in 1982, the Act was expanded to cover all cases where women and men performed 'work of equal value'. A ruling by the European Court of Justice in 1999 removed the two-year cap on back pay claims and allowed claims based on statistical evidence of pay disparities, even in the absence of a clearly identifiable discriminatory practice.[7]

Complementing these legal developments, the Sex Discrimination Act 1975 prohibited both direct and indirect discrimination on the grounds of sex across various domains, including employment, education and service provision. The Act also established the Equal Opportunities Commission (later integrated into the Equality and Human Rights Commission in 2006) to promote gender equality and monitor the implementation of gender-related legislation. However, despite these legislative efforts, the GPG and other gender gaps in the labour market persisted, prompting further policy reforms, particularly in light of research predicting that gender pay equality in the UK would not be achieved until 2067 (Gow and Middlemiss, 2011).

The Equality Act 2010 represented a major legislative effort to consolidate and strengthen existing equality legislation in Britain (Table A.1, Appendix A).[8] The Act introduced nine protected characteristics - age, gender, race, disability, religion, pregnancy and maternity, sexual orientation, gender reassignment, and marriage and civil partnership - aiming to standardise employer obligations and foster equitable workplace environments (Wanrooy et al., 2013). However, regarding equal pay, the Act largely retained the principles established by the Equal Pay Act 1970 and the Sex Discrimination Act 1975, continuing to place the burden of initiating claims on employees. It reaffirmed that equal pay encompasses all contractual terms, including basic pay, bonuses, overtime rates, performance-related benefits, pensions, and other fringe benefits, applying to various employment arrangements, including verbal contracts, apprenticeships, and public officeholders. The Act effectively seeks to ensure that employees of equal value receive equal remuneration while permitting pay differences where objectively justified (Rubery and Koukiadaki, 2016).

The Act also introduced limited provisions for hypothetical comparators in cases of direct discrimination and removed the 'genuine' requirement from the material factor defence. These changes imposed a stricter burden of proof on employers, requiring them to demonstrate that any pay differences were necessary and objectively justified (Gow and Middlemiss, 2011). While the Act included provisions to enhance transparency, such as in the calculation of pay and clarifying the allocation of employees within pay scales, critics, including the Joint Committee on Human Rights of the Institute of Employment Rights, argued that it lacked enforceable mandates compelling employers to proactively monitor and address pay disparities (ibid.).

To enhance transparency, the Equality Act 2010 (Gender Pay Gap Information)

[7] Dr Pamela Mary Enderby v Frenchay Health Authority and Secretary of State for Health (Preliminary rulings) [1993] EUECJ C-127/92 (27 October 1993).

[8] The Equality Act 2010 applies to Britain only. Northern Ireland retains its own equality legislation, broadly comparable to the UK Equal Pay Act 1970 and Sex Discrimination Act 1975 (Jones and Kaya, 2022b).

Regulations 2017 require public and private sector employers with 250 or more employees to report key features of their pay distribution annually on a designated snapshot date - 5th April for private and voluntary sector employers and 31st March for public sector employers.[9,10] These reports must include the raw mean and median GPG in hourly wages, bonus gaps, and the gender distribution across pay quartiles. Employers are also encouraged to provide narrative statements explaining their reported figures, often detailing initiatives to address or justify pay gaps.[11]

The introduction of mandatory GPG reporting was intended to enhance transparency and public accountability to reduce the GPG by strengthening women's relative bargaining power (Jones and Kaya, 2022a; Gamage et al., 2021). However, the regulatory framework has been criticised. It does not require the reporting of adjusted GPGs that account for differences in occupation, education, or experience, nor does it mandate the disclosure of absolute pay levels. These limitations constrain the extent to which the regulations provide a comprehensive assessment of gender pay inequality. Furthermore, enforcement mechanisms remain weak, as penalties are restricted to non-submission rather than inaccuracies in reported data, making compliance the primary enforcement focus (Francis-Devine and Pyper, 2020).

Empirical evidence suggests that, despite the relatively short time frame since their implementation, these regulations have contributed to a narrowing of the GPG in Britain. Using ASHE data from 2013 to 2021 and exploiting variation across firm size and time in the application of the transparency policy, the UK pay transparency regulations are estimated to have led to a 19% reduction in the GPG (Blundell et al., 2025). This decline appears to be driven by a behavioural response, whereby firms with higher initial GPGs in one year reduce their GPG more significantly in the next year. Similar patterns are identified in publicly available GPG data from 2017 to 2021, which highlight the role of comparator organisations in driving change (Jones and Kaya, 2022a). These findings support the hypothesis that public disclosure of gender equality indicators enhances scrutiny and facilitates cross-firm comparisons, amplifying the policy's disciplinary effects.[12]

[9] Although these provisions were included in the Equality Act 2010, their implementation was initially delayed in favour of the voluntary 'Think, Act, Report' framework. However, between 2011 and 2015, only five companies participated, highlighting its limited effectiveness (Close the Gap, 2018).

[10] The UK government suspended enforcement of the 2019 GPG reporting deadlines due to the COVID-19 pandemic, although about 60% of employers still submitted data. The deadline for reporting 2020 data was extended to 5th October 2021.

[11] The UK's approach to GPG reporting is unique in its requirement for public disclosure, enabling inter-firm comparisons. In contrast, other countries, such as Austria, focus on internal transparency, requiring employers to share gender-disaggregated pay data exclusively with employees (Jones and Kaya, 2022a). According to the 2021 OECD Gender Pay Transparency Questionnaire, 18 OECD countries have implemented pay gap reporting or auditing requirements (OECD, 2021). Of these, nine - including Canada, France and Spain - have implemented comprehensive equal pay audits, while the remainder, including Austria, Denmark, and the UK, require only gender-disaggregated pay data without broader audits. Five other OECD countries (Germany, Japan, Korea, Luxembourg, and the United States) require companies to report non-pay gender-disaggregated information, and four others require pay audits for selected companies (Costa Rica, Greece, Turkey, and Ireland). The remaining OECD countries have no equal pay reporting or auditing system in place (OECD, 2021).

[12] Empirical evaluations of these initiatives indicate varying impacts depending on the strength of enforcement mechanisms. For example, in Denmark, where firms with at least 35 employees and 10 employees of each gender in

Since 1999, legislative changes to equality policy in Britain have been accompanied by the process of devolution, which has transferred governance responsibilities from UK central government to separate administrations in Scotland, Wales, and Northern Ireland. These devolved nations have developed distinct governance frameworks and demonstrated renewed commitments to promoting equality (Chaney, 2011; Mooney et al., 2006; O'Hagan and Nesom, 2023; Parken and Ashworth, 2019; Department of Trade and Industry, 2004). For instance, the Government of Wales Act (1998) includes an 'absolute duty' to mainstream equality for all individuals, while the Scotland Act (1998) includes provisions to promote equal opportunities. The divergent equality agendas in Wales and Scotland have been influenced by factors such as the engagement of women's organisations, political will and leadership, active stakeholders, supportive institutional arrangements, and key legislative drivers (O'Hagan and Nesom, 2023; Parken and Ashworth, 2019).

Central to the equality frameworks in Wales and Scotland are the Public Sector Equality Duties (hereinafter, PSED), introduced under the Equality Act 2010 to help public sector organisations better meet the general Britain-wide PSED. This requires public bodies to 'eliminate discrimination..., advance equality of opportunity... [and] foster good relations between different people' in their operations, with enforcement overseen by the Equality and Human Rights Commission (UK Government, 2010, Section 149). This overarching duty is supported by specific duties tailored to each devolved nation (Table A.3, Appendix A).

Each devolved nation has implemented specific duties related to the GPG and pay equality (see Table A.3, Appendix A). In Wales, public sector bodies with more than 150 employees are legally required to systematically address pay gaps across protected characteristics. Employers must establish equality objectives aimed at reducing pay differences between women and men or provide evidence justifying the absence of such objectives (Parken and Ashworth, 2019). These duties emphasise proactive measures, requiring action plans and annual reporting to identify and address the underlying causes of pay gaps, such as the overrepresentation of women in part-time, temporary, and casual employment (Parken and Ashworth, 2019; Parken, 2015). The Welsh PSED framework has evolved to shift the emphasis from mere compliance to achieving substantive outcomes, as reflected in the Well-being and Equalities Working Group and the Gender Equality Review (Parken and Ashworth, 2019).

By contrast, the specific duties in England and Scotland derive from the Gender Equality Duty 2006. Prior to the introduction of the GPG reporting regulations, public

occupational classifications must report gender-disaggregated pay statistics, the GPG decreased by two percentage points following the introduction of reporting requirements. Using a DiD approach, this reduction, representing a 13% decline relative to pre-legislation levels, was attributed to slower male wage growth and increased female representation in firms near the reporting cutoffs in a RDD specification (Bennedsen et al., 2022). In contrast, Austria's 2011 Pay Transparency Law has shown no significant impact on the GPG, likely due to weak enforcement mechanisms, low public awareness, and minimal employer incentives to address pay differences (Gulyas et al., 2023). For a broader evaluation of national pay reporting regulations, see OECD (2021).

bodies in England were only required to have 'due regard' for the need to establish an equality objective concerning equal pay. In Scotland, however, public bodies with over 150 employees (reduced to 20 employees or more in 2016) are required to publish their hourly GPG every two years and provide a statement on their equal pay policy and basic occupational characteristics by gender, disability, and ethnicity every four years. Meanwhile, Northern Ireland operates under a separate framework governed by the Northern Ireland Act 1998, which mandates public sector employers to conduct equality impact assessments of job evaluation schemes (Parken and Ashworth, 2019).

Given these additional equality duties in the public sector, several studies have evaluated their effectiveness. Applying OB and quantile regression decompositions to 2018 ASHE data, research estimates that while a significant portion of the GPG in public sector jobs covered by Pay Review Bodies remains unexplained, it is smaller than in the private sector (Jones and Kaya, 2019). In the public sector, 21% of the GPG is attributed to differences in observable human capital characteristics, with the remainder unexplained. By contrast, in the private sector, just over half of the GPG is estimated to be explained by such factors. These findings raise questions regarding the effectiveness of additional public sector regulations in reducing the GPG and addressing potential discrimination. The quantile regression decomposition further indicates that the public sector GPG above the 80th percentile is entirely unexplained (Jones and Kaya, 2019), a pattern consistent with previous studies documenting a 'glass-ceiling' effect that disproportionately impacts highly educated women (Chzhen and Mumford, 2011).

2.4 Theoretical Approaches

2.4.1 Human Capital Theory

Human capital theory suggests that labour productivity depends not only on physical capital but also on the accumulation of human capital, which includes (the quantity and type of) education, training, skills, and work experience (Becker 1993[1964]; Mincer 1974). In a perfectly competitive labour market, employers pay employees based on their marginal contribution to output.[13] Individuals, in turn, invest in human capital to maximise lifetime earnings, continuing until the marginal benefit of investment equals its marginal cost. This process results in a concave earnings-age profile, reflecting diminishing returns to human capital accumulation over time. The accumulation of human capital has a profound impact on labour force participation and wage trajectories and is widely employed to explain pay gaps, such as those between college and high school graduates (Becker 1993[1964]) or between individuals with rare and common skill sets (Gibons and Waldman, 2004).

[13] The assumptions of a perfectly competitive market, including the presence of many buyers and sellers, price-taking firms that maximise profits, homogenous employees, and perfect information, are challenged on a number of counts (see Anderson et al. 2001 for an overview).

From the perspective of human capital theory, the GPG arises due to gender differences in human capital accumulation. Women's employment patterns, shaped by the unequal distribution of household and caregiving responsibilities, are more likely to involve career interruptions. These discontinuities reduce incentives for women to invest in education, training, and skills, as periods of labour market absence may lead to human capital depreciation (Becker, 1991; Mincer and Polachek, 1974; Polachek, 2004). Human capital accumulation also extends beyond the quantity of education to its type. Women are more likely to select fields of study associated with lower earnings potential, such as education and social sciences, whereas men are disproportionately represented in fields, which offer higher wage returns (Polachek, 1978). Additionally, part-time employment - a common choice among women balancing paid work and caregiving responsibilities - tends to offer fewer opportunities for human capital accumulation, further reinforcing the GPG (Corcoran et al., 1984).[14]

The implications of human capital theory extend to occupational choices (Polachek, 1976; Polachek, 1978; Polachek, 1979; Polachek, 2004; Mincer and Polachek, 1974). Women anticipating intermittent labour market participation may select occupations with lower penalties for employment interruptions. These occupations - often concentrated in feminised occupations, such as the so-called 'five Cs' (cleaning, catering, cashiering, clerical work, and caring; Grimshaw and Rubery 2007) - typically require less formal and informal training and therefore involve lower 'start-up' costs (Polachek, 1979). However, such roles also tend to be characterised by lower wages and limited career progression, further reinforcing the GPG. By contrast, men, who are less likely to anticipate employment interruptions, are more likely to enter occupations that require greater human capital investment and offer higher wage growth potential (Mincer and Polachek, 1974; Polachek, 2004). These gendered patterns contribute to both vertical and horizontal occupational segregation, contributing to wage gaps and poorer job quality for women relative to men.

Despite its widespread application, the human capital theory has been subject to critique. A key criticism is that it tends to naturalise existing gender relations by framing labour market outcomes as the result of individual choices rather than structural inequalities (Becker, 1985; Becker, 1991). This perspective risks overlooking the influence of social and institutional factors, such as cultural norms, employer discrimination, and unequal access to education, in shaping human capital accumulation and labour market outcomes (Lips, 2013; Figart, 1997). The theory also assumes that investment decisions are made freely and rationally, yet this may not hold for women, whose choices may be constrained by societal expectations, employer discrimination, and institutional structures (Pratt and Hanson, 1991). For instance, occupational segregation is not merely a reflection of individual human capital investment decisions but also shaped by broader structural and systemic factors (Becker 1985; Becker 1991).

[14] The impact of childbearing on women's earning may be mitigated by the availability and generosity of childcare policies, which can facilitate the reconciliation of paid employment with household responsibilities.

2.4.2 Labour Market Discrimination Models

Labour market discrimination models offer alternative theoretical approaches for gender inequality in labour market outcomes. The taste-based discrimination model suggests that discrimination arises from the preferences or biases of employers, employees, consumers or governments. These tastes create a willingness to 'pay or forfeit income for [the] privilege' of avoiding or minimising contact with certain groups (Becker 1957, p.14). In the case of gender discrimination, employers may perceive women as more costly than equally productive men, incorporating gender into their utility functions via discrimination coefficients. This leads to higher hiring costs for women, wage premiums for employees with discriminatory preferences, and lower utility for biased customers who interact with female workers.

The model predicts that wage differences between groups may not always materialise if the labour market contains a sufficient number of non-discriminatory participants, leading instead to workplace segregation. However, wage gaps arise when discriminatory preferences coincide with observable group differences. In the absence of significant segregation costs, taste-based discrimination has a limited impact on the GPG (Becker, 1957; Jones and Kaya, 2019).[15] Importantly, in perfectly competitive markets, taste-based discrimination should theoretically be eliminated over time, as non-discriminatory employers who do not experience utility losses, can expand their market share or acquire the assets of discriminatory competitors (Becker, 1957). However, critics argue that discrimination can persist even in competitive markets due to imperfect information, search frictions, and other structural barriers (Arrow, 1973; Altonji and Blank, 1999).

The statistical discrimination model offers an alternative explanation, arguing that employers may engage in rational discrimination when information about the productivity or marginal revenue product of potential employees is incomplete or costly to obtain (Phelps, 1972; Arrow, 1973). In such cases, easily observable characteristics, such as gender or race, may be used as proxies for unobservable productivity, leading to systemic bias (Phelps, 1972). For instance, employers may offer women lower wages based on assumptions about career interruptions or caregiving responsibilities, reinforcing the GPG. Even if average productivity of women and men is identical, discrimination may arise if productivity variance differs. Risk-averse employers may prefer hiring individuals from the group with lower variance to minimise the likelihood of hiring an underperforming worker (England, 1992).

Unlike taste-based discrimination, statistical discrimination may persist even in competitive markets. While improvements in information systems and competition should reduce information asymmetries over time (Aigner and Cain, 1977; Black, 1995;

[15]The original model assumes theses preferences are exogenous, though Becker (1957) briefly acknowledges the role of contact duration, group size, and economic significance in shaping tastes for discrimination. However, this was not fully developed into a dynamic framework.

Blau and Kahn, 1997), statistical discrimination can become self-reinforcing. If employers' beliefs about gender differences influence hiring and promotion decisions, this may affect individual's incentives to invest in skills, reinforcing the initial bias (Coate and Loury, 1993; Arrow, 1973). For example, if women are not promoted or are unable to access higher-paying positions due to assumptions about family-related absences, they may rationally invest less in career development, confirming employers' initial biases.[16]

Beyond these models, structural and collective discrimination models offer alternative explanations for gender differences in the labour market. The crowding model argues that the exclusion of women from certain occupations leads to their overrepresentation in a limited number of occupations, increasing labour supply and driving down wages (Bergmann, 1974). Discrimination may be more pronounced in occupations where social norms reinforce group differences or where individuals from discriminated groups have preferences for certain occupations (Altonji and Blank, 1999). However, for crowding-induced wage gaps to persist, occupational segregation must remain static: otherwise, profit-maximising employers would substitute cheaper 'crowded' labour for more expensive labour in 'uncrowded' occupations with equal productivity, reducing wage gaps. Legal and institutional barriers may further exacerbate occupational segregation by restricting access to certain professions. Pre-labour market factors, such as gender differences in education, also contribute to its persistence. While occupational segregation is often linked to human capital theory, it is not entirely independent of labour market discrimination (Altonji and Blank, 1999). Crowding effects may also be more pronounced in local labour markets where constraints, such as limited spatial mobility further restrict women's employment opportunities, reinforcing occupational segregation (Anderson et al. 2001, discussed further in Section 4.3.1).

2.4.3 Monopsony

Monopsony provides another theoretical approach for understanding persistent gender gaps in labour market outcomes (Robinson, 1933). In a perfectly competitive labour market, employers face a fixed wage rate at which they can hire any number of workers. They have no ability to lower wages without losing workers, nor do they have an incentive to raise wages above the market rate. In contrast, a monopsonistic labour market is characterised by an upward-sloping labour supply curve, requiring firms to raise wages to attract additional workers. However, since wage increases must also apply to existing employees, the marginal cost of labour is greater than the marginal wage rate. As a result, firms employ workers only up to the point where the marginal productivity of labour equal its marginal cost, suppressing wages below competitive equilibrium. The extent of this wage suppression depends on labour supply elasticity: the lower the elasticity, the greater the employer's ability to set wages below marginal productivity.

[16]Distinguishing between taste-based and statistical discrimination presents empirical challenges, though evidence suggests that both forms coexist (Altonji and Blank, 1999).

Although pure monopsony - where a single employer dominates the labour market - is rare, most firms possess some degree of monopsony power. Workers do not immediately leave their jobs in response to wage reductions, allowing employers discretion in wage-setting. Monopsonists exploit workers with a relatively inelastic labour supply by setting wages below their marginal revenue product but equal to or above their reservation wage. Women, on average, tend to have more inelastic labour supply than men due to (real or perceived) preferences for amenities, higher commuting costs, smaller search gains, or constraints related to the size of the local labour market (Hirsch, 2009; Manning, 2003; Black, 1995; Barth and Dale-Olsen, 2009). These constraints disproportionately affect women, as household responsibilities often limit their job choices in terms of location and working hours. Consequently, women find it harder to leave their current employer, reducing their bargaining power and ability to secure alternative job offers. This higher degree of monopsony power over female workers contributes to lower wages and the persistence of the GPG.

While some evidence suggest female labour supply elasticity is at least as high as that of males, monopsony power can still apply at the firm level, where each employer faces an upward-sloping labour supply curve (Manning, 2003; Barth and Dale-Olsen, 2009). Within standard job-to-job search models, labour markets are often segregated into distinct occupational groups with limited short-term mobility. In such markets, firms account for turnover and search frictions when setting wages, which vary according to gender differences in labour supply elasticity (Manning, 2003; Barth and Dale-Olsen, 2009). These asymmetries explain persistent wage gaps even if aggregate labour supply elasticity is similar across genders. As a result, Robinsonian discrimination - where firms exploit differences in worker mobility and bargaining power - is now recognised as a widespread phenomenon in real labour markets (Hirsch et al., 2010, p. 293).

2.5 Empirical Methodologies[17]

2.5.1 Mincerian Wage Equations

Minceriam wage equations are widely used in empirical labour economics as a framework for analysing individual wage determinants, wage distributions, and wage gaps (Mincer, 1958; Mincer, 1974). Rooted in human capital theory (Section 2.4.1), these equations estimate the impact of factors, such as education, work experience, and occupation, on

[17]The study of gender inequality in the labour market increasingly relies on quantitative methodologies to identify its drivers and evaluate the effectiveness of policies. While early feminist critiques argued that 'positivist' quantitative methods failed to adequately capture the lived experiences of women and lacked an intersectional perspective (Mies, 1983; Bowles and Duelli Klein, 1983; Stanley and Wise, 1983), such criticisms often underestimate the potential of these methodologies. Quantitative approaches facilitate the systematic measurement and analysis of gender gaps, identifying the mechanisms of selection and exclusion that shape gender inequality and underlying structural forces (Scott, 2010). Experimental methodologies have gained prominence in labour market research, though they have unique challenges (see Neumark 2018 for a survey of experimental studies on economic discrimination).

wages.[18] The standard functional form of the Mincerian wage equation is given by:

$$\ln W_i = \beta_0 + \boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i \tag{2.2}$$

where the natural logarithm of (hourly, weekly, monthly) wages of individual i (lnW_i) is regressed on a vector of explanatory variables, $\mathbf{X}_i$. The constant term (β_0) reflects baseline wages, while $\boldsymbol{\beta}$ represents the estimated returns to these characteristics. The residual term (ε_i) accounts for unobserved factors and is assumed to follow a normal distribution ($\varepsilon_i \sim N(0, \sigma^2)$). The log-linear structure is widely adopted as it normalises the positively skewed earnings distribution, facilitating the interpretation of explanatory variables in terms of percentage changes in wages.

To analyse the GPG, the standard wage equation is extended to include a female dummy variable, F_i, which equals one when individual i is female and 0 when male:

$$\ln W_i = \beta_0 + \alpha F_i + \boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i \tag{2.3}$$

where α, the coefficient on the female dummy variable, represents the adjusted GPG in log percent, capturing the expected difference in log wages between women and men after controlling for observable productivity-related characteristics. In the absence of additional explanatory variables, α provides an estimate of the raw GPG.[19]

Despite their widespread use in quantifying wage gaps, Mincerian wage equations are subject to several methodological limitations, including omitted variable bias, measurement errors, and unobserved heterogeneity. One key concern is sample selection bias, as only observed wages are included in the estimation. If women are disproportionately excluded from the labour market, the estimated GPG may be understated (Chzhen and Mumford, 2011). To address this bias, researchers commonly employ wage imputation techniques for non-participants (Blau and Kahn, 2006) or apply Heckman's two-step correction procedure (Heckman, 1979).[20] Another limitation is the reliance on a single gender dummy variable, which assumes that the returns to explanatory variables ($\widehat{\boldsymbol{\beta}}$) are identical for women and men. This assumption oversimplifies the complex ways in which gender interacts with social norms, institutional structures, and labour market dynamics (Figart, 1997). While interaction terms between gender and key explanatory variables can partially address this limitation, they do not fully capture the systemic and dynamic nature of gender gaps.

[18] While the choice of explanatory variables in wage equations depends on data availability, there is broad consensus that key factors such as hours worked, occupation, and sector should be included as controls (see discussion in Blau and Kahn 2017).

[19] Figure A.1, Appendix A, presents a graphical representation of the adjusted GPG estimation using a Mincerian wage equation that controls for education, measured in years of schooling. The vertical distance between male and female regression lines represents the adjusted GPG, α.

[20] Heckman's two-step procedure introduces a selection equation to model labour force participation, correcting for potential bias arising from non-random employment decisions (Heckman, 1979).

Despite these critiques, Mincerian wage equations remain a key tool in labour economics due to their methodological simplicity, adaptability, and ability to facilitate cross-sectional and longitudinal comparisons of wage gaps. The empirical Chapters of this thesis build upon Mincerian wage equations to analyse gender gaps across labour markets. By systematically quantifying raw and adjusted GPGs, this approach suggests underlying drivers of GPGs and provides empirical evidence to inform policies aimed at reducing gender inequality in the labour market.

2.5.2 Decomposition Methods

Building on the Mincerian wage equation framework, decomposition methods provide an approach to analyse the drivers of GPGs. One of the most widely used is the OB decomposition (Oaxaca, 1973; Blinder, 1973), which decomposes the average wage difference between two groups - typically males and females ($s \in \{$ male (M) and female $(F)\}$) - into an explained and an unexplained component. Formally, this is achieved by first estimating gender-specific Mincerian wage equations (Equation 2.2):

$$\ln W^s = \beta_0^s + \boldsymbol{\beta}^s \mathbf{X}^s + \varepsilon^s, \tag{2.4}$$

where the notation follows from above, the subscript i is omitted for simplicity, and $\boldsymbol{\beta}^s$ represents the vector of returns to characteristics, which varies by gender s. By adopting a counterfactual approach, the OB decomposition expresses the mean wage difference as:

$$\underbrace{\ln \overline{W}^M - \ln \overline{W}^F}_{\text{Observed GPG}} = \underbrace{(\overline{\mathbf{X}}^M - \overline{\mathbf{X}}^F)\widehat{\boldsymbol{\beta}}^M}_{\text{Explained component}} + \underbrace{(\widehat{\boldsymbol{\beta}}^M - \widehat{\boldsymbol{\beta}}^F)\overline{\mathbf{X}}^F + (\widehat{\beta}_0^M - \widehat{\beta}_0^F)}_{\text{Unexplained component}} \tag{2.5}$$

where a bar above a variable denotes its mean value, and $\widehat{\boldsymbol{\beta}}^s$ is the OLS estimate of $\boldsymbol{\beta}^s$. The explained component captures the portion of the GPG attributable to gender differences in observable characteristics ($\overline{\mathbf{X}}^M - \overline{\mathbf{X}}^F$), while the unexplained component reflects gender differences in returns to these characteristics ($\widehat{\boldsymbol{\beta}}^M - \widehat{\boldsymbol{\beta}}^F$), including differences in intercepts ($\widehat{\beta}_0^M - \widehat{\beta}_0^F$)), which account for group membership effects.

The unexplained component is often interpreted as an upper-bound estimate of labour market discrimination. However, since it also captures unobserved heterogeneity and omitted variables, its interpretation is constrained by data limitations and the potential influence of unmeasured factors. These limitations are well-established in the literature (see Neumark 2018 for a discussion).

Equation 2.5 is typically estimated with men as the reference group, based on the assumption that male wages reflect competitive labour market outcomes. This means that the specification estimates the adjustment needed for women's wages to converge with men's wages. Alternatively, the decomposition could easily be formulated using women as the reference group, which would change the relative magnitudes of the explained and unexplained components, due to the choice of the wage structure used for counterfactual estimation. This classic index problem does not affect the overall size of the mean GPG but influences the decomposition's interpretation. To address this issue, most empirical evidence uses men as the reference group to ensure comparability and then explore the sensitivity of the results to using women as the reference group. The OB decomposition can also be extended by employing pooled wage equations, weighting techniques, or reweighting distributions to account for general equilibrium effects arising from labour market adjustments (Jann, 2008; Firpo, 2017).

Despite its widespread use, the OB decomposition has several limitations. A key limitation is its focus on mean wage gaps, which overlooks potential heterogeneity across the wage distribution. Alternative decomposition methods address this limitation by disaggregating workers based on observable characteristics (e.g., the Brown-Moon-Zoloth decomposition, Brown et al. 1980) or by employing quantile regression decomposition to analyse the GPG at various points of the wage distribution (e.g., Machado and Mata 2005).

Another decomposition method is the Juhn-Murphy-Pierce (hereinafter, JMP) decomposition (Juhn et al., 1991), which is particularly relevant for this thesis as it extends the OB framework to analyse the GPG across areas or over time. The JMP decomposition incorporates residual wage dispersion, distinguishing between price and quantity effects in explaining wage differences and to assess the relative importance of gender-specific factors and wage structures in shaping the GPG. Specifically, the JMP decomposition decomposes the GPG across areas or over time into gender differences in observable characteristics, differences in male returns to these characteristics, differences in the relative wage positions of men and women after controlling for characteristics, and changes in male residual inequality across areas or time periods.[21,22]

2.5.3 Experimental and Quasi-Experimental Approaches

Beyond traditional wage equations, experimental, and quasi-experimental approaches have become increasingly prominent in the study of gender inequality in the labour market, partly as a response to the limitations of purely regression-based approaches

[21] For examples of the JMP decomposition over time, see Blau and Kahn (1997); for analyses across areas, see Jones and Kaya (2022b) and Murillo Huertas et al. (2017).

[22] Following the OB decomposition, the JMP decomposition typically employs the male wage equation as the reference, assuming that male coefficients represent competitive market prices in the absence of discrimination, as they are considered less sensitive to variations in gender discrimination across different contexts (Jones and Kaya, 2022b). While widely used in the literature (e.g., Blau and Kahn 1997; Jones and Kaya 2022a), this assumption has been critiqued (see Yun 2009). Additionally, there is debate over whether to use the full distribution of male and female residuals. This approach has been criticised for assuming identical residual distributions across genders (Yun, 2009) and for potential dependence between residual standard deviation and percentile ranking (see Suen 1997 and Blau and Kahn 1997), though this dependency is not always evident empirically (Kaya, 2023).

outlined above.[23] Among experimental approaches, field experiments, including audit and correspondence studies, are commonly used to measure discrimination in hiring. These studies compare employer responses to job applications that are identical in all respects except for a specific characteristic, such as gender (Bertrand and Mullainathan, 2004) or disability (Antinyan et al., 2024). By contrast, lab experiments provide a controlled setting in which to explore behavioural mechanisms that contribute to gender differences in labour market outcomes, such as differences in job application success rates (e.g., Correll et al. 2007). A comprehensive review of experimental approaches in labour economics is provided by Neumark (2018), who discusses their strengths in isolating causal effects while also acknowledging their limitations, such as concerns over external validity and ethical constraints.

By contrast, quasi-experimental approaches have become central to exploring gender inequality in the labour market, particularly for evaluating policies. These approaches provide a framework for estimating causal effects in the absence of randomised controlled trials by exploiting naturally occurring or policy-driven variations in treatment exposure. By closely mimicking experimental conditions, quasi-experimental methods allow policymakers to assess the effectiveness of policies in real-world settings while maintaining high external validity. Two of the most widely used quasi-experimental approaches in labour economics are the RDD and DiD approaches.[24]

The RDD approach estimates causal effects in settings where treatment assignment is determined by a cutoff in an observed continuous variable that determines policy eligibility. This method compares outcomes for individuals just above and below the cutoff, under the assumption that these individuals are similar in all aspects except for their treatment status. The validity of causal inference in RDD approaches relies on the assumption that individuals cannot precisely manipulate their position relative to the cutoff and that no other discontinuities affect the outcome of interest. While RDD approaches provide internally valid and highly credible estimates, their primary limitation is that findings are localised to individuals near the cutoff, limiting external validity and generalisability.

The DiD approach is particularly well-suited for evaluating policy changes or interventions over time. It compares changes in outcomes between a treatment group (affected by a policy) and a control group (unaffected by a policy) before and after policy implementation. The key identifying assumption is the common trends assumption, which requires that in the absence of the policy, the difference in outcomes between the two groups would have remained constant over time. By controlling for both time-invariant group differences and common time trends, the DiD approach

[23] Qualitative approaches, including interviews, ethnographic studies, and case studies, provide insights into the lived experiences of workers and the structural and cultural drivers of gender inequality in the labour market. However, these methods do not permit causal inference and are therefore distinct from the approaches discussed in this section.

[24] See Section 5.3 for a discussion of each approach in the childcare policy evaluation literature and Section 5.3 for empirical applications.

provides a framework for causal inference. However, its validity depends on the correct specification of treatment effects and the absence of differential pre-trends between treatment and control groups.

2.6 Drivers of the Gender Pay Gap

2.6.1 Evidence from Cross-Country Research

Cross-country research has significantly advanced the understanding of the underlying drivers of the GPG. However, this research faces challenges in harmonising data across countries and disentangling the effects of institutional and cultural factors from economic and demographic drivers (Murillo Huertas et al., 2017). A consistent finding in this literature is the role of wage-setting institutions, such as national minimum wages and collective bargaining mechanisms (including their coverage of non-union workers (Blau and Kahn, 1999)), in shaping GPGs. In general, centralised wage-setting institutions reduce overall wage dispersion (Rowthorn, 1992; Blau and Kahn, 1996a), which can reduce the GPG by limiting wage variation across gender-segregated industries and firms. Since female wage distributions consistently lie below male distributions across countries, centralised systems that consciously raise minimum pay levels tend to reduce the GPG (Blau and Kahn, 2003; Deakin et al., 2015).

There is considerable variation across countries in the degree of wage centralisation and labour market regulation. Classifying countries as 'largely unregulated', 'broadly regulated', or 'highly regulated',[25] a comparative study of GPGs across 26 EU member states estimates that median GPGs are significantly higher in less regulated labour markets than in those with broadly or highly regulated labour markets (Christofides et al., 2013). Similarly, wage dispersion was found to explain the majority of the higher mean GPG in the US relative to nine other industrialised countries, based on harmonised data from the International Social Survey Programme from 1985–1989 (Blau and Kahn, 1996b).

National minimum wages are another wage-setting institution that can influence the GPG by compressing the lower end of the wage distribution (DiNardo et al., 1996). For instance, the decline in US minimum wages between 1979 and 1988 has been identified as contributing to the widening of the GPG during this period (Blau and Kahn, 1999). However, a cross-country analysis across 22 countries suggests that the direct impact of minimum wages on the GPG is modest and diminishes once collective bargaining features are considered (Blau and Kahn, 2003). Increasing collective bargaining coverage from the 25th to the 75th percentile was estimated to reduce national GPGs by 0.10 log

[25] This classification is based on the index developed by Du Caju et al. (2009), which considers trade union density, the level of bargaining, the average length of collective bargaining agreements, and the extent of coordination. The UK, for example, is classified as largely unregulated.

points (ibid.). Nonetheless, the impact of minimum wages on the GPG varies across sectors, industries, wage distributions, and levels of non-compliance (Schäfer and Gottschall, 2015; Arulampalam et al., 2007; Bargain et al., 2019). For example, a quantile regression decomposition of the GPG in the UK (using 1999 BHPS data) and Ireland (based on the 2001 Living in Ireland survey) estimated that the introduction of minimum wages significantly reduced the GPG at the lower end of the wage distribution in Ireland. In contrast, its effect in the UK was negligible, likely due to non-compliance with minimum wage legislation (Bargain et al., 2019).[26]

Evidence from 25 European countries indicates that high collective bargaining coverage and levels of national minimum wages improve gender pay equity among full-time employees, using 2009 EU Statistics on Income and Living Conditions data (Schäfer and Gottschall, 2015). However, the effectiveness of these institutions depends on the level of wage bargaining and union strength. For example, sectoral bargaining in Germany's manufacturing, finance, and health sectors appeared less beneficial for women compared to more localised bargaining arrangements. Additionally, a strong union presence may negatively impact women's earnings, potentially due to male bias in unionised wage-setting mechanisms (ibid.). Supporting this, an analysis of six European countries found that declining union density between 1993 and 2008 corresponded to a larger gap effect in JMP decompositions, indicating an improvement in women's relative wage rankings within the male residual wage distribution (Kaya, 2023). These findings imply that declining unionisation may have disproportionately impacted male workers, contributing to a narrowing of the GPG. Similarly, in the US, a JMP decomposition of the GPG using data from the Panel Study of Income Dynamics suggested that reductions in union strength between 1979 and 1988 narrowed the GPG (Blau and Kahn, 1997).

The impact of wage-setting institutions on the GPG also varies across the wage distribution. A quantile regression analysis of 11 European countries, using data from the European Community Household Panel between 1995 and 2001, identifies differences in wage-setting mechanisms, such as union membership and work-family reconciliation policies, as partial explanations for cross-country and sectoral disparities in GPGs (Arulampalam et al., 2007). Unions, which are often less prevalent at the lower end of the wage distribution, may inadequately represent the interests of low-wage workers. In contrast, the GPG in the public sector is consistently narrower, likely due to wage compression policies that cap high salaries and ensure better remuneration for low-skilled workers (Arulampalam et al., 2007; Korpi et al., 2013).

Cross-country research also highlights the influence of gender-specific policies in shaping labour market outcomes.[27] International variation in these policies is more pronounced

[26] Evidence indicates that the introduction of the national minimum wage in Britain narrowed the GPG across regions, reflecting the spatial distribution of low-paid workers (Robinson 2005, discussed in Section 3.3).

[27] These policies, often referred to as 'women-friendly', aim to promote female labour force participation and reconcile household responsibilities with paid employment, particularly for mothers. However, this term encompasses a broad array of policies, some of which may have contradictory effects on women's employment (discussed

than differences in women's relative human capital levels, particularly among developed countries (Blau and Kahn, 2003). While the expected positive effects of equal employment and anti-discrimination laws on gender equality are relatively unambiguous, the impact of family-friendly policies, such as childcare and parental leave, is more complex. These policies may enhance women's relative earnings and labour force participation by improving work-life balance, but they may also lengthen labour market absences, increasing the perceived cost of employing women, and leading to discrimination in hiring or wages (see Blau and Kahn 2003, Mandel and Semyonov 2005, and Section 4.3 for a fuller theoretical discussion).

Empirical evidence supports this ambiguity. Using hierarchical linear models and data from the Luxembourg Income Study and country-level data from 20 countries, the GPG is estimated to be less pronounced in countries with well-developed family policies, such as Sweden and Norway (Mandel and Semyonov, 2005). However, controlling for cross-country differences in wage structures shows that family-friendly policies can exacerbate occupational segregation and wage disparities among higher-income groups, contributing to the emergence of 'welfare state based glass ceilings' (Datta Gupta et al., 2006b; Korpi et al., 2013). Specifically, in family-friendly policy contexts, highly educated women may have reduced opportunities to attain high income positions (Korpi et al., 2013), while long-term and generous family policies may increase earnings inequality among skilled women (Mandel, 2012). Despite this, quantile regression analyses of the GPG across EU member states indicate that, apart from maternity leave, family-friendly policies are generally associated with lower mean and median GPGs, largely due to their impact on the unexplained GPG component (Christofides et al., 2013). However, these benefits tend to be concentrated at the upper end of the wage distribution, while more generous work-family reconciliation measures at the lower end suppress wages by facilitating labour market entry for previously inactive women. This suggests that the impact of such policies varies along the wage distribution, benefiting some segments of the labour force more than others. Further, a comprehensive meta-analysis suggests that the negative effects of family-friendly policies on women's labour market outcomes may be overstated. Other elements of the policy and legal frameworks, beyond explicit family- or women-friendly measures, likely interact with wage distributions and individual characteristics (Korpi et al., 2013).

Cross-country research also identifies that higher levels of female employment are associated with larger GPGs (Blau and Kahn, 1996b; Blau and Kahn, 2000; Blau and Kahn, 2003; Olivetti and Petrongolo, 2008; Simón, 2012). This may arise because countries with high female labour force participation often have more women entering the labour force at the lower end of the income distribution. Conversely, countries with lower female employment rates, such as Spain or Italy, tend to have smaller GPGs, as the women who participate in these labour markets are generally more highly educated

further in Section 4.3). As such, this umbrella term does not fully capture the multidimensional aims and effects of individual policy measures (Korpi et al., 2013).

and career-oriented. Using data from the European Community Household Panel Survey between 1994 and 2001, Olivetti and Petrongolo (2008) demonstrate that female labour force participation is a key driver of GPG differences between Anglo-Saxon and Southern European countries, showing that national GPGs are negatively correlated with gender employment gaps, consistent with positive selection of women into employment. However, in countries with relatively high female employment rates, such as the UK, selection effects on the GPG are minimal. This suggests that gender employment gaps explain a substantial portion of the observed negative correlation between gender wage and employment gaps.

2.6.2 Evidence from UK Research

UK evidence identifies individual characteristics, work-related characteristics, occupational segregation, and household responsibilities as the primary drivers of the GPG (see for instance, Razzu 2014 and Olsen et al. 2018 for comprehensive reviews). Cross-country studies similarly highlight these factors as key drivers of the international variation in the GPG. However, their impact may be underestimated due to institutional and policy differences across countries (Schäfer and Gottschall, 2015), as well as the relative consistency of women's human capital levels in developed countries (Blau and Kahn, 2003). Instead, there is increasing recognition that within-country variations in GPGs, driven by differences across sectors, workforce compositions, and wage-setting mechanisms, may be as significant as cross-country variation (Rubery et al., 2005; Schäfer and Gottschall, 2015). Despite this, recent decompositions of the UK GPG suggest that a substantial portion remains unexplained, with its magnitude varying across the wage distribution and different sectors (Chzhen and Mumford, 2011; Jones and Kaya, 2019).

Despite differences in data and methodology, UK evidence consistently indicate that individual characteristics traditionally associated with human capital theory have a minimum and diminishing role in explaining the contemporary GPG, despite their continued importance in determining overall wage levels (Olsen and Walby, 2004; Olsen et al., 2018; Swaffield, 2007; Mumford and Smith, 2009). Longitudinal analysis of the BHPS and Understanding Society data estimate that education explained 9.2% of the mean GPG in 1997, 6.6% in 2007 and -4% in 2014-15 (Olsen and Walby, 2004; Olsen et al., 2010; Olsen et al., 2018). This decline reflects women's relative gains in education over time, with women in the UK now outperforming men in terms of grades, qualifications, and participation in tertiary education (Department for Education, 2017), a trend also observed across other OECD countries (Goldin et al., 2006; Blau and Kahn, 2006). Further evidence from three British cohort studies suggests that while education acted as a protective factor for individuals born in 1970 at the age of 30, this was not the case for earlier cohorts born in 1946 and 1958 (Joshi et al., 2007).

Despite the reversal of the gender educational gap, gender differences in subject choices and educational quality continue to contribute to the UK's GPG. Using 1996 LFS data, an OB decomposition of early career graduates estimated that the explained component of the GPG increased from 23.9% to 56% when degree type was controlled for (Machin and Puhani, 2003). Similarly, a cohort study of individuals born in 1985 and 1990 estimated that degree major explained 16% of the national GPG and reduced the unexplained GPG by 11.4% (Chevalier, 2002). These findings suggest that women are more likely to study subjects associated with higher risks of unemployment, over-education, and lower earnings potential, while men tend to graduate in subjects with greater financial returns (ibid., Jones and Kaya 2019). This gender difference may stem from social norms that discourage girls from studying certain subjects based on perceived abilities, while simultaneously pressuring boys to conform to traditional masculine norms (Nagy et al., 2006). These educational choices complicate the measurement of discrimination, as they may reflect both individual preferences and structural constraints in access to higher-return fields (Jones and Kaya 2019, see discussion in Section 2.4).

Other individual characteristics, including ethnicity, disability, personality traits, sexual orientation, and religion, also influence the UK's GPG (e.g., Bryson 2017; Jones et al. 2006; Jones 2008; Longhi and Platt 2008; Longhi and Brynin 2017; Longhi 2017). Ethnicity intersects with gender in complex ways. Evidence suggests that while non-White men generally earn less than White men, non-White women, on average, earn more than White women and men of the same ethnicity (Longhi and Brynin, 2017). This pattern is partially explained by non-White women having higher qualifications and being concentrated in high-wage occupations and regions. However, administrative data from the English NHS suggest variation in the GPG across ethnic groups (Appleby et al., 2021), highlighting the role of racial inequality in shaping the national GPG (Breach and Li, 2017).[28] Similarly, disability is associated with substantial pay penalties that likely exacerbate the GPG (see Jones 2008 for a review). Using pooled QLFS data from 2004-2007, disabled men and women were estimated to experience pay gaps of 11% and 22%, respectively, relative to non-disabled men, suggesting that disabled women face additional challenges and discrimination (Longhi and Platt, 2008). Further evidence from the LFS suggests that the gendered impact of disability has worsened over time, with potential gender differences in the impact of various disabilities on earnings (Jones et al., 2006). Additionally, pay gaps are found to vary on the type and severity of disability (Longhi, 2017).

Beyond observable individual characteristics, limited evidence suggests that personality traits, labour market motivations, and non-cognitive skills are also drivers of the GPG in the UK, although their role is minimal. While early research suggested that personality traits could explain a large portion of the GPG (Chevalier, 2002), more

[28] Data limitations often prevent further disaggregation of ethnicity beyond broad categories, despite the importance of recognising the lived experiences of individuals from different ethnic groups.

recent evidence indicates that their impact is minimal. For example, using combined data from the BHPS and the British Cohort Study from 1991-2002, self-esteem and control were estimated to explain only 1-2 log points of the GPG for employees after a decade in the labour market (Manning and Swaffield, 2008). This is attributed to the relatively small gender differences in personality traits and their limited impact on earnings disparities. Additional evidence from a decomposition of BHPS data suggests that while gender role values impact female wages, they are not a main driver of the national GPG (Swaffield, 2007).

Gender differences in work experience, and relatedly, labour market absences, explain a large proportion of the UK's GPG, consistent with predictions from human capital theory (Jones and Kaya, 2019; Olsen et al., 2018; Mumford and Smith, 2009). For example, analyses using Understanding Society data estimate that gender differences in work experience explain up to 56% of the national GPG (Olsen et al., 2018). Similarly, an OB decomposition of BHPS panel data from 1991-1997 suggests that incorporating detailed measures of labour market experience reduces the unexplained component of the GPG by almost 40% (Swaffield, 2007). However, survey data do not routinely collect comprehensive measures of work experience. Instead, proxies such as age or potential work experience (typically calculated as age minus years of formal education and early childhood years) are commonly used (e.g., Mumford and Smith 2009). These proxies may overestimate actual work experience for individuals with prolonged labour market absences, such as long-term unemployed individuals and mothers, potentially leading to an underestimation of the role of work experience in the GPG (Mumford and Smith, 2009; Jones and Kaya, 2019).

The prevalence of part-time work among women is another key driver of the UK's GPG, as part-time employment is associated with lower human capital accumulation compared to full-time work (Corcoran et al., 1984). Existing research indicates that part-time employment is associated with lower wages, poorer job quality, and occupational downgrading and segregation (Grimshaw and Rubery, 2007; Jones and Kaya, 2019; Mumford and Smith, 2009; Manning and Petrongolo, 2008). Using 2004 WERS data, an OB decomposition estimated that 7.1 log percentage points of the pay gap between full-time and part-time female employees were attributable to full-time employees working in higher paying occupations and having more productivity enhancing individual and workplace characteristics. The remaining 10.8 log percentage points of the gap resulted from lower returns to these characteristics (Mumford and Smith, 2009). However, evidence from the early 2000s suggested that part-time work experience had a limited impact on wages and did not significantly explain the GPG (Joshi et al., 2007; Olsen and Walby, 2004). More recent analysis using Understanding Society data suggests that part-time employment mitigated the GPG by 20% compared to men with similar part-time work histories (Olsen et al., 2018). This shift is partly attributable to an increasing proportion of previously full-time female employees transitioning into comparable part-time roles as a means of job retention.

Crucially, part-time employment and time out of the labour market are closely linked to parenthood, particularly among women. The effects of part-time work on wages and career progression cannot be fully understood without considering the role of childcare responsibilities and family-related career interruptions. Section 5.2.1 provides further discussion of the significant differences in labour market outcomes between individuals with and without dependent children, as well as the gendered nature of these differences in the UK. Section 5.3 provides empirical evidence of the role of childcare policy on mitigating these gender differences.

Other work-related characteristics also contribute to explaining the UK GPG, although to varying degrees. While temporary contracts are more prevalent among women and associated with lower earnings than permanent employment (Arulampalam et al., 2007), an OB decomposition of repeated cross-sectional LFS data from 1993 to 2014 estimated that temporary contracts explained a negligible portion of the GPG (Brynin, 2017). Similarly, job tenure, which reflects skills acquired through on-the-job training and influences career progression, has a limited role in explaining the national GPG, despite women generally having shorter job tenure due to career interruptions (Brynin, 2017). Trade union membership, which is higher among women and particularly prevalent in the public sector (Bryson and Forth, 2017; Webb et al., 2019), is estimated to have a wage premium of around 10% (Bryson, 2014). While this has contributed to narrowing the GPG, its impact was small, estimated at 1.2% in 2014/15 Understanding Society data (Olsen et al., 2018).

Firm size and workplace characteristics also contribute to the UK's GPG, although their effects are complex and sometimes contradictory. While larger firms historically offered wage premiums, recent evidence suggests these premiums are diminishing (Bloom et al., 2018; Even and Macpherson, 2012). Analysis combining data from the 1991 BHPS, the General Household Survey of 1983, and the 1984 and 1990 Workplace Industrial Relations Surveys indicates that firm size effects are more pronounced for women in the private sector than for men, with women facing a greater wage penalty for employment in smaller firms (Green et al., 1996). More recent analysis using ASHE 2002-2016 data estimate that firm-specific wage effects account for approximately 16% of the UK GPG, as men are more likely to be employed by higher-paying firms (Jewell et al., 2020).[29] Additionally, evidence from WERS data suggests that workplace segregation, measured as the percentage of female employees within a workplace, explains 29.1% of the GPG (Mumford and Smith, 2009).

Occupational segregation, both horizontal (across industries) and vertical (within organisational hierarchies), is consistently identified as a significant driver of the GPG in Britain (Mumford and Smith, 2007; Mumford and Smith, 2009; Olsen et al., 2010; Olsen et al., 2018). However, its magnitude varies depending on the measure used, and there is ongoing debate regarding the extent to which it reflects discrimination rather than

[29] This analysis applied the decomposition method proposed by Gelbach (2016) to isolate the contribution of employer-specific wage effects to the GPG after adjusting for observable characteristics.

individual choices (e.g., Blau and Kahn 2000; see discussion in Section 2.4). Using a measure based on the percentage of men in occupations, OB decompositions of BHPS and Understanding Society data estimate that occupational segregation explained 15% of the national GPG in 1997, rising to 19% in 2014/15 (Olsen et al., 2010; Olsen et al., 2018). Alternative estimates derived from WERS and LFS data suggest a declining role of occupational segregation, likely reflecting broader societal changes over time (Brynin, 2017; Mumford and Smith, 2007), a trend also observed in the US (Blau and Kahn, 2000; Blau and Kahn, 2017). Additionally, evidence from 2004 WERS data indicates that occupational segregation, in combination with workplace segregation, plays a larger role in explaining the GPG among part-time employees than full-time employees (Mumford and Smith, 2009).

Vertical occupational segregation also contributes to the GPG, as men dominate high-status positions even within traditionally female-dominated occupations (Charles, 2003). Women are disproportionately concentrated in low-paid roles, including the so-called 'five Cs' (cleaning, catering, clerical, cashiering, and caring - Grimshaw and Rubery 2007), and face barriers to career progression, often referred to as the 'glass ceiling'. Evidence from the UK Skills Surveys and the EU KLEMS database indicates that men are more likely to perform tasks associated with technical change, managerial responsibilities, and financial decision-making, which are associated with higher wage returns, which in turn exacerbate the GPG (Lindley, 2012). Further, gender differences in industry allocation have been estimated to account for 29% of the national GPG in 2014/15, though the effect varies significantly by sector (Olsen et al., 2018).

Decomposition of the GPG in BHPS data from 1997-2015 suggest that public sector employment mitigates the GPG (Olsen et al., 2010), likely due to the public sector wage premium, which benefits women more than men (Jones et al., 2018; Blackaby et al., 2012b). Evidence from a decomposition of NES data from 1986-1995 attributes this to the centralisation of wage-setting in the public sector, which is estimated to have narrowed the overall GPG during this period (Grimshaw, 2000). However, an alternative decomposition of pooled 1997–2015 LFS data suggests that within-sector gender pay differentials are the primary determinant of the national GPG rather than gender differences in sectoral allocation. In the absence of within-sector GPGs, women would, on average, earn more than men (Jones et al., 2018).

The GPG in Britain has a distinct lifecycle pattern, varying significantly with age (e.g., Figure 4.1). At labour market entry, the GPG is estimated to be small and statistically insignificant but begins to widen for individuals in their mid-to-late 20s, particularly among university graduates. It continues to widen, peaking between the ages of 45 and 50, before narrowing again (Costa Dias et al., 2020). This pattern is largely driven by the sustained increase in male wages, particularly among highly educated men, alongside stagnation of female wages beyond their mid-20s. This age profile is often interrupted as a proxy for human capital accumulation, reflecting career interruptions and labour market penalties associated with parenthood. These penalties arise from career interruptions (Bertrand et al., 2010), the high wage penalties of career breaks and flexibility in high-wage occupations (Goldin, 2014), the impact of parenthood on occupational, sectoral, and firm choices (Kleven et al., 2019), and the tendency of mothers to shift to working part-time after the birth of a child (Costa Dias et al., 2020; Olsen et al., 2018). Each of these factors has asymmetric effects on men's and women's earnings, contributing to the widening GPG over the lifecycle (Rubery, 2008).

Empirical evidence from the UK consistently demonstrates that the GPG widens substantially following the birth of the first child (Harkness, 1996; Harkness, 2005; Rubery, 2008). Descriptive analysis of BHPS and Understanding Society panel data from 1991-2017 indicates that the GPG remains relatively stable at 7-12% before childbirth but subsequently increases steadily, reaching 33% as women transition into part-time employment, while men's labour market participation remains largely unaffected (Costa Dias et al., 2020). Alongside this, evidence from Understanding Society data between 2009 and 2014 suggests that broader household compositions and responsibilities further contribute to the GPG. The GPG is largest among married individuals, and time spent on housework is negatively correlated with hours worked. However, housework only appears to significantly impact wages when individuals spend more than 10 hours per week on housework, which applies to a relatively small proportion of the population (Brynin, 2017). This is discussed further in Section 4.6.3.

Finally, the estimated unexplained component of the GPG in the UK is consistently estimated to be significant, though its magnitude varies by data and method. An OB decomposition of pooled QLFS data from 2010 to 2014 estimates that over two-thirds of the national GPG is unexplained (Brynin, 2017). While this is often interpreted as a measure of wage discrimination (Section 2.5.2), such an interpretation has well-documented limitations (Neumark, 2018). In particular, this estimate is likely overstated due to the omission of key controls, such as industry and trade union status. Alternative estimates incorporating additional explanatory variables suggest that between 35% and 50% of the national GPG remains unexplained (Harkness, 1996; Olsen et al., 2010; Mumford and Smith, 2007; Mumford and Smith, 2009; Butcher et al., 2019), though these figure may still overstate the extent of labour market discrimination in the UK.

2.7 Conclusion

This review of international and British evidence on gender inequality in the labour market provides context for the empirical Chapters of this thesis. First, the choice of definitions, measurements, and data significantly impacts the estimation and comparison of the GPG and other gender gaps across space. Variations in methodology can contribute to inconsistencies in reported estimates, driving some of the variation in gender gaps across labour markets. Second, the UK's legislative framework has shaped the magnitude of gender gaps in the labour market. Policies such as the Equal Pay Act (1970), the Sex Discrimination Act (1975), and subsequent reforms, including gender pay gap reporting regulations, have influenced gender gaps. However, while these policies aim to reduce inequality, their effectiveness varies depending on enforcement mechanisms, sectoral differences, and interactions with broader labour market structures.

Third, theoretical approaches to gender inequality provide the basis for empirical methodologies used to study the GPG. Decomposition methods, such as the OB decomposition, are widely employed to distinguish between explained and unexplained components of GPGs. While the unexplained component is often interpreted as a measure of labour market discrimination, such an interpretation has well-documented limitations. Additionally, quasi-experimental approaches are useful to evaluate the effectiveness of policies aimed at reducing gender inequality in the labour market. Finally, both international and British empirical research provides evidence on the drivers of the GPG and its variation across labour markets. Cross-country comparisons highlight the role of institutional factors, such as the degree of wage centralisation, policies and labour market structures, in shaping gender gaps. UK-based research emphasises the importance of individual characteristics, work-related characteristics, occupational segregation, and household responsibilities in influencing gender gaps.

Chapter 3

Gender Pay Gaps across Areas in Britain

3.1 Introduction

The international variation in the GPG is well-documented (e.g., Figure 2.1 and discussion in Section 2.3). Cross-country research frequently employs established decomposition methods, such as the OB decomposition (Oaxaca, 1973; Blinder, 1973), to examine the drivers of raw GPGs, their spatial variation, and the extent to which they remain 'unexplained' by observable personal and employment-related characteristics.[1] These studies highlight the role of national wage structures, policy frameworks, and gender differences in both characteristics and their returns in shaping international disparities (e.g. Blau and Kahn 1996b; Blau and Kahn 2003; Christofides et al. 2013; see discussion in Section 2.6.1). Yet progress towards narrowing the gap has slowed (Kaya, 2023), including in the UK (Figure 2.2).

One limitation of cross-country studies is the difficulty of harmonising data across countries and accounting for unobserved heterogeneity. Given these challenges - and the growing recognition that within-country variation in the GPG can be as large as international differences - recent research has increasingly turned to subnational analyses. This approach makes it possible to examine whether the drivers of cross-country variation also explain disparities within countries, while holding institutional and cultural settings more constant.

The UK provides a valuable case for this type of analysis. National studies show that a substantial share of the GPG remains unexplained, even after accounting for selection into work (Chzhen and Mumford, 2011), firm characteristics (Mumford and Smith, 2009), firm-fixed effects (Jewell et al., 2020), and personality traits (Manning and

[1] The 'unexplained' component in wage decompositions is often interpreted as a measure of wage discrimination. However, this interpretation should be approached with caution, as its limitations are well recognised (Neumark 2018, Section 2.5.2).

Swaffield, 2008). The geographical dimension has also been acknowledged, but largely as a control: regional fixed effects are commonly used to capture differences in wage levels across areas (Butcher et al., 2019; Jones et al., 2018; Jones and Kaya, 2019; Mumford and Smith, 2009; Olsen et al., 2010). Beyond this, research has identified urban–rural differences in the GPG (Phimister, 2005), consistent with spatial monopsony models predicting smaller unexplained GPGs in more competitive labour markets (Hirsch et al., 2013). At the same time, the UK policy environment explicitly recognises the importance of geography: the government's 'levelling up' agenda (2019–2022) targeted spatial inequalities, while devolution has introduced distinct governance structures and gender equality policies across nations (Section 2.3).

Despite this, important gaps remain. First, much of the UK literature has treated geography as a background control rather than a central focus, leaving the spatial dynamics of the GPG underexplored. Second, existing within-country studies often emphasise regional or urban–rural divides, overlooking the potentially greater heterogeneity at smaller geographical levels. Third, while decomposition studies tend to highlight the unexplained component, less is known about the extent to which this varies on the basis of other spatial characteristics. This Chapter addresses these gaps by applying OB decompositions to 2022 ASHE data (ONS, 2022a), examining the GPG across Britain at three geographical levels: national, regional (11 NUTS 1 regions), and local (160 NUTS 3 regions) (see Section 2.2.3 for details). It contributes to the literature in three ways: (i) documenting the scale of intra-regional and local variation in the GPG, (ii) assessing the extent to which this variation reflects gender differences in productive characteristics versus unexplained components, and (iii) examining how local labour market characteristics — such as industrial structure, unemployment, and rurality — help to account for observed disparities. The analysis is guided by the following research question:

Why do gender pay gaps vary across areas in Britain?

The results reveal substantial variation in both the magnitude and determinants of GPGs across areas. Drivers well established in cross-country research (Section 2.6) are also found to shape spatial differences within Britain, though much of this variation is obscured at higher geographical levels, which aggregate diverse localities. Disparities across regions are considerably smaller than those observed across local areas within regions. The scale of intra-regional variation in Britain is comparable to that found in Spain, where the GPG ranged from 0.020 log points in Extremadura (2002 and 2006) to 0.315 log points in Asturias (2010) — a spread similar in size to differences observed across European countries (Murillo Huertas et al., 2017). Further, the analysis shows that most of the variation across British areas arises from gendered employment distributions, while the unexplained component remains relatively stable. This suggests that areas with lower GPGs are not necessarily more equitable, echoing findings from Northern Ireland (Jones and Kaya, 2022b).

Finally, the research explores how broader contextual factors influence GPGs across areas. This recognises the potential influence of local labour market conditions on women's decision to participate in the labour force, the intensity of their participation, and their wage outcomes. Despite relatively small differences in unexplained GPGs across local areas within Britain, the findings indicate that local area characteristics — such as industrial composition, unemployment rates, and rurality — contribute to the spatial disparities. This supports the suggestion that spatial variations in economic opportunities across areas partially explain spatial differences in the GPG, consistent with (Fuchs et al., 2021).

The Chapter is structured as follows: Section 3.2 provides evidence on the variation in the GPG across areas within Britain. Section 3.3 builds on the discussion in Section 2.6 by reviewing the drivers of GPGs across areas and the potential influence of area characteristics. Section 3.4 addresses the primary question of why GPGs vary across areas within Britain, by describing the data, methodology and presenting the results of the analysis. Section 3.5 examines the role of broader contextual factors in shaping the variation of the GPGs across areas within Britain. Finally, Section 3.6 concludes the chapter.

3.2 Variation in the Gender Pay Gap Across Areas within Britain

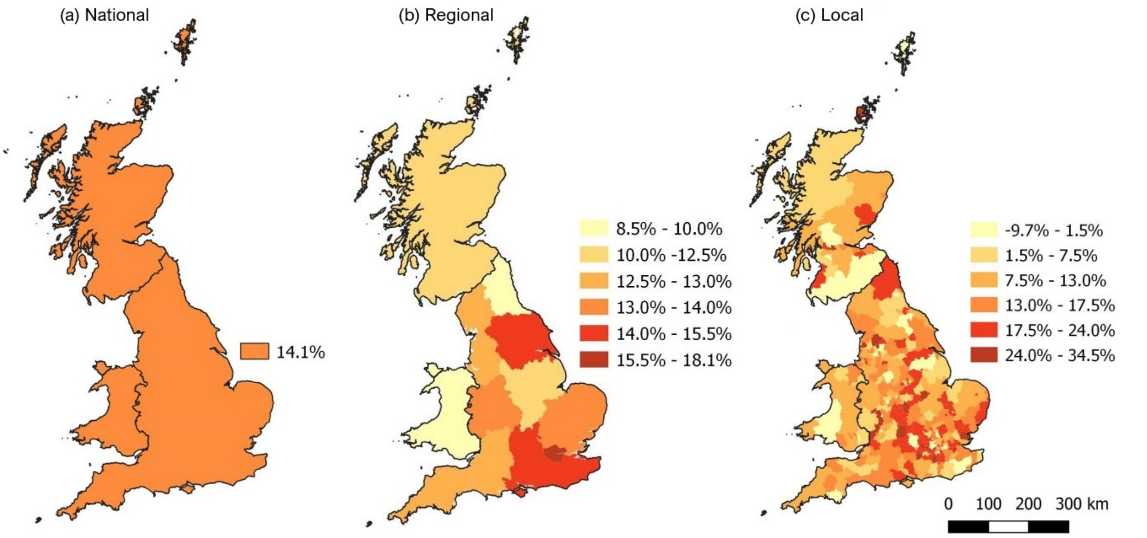
There is substantial variation in the raw GPG across areas in Britain (Figure 3.1). Using ASHE data, the ONS estimated that the mean hourly GPG for all employees in Britain was 14.1% in 2022, though it varied across regions, ranging from 8.5% in Wales to 18.1% in London. Variation was estimated to be even greater across local authorities, varying from -9.7% in Dumfries and Galloway — implying that women earned more than men on average — to 34.5% in Maldon, Essex.[2,3]

The spatial variation in the raw mean GPG, as estimated by the ONS, has a distinctive geographical pattern at both regional and local levels (Figure 3.1). London has the highest raw GPG, closely followed by its surrounding regions, while the devolved nations and the North East have the smallest GPGs. An exception is Yorkshire and the Humber, which has a GPG comparable to London and the South East. This spatial pattern is broadly mirrored at the local authority level, albeit with greater spatial heterogeneity. Further, intra-regional variation often exceeds inter-regional differences. For example, in Scotland, four of the 20 local authorities (Dumfries and Galloway, East Renfrewshire, the Scottish Borders, and the Shetland Islands) have negative GPGs,

[2] These estimates are based on employees' workplace areas to align with the analysis in this Chapter and with the analysis of the variation in the GPG across areas in Germany (Fuchs et al., 2021) and Spain (Murillo Huertas et al., 2017). Section 3.4 provides a justification for the focus on workplace area, although the sensitivity of the results are explored when the analysis is based on an employees' area of residence (see ONS 2022b).

[3] The ONS does not publish GPG estimates at the NUTS 3 level. While local authority data provide a closely related alternative, caution is needed when interpreting estimates for less populous local authorities.

Figure 3.1: Spatial Variation in the Mean Hourly GPG across Areas, by Geographical Level



Notes: (i) Figures are derived from ONS estimates of raw mean hourly GPGs from the ASHE and are based on employees' workplace locations. (ii) The GPG is calculated as the difference between mean hourly wages (excluding overtime) of men and women as a proportion of mean hourly wages (excluding overtime) of men. (iii) The mean is derived by summing all wages in a given sample and dividing by the number of observations (i.e. jobs). The mean can be disproportionately influenced by a relatively small number of high-paying jobs (see Section 2.2).

Source: Original data sourced from ASHE 2022, GPG estimates analysed and complied by ONS (2022b)

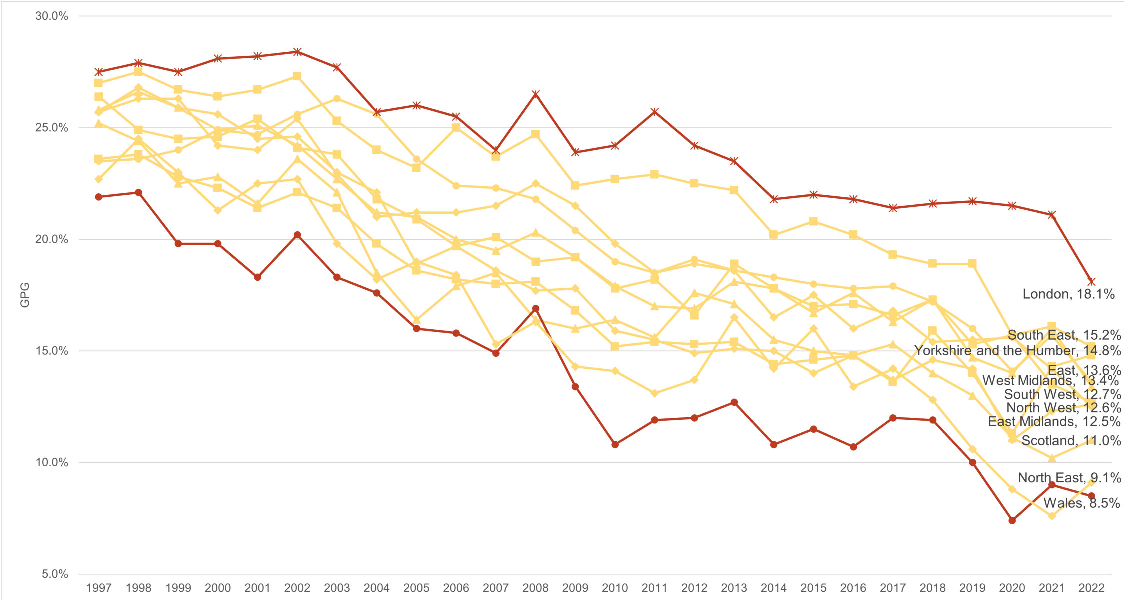
whereas three others (East Dunbartonshire, Orkney Islands, and South Ayrshire) record gaps above 20%, similar to those found in London's local authorities (Figure 3.1).

This spatial pattern has remained stable over time (Figure 3.2). Between 1997 and 2022, London and its surrounding regions consistently had the highest GPG for all employees, while Wales and the North East had the lowest. Although the GPG declined across all regions during this period - by an average of 12.1 percentage points - the gap between the highest and lowest GPG regions widened. In 1997, this difference was 5.6 percentage points; by 2022, it had almost doubled to 9.6 percentage points. This divergence reflects uneven rates of decline: in Wales, the GPG fell by 13.4 percentage points, compared with only 9.4 percentage points in London. Long-term ASHE data suggest that London's relatively slow progress — despite its historically lower GPG and its contribution to reducing the national GPG during the 1990s (Robinson, 2005) — has played a key role in driving this widening regional gap (ONS, 2017).

The widening disparity in the GPG across areas has become increasingly relevant in contemporary policy debates. The UK government's 'levelling up' agenda (2019-2022), along with the continuing process of devolution and decentralisation, has contributed to the emergence of distinct policy environments across the UK, with potentially implications for the geography of gender inequality.[4] However, empirical research has

[4]While key labour market policies, such as the minimum wage and the welfare system, remain reserved powers at Westminster, others — such as education, skills training, and equal opportunities — are devolved to varying degrees across the four nations (see Section 2.3 and Table A.2, Appendix A). These devolved powers create distinct

Figure 3.2: Raw Mean Hourly GPGs across Regions, from 1997-2022



Notes: (i) Figures are derived from ONS estimates of raw mean hourly GPG from the ASHE and the New Earnings Survey prior to 2004, based on employees' workplace locations. (ii) The GPG is calculated as the difference between mean hourly wages (excluding overtime) of men and women as a proportion of mean hourly wages (excluding overtime) of men. (iii) The mean is derived by summing all wages in a given sample and dividing by the number of observations (i.e. jobs). The mean can be disproportionately influenced by a relatively small number of high-paying jobs (see Section 2.2). (iv) Data discontinuities occurred in the ASHE/NES in 2004, 2006 and 2011.

Source: Original data sourced from ASHE 2004-2022 and New Earnings Survey 1997-2004; GPG estimates analysed and compiled by ONS (2022b).

not fully disentangled the drivers of this regional divergence, nor the extent to which it reflects a distinctive 'London effect', warranting further investigation.

3.3 Literature Review of the Gender Pay Gap Across Areas

3.3.1 Drivers of the Spatial Variation in Gender Pay Gaps

Cross-country research highlights the role of wage-setting institutions, such as national minimum wages and collective bargaining mechanisms (including their coverage of non-union workers), in explaining variation in the GPG across countries (e.g. Christofides et al. 2013; Schäfer and Gottschall 2015; Section 2.6.1). In contrast, research examining the national GPG in the UK emphasise the influence of individual, work-related, and household characteristics (e.g., Olsen et al. 2018; Razzu 2014; Section 2.6.2). Although this literature typically includes geographic controls (often in the form of regional fixed effects), such approaches fail to capture how the impact of these characteristics varies across areas within a country.

policy contexts that may generate heterogeneous effects on the GPG across regions.

Challenges associated with cross-country comparisons, including issues of data harmonisation and institutional heterogeneity, have increasingly directed attention towards the within-country variation in the GPG (e.g., Murillo Huertas et al. 2017 for Spain; Fuchs et al. 2021 for Germany). This body of research applies the same decomposition methodologies, such as the OB and JMP decompositions, to investigate the drivers of the GPG across areas. The interpretation of these analyses aligns closely with national-level research (see Section 2.5.2 for an overview of their interpretation).

In the UK, research on the variation in the GPG has predominantly focused on areas at the extremes of the GPG distribution. For instance, Jones and Kaya (2022b) examine the relatively low, and sometimes negative, GPG in Northern Ireland, while Stewart (2014) focuses on the high mean and median GPGs in London. In contrast, more comprehensive spatial analyses have been conducted in Spain (Murillo Huertas et al., 2017) and Germany (Fuchs et al., 2021) (see Table B.1, Appendix B for an overview of this literature). Evidence from these studies suggests that drivers of national GPGs also shape GPGs across areas, though their relative importance varies depending on local economic, social, and institutional contexts. Moreover, area-level characteristics, such as industrial composition, inequality, and labour market structures, which are often obscured in national-level analyses, emerge as important drivers of the variation in the GPG across areas.

Wage-setting institutions influence wage levels in areas by shaping workforce composition, wage structures, and wage dispersion (Section 2.6.1). While institutional frameworks tend to be more homogenous within countries than across them, spatial variations in the coverage, strength, or implementation of such institutions may still contribute to the variation in the GPG across areas. Such heterogeneity can arise from differences in workforce composition, average pay levels, and gendered patterns of employment across areas, leading to divergent local effects of labour market institutions.

One such institution is the national minimum wage, whose impact on the GPG has been found to vary across areas due to the geographic distribution of low-paid workers by gender. Using a DiD approach with pooled LFS data from 1993 to 2000, the impact of the introduction of the national minimum wage is estimated to have had a more substantial narrowing effect on the GPG in regions with a higher proportion of low-paid women, such as the East Midlands, East Anglia, and Yorkshire, though the overall impact was relatively modest (Robinson, 2005). This finding aligns with national-level evidence based on quantile regression analysis of LFS data from 1998 and 1999, which indicates that the national minimum wage primarily affected wages at the lower end of the wage distribution (Robinson, 2002).[5] The continuing process of devolution and decentralisation in the UK, which created increasingly divergent legislative environments

[5]This evidence suggests that the immediate impact of the national minimum wage on the national GPG was limited. While a decline in the raw mean GPG was observed between 1998 and 1999 and subsequently between 1999 and 2000, this reduction appears to have been driven more by changes at the upper end of the pay distribution than by improvements at the bottom (Robinson 2002, Section 2.6.2).

across the UK, potentially generating new spatial heterogeneities in wage-setting institutions, with implications for the GPG across areas within Britain.

Relatedly, and consistent with international evidence highlighting the significance of national wage structures (Section 2.6.1), evidence highlights the role of wage compression in narrowing GPGs across areas. For instance, evidence from the JMP decomposition of the GPG between Northern Ireland and the rest of the UK identifies the narrowing impact of Northern Ireland's more compressed earnings distribution, which disproportionately benefits women. This compression reflects both the higher proportion of low paid employees - increasing the relevance of the national minimum wage - and comparatively high union membership, particularly among women (Jones and Kaya, 2022b). Similarly, OB decompositions of the GPG across local areas in Germany demonstrate that greater wage compression (measured as the absolute deviation from the establishment wage median) is associated with smaller GPGs. Conversely, areas with greater wage dispersion tend to have larger GPGs (Fuchs et al., 2021).

The role of individual and work-related characteristics in explaining the variation in the GPG across areas broadly mirrors their influence at the national level. For example, gender differences in education are estimated to make the largest negative contribution (alongside occupation) to the GPG in Northern Ireland, reflecting women's higher qualifications compared to men. However, this effect is partially offset by higher male returns to qualifications (Jones and Kaya, 2022b). Women's longer average job tenure further narrows the GPG in Northern Ireland. Similarly, OB decompositions of the GPG across local areas in Germany emphasise the role of gender differences in qualifications, mitigating the GPG in low GPG areas but exacerbating it in areas with larger gaps (Fuchs et al., 2021).[6] Comparable patterns are evident in Spain, where OB decompositions suggest that women, on average, have more productive characteristics than men. This implies that the GPG in all Spanish regions is essentially driven by gender differences in the returns to these characteristics (Murillo Huertas et al., 2017).

The wider GPG in London, except within the top third of the wage distribution, is largely explained by gender differences in individual and work-related characteristics, including age, firm size, and collective bargaining coverage. A counterfactual analysis suggests that if full-time employees in London had the same characteristics as those in the rest of Britain, the adjusted median GPG would be three percentage points lower, rather than the observed three percentage points higher (Stewart, 2014). Evidence from Germany also highlights the role of establishment size in explaining spatial variation of the GPG: the relationship is negative in regions with smaller gaps but positive in regions with larger gaps (Fuchs et al., 2021). This may reflect the tendency for areas with smaller GPGs to have smaller workplaces with lower wage dispersion, rather than men disproportionately sorting into high paying firms or receiving pay premiums, as at the national level (Arulampalam et al., 2007; Goldin et al., 2017).

[6] This likely reflects Germany's pronounced regional disparities in education, due to East German women having particularly high levels of education (Minkus and Busch-Heizmann, 2020).

Variation in the GPG across areas may also result from different local demand for occupations. Regional economic structures can interact with occupational segregation to create distinct employment opportunities for men and women (Hanson and Pratt, 1995; Perales and Vidal, 2015; Combes and Gobillon, 2015). The OB decomposition of the GPG in Northern Ireland suggests that gender differences in occupational allocation significantly reduce the explained GPG, indicating that women are more likely than men to be employed in higher-paying occupations (Jones and Kaya, 2022b). While this may partially reflect the focus on full-time employees, similar spatial variation is observed in Germany (Fuchs et al., 2021). In contrast, gender differences in industrial allocation widen the GPG in Northern Ireland (Jones and Kaya, 2022b), consistent with German evidence showing that spatial disparities in occupational distributions across industries contribute to higher GPGs in certain local areas (Fuchs et al., 2021). Despite this, neither the Northern Irish nor German evidence finds that the spatial distribution of public sector employment explains variation in the GPG (Jones and Kaya, 2022b; Fuchs et al., 2021).[7]

Theoretical approaches suggest that discrimination may vary across areas (e.g. Robinsonian discrimination; Section 2.4). However, the evidence consistently suggests that most spatial variation in the GPG reflects gender differences in observable characteristics, while the unexplained component - capturing differences in returns to characteristics and unobserved characteristics (Section 2.5.2) - tends to remain relatively stable across areas (Jones and Kaya, 2022b; Fuchs et al., 2021; Murillo Huertas et al., 2017). For instance, in Northern Ireland the relatively low mean full-time GPG is estimated to be entirely attributable to women possessing more productive characteristics than men, with the unexplained component larger than the raw GPG and comparable to the rest of the UK (Jones and Kaya, 2022b). Similarly, German local areas with small GPGs are characterised by women having more productive characteristics than men (Fuchs et al., 2021). These spatial patterns mirror UK evidence, showing a relatively stable unexplained GPG between 1997 and 2015 (Jones et al., 2018). In contrast, evidence from Spain suggests that the unexplained component varies across areas, though less sharply than the raw GPG (Murillo Huertas et al., 2017).

3.3.2 Gender Pay Gaps and Area Characteristics

Theoretical approaches to gender inequality in the labour market suggest that broader contextual factors, often omitted from decomposition analyses due to data limitations, may contribute to the variation in the GPG across areas (Section 2.4). For instance, the spatial monopsony model emphasises the role of competition in influencing the (unexplained) GPG across areas. Under spatial monopsony conditions, employers have

[7] While descriptive analysis suggests that Northern Ireland's relatively high female public sector employment may mitigate the GPG (Mac Flynn, 2014), OB decompositions reveal that this largely reflects women in the public sector possessing more productive characteristics than men, with the unexplained GPG similar to that in the private sector (Jones and Kaya, 2022b).

greater wage-setting power in areas with limited alternative employment opportunities, enabling them to offer lower wages, particularly to women, who may have lower spatial mobility due to household responsibilities or other constraints. As a result, larger GPGs are expected in areas with weaker labour market competition (Hirsch, 2009; Hirsch et al., 2013).

Empirical evidence largely supports the predictions of the spatial monopsony model, consistently finding that rural or less densely populated areas tend to have larger GPGs compared to urban or more densely populated areas (Phimister, 2005; Krug and Nisic, 2011; Bacolod, 2017; Hirsch et al., 2013; Murillo Huertas et al., 2017). Using micro-data from Western Germany from 1975 to 2004, the GPG is estimated to be, on average, a stable 13 percentage points higher in rural areas than urban areas. This is primarily driven by the substantially lower unexplained component of the GPG in large urban areas (Hirsch et al., 2013). Consistent with this pattern, evidence indicates that women in Germany are more likely to work in denser labour markets. Consequently, gender differences in urban areas reduce the German national GPG when decomposed, suggesting that women derive larger benefits from agglomeration economies (Fuchs et al., 2021). Panel data from the BHPS similarly reveal a larger urban wage premium for women compared to men in the UK. Women in urban areas also experience lower wage depreciation following interruptions in their labour market participation (Phimister, 2005).

Labour market competition may also imply that the unemployment rate influences the variation in the GPG across areas, although this relationship has not been fully explored. Evidence from Germany suggests that women are more likely to work in local areas with higher unemployment rates, a pattern that marginally exacerbates the national GPG (Fuchs et al., 2021). Panel data models with the raw and unexplained GPG as dependent variables across the Spanish regions indicate that higher female employment rates are associated with larger GPGs and unexplained components (Murillo Huertas et al., 2017). This may reflect positive selection effects of women in high unemployment areas, reflecting similar conclusions drawn from the analysis of ethnic wage gaps across areas in Britain using pooled LFS data from 2001 to 2017 (Longhi, 2020).

Further evidence suggests that wage inequality may also contribute to the spatial variation in the GPG (Fuchs et al., 2021; Blackaby et al., 2012a), though this factor was found to be statistically insignificant across Spanish regions (Murillo Huertas et al., 2017). Descriptive wage data for full-time employees by gender across UK regions in 2011 illustrate that regions such as Northern Ireland and Wales had the smallest regional GPGs. This is largely attributable to substantially lower average hourly earnings for full-time men compared to their counterparts in other regions of the UK, alongside lower wages for women in these regions (Blackaby et al., 2012a). Similar findings are also documented across German local areas (Fuchs et al., 2021).

Given cross-country evidence (Olivetti and Petrongolo, 2014; Kaya, 2023), it has also been suggested that the structure of labour demand across areas may contribute to the spatial variation of the GPG. For instance, a decline in the manufacturing employment in certain regions, coupled with the expansion of the service sector, may encourage greater female labour force participation. However, women entering the labour market under these conditions may be disproportionately concentrated in lower-paid sectors compared to men previously employed in manufacturing. Despite this theoretical link, empirical evidence remains limited, with no significant relationship found between the share of the service industry and the raw and unexplained GPG across Spanish regions (Murillo Huertas et al., 2017). However, sensitivity analysis of GPG decompositions across German local areas suggests that regional economic opportunities play a critical role in explaining GPG variation (Fuchs et al., 2021). Stronger evidence also exists concerning the role of industrial structure in explaining ethnic pay gaps across areas, driven by the combined effects of regional industrial specialisation and residential sorting (Longhi, 2020). Building on this literature, this chapter moves beyond a focus on the unexplained gap to examine how local labour market characteristics — including industrial structure, unemployment, and rurality — contribute to differences in the GPG across areas in Britain.

3.4 Why do Gender Pay Gaps Vary across Areas within Britain?

3.4.1 Data

Annual Survey of Hours and Earnings

The analysis is based on data from the ASHE, which is the main source of earnings data in the UK (ONS, 2022a), containing comprehensive and reliable information on the structure and distribution of earnings.[8] ASHE data are collected from a random 1% sample of all employees based on National Insurance numbers from HM Revenue and Customs' Pay As You Earn system. This sampling approach ensures a sufficiently large sample, enabling analysis of the spatial variation in the GPG across areas and providing a sample size of at least 200 individuals, and at least 100 of each gender in every regional (NUTS 1) and local (NUTS 3) area (to meet this threshold, 13 local areas are aggregated, detailed below). This large sample size facilitates the inclusion of a range of well-established determinants of earnings (Blau and Kahn, 2017) at both regional and local levels. The ASHE's sample size also surpasses that of comparable British data, including LFS or Understanding Society data, which may have insufficient sample sizes for certain areas, limiting their suitability for spatial analysis (Section 2.2.4).

[8] As the data for this project is confidential and potentially disclosive, the ASHE is accessed through the UK Data Service via the SDS for projects where the researchers are accredited and where there is clear public benefit. This project was approved for the use of these data and all outputs have been subject to disclosure control. Full details are available via the SDS, which collates data for employees in Britain; ASHE data for Northern Ireland is collected by the Northern Ireland Statistics and Research Agency.

Unlike household surveys frequently used in British GPG research, the ASHE is based on employer payroll records, which are subject to legal sanctions for misreporting. This increases the accuracy of earnings data compared to self-reported measures, which are prone to error, particularly at the top of the wage distribution (Ormerod and Ritchie, 2007). Self-reported data, such as the LFS and Understanding Society, may introduce bias into GPG estimates due to gender differences in response rates and reported income. Theurl and Winner (2011), for example, highlighted such biases in GPG estimation for Austrian physicians between 2000 and 2004.

A further advantage of the ASHE is its national representativeness, enabling comparison of estimated GPGs with those from the ONS (as presented in Figure 3.1). However, a key limitation of the ASHE is its relatively narrow set of individual characteristics known to influence earnings and the GPG, such as disability, ethnicity, nationality, country of birth, and qualifications (Sections 2.6, 3.3.1).[9,10] While these data limitations may introduce omitted variable bias, potentially leading to overstating discrimination, the primary aim of this research is not to provide a precise estimate of discrimination. Rather, the objective is to investigate how far the drivers of national GPGs help to account for the substantial spatial variation observed across areas, and to move beyond a narrow focus on unexplained gaps by examining how local labour market conditions shape pay inequalities between women and men. The ASHE's detailed coverage of earnings, paid hours, and occupations across all industries and areas therefore provides a unique opportunity to generate the first within-Britain analysis of how geography interacts with the GPG, complementing and extending existing national-level studies.

The research provides 'contemporary' evidence on GPGs across areas at different geographical levels in Britain for the 'current' period, based on 2022 ASHE data (ONS, 2022a). This is the first full year post-pandemic where furlough was not applicable, although sensitivity analysis is conducted with 2019 ASHE data to avoid potential impacts of the Covid-19 pandemic (see Section 2.2.4, 3.4). The sample is restricted to working-age employees aged between 16-65 years, who are paid an adult rate and whose earnings are not affected by absences. Individuals with missing values for any explanatory or analytical variable are excluded (Table B.3, Appendix B). Weights are applied to calibrate ASHE returns to job totals from the LFS, based on stratum and LFS population totals. However, all reported sample sizes (denoted as N) refer to unweighted observations. These weights, based on age group, sex, occupation and region, ensure that estimates are representative of respective populations and reduce potential downwards non-response and upwards non-sampling bias (ONS, 2018a).

[9] Alternative data, such as the LFS or Understanding Society, offer richer individual-level data but are unsuitable for analysing the GPG across areas due to their smaller sample sizes. Furthermore, using such data would preclude direct comparison with ONS estimates. While some ASHE variables serve as proxies for missing characteristics — age for labour market experience and occupation for educational attainment — these proxies are imperfect (Gibbons et al., 2014).

[10] It is common to have a relatively restricted set of individual characteristics when using payroll data. A potentially important omission in the ASHE is a control for dependent children (Grimshaw and Rubery, 2015; Costa Dias et al., 2020), which may influence hourly pay over the lifecycle due to lower human capital accumulation and may have varying effects across areas.

After applying these restrictions, 15,734 employees (7,144 men and 8,590 women) are excluded, resulting in a final national sample of 124,963 employees. This includes 58,525 men and 66,438 women (Table B.2, Appendix B).

Areas

Following the analysis of the GPG across areas in Germany and Spain (Murillo Huertas et al., 2017; Fuchs et al., 2021),[11] the research uses the NUTS classification system (Section 2.2.3) to conduct analysis at the following geographical levels:

- National - referring to Britain.
- Regional - referring to the 11 NUTS 1 regions in Britain.
- Local - referring to 160 out of a possible 168 NUTS 3 regions in Britain.

The national level analysis provides an overview of the drivers of the GPG in Britain, serving as a benchmark for comparison with prior research, as well as with regional and local analyses. The regional and local level analyses identify the extent to which these drivers vary across areas and geographical levels.

The unweighted sample size by gender for each area is provided in Table B.2, Appendix B. At the regional level, sample sizes range from 5,069 in the North East to 17,173 in the South East. At the local level, sample sizes range from 212 in Torbay to 3,001 in Camden and City of London. To ensure no statistical disclosure, local areas are aggregated where necessary to meet the minimum sample size threshold. As a result, the following aggregations are made:

- Portsmouth is combined with the Isle of Wight, forming the Portsmouth and Isle of Wight local area, with a sample size of 716 employees (324 men and 392 women).
- The Isle of Anglesey is combined with Gwynedd, forming the Anglesey and Gwynedd local area, with a sample size of 329 employees (154 men and 175 women). These areas share historical administrative ties and coordinate on certain policies, including on the rollout of the Childcare Offer for Wales (Chapter 5).
- Powys is combined with South West Wales, forming the South West and Mid Wales local area, with a sample size of 846 employees (339 men and 507 women). These areas share common labour market characteristics, including their rurality and significant proportion of employment in the agricultural industry.
- The Eilean Siar (Western Islands), Orkney Islands, Shetland Islands, Caithness & Sutherland and Ross & Cromarty and Lochaber, Skye and Lochalsh, Arran &

[11] Fuchs et al. (2021) study the GPG at the NUTS 3 regional level in Germany, while Murillo Huertas et al. (2017) examine the GPG at the NUTS 2 regional level in Spain (see Table B.1, Appendix B).

Cumbrae and Argyll & Bute are combined to form the Highlands and Islands local area, with a sample size of 461 employees (197 men and 264 women).

- East Ayrshire and North Ayrshire Mainland is combined with South Ayrshire to form the Ayrshire local area, with a sample size of 674 employees (246 men and 428 women).

Consistent with analyses of the GPG across areas in Germany and Northern Ireland (Fuchs et al., 2021; Jones and Kaya, 2022b), the analysis is based on an individual's place of work, derived from the work region variable in the ASHE (*WGOR*). This is preferred over place of residence, as wages are primarily determined by the demand for labour and the wage-setting practices of employers in the location of the job (Fuchs et al., 2021; Glaeser and Maré, 2001). A potential limitation is that place of work may be endogenous to migration decisions, particularly among higher-skilled workers who are more geographically mobile and may relocate in response to local job opportunities. If migration patterns differ systematically by gender, this could influence observed spatial differences in the GPG. In practice, cross-regional commuting is relatively limited (12.38% of employees commute across regions), though commuting is more common at the local level (41.60% of employees work outside their local area). Sensitivity analysis explores this issue by using re-estimating the GPG using place of residence, excluding commuters, and excluding individuals who changed work region between 2018 and 2019 (Section 3.4).

Hourly Pay

Following the established GPG literature (Section 2.6), the main dependent variable is hourly earnings excluding overtime. This measure adjusts gross hourly pay during the reference period by the number of hours worked and aligns with the ONS's preferred definition of hourly pay for GPG estimation (Section 2.2, Equation 2.1). Excluding overtime is particularly important, as men, on average, work more hours than women and are more likely to receive overtime pay, which often includes a wage premium. Failing to account for these differences would lead to an upward bias in GPG estimates. This definition is also consistent with the hourly pay measure used for the GPG Reporting legislation (Section 2.3). Alternative definitions of hourly earnings are explored in the sensitivity analysis (Section 3.4).

Descriptive statistics for hourly pay, by gender, are reported for national, regional, and selected local areas in Table 3.1. Substantial variation in mean hourly earnings is observed across areas and between genders. Figure 3.6 visually represents this variation.

Explanatory Variables

The analysis controls for a range of well-established determinants of earnings, drawing on the GPG literature (Blau and Kahn 2017, Section 2.6 and 3.3.1). These explanatory variables are grouped into four categories: individual characteristics, workplace characteristics, occupation, and sector. Full details on the definition and derivation of each variable, as well as the dependent variable are provided in Table B.3, Appendix B.

While the ASHE is limited in terms of individual characteristics, the research controls for age (and age-squared) (commonly used as a proxy for work experience, Jones and Kaya 2024), job tenure (and tenure squared) (measuring the length of time an employee has worked in their current organisation), a full-time employment dummy and a temporary contract indicator.[12] Workplace characteristics include firm size, banded according to the number of employees as defined by the ONS, and an indicator for collective agreement coverage.

Occupational controls are based on the SOC unit groups. To ensure no statistical disclosure, the analysis at the local level aggregates these unit groups into three broad occupational skill groups, following the International Standard Classification of Occupations (ILOSTAT, 2011). This classification is consistent with previous empirical research (Fernández-Reino and Rienzo, 2023). Each skill group contains a minimum of 30 individuals of each gender in each local area:

- High-skilled occupations: Occupations requiring significant human capital, encompassing the Managers & Senior Officials, Professional, and Associate Professional occupations.
- Medium-skilled occupations: Occupations typically requiring upper secondary education, vocational training, or some tertiary education, including Administrative, Skilled Trades, and Personal Service occupations.
- Low-skilled occupations: Occupations involving routine tasks or requiring lower educational qualifications, including Sales & Customer Service, Process, Plant & Machine Operatives, and Elementary occupations.

Finally, sector of employment is defined using a public sector indicator. While ASHE data offer several advantages, including a large sample size and accurate earnings data, the geographical dispersion of industries limits the ability to control for detailed industry effects. While the public sector indicator partially addresses this, the role of industry composition is further examined as an area-level characteristic in Section 3.5.

3.4.2 Methodology

Estimating Raw and Adjusted Mean Hourly Gender Pay Gaps across Areas

The variation in the raw mean hourly GPG for all employees across areas a at geographical level $g \in \{national, regional, local\}$ is explored using estimates from

[12] The ASHE defines full-time employees as those working more than 30 hours per week (or 25 hours for those in teaching professions).

Mincerian wage equations that pools employees across gender and areas, following the approach of Fuchs et al. (2021). The analysis is then extended to explore how controlling for successive explanatory variables affects the mean hourly GPG across areas and how the adjusted GPG varies geographically. Formally, the Mincerian wage equation takes the form:

$$\ln W_{ia}^{g} = \beta_{0a}^{g} + \alpha_{a}^{g} F_{ia}^{g} + \varepsilon_{ia}^{g} \tag{3.1}$$

where the natural logarithm of hourly wages for employee i in area a at geographical level g (lnW_{ia}^{g}) is regressed on a (female) gender indicator (F_{ia}^{g}), which equals one if the employee is female and zero if they are male. ε_{ia}^{g} is the random residual term, $\varepsilon_{ia}^{g} \sim N(0, \sigma^2)$. The raw mean hourly GPG in log points for area a at level g is given by α_{a}^{g}, which can be converted into a percentage by:

$$GPG = e^{\alpha_{a}^{g}} - 1 \tag{3.2}$$

This specification aligns statistically with the ONS methodology (Section 2.2, Equation 2.1), so that the research validates official estimates of the raw mean hourly GPG across areas. Small differences may arise as the analysis conditions the data on explanatory variables (Table B.3, Appendix B). A key advantage of this regression framework is that it provides the statistical significance of GPG estimates.

The baseline GPG estimates are calculated for all employees to maximise sample size and to capture sources of gender inequality in the labour market. This approach recognises that women are overrepresented in part-time roles, which tend to have lower returns to characteristics relative to full-time work (Section 2.4).[13]

To estimate adjusted mean hourly GPGs across areas, the analysis incorporates controls for individual characteristics (including demographic and work-related factors), workplace characteristics, occupation, and sector of employment (Table B.3, Appendix B). This results in five specifications. Given the theoretical and empirical relationship between these characteristics and national GPGs, this approach examines their role in driving variation in the GPG across areas. This analysis complements existing literature, which highlights the importance of these drivers in shaping the spatial distribution, while acknowledging that their effects may vary across local labour markets (Fuchs et al., 2021). The Mincerian wage equation is adapted as follows:

$$\ln W_{ia}^{g} = \beta_{0a}^{g} + \alpha_{a}^{g} F_{ia}^{g} + \boldsymbol{\beta}_{a}^{g} \mathbf{X}_{ia}^{g} + \varepsilon_{ia}^{g} \tag{3.3}$$

where the notation follows from above, and $\mathbf{X}_{ia}^{g}$ is a vector of individual characteristics,

[13] A sensitivity analysis is conducted by restricting the sample to full-time employees, allowing for a comparison between male and female workers with similar labour market commitment (Blau and Kahn 2017, Section 3.4).

workplace characteristics, occupation, and sector of employment. $\boldsymbol{\beta}_a^g$ is the corresponding vector of estimated returns to these characteristics. The adjusted mean hourly GPG in log points for area a at geographical level g is given by α_a^g, which can be converted into a percent using Equation 3.2.

Decomposing raw Gender Pay Gaps across areas within Britain

To explore the variation in the mean GPG across areas and identify its underlying drivers, the research employs the standard OB decomposition method (Oaxaca, 1973; Blinder, 1973), widely used in the analysis of the national GPG in Britain and across areas (Section 2.6, 3.3.1). Consistent with prior literature, the decomposition isolates the portion of the GPG attributable to gender differences in observable characteristics from unobservable influences on GPGs across areas. The latter component is typically interpreted as an upper bound measure of labour market discrimination, as it also captures gender differences in productivity, preferences, and other unobservable individual and workplace characteristics. These limitations are well-established (Neumark, 2018) and should be carefully considered, particularly given the data constraints of the ASHE (Section 3.4). For example, the ASHE lacks data on key variables such as dependent children and work experience, which may bias the unexplained GPGs upwards, underscoring the need for caution when interpreting this component as a direct measure of wage discrimination. However, even in the presence of a larger set of individual characteristics, including disability, ethnicity, nationality, country of birth, and qualifications, as in the QLFS analysis in Chapter 4 and the analysis of the GPG in Northern Ireland (Jones and Kaya, 2022b), the unexplained component is still likely to overstate discrimination.

The decomposition is based on separate estimations of Equation 3.3 by gender $s \in \{\text{male } (M) \text{ and female } (F)\}$:

$$\ln W_a^{gs} = \beta_{0a}^{gs} + \boldsymbol{\beta}_a^{gs}\mathbf{X}_a^{gs} + \varepsilon_a^{gs} \tag{3.4}$$

where the notation follows from above, and the vector of returns to characteristics $\boldsymbol{\beta}_a^{gs}$ is estimated separately by gender s and for each area a at geographical level g.[14] The explanatory variables included in $\mathbf{X}_a^{gs}$ correspond to the most comprehensive adjusted GPG specification in the pooled model above, controlling for individual characteristics, workplace characteristics, occupation, and sector of employment.

This approach enables the returns to characteristics to vary by gender (s) and across areas (a), facilitating the OB decomposition of raw GPGs into explained and unexplained components using the resulting gender coefficients ($\boldsymbol{\beta}_a^{gs}$) and observed endowments ($\mathbf{X}_a^{gs}$):

[14] For simplicity, subscript i is omitted.

$$\underbrace{\ln \overline{W}_a^{gM} - \ln \overline{W}_a^{gF}}_{\text{Observed GPG}} = \underbrace{(\overline{\mathbf{X}}_a^{gM} - \overline{\mathbf{X}}_a^{gF})\widehat{\boldsymbol{\beta}}_a^{gM}}_{\text{explained part}} + \underbrace{(\widehat{\boldsymbol{\beta}}_a^{gM} - \widehat{\boldsymbol{\beta}}_a^{gF})\overline{\mathbf{X}}_a^{gF} + (\widehat{\beta}_{0a}^{gM} - \widehat{\beta}_{0a}^{gF})}_{\text{unexplained part}} \tag{3.5}$$

where the bar above a variable denotes its mean value and $\widehat{\boldsymbol{\beta}}_a^{gs}$ is the OLS estimate of $\boldsymbol{\beta}_a^{gs}$. In this equation, the explained component measures the portion of the mean hourly GPG attributable to gender differences in observable characteristics, while the unexplained component captures the portion arising from gender differences in the returns to these characteristics. The latter is often interpreted as indicative of wage discrimination but also includes the constants and captures the influence of all unobserved wage determinants that are not accounted for in the model (see discussion above).

Following the empirical GPG literature (see Blau and Kahn 2017), Equation 3.5 uses males as the reference group, implying that the hourly wage of an average woman at male returns is the counterfactual ($\overline{\mathbf{X}}_a^{gF}\widehat{\boldsymbol{\beta}}_a^{gM}$). This approach assumes that male earnings reflect competitive prices (see Section 2.5.2 for a discussion on reference groups and the index problem). To assess the sensitivity of these findings to the choice of the reference group, Section 3.4 explores alternative specifications, including re-weighting the difference in characteristics using female returns and estimating returns using a pooled model with a gender dummy variable, following the methodology of Fortin (2008).

3.4.3 Descriptive Statistics

Table 3.1 reports mean hourly wages by gender for all regions, alongside five selected local areas selected according to their position in the distribution of mean hourly pay (minimum, 25th percentile, median, 75th percentile, and maximum). At the regional level, mean hourly wages range from £16.43 in the North East to £25.01 in London. At the local level, the dispersion is even greater, ranging from £14.22 in Torbay to £33.80 in Tower Hamlets. While such regional and local variation in hourly wages is also documented in the ASHE by the ONS (ONS, 2022b), the magnitude of this variation appears significantly larger than in other data, such as the WERS (Butcher et al., 2019) and the QLFS (Jones and Kaya, 2022b). For example, pooled 2016-2019 QLFS estimates suggest that average wages in Northern Ireland were lower than in Torbay, possibly reflecting the greater susceptibility of self-reported wage data to measurement error.

Examining the gender gap, expressed as a percentage of the male mean hourly wage, shows that areas with higher mean hourly wages tend to have larger gender gaps. For instance, London has the highest hourly wages for both women (£22.29) and men (£27.20), alongside the largest gap (18.05%). In contrast, the North East, with the lowest mean hourly wages for both genders (£15.58 for women and £17.17 for men), has the second smallest gender gap of 9.26%, after Wales. Wales also reports the third lowest mean hourly wage for all employees and for both women and men.

Table 3.1: Hourly Wages by Gender in Selected Areas, for all employees

	All	Men	Women	Gap (%)
National	£18.88	£20.17	£17.29	14.28
N	*124,963*	*58,525*	*66,438*	
Regional				
North East (England)	£16.43	£17.17	£15.58	9.26
N	*5,069*	*2,290*	*2,779*	
North West (England)	£17.47	£18.55	£16.20	12.67
N	*14,105*	*6,566*	*7,539*	
Yorkshire and the Humber	£16.71	£17.90	£15.22	14.97
N	*11,358*	*5,381*	*5,977*	
East Midlands (England)	£16.81	£17.84	£15.51	13.06
N	*8,943*	*4,238*	*4,705*	
West Midlands (England)	£17.56	£18.68	£16.11	13.76
N	*11,190*	*5,401*	*5,789*	
East of England	£18.08	£19.23	£16.59	13.73
N	*11,595*	*5,520*	*6,075*	
London	£25.01	£27.20	£22.29	18.05
N	*17,173*	*8,262*	*8,911*	
South East (England)	£19.15	£20.54	£17.41	15.24
N	*16,723*	*7,833*	*8,890*	
South West (England)	£17.46	£18.49	£16.13	12.76
N	*10,805*	*5,171*	*5,634*	
Wales	£16.69	£17.39	£15.91	8.51
N	*6,011*	*2,680*	*3,331*	
Scotland	£18.31	£19.36	£17.21	11.11
N	*11,991*	*5,183*	*6,808*	
Selected Local Areas (based on distribution of mean hourly pay)				
Minimum: Torbay	£14.22	£14.91	£13.40	10.13
N	*212*	*100*	*112*	
25th percentile: Kingston upon Hull	£16.37	£17.31	£15.25	11.90
N	*550*	*251*	*299*	
Median: Northumberland	£17.21	£19.41	£15.00	22.72
N	*503*	*207*	*296*	
75th percentile: Warwickshire County Council	£18.83	£20.52	£16.24	20.86
N	*1,228*	*620*	*608*	
Maximum: Tower Hamlets	£33.80	£36.41	£29.71	18.40
N	*1,089*	*589*	*500*	

Notes: (i) Mean hourly wages relate to the respective estimation sample, defined according to ASHE guidance. (ii) The gap is measured as a percentage of the relevant male figure in each case.

Source: Author calculations based on weighted ASHE 2022 data.

A further breakdown of mean hourly wages by full-time status is provided in Table B.4, Appendix B. The regional pattern is broadly consistent for full-time employees, with higher paying regions also having larger gender gaps. By contrast, several regions report negative gaps among part-time employees, particularly in higher-paying regions, reflecting women's greater selection into part-time work. This pattern is consistent with national-level evidence (Mumford and Smith, 2009).

The regional pattern in hourly wages and gender gaps is mostly reflected at the local level. Torbay records the lowest mean hourly wage for all employees at £14.22 and the lowest gender gap at 10.13%. However, Northumberland, which represents the median of local areas by mean wage, shows a larger gender gap than Warwickshire County Council and Tower Hamlets, despite both having higher mean hourly wages. Similar patterns are also observed when restricting the sample to full-time employees (Table B.4, Appendix B). Among part-time employees, Tower Hamlets has the highest mean hourly wage (£21.09) but one of the lowest wages for part-time men, producing a substantial negative gap in favour of women. This likely results its industrial composition, with a high concentration of employees in the Business, Services and Finance (K, L, M, N) industry and in high-skilled occupations (Table B.5, Appendix B). The overall distribution of estimated GPG across local areas from the regression analysis is shown in Figure 3.4.

A comprehensive set of summary statistics for all explanatory variables and their means by gender is presented in Table B.5, Appendix B. To illustrate patterns across the distribution of gender gaps, the table highlights three regions — the North East, North West, and London — representing lower, median, and higher points in the regional distribution (Table 3.1). These indicate relatively consistent patterns across areas, confirming well-documented gender and regional disparities. Female employees are more likely to be in part-time employment than male employees in all regions, with part-time work more prevalent in lower-pay regions. Women are also more likely to have their wages set by collective agreements and to be employed in the public sector, especially in regions with lower mean hourly wages, such as the North East. These patterns align with evidence that regions experiencing significant industrial decline since the 1970s tend to have lower 'contemporary' GPGs (Jones et al., 2018), as also documented in Northern Ireland, (Jones and Kaya, 2022b). In contrast, there is little evidence of cross-regional gender differences in temporary employment or firm size, though regions with higher mean hourly wages tend to have shorter job tenure, consistent with agglomeration economies in Britain (Glaeser and Maré, 2001).

Occupational segregation by gender also varies across regions. Male employees dominate the Mangers & Senior Officials, Skilled Trades, and Process, Plant & Machine Operatives occupations, while female employees are overrepresented in the Administrative, Personal Services, and Sales & Customer Service occupations. London has lower occupational segregation than the North East (as measured by gender differences in the share of employees across occupations), and a higher proportion of both male and female employees in the Professional and Mangers & Senior Official occupations.

A full set of summary statistics for all explanatory variables by gender in local areas is provided in Table B.5, Appendix B. To illustrate variation across the local distribution of wages and gender gaps, three areas are highlighted - Torbay, Northumberland, and Tower Hamlets (situated in the South West, North East and London regions, respectively). These are selected to represent points at the lower, middle, and upper parts of the local distribution of mean hourly pay (Table 3.1), rather than as unique cases. They broadly reflect the patterns observed at the regional level, though with greater local variation. For example, part-time employment is more common among women in all areas, but the proportion of both male and female part-time employees is significantly higher in Torbay than in Tower Hamlets. Similarly, the public sector employs a greater share of women in lower-wage areas, though the local distribution of collective agreements differs from the regional pattern - in Torbay, a higher proportion of men than women are covered by collective agreements, whereas Northumberland shows overall higher coverage than Torbay. These deviations likely reflect local economic and industrial conditions, as suggested at the regional level.

Unlike the regional findings, there are no substantial gender differences in temporary employment or firm size across local areas. Moreover, the established regional pattern linking higher wages to shorter job tenure does not hold at the local level. Despite economic differences, Torbay and Tower Hamlets have similar average job tenures.

Occupational segregation by gender and across area is also evident at the local level, though it is less clearly defined due to the grouping of occupations into three skill-based categories (Table B.3, Appendix B). Male employees dominate the high-skilled occupational group across local areas, with limited variation across area. Similarly, female employees dominate the medium-skilled occupational group, again with minimal variation. However, in the low-skilled occupational group, Torbay and Northumberland employ more men, while Tower Hamlets shows a more gender-balanced distribution. These reflects the distinct local economic structure of Tower Hamlets, with its concentration in high-skilled employment.

The summary statistics provide valuable insights into gender and regional disparities in hourly wages and occupational distribution at the national, regional, and local levels in Britain. The patterns are broadly consistent with existing national-level evidence, reinforcing the persistence of gender and spatial inequalities. Across all areas, women are more likely to work part-time, to have their wages determined through collective agreements, and to be employed in the public sector, particularly in lower-wage areas. These drivers may serve as mitigating factors in shaping GPGs, suggesting a role for certain labour market structures and institutional arrangements. At the same time, occupational segregation by gender remains evident, though it is somewhat less pronounced in higher-wage regions and localities. Taken together, these findings provide an explanation for the spatial variation in gender pay gaps within Britain and lay the groundwork for the regression analyses and decompositions in the following chapters.

3.4.4 The Magnitude and Variation of Gender Pay Gaps Across Areas

Gender Pay Gaps at the National and Regional Level

Table 3.2 presents estimates of mean hourly GPGs across areas for all employees at the national and regional levels. Raw GPGs are estimated from Equation 3.1, which pools employees across gender and areas, regressing log hourly pay on a female dummy variable and a constant. The coefficient on the female dummy variable represents the raw GPG in log percent, capturing the difference in hourly pay between women and men without adjusting for characteristics. The adjusted GPG accounts for potential differences in characteristics between women and men by successively controlling for individual characteristics, workplace characteristics, occupation, and sector (columns (2)-(5)). Full coefficient estimates for the areas with the lowest, median, and highest raw GPG at national and regional levels are provided in Table B.6, Appendix B.

Table 3.2: Adjusted Gender Pay Gaps across Areas for All Employees, National and Regional Levels

	(1)	(2)	(3)	(4)	(5)
National	-0.140***	-0.080***	-0.088***	-0.094***	-0.093***
N:124,963	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Regional					
North East (England)	-0.105***	-0.059***	-0.074***	-0.076***	-0.080***
N: 5,069	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)
North West (England)	-0.125***	-0.074***	-0.086***	-0.093***	-0.095***
N: 14,105	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Yorkshire and the Humber	-0.151***	-0.092***	-0.097***	-0.110***	-0.111***
N: 11,358	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
East Midlands (England)	-0.138***	-0.084***	-0.093***	-0.087***	-0.087***
N: 8,943	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)
West Midlands (England)	-0.139***	-0.084***	-0.097***	-0.104***	-0.103***
N: 11,190	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
East of England	-0.129***	-0.072***	-0.083***	-0.090***	-0.091***
N: 11,595	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
London	-0.156***	-0.087***	-0.091***	-0.080***	-0.075***
N: 17,173	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)
South East (England)	-0.153***	-0.095***	-0.099***	-0.098***	-0.096***
N: 16,723	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)
South West (England)	-0.129***	-0.078***	-0.089***	-0.085***	-0.085***
N: 10,805	(0.009)	(0.008)	(0.008)	(0.007)	(0.008)
Wales	-0.097***	-0.056***	-0.077***	-0.083***	-0.086***
N: 6,001	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)
Scotland	-0.117***	-0.067***	-0.083***	-0.094***	-0.094***
N: 11,991	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
Individual characteristics	No	Yes	Yes	Yes	Yes
Workplace characteristics	No	No	Yes	Yes	Yes
Occupation	No	No	No	Yes	Yes
Sector	No	No	No	No	Yes

Notes: (i) Coefficient estimates are based on a pooled OLS earnings equation. (ii) Males, small firm size and the Administrative occupation are the reference categories. (iii) All models include a constant term. (iv) Standard errors are in parenthesis. (v) $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Source: Author calculations based on weighted ASHE 2022 data.

The national raw mean GPG is estimated at 14.0 log percent (15.03%) (column (1)), suggesting substantial gender inequality in the British labour market. This estimate aligns closely with the equivalent ONS estimate of 14.1% (ONS, 2022b).[15] At the regional level, the raw mean GPG varies from 9.7 log points (10.19%) in Wales to 15.6

[15] Disparities between estimates and official statistics arise from sample differences (see Section 3.4 for details).

log points (16.88%) in London, consistent with the descriptive statistics (Section 3.4). While this variation aligns with evidence from pooled LFS 2016-2019 data (Jones and Kaya, 2022b), it also highlights temporal changes. In pooled 1997-2000 LFS data, the highest raw GPG was in the South East (35.9 log points), whereas London had one of the lowest (18.7 log points) (Robinson, 2005). This indicates regional divergence in GPG trends and London's comparatively slow progress in narrowing the gap (see discussion in Section 3.2, Figure 3.2).

Figure 3.3a illustrates the variation in the raw GPG across areas at the regional level, revealing a distinct spatial pattern. Larger raw GPGs are concentrated in regions in the south-east, gradually decreasing in more distant areas. However, Yorkshire and the Humber diverges from this trend, with a raw GPG comparable to that of the South East.

Adjusting for individual characteristics substantially narrows the GPG across all areas (column (2)), with adjusted GPGs ranging from 5.6 log points (5.76%) in Wales to 9.5 log points (9.97%) in Scotland. This suggests that gender differences in individual characteristics account for a large proportion of regional GPG variation. For example, in London, controlling for individual characteristics narrows the estimated GPG by 6.9 log points, largely due to the inclusion of a full-time indicator (Table B.6, Appendix B). These findings are consistent with prior analyses of the GPG in the UK (Olsen et al., 2018) and Northern Ireland (Jones and Kaya, 2022b), where educational controls reduce adjusted GPGs.

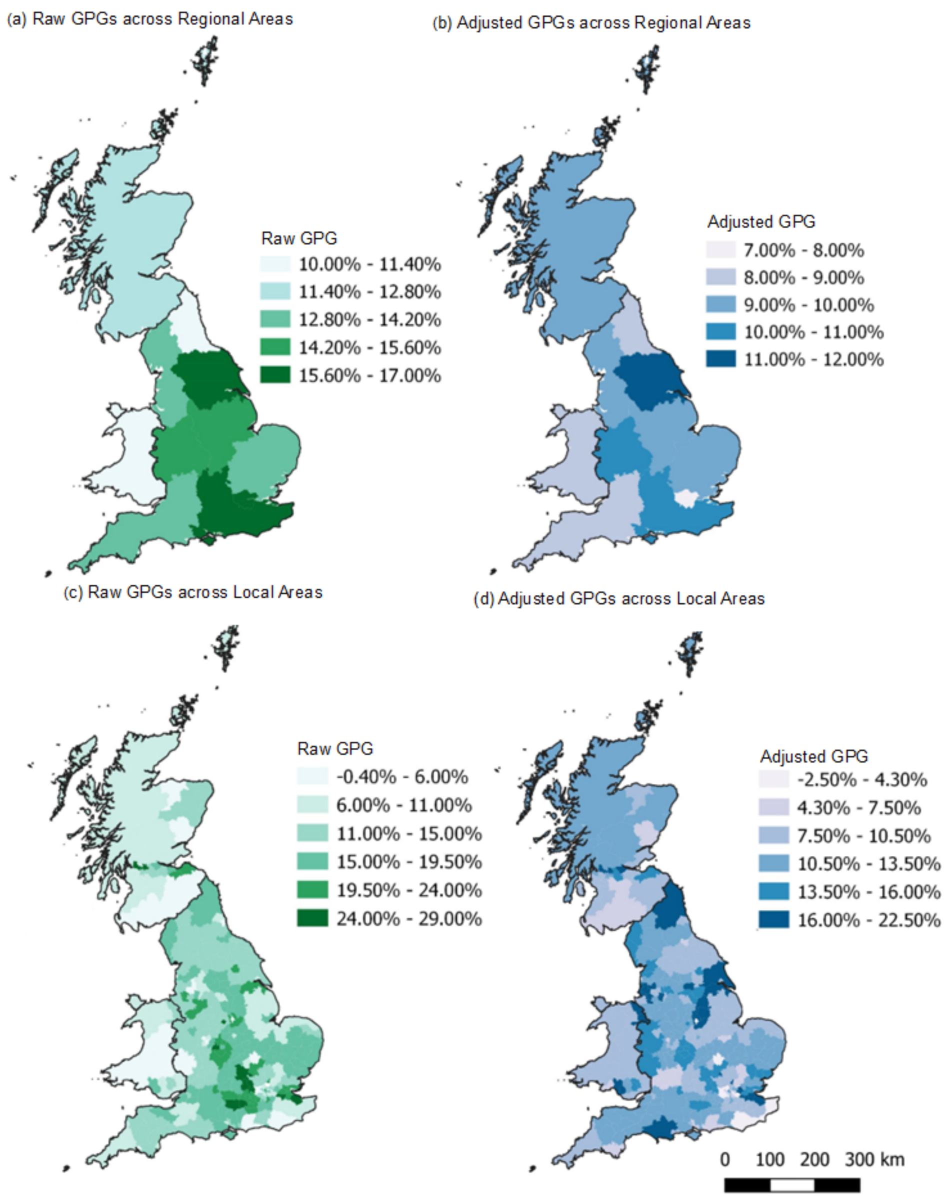
Adjusting for workplace characteristics (excluding occupation and sector, column (3)) increases the estimated GPG across areas. In contrast, controlling for occupational SOC unit group (column (4)) and public sector employment (column (5)) has a limited impact on both the magnitude and the spatial variation of the GPG.

In the most comprehensive specification, the adjusted national GPG is estimated at 9.3 log points (9.75%), with the regional variation ranging from 7.5 log points (7.79%) in London to 11.1 log points (11.74%) in Yorkshire and the Humber. These adjusted GPGs are consistently lower than the corresponding raw estimates, in line with prior research at national and regional levels in Britain (Olsen et al., 2018; Jones and Kaya, 2022b). While the range of adjusted GPGs across regions is narrower than that of raw GPGs (and local-level variations within regions, Figure 3.5), there is still substantial variation in the adjusted GPGs across regions (Figure 3.3b).

Table B.6, Appendix B presents full coefficient estimates for Britain, Wales, the South West, and London, representing the national area and the regions with the lowest, median, and highest raw GPGs. These estimates broadly align with prior analyses of the GPG in the UK (Olsen et al., 2018)), Northern Ireland (Jones and Kaya, 2022b), and comparable studies in Germany and Spain (Fuchs et al., 2021; Murillo Huertas et al., 2017).

Among individual characteristics, age and tenure have a significant, positive impact on

Figure 3.3: Raw and Adjusted Gender Pay Gaps across Areas at the Regional and Local Levels



Notes: (i) Estimates are based on a pooled OLS earnings equation and converted to a percentage through Equation 3.2. (ii) The adjusted GPG controls for individual characteristics (age, age-squared, tenure, tenure-squared, full-time employment, permanent contract), workplace characteristics (firm size, collective agreement), occupations (based on SOC unit group) and public sector. Males, small firm size and the Administrative occupation are the reference categories. All models also include a constant term. (iii) Sample sizes for each area can be found in Table B.2, Appendix B

Source: Author calculations based on weighted ASHE 2022 data.

hourly wages across regions, with evidence of diminishing returns, suggesting their role as proxies for work experience. Regarding workplace characteristics, employment in larger firms is associated with higher wages, with returns increasing progressively as firm size grows. The impact of collective wage agreements varies across regions: while positive and significant in Wales, it is either non-significant or negative in regions with larger raw GPGs.

Turning to occupational controls, which capture employment heterogeneity, the expected pattern emerges. Higher-skilled occupations earn significant wage premiums relative to the Administrative reference category, and these premiums increase along the regional GPG distribution, where men are disproportionately represented (Table B.5, Appendix B). Conversely, lower-skilled occupations generally have significant wage penalties, except for the Skilled Trades occupation in Wales, where earnings exceed those in the Administrative occupation. In Wales and the South West, employment in Elementary occupations is associated with the largest wage penalty, whereas in London, the lowest returns are observed in the Sales & Customer Services and Personal Service occupations. Public sector employment is associated with a significant wage premium in Wales and the South West, consistent with findings in Northern Ireland (Jones and Kaya, 2022b). However, at the national level and in London, public sector employment is associated with lower wages, consistent with broader UK trends (ibid.).

Taken together, these patterns indicate that the gap between raw and adjusted GPGs is shaped by different factors depending on region and position within the GPG distribution. This suggests that both individual characteristics and local labour market structures play distinct roles in driving gender pay inequality across Britain.

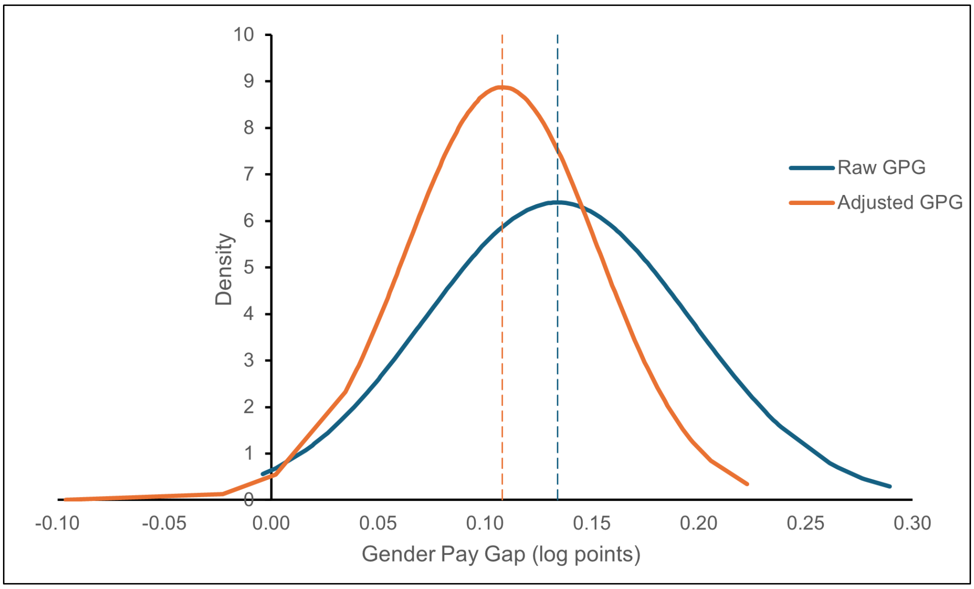
Gender Pay Gaps at the Local Level

Table B.7, Appendix B, presents the raw and adjusted mean hourly GPG estimates across areas at the local level for all employees. The raw mean GPG ranges from -0.4 log points (-0.40%) in Enfield to 25.4 log points (28.92%) in Solihull (column (1)). This degree of variation is comparable to that observed across local areas in Germany and Spain (Fuchs et al., 2021; Murillo Huertas et al., 2017) and aligns with broader cross-country differences in raw GPGs within Europe (Section 2.6.1).[16] These similarities suggest that Britain has a GPG distribution broadly representative of Europe. Full coefficient estimates for the areas with the lowest, median, and highest raw GPGs are provided in Table B.8, Appendix B.

This geographical variation is illustrated in Figure 3.3c, which maps the raw GPGs across areas at the local level. Consistent with regional patterns, the raw GPG is generally highest in localities in the south-east and gradually declines in more peripheral areas. However, this trend is largely driven by a few localities with particularly high GPGs. Figure 3.4 presents the kernel density of the raw GPG (blue), complementing the tabulated results by illustrating the full distribution rather than focusing on select localities. The mean of the raw distribution is around 0.1339 log points, but the spread highlights substantial local dispersion. This underscores both the persistence of underlying structural differences and the extent of intra-regional heterogeneity, patterns that would be obscured by regional or national averages.

[16] In European Structure of Earnings Survey 2021 data, the raw GPG across EU-27 member states ranged from -0.2% in Luxembourg to 20.5% in Estonia (Eurostat, 2023).

Figure 3.4: Local distribution of the Estimated Raw and Adjusted GPG



Notes: The blue line shows the distribution of raw GPGs across local areas (mean = 0.1339 log points). (ii) The orange line shows the distribution of adjusted GPGs across local areas (mean = 0.1085 log points). (iii) Sample sizes for each area are provided in Table B.2, Appendix B.

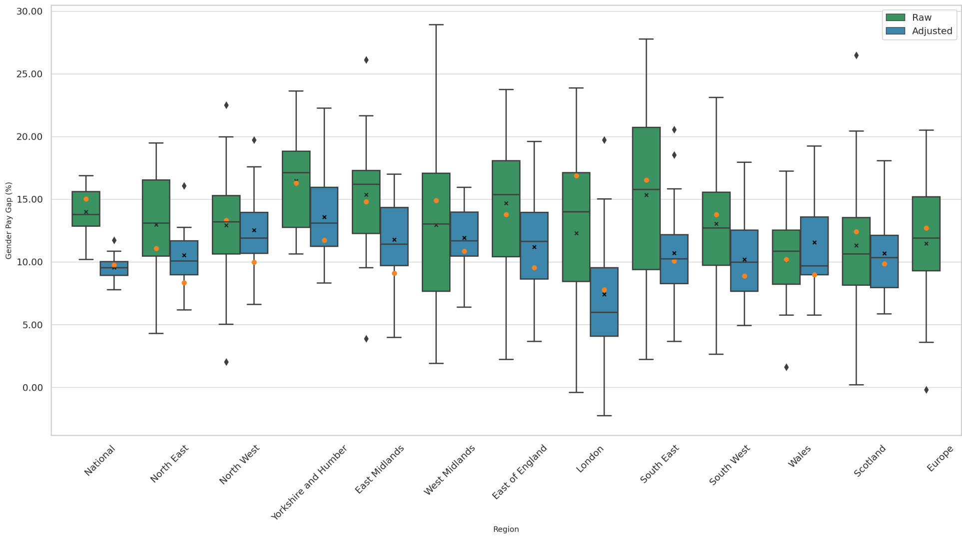
Source: Author calculations based on weighted ASHE 2022 data.

The variation in raw GPGs across local areas is greater than that observed at the regional level. As illustrated by the green bars in Figure 3.5, the interquartile range across local areas exceeds that across regions, suggesting that disparities within regions are larger than those between them. Intra-regional variation in the raw GPG is at least twice as large as inter-regional differences, with the highest variation observed in London, the South East, and the East of England, and the lowest in Wales, the North East, and Yorkshire and the Humber.

Following the analysis of the GPG across local areas in Germany (Fuchs et al., 2021), Figure 3.6 illustrates the relationship between the raw GPG and hourly wages by gender across all areas (see Table 3.1 for detailed hourly wage statistics at different geographical levels). When local areas are sorted in ascending order of the raw GPG, women's wages exhibit relatively little variation, whereas men's wages are substantially higher in areas with large GPGs. Some London localities, however, deviate from this pattern, showing high wages for both men and women alongside relatively low GPGs. This is reflected in the linear trend lines, which are flatter for women's wages than for men's. These findings reinforce evidence from Germany that local GPGs are more strongly correlated with variations in men's wages than in women's (ibid.), suggesting that disparities in men's wages across areas primarily drive the observed variation in the GPG.

Adjusting for individual characteristics narrows the GPG across most local areas by an average of five log points (column (2)). In some areas, this adjustment results in a GPG in favour of women, suggesting that individual characteristics explain a large portion of

Figure 3.5: Variation in Raw and Adjusted Gender Pay Gaps Across Regional and Local Areas



Notes: (i) The box plots illustrate the distribution of the raw (green) and adjusted (blue) GPG across regions in Britain and across local areas within each region. (ii) The box represents the interquartile range of GPGs across local areas within each region. The horizontal line inside the box indicates the median GPG, while the black 'x' marker represents the mean GPG. The whiskers extend to 1.5 times the interquartile range, capturing most of the variation within each region. Outliers (black diamonds) represent local areas with extreme GPG values. The orange dots indicate the estimated mean GPG for each region. (iii) Sample sizes for areas are provided in Table B.2, Appendix B.

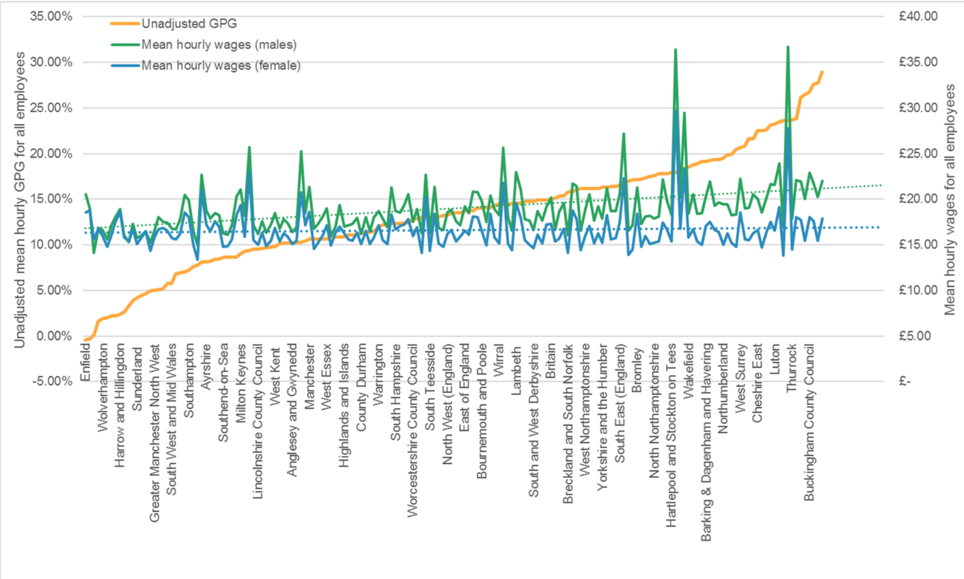
Source: Author calculations based on weighted ASHE 2022 data.

the GPG across areas, consistent with regional level findings. This effect is primarily driven by controlling for part-time employment, indicating the higher proportion of women working part-time across local areas. This aligns with prior UK studies (e.g. Olsen et al. 2018) and is supported by the descriptive statistics (Table B.5, Appendix B).

Controlling for workplace characteristics (excluding occupational skill group and public sector employment, column (3)) generally widens the GPG across areas, mirroring the regional findings, though the effect is not uniform. In contrast, controlling for occupational skill groups (column (4)) has a more pronounced impact locally, widening the GPG by an average of 1.5 log points, except in several London localities, including Tower Hamlets, where it narrows the GPG. This reflects the concentration of women in higher-skilled occupations in London, particularly in the financial industry, relative to other localities (Table B.5, Appendix B). The impact of public sector employment is minimal, altering local GPGs by less than one log point, consistent with regional findings and evidence from Northern Ireland (Jones and Kaya, 2022b).

In the most comprehensive specification (column (5)), the adjusted GPG is estimated to range from -2.3 log points (-2.27%) in Ealing to 20.1 log points (22.26%) in North and North East Lincolnshire. As in the regional analysis, adjusted GPGs are substantially smaller than their corresponding raw GPGs, as illustrated by the blue bars in Figure 3.5. Figure 3.4 presents the kernel density of the adjusted GPG (orange), with a

Figure 3.6: Hourly Wages by Gender and the GPG across Areas at the Local Level



Notes: (i) Wages are calculated for all employees as the mean of weighted ASHE 2022 data, as defined according to the ASHE guidance, in each area by gender. (ii) GPG estimates are derived from an OLS earnings equation of weighted ASHE 2022 data. (iii) Local areas are sorted in increasing order of their GPG. (iv) The linear trend lines depict the generalised level of the wages of women and men in the sorted areas (x). (v) Sample sizes for areas are provided in Table B.2, Appendix B.

Source: Author calculations based on weighted ASHE 2022 data.

mean of 0.1085 log points, showing a narrower distribution than the raw GPG. This suggests that a substantial portion of the GPG can be explained by observable labour market characteristics. However, the range of adjusted GPGs across local areas remains three times wider than the variation observed across regions (Figure 3.5).

Unlike the regional and raw GPG analysis at the local level, the adjusted GPG does not have a clear geographical pattern. Some local areas, such as Northumberland, Dorset County Council, and Bridgend and Neath Port Talbot, stand out with relatively large adjusted GPGs, potentially reflecting the role of industrial legacy (Figure 3.3d). In contrast, most local areas in London have low adjusted GPGs despite high raw GPGs, suggesting that gender differences in observable characteristics account for a larger portion of the raw GPG in these areas, explored by the OB decompositions below.

Table B.7, Appendix B, provides the full coefficient estimates for Enfield, South Teesside, and Solihull, representing the local areas with the lowest, median, and highest raw GPGs, respectively. These estimates broadly align with regional patterns, and findings from Germany, Spain and Northern Ireland (Fuchs et al., 2021; Murillo Huertas et al., 2017; Jones and Kaya, 2022b). They also suggest that factors well-established in explaining cross-country variations in the GPG (discussed in Section 2.6) contribute to significant variation in the GPG across areas. However, the statistical significance of the coefficients varies across local areas, particularly in areas with lower GPGs. Despite this variation, there is substantial differences in coefficient magnitudes across local areas. For a comprehensive view of how each variable contributes to the GPG across all local areas, see the OB decomposition analysis in Section 3.4, which captures the full variation beyond these selected areas.

As in the regional analysis, age and tenure have a significant, positive impact on hourly wages across local areas, with evidence of diminishing returns, though the statistical significance is not always consistent. Part-time employment is consistently associated with lower hourly earnings across all local areas and remains statistically significant in most specifications, except in Enfield in the most comprehensive specification. Unlike at the regional level, the effect of firm size varies across localities. In Enfield, larger firms are associated with lower earnings relative to smaller firms, whereas in South Teesside and Solihull, the opposite is observed. Similarly, the impact of collective agreements differs by local area: positive in Solihull, but negative or insignificant in Enfield and South Teesside.

Occupational skill groups largely behave as expected, with high- and medium-skilled occupations generally yielding higher hourly wages than low-skilled occupations, consistent with the human capital model (see Section 2.4 for a discussion on theoretical approaches). An exception is observed in Solihull, where medium-skilled occupations are associated with lower returns than low-skilled occupations, reflecting the broader pattern of men being overrepresented in areas with high raw GPGs (Table B.5, Appendix B). The wage premium for high-skilled occupations is more pronounced in Enfield, where the raw GPG is lower. Public sector employment mirrors regional patterns, providing a substantial wage advantage in areas with smaller GPGs, such as Enfield, but lower relative wages in areas with larger raw GPGs, such as Solihull.

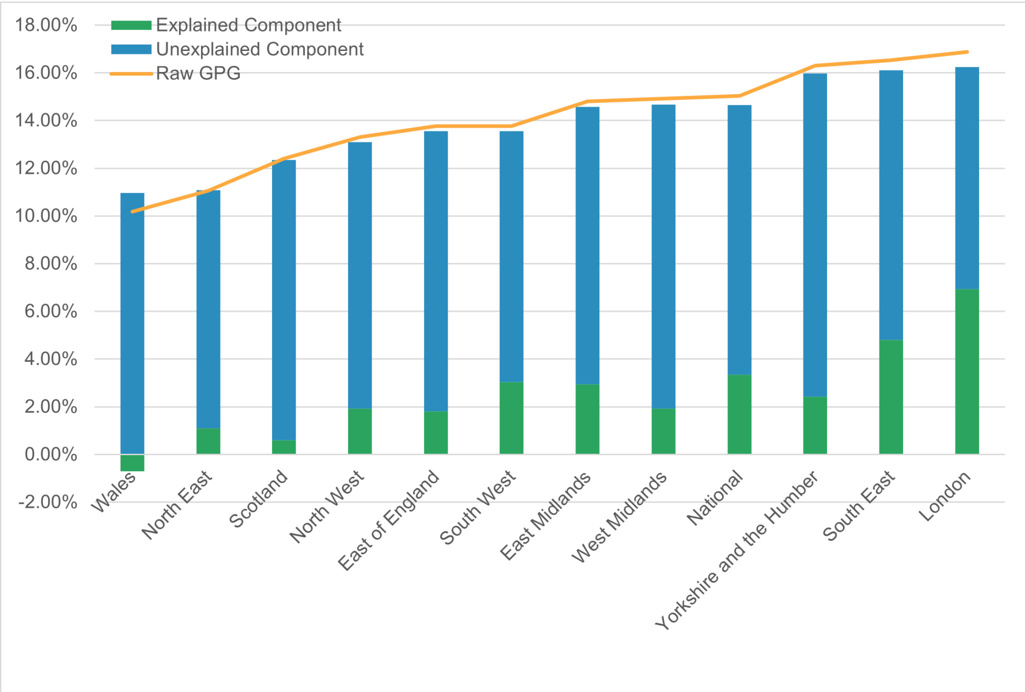
These differences in returns across areas highlight the importance of conducting analyses at the local level. Examining GPGs at this finer spatial scale, provides a more detailed and nuanced understanding of wage disparities, revealing patterns that may be obscured in regional or national aggregates.

3.4.5 Decomposition of Gender Pay Gaps Across Areas within Britain

Decomposing Gender Pay Gaps at the National and Regional Levels

The OB decompositions of raw mean hourly GPGs across areas at the national and regional levels are presented in Table B.9, Appendix B, and illustrated in Figure 3.7, where regions are sorted by the magnitude of their raw GPGs. These decompositions correspond to the estimation of Equation 3.5, using the most comprehensive specification and evaluated at male coefficients. Consistent with previous decompositions of the UK's GPG (e.g., Olsen et al. 2018), the findings indicate that only a modest portion of the national raw GPG can be attributed to gender differences in observed characteristics. Specifically, the explained component accounts for 35.1% of

Figure 3.7: The Explained and Unexplained Component of the Gender Pay Gap across Areas, Regional Level



Notes: (i) Estimates are based on an OB decomposition of mean hourly GPGs across areas using relevant male coefficients as the baseline. (ii) The specification includes individual characteristics (age, age-squared, tenure, tenure-squared and a part-time and a temporary contract indicator), workplace characteristics (firm size and a collective agreement indicator), occupations, and public sector employment. (iii) Areas are sorted in increasing order of their raw GPG. (iv) Small discrepancies between the sum of the explained and unexplained components and raw GPGs are a result of rounding.

Source: Author calculations based on weighted ASHE 2022 data.

the raw GPG, leaving the majority unexplained. This aligns closely with previous estimates despite differences in data sources, time periods, and sample criteria (e.g., Jones and Kaya 2022b; Olsen et al. 2018; Mumford and Smith 2007).

The explained component is positive across all regions except Wales, indicating that, on average, men have more productivity-enhancing characteristics than women. However, its magnitude is relatively modest, explaining less than a third of the raw GPG in most regions. An exception is London, where the explained component accounts for 43.1% of the 16.88% raw GPG. These findings suggest that only a small share of regional GPGs can be attributed to gender differences in individual characteristics, workplace characteristics, occupations, and sectors. Instead, the majority remains unexplained, likely reflecting gender differences in the returns to these characteristics or the influence of unobserved factors, which are further explored in Section 3.5. While the unexplained component can be cautiously interpreted as an upper bound of wage discrimination, even a more comprehensive set of control variables (e.g., disability status, ethnicity, etc.) is likely to overstate the extent of direct wage discrimination (as discussed in Section 3.4).

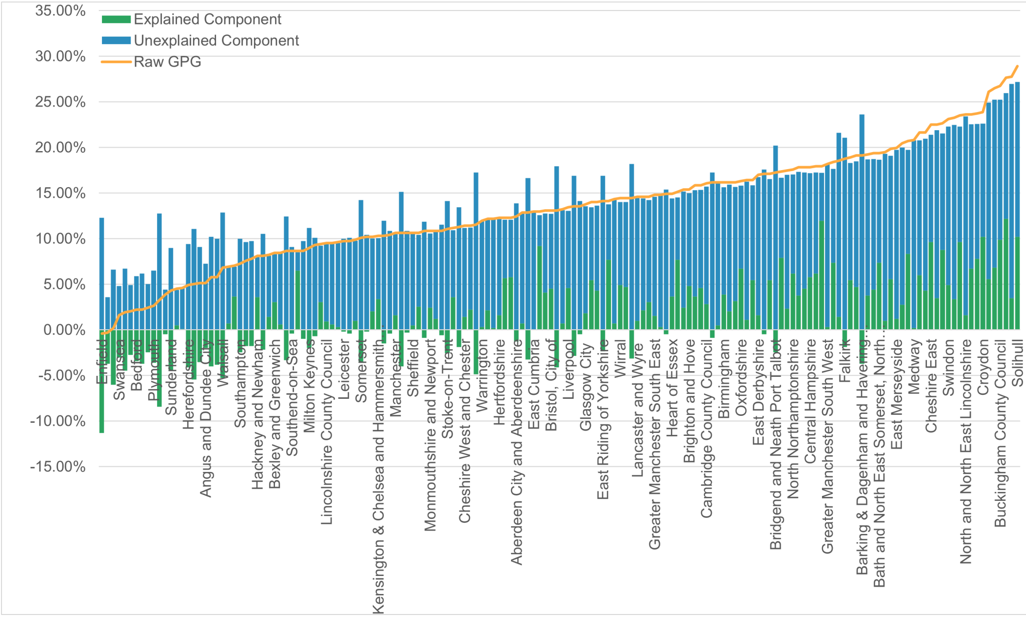
Figure 3.7 demonstrates that regions with larger raw GPGs tend to have larger explained components, both in absolute and proportional terms. This suggests that variation in the GPG across regions is primarily driven by differences in the distribution of employees across regions rather than by regional differences in gender-specific wage structures. In contrast, the unexplained component exhibits relatively little variation across regions, as shown by the linear trend lines in Figure B.1, Appendix B, which aggregate decomposition components across the sorted regions, following Fuchs et al. (2021). While regional differences in the explained component contribute to overall variation in the raw GPG, the unexplained component remains relatively stable, a pattern also documented in Germany (Fuchs et al., 2021).

The contrast between Wales and London - as the regions with the lowest and highest raw GPGs, respectively - illustrates this pattern. In Wales, the explained component is estimated at -0.7 log points (-0.70%) of the 9.7 log point (10.19%) raw GPG, suggesting that women, on average, have more productivity-enhancing characteristics than men. In London, the explained component accounts for 6.7 log points (6.93%) of the 15.6 log point (16.88%) raw GPG. Despite these regional differences in the explained component, the magnitude of the unexplained components in Wales and London remain closely aligned at 10.4 log points (10.96%) and 8.9 log points (9.31%), respectively. If cautiously interpreted as a measure of gender pay inequality, these findings indicate broadly similar levels of gender pay inequality across regions within Britain. This aligns with evidence from Northern Ireland, where the unexplained component of the raw GPG closely mirrors that of the rest of the UK, despite a small or sometimes negative raw GPG (Jones and Kaya, 2022b). The pattern in which regions with lower raw GPGs have small or even negative explained components is also consistent with findings from Germany (Fuchs et al., 2021), Northern Ireland (Jones and Kaya, 2022b), and several EU countries, including Belgium, Poland, Portugal, and Italy (Christofides et al., 2013). Taken together, these patterns suggests that variation in the raw GPG across regions primarily reflects gendered labour market sorting rather than regional differences in pay-setting practices.

Decomposing Gender Pay Gaps at the Local Level

The OB decompositions of raw mean hourly GPGs across areas at the local level, based on the most comprehensive specification and evaluated using male coefficients, are presented in Table B.9, Appendix B and illustrated in Figure 3.8. In this figure, localities are sorted by the magnitude of their respective raw GPGs. Consistent with findings for Wales, 55 local areas have a negative explained component, indicating that women in these areas, on average, have more productivity-enhancing characteristics than their male counterparts. These localities are concentrated at the lower end of the GPG distribution, implying that negative explained components act to mitigate raw GPGs. However, as all localities have unexplained components in favour of men, a lower raw GPG does not necessarily imply greater gender pay equality. This pattern mirrors the regional analysis and aligns with evidence from Germany, Spain, and Northern

Figure 3.8: Explained and Unexplained Components of Gender Pay Gaps across Areas, Local Level



Notes: (i) Estimates are based on an OB decomposition of mean hourly GPGs across areas using relevant male coefficients as the baseline. (ii) The specification includes individual characteristics (age, age-squared, tenure, tenure-squared and a part-time and a temporary contract indicator), workplace characteristics (firm size and a collective agreement indicator), occupational skill groups, and public sector employment. (iii) Areas are sorted in increasing order of their raw GPG. (iv) Small discrepancies between the sum of the explained and unexplained components and raw GPGs are a result of rounding.

Source: Author calculations based on weighted ASHE 2022 data.

Ireland (Fuchs et al., 2021; Murillo Huertas et al., 2017; Jones and Kaya, 2022b).

At the local level, the decomposition results largely parallel regional patterns. The explained component remains relatively modest across local areas, typically accounting for less than 50% of the raw GPG (Table B.9, Appendix B).[17] The variation in the raw GPG is primarily driven by differences in the magnitude of the explained component, while the unexplained component is comparatively more. However, the unexplained component shows greater variance across local areas than across regions, warranting further investigation in Section 3.5.

The variation in both the explained and unexplained components of GPGs across localities is further illustrated in Figure 3.8 and Figure B.1, Appendix B, where localities are sorted by the magnitude of their respective raw GPGs. The results indicate that the variation in explained components across local areas is similar to that observed at the regional level, as reflected in the gradients of the explained linear trend lines in Figure B.1, Appendix B. While the unexplained component has slightly greater variability at the local level than at the regional level, this variation remains smaller than that of the explained component across localities. These findings, which align with evidence from Germany (Fuchs et al., 2021), suggest that differences in the relevance of

[17] Where the explained component exceeds 50%, this is usually due to a statistically insignificant raw GPG.

observed wage determinants are the main driver of variation in explained components across areas. In contrast, the unexplained component remains relatively stable across areas.

This pattern is demonstrated by comparing localities with the smallest and largest raw GPGs - Enfield and Solihull, respectively. In Enfield, the explained component is estimated at -12.0 log points (-11.31%) of the raw GPG of -0.4 log points (-0.40%), indicating that women working in this locality, on average, have more productivity-enhancing characteristics than men. In the absence of other factors, this would imply a female wage advantage. However, the unexplained component in Enfield is 11.6 log points (12.30%), offsetting the explained component and resulting in a smaller, albeit still positive, wage advantage for women. By contrast, in Solihull, the explained component accounts for 9.7 log points (10.19%) of the raw GPG of 25.4 log points (28.92%), highlighting the extent to which gender differences in observable characteristics favour men. Additionally, the unexplained component contributes 15.7 log points (17.00%), further contributing to men's wage advantage in this locality.

Detailed Decompositions of the Gender Pay Gap Across Areas

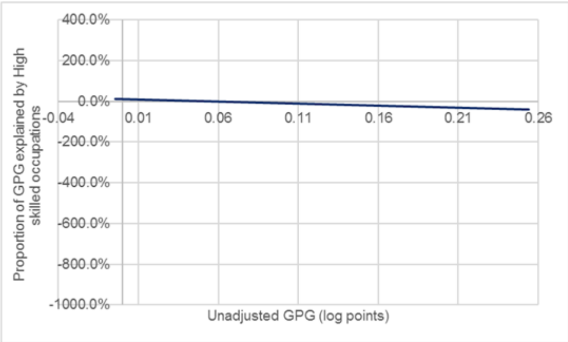
Detailed decompositions of the explained components of the raw GPGs for Britain, Wales, and London - representing the national level and the regions with the lowest and highest raw GPGs, respectively - are presented in the lower panel of Table B.10, Appendix B. These decompositions identify the contributions of each characteristic to the explained component of the GPG, using male wage coefficients as the reference. Consistent with prior analyses of GPGs in the UK (Olsen et al., 2018; Jones and Kaya, 2022b), occupational segregation emerges as a primary driver of the explained GPGs.

Higher skilled occupations, such as the Managers & Senior Officials and Professional occupations, contribute to widening the explained GPGs. Conversely, lower skilled occupations, including the Process, Plant & Machine Operatives and Elementary occupations, act to mitigate it. This occupational effect is particularly pronounced in Wales, where the raw GPG is smaller and the explained component favours women. These findings align with evidence from Northern Ireland, where occupational gender differences (measured by a dissimilarity index analysis) similarly make the largest (negative) contribution to the explained GPG (Jones and Kaya, 2022b).

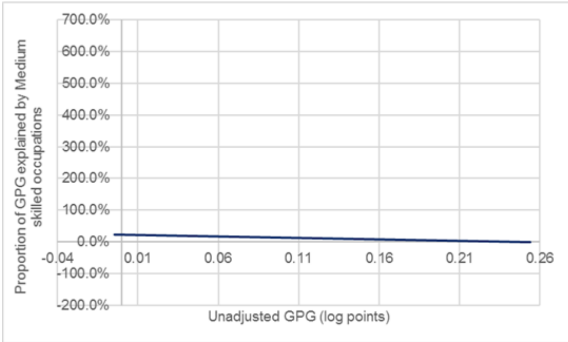
Similar detailed decompositions for Enfield and Solihull — the local areas with the lowest and highest raw GPGs, respectively — are presented in the lower panel of Table B.11, Appendix B. Echoing the regional-level results, occupational segregation remains the largest contributor to the explained component of local GPGs. However, unlike at the national and regional levels—where gender sorting into higher-skilled occupations widens GPGs—in both Enfield and Solihull gender differences in high- and medium-skilled occupations mitigate explained GPGs. This suggests that regional-level analyses may obscure significant local labour market heterogeneity.

Figure 3.9: Contribution of Occupational Skill Groups to the Gender Pay Gap Across Local Areas

(a) High skilled occupations



(b) Medium skilled occupations



Notes: (i) Estimates are based on OB decompositions of mean GPGs across local areas in Britain, using relevant male wage coefficients as the reference. (ii) The 160 local areas are sorted in increasing order of their raw GPG. Dumfries and Galloway is excluded from the analysis of medium-skilled occupations, as the proportion explained exceeds 1000%. (iii) Linear trend lines illustrate spatial variations in the contribution of each explanatory variable to the GPG across the ranked areas.

Source: Author calculations based on weighted ASHE 2022 data.

Figures 3.9a and b plot linear trend lines to summarise how the contributions of high-skilled and medium-skilled occupations vary across localities, following the approach of Fuchs et al. (2021). The intersections of these lines with the horizontal axis suggest that the influence of occupational skill groups on the GPG is spatially heterogeneous, mirroring findings in Germany (Fuchs et al., 2021) and reflecting prior research in England and Wales that emphasises the role of local labour market characteristics (Perales and Vidal, 2015). This is explored further in Section 3.5.

Specifically, high-skilled and medium-skilled occupations, relative to low-skilled occupations, mitigate raw GPGs in areas with lower raw GPGs but gradually transition to having a minimal effect in areas with medium and high GPGs. This pattern suggests that in areas with relatively high GPGs, gender-based occupational sorting into high-skilled and medium-skilled roles amplifies wage disparities. A similar trend is observed at the regional level. Compared to Administrative occupations, Personal Service occupations have a stronger positive impact on the raw GPG in low GPG areas, though this effect diminishes in higher-GPG areas. In contrast, employment in Elementary occupations appears to mitigate the GPG in low-GPG areas, potentially reflecting more gender-balanced wage structures within these roles. These trends are particularly evident in Wales and London (see Table B.10, Appendix B).

Beyond occupational segregation, workplace characteristics also contribute to variation in the GPG across areas. The distribution of employees across firm sizes partially offsets the GPG in both London and Wales. By contrast, in Solihull, gender differences in employment within enterprise firms account for 36.1% to the explained GPG. Similarly, gender differences in collective agreements widen the explained GPG in both Enfield and Solihull (Table B.11, Appendix B). Gender differences in full-time employment further contribute to widening the explained component in Wales, London, and Solihull, but have a negligible effect in Enfield.

Despite these observed differences, the visual depictions of the contribution of characteristics along the GPG distribution, suggest that relatively few explanatory variables have significant variation in their impact on the GPG (i.e. their trend lines do not intersect the horizontal axis, Figure B.2, Appendix B). This contrasts with findings from Germany, where nearly all characteristics exhibited spatial variation in their contribution (Fuchs et al., 2021). However, the differences observed across local areas in Britain indicate that variation in the raw GPG is partly driven by greater heterogeneity at the local level. This highlights the need for more granular, local-level analyses, as national or regional averages may mask significant differences across smaller labour markets.

Overall, the OB decompositions across areas in Britain indicate that the drivers of the national GPG are broadly applicable at the regional and local levels, consistent with evidence from Germany (Fuchs et al., 2021), Spain (Murillo Huertas et al., 2017) and Northern Ireland (Jones and Kaya, 2022b). However, while the broad explanatory patterns are similar, regional analyses often obscure the more pronounced heterogeneity observed at the local level. This underscores the analytical value of adopting a multi-geographical approach to understanding the GPG.

3.4.6 Sensitivity Analysis

The sensitivity of the OB decompositions of the GPG across areas is explored with respect to a series of alternative methodological choices, samples, and model specifications. The baseline decomposition follows the standard approach in the GPG literature by using male wage coefficients as the reference group, under the assumption that male wages reflect competitive market outcomes (see discussion in Section 2.5.2, Jann 2008). However, as the choice of weighting scheme can influence decomposition results, sensitivity analysis is conducted to re-estimate the decompositions for Britain, Wales, London, Enfield, and Solihull using pooled and female wage coefficients as alternative reference groups.[18]

While caution is warranted when interpreting decompositions based on reference groups other than male coefficients (Blau and Kahn, 2017), the results indicate that the baseline decompositions remain largely robust to this choice. The explained component varies across areas, with lower raw GPGs often associated with small or even negative explained components (i.e., favouring women). In contrast, the unexplained component remains relatively stable, although with greater variability at the local level. Detailed decomposition results using pooled and female coefficients are provided in Tables B.12

[18] The pooled specification incorporates a gender dummy variable following Fortin (2008), approximating a hypothetical wage structure that reflects overall market conditions.

and B.13, Appendix B. Comparisons across reference groups show broadly consistent patterns at both national and regional levels, though results for Wales are more variable, reflecting the statistical insignificance of its explained component. These findings reinforce the importance of gender differences in occupations in explaining the variation in the raw GPG across areas, aligning with evidence from Northern Ireland (Jones and Kaya, 2022b).

The baseline OB decompositions are also robust to alternative data. Specifications (3) and (4) present the decompositions for the selected areas using unweighted ASHE 2022 data and weighted ASHE 2019 data, respectively (Table B.14, Appendix B). Unweighted 2022 data are employed due to concerns that post-pandemic survey weights may introduce bias, while 2019 data serve to mitigate potential pandemic-related distortions. Interestingly, a substantial difference in the raw GPG is estimated in Enfield between 2019 and 2022. In 2019, the raw GPG was considerably larger and more aligned with other London boroughs, whereas by 2022, it had narrowed significantly. This shift is primarily attributable to changes in the explained component across the two years, while the unexplained component remains statistically unchanged.

Sensitivity analysis is also conducted with respect to different samples and model specifications (Table B.14, Appendix B). Specification (5) restricts the analysis to full-time employees, recognising that this subgroup has stronger labour market attachment and comparability across genders (Blau and Kahn, 2017). Specification (6) excludes employees working overtime to address potential biases arising from gender differences in overtime hours. Specification (7) re-estimates the decompositions using hourly pay inclusive of overtime. Specification (8) adds industry controls at the one-digit SIC level, while Specification (9) omits occupational and public sector controls to assess the extent to which gender segregation across industries and occupations influences the explained and unexplained components of the GPG. The exclusion of occupational and public sector controls may also capture the indirect influence of trade union membership, as this is often mediated through these variables (Jones and Kaya, 2022b). Finally, Specification (10) estimates the median GPG, given its prominence in policy discourse (Section 2.2), following Machado and Mata (2005) with standard errors obtained via bootstrapping over 500 replications.

The key patterns observed in the baseline decompositions remain robust across alterative model specifications at the national level. However, restricting the sample to full-time employees reveals that women in full-time employment, on average, have more productive characteristics than men. This reflects systematic differences between women in full-time and part-time employment, both in individual and workplace characteristics as well as occupational segregation. These findings align with evidence that approximately 25% of women moving from full-time to part-time employment experience occupational downgrading, as shown in NES and BHPS panel data from 1991-2001 (Connolly and Gregory, 2008).

The robustness of the results extends to the regional level. Regions with smaller raw GPGs tend to have smaller or even negative explained components, while regions with larger raw GPGs have higher explained components. For instance, across various specifications, the explained component in Wales consistently favours women. When restricted to full-time employees, the explained component in Wales accounts for -69.6% of the raw GPG, compared to 28.3% in London. While the magnitude of the raw GPG remains broadly stable across areas, most variation arises from the explained component, with the unexplained component remaining relatively consistent.

At the local level, the sensitivity analysis exhibits greater heterogeneity, though the general patterns hold: areas with larger raw GPGs tend to have larger explained gaps, both in absolute terms and as a proportion of the raw GPG. This heterogeneity underscores the importance of local-level analysis, as such variation may be masked in more aggregated regional or national analyses. Restricting the sample to full-time employees further highlights the role of selection effects. For instance, in Enfield and Solihull, the explained component becomes more favourable to women under this specification compared to baseline results.

Potential biases may also arise from the main analysis being based on workplace location rather than location of residence. This raises endogeneity concerns, as individuals' ability to migrate and commute in response to labour market conditions may influence the results. Since men tend to have higher mobility than women in the UK, they may be more likely to access higher-paying jobs that require commuting or relocation, potentially introducing bias into the decompositions. To address this, decompositions are re-estimated based on individuals' place of residence (Specification (11)), excluding commuters across regions (Specification (12)) and localities (Specification (13)). Finally, individuals who changed workplace area between 2018 and 2019 are excluded from the 2019 decompositions (Specification (14)) to account for job-related selection effects.[19]

These re-estimations broadly confirm the robustness of the main results, though with some variation. When defined by residence, both Wales and Enfield show an an explained component favouring women alongside a raw GPG in favour of men. In Solihull, the explained component is lower when defined by residence, suggesting that men benefit more from commuting. Excluding commuters reinforces this finding, with the explained component favouring women, indicating that non-commuting women often possess more productivity-related characteristics. By contrast, restricting the sample to individuals who reside and work in Enfield produces results consistent with the main analysis. Together, these patterns highlight the role of commuting and migration incentives in shaping the geography of the GPG.

[19]The use of 2019 data mitigates potential pandemic-related distortions in 2020 and 2021 data.

3.5 Area Characteristics and Gender Pay Gaps within Britain

The OB decompositions indicate that gender differences in individual and workplace characteristics, occupations, sector of employment, and the spatial allocation of employees substantially contribute to the observed variation in the raw GPG across areas. However, as discussed in the literature reviews (Sections 2.6 and 3.3), broader contextual factors - such as wage-setting institutions, local labour market characteristics, and other economic and demographic characteristics - are also likely to shape variation in the GPG. These factors cannot be incorporated into the OB decompositions due to data limitations of the ASHE, yet they may influence the GPG by affecting women's decisions to participate in the labour force, the intensity of their participation, and the treatment they may receive in the labour market (Murillo Huertas et al., 2017). Exploring these area-level factors therefore provides an important complementary perspective on the drivers of contemporary GPGs.

To examine these relationships, correlation coefficients are estimated between a range of area-level indicators and the raw, explained, and unexplained GPGs across local areas.[20] These GPG measures are obtained from the OB decompositions at the local level, offering a more granular perspective than analyses based on regional or national averages. This approach builds on prior research by Murillo Huertas et al. (2017) and Longhi (2020), who emphasise that variation in the unexplained component of gender and ethnic pay gaps should not be exclusively interpreted as evidence of discrimination but may also reflect broader contextual influences. In line with this research, the analysis considers a range of area-level characteristics (detailed in Table B.15, Appendix B), capturing dimensions of area deprivation, industrial composition, and local labour market structure. These characteristics are informed by the empirical literature on spatial labour market disparities (Section 3.3.2). Where possible, data on area characteristics are constructed from the ASHE and supplemented with external sources, with methodological adjustments implemented to ensure robustness and prevent statistical disclosure, as documented in Table B.16, Appendix B.

The estimated correlation coefficients between area characteristics and the raw, explained, and unexplained GPGs are presented in Table B.16, Appendix B. For the raw and explained components, most correlations align with theoretical expectations and existing empirical evidence. Specifically, local areas with higher relative deprivation, lower wage inequality, greater trade union membership, and a larger public sector workforce tend to have lower GPGs. Similarly, areas with higher employment shares in female-dominated industries, such as Public administration, Education and Social Work,

[20] The decision to estimate correlations rather than regressions is motivated by the objective of providing a descriptive overview of associations between area characteristics and GPGs, rather than establishing causal relationships. Given the cross-sectional nature of the data and risks of omitted variable bias and reverse causality, regression models could produce misleading results. Correlation coefficients, in contrast, offer a transparent and interpretable means of assessing the strength and direction of these associations. This approach serves as an initial step to inform future research and highlight potential area-level drivers of GPG variation.

exhibit lower raw and explained GPGs. Conversely, areas with greater concentrations of male-dominated industries, such as Non-manufacturing and Business and Services and Finance, are associated with higher GPGs, though this relationship appears to be partly driven by London, where high raw GPGs coincide with a high concentration of employees in these industries.

Additionally, high population density, proxied by the proportion of rural population, is estimated to be associated with lower raw GPGs. This supports the monopolistic competition framework, which suggests that densely populated labour markets are more competitive, constraining employers' ability to discriminate against women (see Section 2.4.2; Hirsch et al. 2013; Robinson 1933). This pattern is consistent with empirical findings from Germany (Hirsch et al., 2013) and Spain (Murillo Huertas et al., 2017).

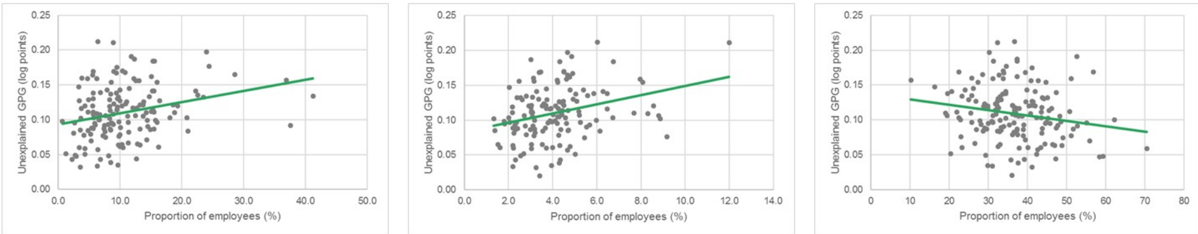
An exception to the expected patterns concerns the relationship between the unemployment rate and the GPG. Areas with higher unemployment rates tend to have lower raw and explained GPGs, irrespective of gender. This is contrary to the spatial monopsony hypothesis, which would predict lower unexplained components in more competitive labour markets (Hirsch et al., 2013). This results again appears to be influenced by London, where relatively high unemployment coincides with lower unexplained gaps. One possible interpretation is that workforce composition and sectoral specialisation exert stronger influences on GPG variation than local competitive pressures, though this remains tentative.

Overall, relatively few correlations are statistically significant. This largely reflects the modest variation in unexplained GPGs across local areas (Figure 3.8), in contrast with findings from Spain, where larger regional differences in the unexplained component yielded stronger correlations with area characteristics (Murillo Huertas et al., 2017). Moreover, some area characteristics may overlap with individual and workplace characteristics already included in the decompositions, reducing their explanatory power for the unexplained component. Area deprivation, for instance, shows no consistent pattern and generally weak correlations once these overlaps are accounted for.

An exception is the significant positive correlation between unexplained GPGs and the proportion of employees in the Manufacturing and Construction industries. This contrasts with the negative, non-significant correlation between these industries and explained GPGs (Figure 3.10a, b). Although this pattern requires cautious interpretation, it may suggest higher levels of discrimination in these industries. This interpretation aligns with descriptive evidence from Germany, where the largest local GPGs are observed in areas where men predominately occupy machine-building and operational roles (Fuchs et al., 2021). Sensitivity analysis reinforces this, suggesting that the unexplained component in the Manufacturing industry remains consistently larger across nearly all local area in Germany (ibid.), a pattern also observed across regions within Britain (Table B.17, Appendix B). In all regions (except London and the North

Figure 3.10: Correlation Coefficients between Unexplained GPGs and Industrial Composition

(a) Manufacturing industry (b) Construction industry (c) Public Administration, Education and Social Work industry



Notes: (i) Estimates are based on OB decomposition of mean GPGs across local areas, using relevant male wage coefficients as the reference. (ii) Industrial composition is based on the proportion of employees in broad industry groups, based on SIC 2007 codes. (iii) Linear trend lines depict the correlation coefficient between the proportion of employees in each industry and the estimated unexplained GPGs. (iv) Each point represents a local area. (v) Local areas with fewer than 10 employees in a sector group are excluded to ensure robustness (Manufacturing 152 local areas; Construction 143 local areas; Public admin, Education and Social Work 160 local areas).

Source: Author calculations based on weighted ASHE 2022 data.

West), the unexplained component in the Manufacturing and Construction industries accounts for at least 70% of the raw GPG. This suggests that the observed correlations are not solely driven by the relatively small number of women employed in these industries in areas, but rather reflects systematic structural differences that warrant further investigation.

In contrast, the unexplained GPG is significantly negatively correlated with the share of employees in the Public Administration, Education, and Social Work industry (Figure 3.10c). As a traditionally female dominated industry, this finding challenges prevailing narratives that the unexplained component has persisted in the public sector despite equality initiatives, including the PSEDs (see Section 2.3, Jones and Kaya 2019). Instead, it supports evidence that the public sector wage premium disproportionately benefits women, thereby reducing the unexplained component (Blackaby et al., 2012a; Jones et al., 2018). This contrasts with findings from Germany and Northern Ireland, which suggest that women's concentration in public sector jobs has limited capacity to explain GPG variation (Fuchs et al., 2021; Jones and Kaya, 2019). Despite this, no significant correlation is estimated between the unexplained component and the broader measure of public sector employment, suggesting that the effect is not simply about sector size but the quality of opportunities the sector provides women in certain local labour markets (Fuchs et al., 2021; Jones et al., 2018). A similar pattern emerges concerning the strength of trade union membership in local areas - a characteristic often associated with public sector employment (Webb et al., 2019).

Table B.16, Appendix B further suggests that both unemployment and rurality contribute to variation in the unexplained GPG across local areas. As expected, areas with a higher proportion of rural residents tend to exhibit larger unexplained gaps. This finding is consistent with the spatial monopsony framework, which suggests that limited employer competition in rural labour markets reduces wage pressures and exacerbates pay gaps (Hirsch et al., 2013; Robinson, 1933). In contrast, the negative correlation between unemployment rate and unexplained gaps run counter to theoretical expectations. Despite this inconsistency, the findings reinforce the idea that the unexplained component is shaped by local area characteristics. Taken together, they highlight the need for further research into how local structures and economic dynamics interact to produce persistent gender inequalities.

3.6 Conclusion

Despite renewed policy efforts to reduce GPGs and the increased political focus on spatial inequalities through the UK Government's 'levelling up agenda', significant variation in the raw GPG persists across areas within Britain. Using comprehensive and reliable payroll data from the 2022 ASHE, this Chapter makes a central contribution showing that the raw national GPG of 15.03% conceals substantial spatial heterogeneity. At the regional level, the raw GPG varies from 10.19% in Wales to 16.88% in London, but variation is even greater at the local level, with estimates from -0.40% in Enfield to 28.92% in Solihull. This highlights the value of moving beyond aggregate statistics to uncover underlying drivers of inequality. Further, the larger local GPG variation within regions than across regions are comparable to cross-country differences in the European context, as also observed in Spain (Murillo Huertas et al., 2017).

The research also presents new evidence on the magnitude and determinants of the raw GPG across areas within Britain. It identifies that drivers well-established to determine cross-country variation in the GPG also shape variation across areas. In particular, occupational segregation - long identified as a driver of international differences - also explains variation within Britain, demonstrating the spatial dimension of segregation. Unlike comparable German evidence (Fuchs et al., 2021), however, only a limited number of explanatory variables are found to have heterogeneous effects across the distribution of local GPGs.

Using the OB decomposition method, the research further decomposes the raw GPG across areas into explained and unexplained components. These reveal that most spatial variation results from gender differences in the distribution of employees working across areas - an effect more pronounced at the local rather than the regional level. In some areas, the explained component indicates that women, on average, have more productive characteristics than men. Despite this, across all local areas, explained components account for less than 50% of the raw GPG, leaving the majority unexplained. The unexplained component consistently favours men, varies modestly across areas, and is more volatile locally. This challenges the notion that a low raw GPG signals greater gender equality, echoing similar results for Northern Ireland (Jones and Kaya, 2022b).

While a large portion of the raw GPG across areas within Britain remains unexplained, caution is required when interpreting this component as a direct measure of discrimination. Accurately quantifying discrimination requires comprehensive data on all wage determinants. Given the limited set of individual characteristics available in the ASHE, the analysis may overestimate discrimination due to omitted variable bias. Consequently, the research extends its analysis by exploring the relationship between area-level characteristics and the unexplained component across areas. The findings suggest that, although the unexplained component remains relatively stable across areas, it varies systematically on the basis of local labour market characteristics, including industrial composition, unemployment rates, and rurality. Specifically, areas with a high proportion of employees in the Manufacturing and Construction industries have larger unexplained components, while areas with a greater proportion of employees in the Public Administration, Education and Social Work industry have smaller ones. This aligns with German evidence on industry-specific effects (Fuchs et al., 2021), but suggests that local industrial composition in Britain is a key, and relatively underexplored, driver of the GPG.

This research has important policy implications for addressing both GPGs and broader labour market inequalities within Britain. First, the findings demonstrate that national GPG reporting obscures substantial spatial variation, with local labour market characteristics and gender differences in the distribution of employees across areas driving much of this variation. This suggests that policy design must embed gender pay considerations into local and regional economic strategies. For example, a gender equity dimension could be incorporated into devolution deals and local growth funds, which would have strengthened the 'Levelling Up' agenda by ensuring that economic regeneration is also gender-inclusive.

Second, since areas with lower GPGs do not necessarily reflect greater gender equality but may instead result from the spatial distribution of workers and industries, targeted interventions should address occupational segregation in male-dominated industries. Expanding place-based training and apprenticeship schemes could improve women's access to high-paying roles in the Manufacturing and Construction industries. Third, local recruitment and progression policies should focus on tackling structural barriers to women's employment. Examples include employer incentives for inclusive hiring, stronger enforcement of flexible working rights, and childcare support tied to employment sectors. These measures would not only reduce gender inequalities in pay but also improve local labour market participation. Finally, the evidence that public sector employment is associated with smaller unexplained components highlights its role as a relative equaliser. One policy response could be to extend the principles of the PSED to private sector employers, requiring them to more systematically assess and address gender disparities in pay and progression.

A natural extension of this research would be a temporal analysis of how GPGs have evolved across areas within Britain, particularly given the increasing regional divergence since 1997 (Figure 3.2). Investigating the factors contributing to this growing spatial divergence would provide deeper insights into the underlying dynamics and help assess whether the widening gap is driven by a London effect. Additionally, future research would benefit from access to richer individual-level data to capture a more comprehensive set of wage determinants. This would help mitigate potential omitted variable bias and provide a more accurate estimate of the drivers of raw GPGs.

Chapter 4

Commuting and the Gender Pay Gap in the UK

4.1 Introduction

Extensive empirical evidence suggests that the majority of GPGs in the UK remain unexplained (see Chapter 3). While traditional explanations have largely focused on wage determinants and pay structures (see Blau and Kahn 2017 for an overview), there is growing recognition of the role of non-wage amenities, such as temporal flexibility, which are often associated with wage penalties (Goldin, 2014). Among these amenities, commuting - the regular journey between home and work - has received relatively little attention, despite its potential impact on gendered labour market outcomes. For instance, commuting may exacerbate the GPG if women prioritise job flexibility, willingly trading off higher wages for shorter commutes (Mas and Pallais, 2017; Wiswall and Zafar, 2018; Goldin, 2014). Moreover, commuting interacts with spatial labour market characteristics, contributing to regional and local variations in the unexplained GPG within Britain (Chapter 3).

Commuting is strongly gendered (Hanson, 2010; Reuschke and Houston, 2020). Empirical evidence suggests that, on average, women commute shorter distances and spend less time commuting than men (e.g., Roberts et al. 2011; McQuaid and Chen 2012; ONS 2019a; Joshi et al. 2007; Nafilyan 2020 for UK-specific evidence). This CGG has substantial implications for job accessibility, employment opportunities, and broader labour market outcomes (Clark et al., 2020). Shorter commute times may restrict women's access to higher-paying jobs located further from residential areas, creating a form of 'spatial entrapment' that limits their participation in labour markets with better job opportunities and higher wages (England, 1993; Rapino and Cooke, 2011; Wheatley, 2013; Crane, 2007; Petrongolo and Ronchi, 2020).[1] Additionally, commuting is

[1]This interpretation assumes that workers do not relocate in response to job opportunities. Relocation behaviour, however, is itself shaped by education, family structure, and housing constraints, which may differ

associated with negative outcomes, including increased stress, adverse health effects, and lower well-being (Gottholmseder et al., 2009; Stutzer and Frey, 2008; Evans et al., 2002; Koslowsky et al., 1995; Hansson et al., 2011; Künn-Nelen, 2016; Roberts et al., 2011; Dickerson et al., 2014). These negative outcomes are disproportionately experienced by women, particularly those balancing work and home responsibilities.

This chapter investigates the role of commuting in shaping the GPG in the UK, addressing the following primary research questions:

a. What drives the Gender Gap in Commuting in the UK?

b. To what extent does commuting drive the Gender Pay Gap in the UK?

The existing UK evidence on the CGG is relatively limited (e.g., McQuaid 2009; McQuaid and Chen 2012; Anderson et al. 2001; Laird 2006), and much of it predates the COVID-19 pandemic, which significantly altered commuting behaviours through the widespread adoption of home and hybrid working. Emerging evidence suggests that these changes have the potential to reduce gender gaps in commuting and related labour market outcomes (Le Barbanchon et al., 2021; Meekes and Hassink, 2022; Farré et al., 2023). For instance, working from home has been shown to reduce both time and stress associated with commuting, with pronounced benefits for women (Alipour et al., 2021; Adams-Prassl et al., 2022; Barrero et al., 2021; Arntz et al., 2022; Nagler et al., 2024; Maestas et al., 2023; Datta, 2019; Aksoy et al., 2022). However, there is also evidence that home working can reinforce gender inequalities, as jobs with higher home-working potential often exhibit larger GPGs, partly reflecting gender differences in time use and work allocation (Bonacini et al., 2024; Pabilonia and Vernon, 2022). Given this, the Chapter makes two contributions. First, it provides contemporary evidence on the drivers of the CGG, focusing on household and job-related factors in the current context. Second, it examines the extent to which gender differences in commuting help to explain the GPG in the UK, thereby linking the literatures on commuting and wage inequality that have typically been studied separately.

The Chapter also contributes to the debate over whether household responsibilities or labour market structures primarily drive the CGG. It finds support for both, suggesting that these factors interact in shaping women's shorter commute times. In addition, the analysis addresses the challenge of establishing a causal link between commuting and wages, an area where evidence remains limited. The two are likely to be jointly determined: workers may accept lower wages in exchange for shorter commutes (reverse causality); unobserved factors such as local labour demand or job quality may affect both wages and commuting (omitted variable bias); and commuting and wages are often chosen together in the job search process (simultaneity). Prior studies that account for these issues - through sample constraints, instrumental variable approaches, or job

systematically across groups.

duration models - estimate that commuting explains 10-25% of the raw GPG (Caldwell and Danieli, 2024; Gutierrez, 2018; Le Barbanchon et al., 2021; Ekberg and Widegren, 2019; Farré et al., 2023). This suggests that commuting is an important, yet often overlooked, driver of the GPG.

The analysis provides 'contemporary' evidence on the drivers of the CGG and the relationship between commute time and the GPG for the 'current period' using pooled (End User License) QLFS data from the fourth quarter of 2022 and 2023 - the only quarters in which commuting data is collected (ONS, 2024d; ONS, 2024c). This constitutes the first study to examine the relationship between commuting and the GPG in the UK following the significant shifts in commuting behaviour induced by the COVID-19 pandemic. The primary approach employs OB decompositions of both the raw CGG and the raw GPG to estimate the extent to which commuting contributes to this gap. To explore potential endogeneity between commuting and wages, the Chapter also employs an instrumental variable (hereinafter, IV) approach using two-stage least squares (hereinafter, 2SLS) regression. Despite the challenges in finding a suitable IV for commuting (see Manning 2003), the analysis instruments individual commute times using the average commute time of workers in the same industry sector (one-digit SIC). This approach assumes that industry-level commuting norms influence individual commuting behaviour without directly affecting individual wages. The 2SLS specification is preferred as it accounts for potential endogeneity, providing more accurate estimates of the effect of commuting as a driver of the GPG in the UK. Given concerns about whether commuting decisions are jointly determined with wages during job search, and the challenges in identifying a valid instrument, these IV results are interpreted as indicative robustness checks rather than definitive causal estimates.

The analysis estimates a substantial raw mean CGG of 13.35%, consistent with pre-pandemic analyses (e.g., Reuschke and Houston 2020) and underscoring persistent gender differences in spatial labour market mobility. Key determinants of commute times include educational attainment, occupation, and workplace region, potentially reflecting the limited access to jobs that are higher skilled and have longer commutes. In contrast, household variables exert minimal direct influence on commute times, emphasising the interplay of supply-side and demand-side factors in shaping gendered commuting behaviours. Despite this, the majority of the CGG remains unexplained, likely reflecting the role of unobserved preferences, unmeasured characteristics, or stochastic factors. Among the explained components, job characteristics - particularly full-time employment and public sector employment - emerge as the most significant contributors. Region of workplace also plays a crucial role, emphasising the spatial dimensions of gendered commuting behaviour (Fuchs et al., 2024; Rapino and Cooke, 2011). While household variables show limited direct impact on the CGG, further analysis indicates an association between the presence of school-aged children and shorter commute times for women under 40. This suggests that childcare responsibilities may shape women's commuting choices, though the cross-sectional nature of the data precludes strong causal claims. Nonetheless, this association is consistent with the broader literature on the ‘child penalty’ following the birth of the first child (Kleven et al., 2019).

The analysis also estimates a substantial raw mean GPG of 16.2%, with the majority remaining unexplained, even after accounting for more comprehensive individual characteristics (e.g., education) and household variables (e.g., children) than the analysis in Chapter 3, as well as commute time. OB decompositions suggest that gender differences in commute times explain up to 10.14% of the raw GPG, consistent with prior research (Caldwell and Danieli, 2024; Gutierrez, 2018; Le Barbanchon et al., 2021; Ekberg and Widegren, 2019; Farré et al., 2023). The magnitude of this contribution exceeds that of many individual and job-related characteristics frequently examined in the literature, such as tenure, occupation, and firm size, and is comparable to the well-documented role of public sector employment (Jones and Kaya, 2019). These results suggest that women may require higher wage compensation for longer commutes to offset the disutility associated with commuting, while shorter commutes may be associated with wage penalties due to restricted job opportunities. One plausible mechanism is women’s disproportionate household responsibilities, which may heighten the trade-off between wages and commuting.

Taken together, the evidence highlights the spatial dimensions of wage determination, even as commuting behaviours evolve in the post-pandemic context. The Chapter is structured as follows: Section 4.2 outlines the measurement and evidence of gender differences in commuting in the UK, with a particular focus on the post-pandemic context. Section 4.3 reviews the theoretical and empirical literature on the drivers of these differences and on how commuting may shape the GPG, while also addressing potential endogeneity between commuting and wages. Section 4.4 and Section 4.5 describe the data and methodology. Section 4.6 presents the analysis of the CGG and its drivers, with a focus on household composition. Section 4.7 turns to the GPG, examining the role of commute time as a potential driver. Section 4.8 presents sensitivity checks, and Section 4.9 concludes.

4.2 Commuting in the UK

4.2.1 Measures of Commuting

Typically defined as the routine travel between home and the workplace, commuting is measured in the UK through various data sources, as summarised in Table C.1, Appendix C.[2] Commuting can be measured in terms of distance or time, although the

[2]Some studies adopt restrictive thresholds, such as journeys exceeding two hours daily travel or 30 kilometres, while others consider only cross-border commutes (Wagner and Mulder, 2015; Limmer and Schneider, 2008; Sandow, 2014; Reichelt and Haas, 2015). Mobile phone data has also emerged as a tool for capturing regional commuting patterns (ONS, 2021).

two are distinct and often derived using different methodologies (Gimenez-Nadal and Molina, 2016). Actual commute distances are not normally known (particularly via car), so that information on the 'shortest' route is typically used (Rietveld et al., 1999). By contrast, when actual commute times are used, commuters tend to include ancillary activities such as walking to their final destination. Further, shorter commute times tend to be underestimated, whereas relatively longer commute times tend to be overestimated (see discussion in Gimenez-Nadal and Molina 2016).

Direct measures of commuting in the UK are derived from self-reported data in household surveys, such as Understanding Society and the QLFS. Respondents are asked to report either the distance to their workplace or their commute time.[3] These self-reported measures are susceptible to measurement error, influenced by socio-demographic factors such as income, education, occupational status, and neighbourhood satisfaction (Witlox, 2007; Clark et al., 2020). Respondents also tend to round commute times to the nearest five minutes, particularly for shorter commutes, leading to additional inaccuracies (Rietveld et al., 1999). Despite these limitations, self-reported measures provide insights into the subjective commuting experience, capturing factors such as traffic congestion and accessibility, which simple distance measures cannot (Van Ommeren and Straaten, 2008; Giménez-Nadal et al., 2018).

Indirect measures of commuting in the UK are derived from administrative data, such as the ASHE and the Census. These calculate geometric distances between home and workplace postcodes (Petrongolo and Ronchi, 2020) or estimate commute times using transport planning tools (Nafilyan, 2020). While these methods provide objective data, they may not reflect actual travel routes and often assume fixed arrival times and car travel, limiting their accuracy[4] Additionally, ASHE data can overestimate commuting distances when the employer's PAYE address is used instead of an employee's actual local worksite, potentially skewing commuting estimates for employees of large, multi-site employers. Similarly, Census commuting data should be cautiously interpreted, as commutes captured during the 2021 Census may have been affected by the COVID-19 pandemic and the associated restrictions (see Section 4.2.3 for a discussion of the pandemic's lasting impact on commuting data and Section 2.2.4 for a broader discussion of the impact of Covid-19 on data).

Despite these methodological differences, comparisons between direct and indirect commuting measures generally reveal consistent patterns. For instance, a 2017 comparison of self-reported QLFS commute times and ASHE-based estimates showed similar distributions, with the main discrepancy being the proportion of employees

[3]Understanding Society asks, "*How far in miles do you live from your usual place of work?*," and includes prompts for commute-related difficulties. The QLFS asks "*How long in total does it take you to travel from home to work?*" in minutes. This is only captured in the fourth quarter annually and only for those who commute regularly, potentially capturing some, but not all, hybrid workers (see discussion in Section 4.4).

[4]For instance, a study of the GPG in Britain estimated commute times by assuming a 9am Monday arrival and defaulting to car travel for all commuters outside London, where public transport was assumed (Nafilyan, 2020). These assumptions risk oversimplifying actual commuting patterns.

reporting commute times exceeding an hour. In the QLFS, 6.3% of respondents reported commutes over an hour, compared to 11.1% in ASHE data (Nafilyan, 2020). This difference likely reflects the inclusion of employees who live far from their workplace but do not commute daily, or from discrepancies between an employer's PAYE address and an employee's actual work location in the ASHE (see discussion in Section 3.4). Excluding commute times exceeding an hour from ASHE data reduced this discrepancy, supporting broad comparability between the two datasets (ibid.).

The rise of hybrid working and working from home further complicates measures of commuting. Traditional measures fail to fully capture the commuting patterns of individuals who work partly or fully from home, highlighting the need for updated tools and metrics. The Opinions and Lifestyle Survey, for example, is more adaptable as it tracks changes in commuting frequency, transport modes, and work arrangements. However, its smaller sample size limits its capacity for detailed demographic analysis (see Table C.1, Appendix C). The survey was particularly useful during the pandemic for capturing rapid shifts in commuting behaviour, but since mid-2022 its focus has shifted towards issues such as industrial action, reflecting wider concerns in transport and labour markets.

4.2.2 Evidence of Commuting Patterns

Commuting patterns in the UK differ significantly from those in other Western European countries, with UK employees generally commuting for longer. Analysis of the European Working Conditions Survey across 15 western European countries estimated a mean two-way commute time of 49.04 minutes in the UK, based on pooled and weighted data from 2010 and 2015 (Giménez-Nadal et al., 2022). This is remarkably similar to the mean one-way commute time estimated from the 2022 QLFS of 27.3 minutes for all employees in Britain (Transport Statistics Great Britain, 2022), as well as 2018 ASHE data of 28.57 minutes, estimated using a trip planner app (ONS, 2019a).

A persistent gender gap in commute times is evident in the UK, with men consistently averaging longer commutes than women. Analysis of 2018 ASHE data estimated the mean commute time at 32.48 minutes for men and 24.95 minutes for women, corresponding to a CGG of 23.18% (ONS, 2019a). Similarly, the 2022 QLFS reported mean commute times of 29.3 minutes for men and 25.2 minutes for women, corresponding to a slightly smaller but still substantial CGG of 13.99% (Transport Statistics Great Britain, 2022).[5] This CGG is well-documented and has remained relatively stable over time (ONS, 2019a; Blumen, 1994; Pooley and Turnball, 2000; Roberts et al., 2011; Nafilyan, 2020). Longitudinal ASHE data from 2002 to 2018 reveal a consistent median gender gap of approximately five minutes, with both men's and

[5]The discrepancy in CGG estimates between the 2018 ASHE and 2022 QLFS data is likely attributable to differences in time periods and measurement methods: the ASHE relies on indirect estimates, whilst the QLFS uses a direct measure.

women's commute times increasing by around three minutes over the period (ONS, 2019a). Cross-national evidence suggests that the CGG is less pronounced in Nordic countries, where supportive policies and cultural norms promote greater gender equality (Giménez-Nadal et al., 2022).

Commuting patterns also have a spatial dimension within the UK. Data from the 2022 QLFS indicate that commute times tend to be longer in urbanised regions such as Central and Inner London, Greater Manchester, and the South East, compared to shorter average commutes in rural areas like the North East, Yorkshire, and Wales (Transport Statistics Great Britain, 2022).[6] The CGG also varies across regions, with women in Central London commuting on average 4.8 minutes longer than men, while men in the South East and South West commute 6.8 and 5.7 minutes longer, respectively (ONS, 2018b). These spatial patterns reflect men's higher propensity for cross-regional commuting. Further, among the 20 largest travel-to-work areas in Britain,[7] gender differences in commute times only become pronounced after the age 30, particularly around London (ONS, 2019b). This may reflect household relocation decisions after the birth of a first child, with men continuing to commute into the city.

Figure 4.1 illustrates how the CGG evolves with age, remaining negligible until the mid-20s and peaking in the mid-40s at approximately eight minutes (ONS, 2019a). This trend mirrors the unadjusted median GPG in weekly earnings, which widens over the same period as men's earnings continue to rise while women's earnings plateau (ibid., Figure 4.1).[8] This age-related divergence supports theories suggesting that women opt for shorter commutes due to household responsibilities (as discussed in Section 4.3.1; Mas and Pallais 2017; Wiswall and Zafar 2018; Goldin 2014; Bertrand 2011). Longitudinal analysis of the BHPS further indicates that commute times diverge significantly for mothers and fathers following the birth of their first child, resulting in a sustained CGG of 24% (Petrongolo and Ronchi, 2020).

4.2.3 Commuting, Covid-19 and Working from Home

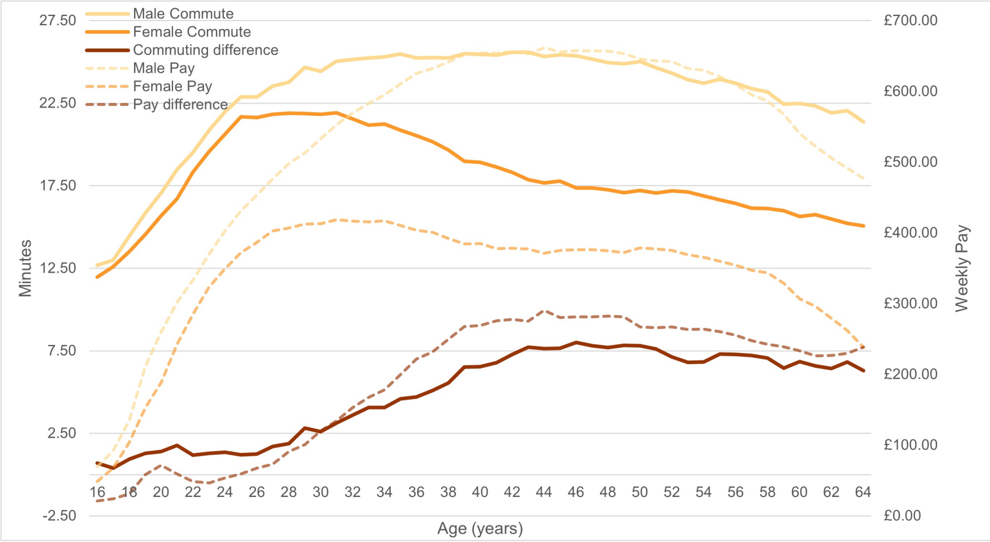
The COVID-19 pandemic led to unprecedented changes in commuting behaviour across the UK, largely driven by national and regional public health measures that prompted a widespread shift to working from home and hybrid working. In April 2020, Labour Market Survey data indicated that nearly half of employed individuals were working from home, reflecting the immediate impact of the pandemic on commuting behaviour (ONS, 2020). This transition proved persistent, with the proportion of home-based

[6] Commute times also vary significantly by transport mode, from an average of 15 minutes for walking to 63 minutes for rail, which may contribute to regional differences (ONS, 2019a).

[7] The 20 largest travel-to-work areas are London, Manchester, Birmingham, Slough and Heathrow, Glasgow, Newcastle, Liverpool, Leicester, Sheffield, Bristol, Nottingham, Warrington and Wigan, Leeds, Cardiff, Wolverhampton and Walsall, Luton, Cambridge, Southampton, Edinburgh, and Guildford and Aldershot.

[8] This mirrors the lifecycle of the adjusted GPG when controlling for year effects, age, industry, occupation and region and employment type (Petrongolo and Ronchi, 2020).

Figure 4.1: Median Commute Time and Weekly Pay in Britain, by Gender and Age, ASHE 2010-2018



Notes: (i) The median commute time is estimated indirectly via a trip planner app based on home and work postcodes. (ii) The median weekly pay is expressed in real value for 2018 and calculated using survey weights.

Source: ONS (2019a) estimates from ASHE 2010-2018 pooled data

workers more than doubling between late 2019 and early 2022, significantly reducing overall commuting prevalence (ONS, 2022e). However, this shift varied across regions and industries. Scotland had the highest rates of remote work, while Northern Ireland reported the lowest. London experienced the largest shift, likely due to its high concentration of high wage, desk-based occupations conducive to remote work (Figure C.1, Appendix C; Meyrick 2022). By early 2022, 14.3% of non-remote workers engaged in hybrid work at least once per week, with hybrid work being most common in London and least common in the East Midlands (ONS, 2022e). Despite these shifts, data from the 2021 Census, conducted during a period of lockdown and strict public health measures, indicated that nearly 70% of UK workers continued to commute regularly, with 19.1 million individuals reporting consistent commuting patterns (ONS, 2022g).[9]

The increasing prevalence of working from home and hybrid working introduces challenges in accurately measuring commuting patterns (Section 4.2.1). Data from the Opinions and Lifecycle Survey indicate that between September 2022 and January 2023, 16% of working adults worked exclusively from home, while 28% engaged in hybrid work arrangements (ONS, 2023b). These individuals had distinct socio-economic characteristics. They were predominantly older, white, had higher incomes, and were more educated. Parents with dependent children were particularly likely to engage in

[9]The date of the Census (March 21, 2021) was conducted during a 'stay at home' order, complicating the interpretation of the data. Many individuals were either furloughed or affected by temporary workplace closures. The guidance issued for the travel-to-work question asked respondents about their pre-pandemic commuting habits if their routines had been altered. However, inconsistencies between these responses and administrative data suggest variation in how respondents interpreted and followed this guidance, resulting in a mix of pandemic and pre-pandemic commuting behaviours in the dataset.

hybrid working, regardless of their child's age. London had the highest rates of hybrid working, particularly among commuters using rail, underground, or metro services (ONS, 2023b). These trends have persisted despite changing economic and public health conditions, with nearly 40% of working adults engaging in some form of remote work as of early 2023 (Urban Transport Group, 2023).

The pandemic also contributed to narrowing the gender gap in home working, as both men and women increasingly adopted working from home, albeit with regional variation (ONS, 2022e). Women experienced larger increases in remote working across most UK regions between late 2019 and early 2022, with the exception of the North East (Figure C.1, Appendix C). Recent research suggests that increased hybrid and home working could reduce gender gaps in labour market outcomes (e.g. Nagler et al. 2024; Arntz et al. 2022). However, the occupations where remote work is most feasible are also those with relatively high GPGs (Bonacini et al., 2024; Pabilonia and Vernon, 2022).

Despite the widespread adoption of home and hybrid work, a substantial share of the workforce remains unable to work from home. Access to remote work is shaped by structural factors such as location, occupation, and gender (Deole et al., 2023). A 2021 panel survey, for example, found that over 90% of manual workers had returned to full-time, in-person roles, compared to 55% of those in sales and service roles in Great Britain (Magriço et al., 2023). Further, home working is strongly correlated with higher household incomes, underscoring the continued relevance of commuting in shaping labour market experiences, particularly for lower-income workers.

4.3 Literature Review of Commuting and the Gender Pay Gap

4.3.1 Gender Differences in Commuting

Gender differences in commuting behaviour are well-documented across various geographical contexts and time periods. Empirical evidence consistently shows that women tend to commute shorter distances and spend less time commuting than men (e.g., Roberts et al. 2011; Madden 1981; Hanson and Johnston 1985; McQuaid and Chen 2012; Dargay and Van Ommeren 2005; Giménez-Nadal et al. 2022; see also Section 4.2.2). Women are also more likely to engage in 'trip-chaining', combining commutes with non-work trips such as child-related errands and shopping, reflecting the dual demands of paid work and domestic responsibilities that disproportionately fall on women (Duncan, 2016; Lee et al., 2007; McGuckin et al., 2005; Mauch and Taylor, 1997). These commuting patterns are often attributed to women's need to balance work with household responsibilities, their lower average wages, and their employment patterns in geographically dispersed or locally concentrated occupations and sectors

(MacDonald, 1999).[10]

One explanation for these patterns is the Household Responsibility Hypothesis, which attributes women's shorter commutes to traditional gender roles that disproportionately assign greater domestic responsibilities to women. These responsibilities limit women's labour market mobility by constraining spatial access to higher-paying jobs, which are typically located further from residential areas (Johnston-Anumonwo, 1997; Gimenez-Nadal and Molina, 2016; Wheatley, 2013; Turner and Niemeier, 1997; Hanson, 2010; MacDonald, 1999; Crane, 2007). Empirical studies frequently use household characteristics, such as marital status and the presence of children, as proxies for household responsibilities to assess their impact on commuting patterns.

Evidence on the relationship between commuting and household responsibilities is mixed (e.g., Fan 2017; Sandow 2008; Sandow and Westin 2010; Gimenez-Nadal and Molina 2016; Sermons and Koppelman 2001). For instance, analysis of Dutch Time Use Survey data from 2000 and 2005 using propensity score matching found that household and childcare responsibilities were associated with significantly reduced women's commute time, with effects more than double those observed for men (Gimenez-Nadal and Molina, 2016). Similarly, pooled data from the American Time Use Survey (2003-2010) indicated that marital status and the number of children were linked to shorter commute times for women (Fan, 2017). Consistent patterns were reported in the 2001, 2009, and 2017 US National Household Travel Surveys, which highlighted that childcare responsibilities restricted women's commuting distances, particularly in dual-earner households with children aged six to 15 years (Kwon and Akar, 2022).

However, not all evidence supports the Household Responsibility Hypothesis. Analysis of the 1991 Transit Panel Study in Los Angeles found no significant impact of children on commuting distances for either gender, though the CGG was more pronounced among white respondents (Kim, 1994).[11] Similarly, analysis of the 1977 Baltimore Travel Demand Data found no significant impact of children on women's commuting distances (Hanson and Johnston, 1985). In some cases, children were even associated with increase commute times for women. For example, using the 1980 Annual Housing Survey, young children were estimated to be associated with an average increase in commute time of 8 minutes (26%) for female heads of households, compared to only 2.7 minutes per child for men (White, 1986). Japanese data from the Panel Survey of Consumers (1993-2002) similarly suggested that having a child aged zero to six years increased commute times for married women by over 7 minutes (Iwata and Tamada,

[10] Other determinants of commuting behaviour include earnings, education, age, ethnicity, residential location, access to transportation, and household constraints (e.g., Ihlanfeldt and Sjoquist 1990; Taylor and Ong 1995; Molho 1995, see Reuschke and Houston 2020 for an overview). External factors such as weather conditions, congestion, and infrastructure can also influence commuting patterns but are often difficult to model quantitatively (White, 1986; Rouwendal and Rietveld, 1994; Benito and Oswald, 2000; Van Ommeren et al., 1999; Van Ommeren and Straaten, 2008). Cross-country analyses indicate that commuting models typically have low explanatory power (R^2), with exceptions in Ireland and the Netherlands (Giménez-Nadal et al., 2022).

[11] Ethnic differences in commuting patterns highlight the intersection of gender with factors such as income, employment status, location, and car availability (Mauch and Taylor, 1997; McLafferty and Preston, 1997).

2014). In the UK, analysis of Understanding Society data (2009–2017) found minimal effects of household characteristics on women's commute times, although there was some evidence that women who do more housework actually have longer commutes, possibly due to career interruptions or non-employment spells rather than household responsibilities (Reuschke and Houston, 2020).

Household composition, particularly the presence of a secondary earner, further influences gendered commuting patterns. As secondary earners, women often face constrained job choices, since residential location decisions tend to prioritise the labour market needs of primary earners, who are typically men (Green, 1997; Hanson and Pratt, 1995; Singell and Lillydahl, 1986). This dynamic may prompt women to accept jobs closer to home, potentially foregoing higher-paying employment opportunities in more distant labour markets (Madden, 1981; Hanson and Pratt, 1995; Rouwendal, 2004; Wheatley, 2013; Hanson and Pratt, 1991). Empirical evidence from Portland suggests that spousal commuting patterns are interdependent, with a secondary earner's commute becoming longer when the primary earner's commute is shorter (Davis, 1993). In the UK, longitudinal data from the BHPS (1991-2003) revealed that a larger proportion of women than men are 'tied migrants', relocating primarily for their partner's job (Taylor, 2007). Further analysis of the BHPS (1992–2008) suggests that men increase their commute times upon entering a co-residential union, while childless women maintain their commute times and mothers reduce theirs to accommodate household and childcare demands (Lersch and Kleiner, 2018). However, commuting patterns across 16 urban areas in Denmark suggest that households may occasionally prioritise the wife's employment location in residential decisions, even when the husband is the primary earner (Tkocz and Kristemen, 1994).

The Labour Market Structure Hypothesis provides a complementary perspective on gendered commuting patterns, attributing women's shorter commutes to structural factors such as occupational segregation and lower wages. Since women are overrepresented in part-time, lower-paid, and female-dominated occupations (e.g. service and care occupations), they are more likely to work in geographically dispersed, locally concentrated jobs that require shorter commutes (Roberts and Taylor, 2017; Sandow, 2008; Hanson and Pratt, 1995; Johnston-Anumonwo, 1997). These occupations also provide greater flexibility to balance work and household responsibilities (Madden, 1981; Marcén and Morales, 2021; Kimbrough, 2016). In addition, financial constraints associated with lower wages make longer commutes less viable, while women's reliance on local social networks for job searches may further reinforce proximity-based employment patterns (Hanson and Pratt, 1995).

Empirical evidence largely supports the Labour Market Structure hypothesis. In Sweden, women's shorter commutes are primarily attributed to their lower wages, with willingness to commute longer distances increasing only at higher income levels (Beck and Hess, 2016). In Massachusetts, women in male-dominated industries had commuting patterns comparable to men, whereas those in female-dominated sectors had significantly shorter commutes, underscoring the role of occupational segregation or job type (Hanson and Pratt, 1995; Madden, 1981). Similarly, analysis of Baltimore's 1977 Travel Demand Data linked women's shorter commutes to lower wages, concentration in female-dominated occupations, and greater reliance on public transport or carpooling (Hanson and Johnston, 1985). However, persistent gender differences in commuting, even within similar occupations, suggest that labour market structures alone do not fully explain observed gender differences (Gordon et al., 1989).

Although both hypotheses emphasise different mechanisms, they are not mutually exclusive. Instead, they reflect intersecting dimensions of gendered commuting behaviour (Lee et al., 2022; Roberts and Taylor, 2017; MacDonald, 1999). Structural constraints, such as occupational segregation, may amplify the effects of household responsibilities by limiting women's access to higher-paying jobs located further from residential areas. Conversely, household responsibilities can reinforce structural disadvantages by limiting women's ability to pursue geographically distant employment opportunities. Empirical evidence from an OB decomposition of the CGG in Germany, using administrative data, indicates that men's occupational structures significantly contribute to their longer commutes, whereas women's commutes are more tightly constrained by household responsibilities, particularly in rural areas (Fuchs et al., 2024). Similarly, an OB decomposition of the Spanish CGG, based on the Spanish Quality of Life at Work Survey (2007–2010), shows that labour market structures and household responsibilities interact to disproportionately limit women's commuting opportunities, particularly for those with family obligations and lower education levels (Casado-Díaz et al., 2023). Collectively, these findings suggest that gender differences in commuting reflect a complex interplay of household responsibilities, labour market structures, and broader contextual factors that reinforce persistent spatial inequalities.

4.3.2 Commuting and the Gender Pay Gap

The GPG can be partially attributed to differences in commuting behaviour between women and men. Empirical evidence consistently indicates that men tend to commute longer distances, often securing higher-paying jobs as a result, whereas women generally prioritise shorter commutes due to household responsibilities or personal preferences. This pattern reinforces the GPG, as longer commutes are associated with higher earnings in many contexts (Caldwell and Danieli, 2024; Fluchtmann et al., 2024; Madden, 1981). This relationship aligns with the theory of compensating wage differentials, which suggests that workers are compensated with wage premiums for the disutility of commuting (Manning, 2003; Zax, 1991). Evidence supporting a positive relationship between commuting and wages has been well-documented in the US, Europe, and the UK (e.g., Morris and Zhou 2018; Ross and Zenou 2008; Madden 1985; Madden 1981;

Mulalic et al. 2014; Rouwendal 1999; Ekberg and Widegren 2019; Laird 2006).[12]

However, evidence of 'wasteful commuting' – where longer commutes are not adequately compensated by higher wages (Hamilton and Röell, 1982) - complicates this framework. This issue is particularly relevant for women, who often face constraints such as lower residential mobility and fewer higher-paying job opportunities. Evidence from the Scottish Household Survey supports both a positive relationship between commuting and wages, and the existence of 'wasteful commuting' in a simple OLS model.[13] It also estimated that male workers were overcompensated for additional commuting costs by 2%, whereas women's wages failed to include an allowance for such costs. This disparity was attributed to women's constrained labour market power and residential mobility compared to men (Laird, 2006).

Establishing the causal relationship between commuting and wages, and its role as a driver of the GPG, is complicated by endogeneity (Manning, 2003; Gibbons and Machin, 2006; Mulalic et al., 2014). One source of endogeneity is reverse causality, as wages can influence commuting decisions rather than commuting directly determining wages. Higher income households, for example, may choose to reside in suburban or rural areas with better amenities despite longer commutes (Van Ommeren et al., 2000). This raises the question of whether higher wages genuinely compensate for the disutility of commuting or simply reflect residential preferences of wealthier individuals. This pattern is pronounced in the US, where higher income households often live further from city centres, in contrast to trends in Europe (Brueckner et al., 1999). Furthermore, omitted variable bias complicates the analysis, as unobserved factors such as ambition, household responsibilities, and firm-specific characteristics may simultaneously influence both wages and commuting patterns (Gutiérrez-i-Puigarnau et al., 2016). Household decision-making introduces additional complexity, as joint residential and workplace decisions often obscure individual-level relationships between commuting and wages (Roberts and Taylor, 2017).

The most efficient method to address endogeneity involves using IVs within a 2SLS model to isolate exogenous variation in commuting behaviour. However, suitable instruments are difficult to identify due to the interconnectedness of commuting, residential preferences, and labour market outcomes (Manning, 2003). Alternative approaches include fixed effects models (Manning, 2003; Gutiérrez-i-Puigarnau and Van Ommeren, 2015; Mulalic et al., 2014; Benito and Oswald, 2000; Van Ommeren et al., 1999), sample restrictions (e.g., analyses limited to job movers, Gutiérrez-i-Puigarnau et al. 2016), job duration models (e.g. Van Ommeren et al. 2000; Isacsson and Swärdh 2007; Isacsson et al. 2013) and quasi-experimental designs (e.g., Mulalic et al. 2014). For instance, evidence from Denmark exploiting firm relocations as

[12]The impact of commuting on employment has also been extensively studied (e.g., Ihlanfeldt and Sjoquist 1998). For instance, Zax (1991) found that employer relocations from downtown Detroit to the suburbs led to higher quit rates for black employees compared to white employees, likely due to differences in mobility in the housing market and/or transport access.

[13]The Scottish Household Survey contains more detailed data on commuting costs and location than the BHPS.

a quasi-natural experiment found that longer commuting distances were associated with moderate wage increases, with stronger effects observed among men and individuals with higher educational levels. These wage adjustments occurred gradually over a three-year period highlighting the dynamic nature of this relationship (Mulalic et al., 2014).

Despite challenges posed by endogeneity, robust evidence suggests that gender differences in commuting behaviour contribute to the GPG (e.g., Gutierrez 2018; Liu and Su 2024; Borghorst et al. 2024; Le Barbanchon et al. 2021; Troncoso et al. 2021; Farré et al. 2023; Wu et al. 2024).[14] In the UK, an OB decomposition of the raw GPG using pooled QLFS data from 1999 and 2000 attributed almost 5% to gender differences in commute time (Anderson et al., 2001).[15] This effect was linked to women's household responsibilities, shorter working hours, and overrepresentation in the service sector, where jobs are more evenly distributed and located closer to residential areas. Similarly, analysis of British Birth Cohort Studies estimated a positive association between commute time and wages for individuals in their early thirties, attributing approximately 1% of the GPG in this cohort to commuting (Joshi and Paci, 1998). While these estimated effects were relatively small, neither study fully addressed potential endogeneity, although they argue that endogeneity is less of a concern for women's wages, as constraints on their commuting behaviour tend to be external to their employment (e.g., household responsibilities). In contrast, men's commuting decisions are more likely to reflect a simultaneous consideration of wages and commute times, introducing greater potential for endogeneity in their wage estimates (Anderson et al., 2001).[16,17]

Controlling for endogeneity further strengthens the evidence that commuting is a driver of the GPG. Despite challenges in identifying suitable IVs for commuting (Manning, 2003), an analysis employing district of residence, industry, and occupation as instruments estimated that gender differences in commute time explained 47% of the GPG attributed to observable worker characteristics. This estimate is considerably

[14] Early US and Canada studies suggested that spatial factors had a limited impact on the GPG (Madden and Chiu, 1990; Miller, 2013; Howell and Bronson, 1996). For instance, simulations using 1980 Public Use Microdata Sample data on two-earner households in Detroit and Philadelphia estimated relocating women's residences within these cities produced minimal effects on the GPG (Madden and Chiu, 1990). However, more recent research attributes this to the smaller CGG in urban areas, where shorter commutes and accessible public transport mitigate spatial constraints on wage gaps (Fuchs et al., 2024).

[15] Controls included age, ethnicity, disability, family situation (defined, as single, partnered, single or partnered with one child, two children or more than two children), qualifications, tenure, hours of work, flexible work arrangement, permanent contract, overtime, supervisory responsibility, occupation, firm size, sector, industry, unionised pay, commute time, and region of residence.

[16] Anderson et al. (2001) further decompose the CGG using fewer controls than in the wage equation. This analysis attributes 40% of the CGG to differences in characteristics between women and men, with working hours accounting for the largest share, alongside qualifications, sector, industry, employer size and region of residence.

[17] Commuting also explains gender differences in non-wage labour market outcomes. For instance, using longitudinal ASHE data from 2002-2019 restricted to job movers, men were estimated to have higher wage returns from voluntary job changes, while women received higher proximity returns, implying a stronger preference for shorter commutes (Petrongolo and Ronchi, 2020). Similarly, quantitative spatial models indicate that women with children are less likely to participate in the labour force in large cities due to longer commutes (Moreno-Maldonado, 2022). Using ASHE data (2008-2016) and a Cox proportional hazard model, longer commute times were shown to increase job separation probabilities more for women than men; women required a 19.5% increase in hourly wages to commute an additional 10 minutes one-way, compared to 12.5% for men (Nafilyan, 2020).

higher than the 10% and 8% estimated using OLS and Heckman selection models, respectively (Troncoso et al., 2021).[18] Similarly, an IV study using city shape as an instrument revealed a larger impact of commuting on labour supply than OLS estimates. Analysis of U.S. Census microdata and American Community Survey data from 1980 to 2011 demonstrated that married women with more or younger children significantly reduced their labour supply as commute times increased, whereas men and childless married women showed greater resilience to commuting costs (Farré et al., 2023).

Models of job search incorporating commuting further highlight gender differences in willingness to commute, explaining approximately 10% of the gender gap in re-employment wages based on French administrative data from 2006 to 2013 (Le Barbanchon et al., 2021). In Germany, analysis of matched employer-employee administrative data based on Social Security records from 1993-2014 estimated that gender differences in commuting contributed approximately 4% to the GPG, or about 20% of the overall unadjusted GPG. These findings suggest that women's restricted employment options, combined with higher marginal commuting costs rooted in gender norms and stereotypes, are drivers of the GPG (Caldwell and Danieli, 2024). In Sweden, wage data from 71 local labour markets revealed that men commute longer distances and earn higher wages, particularly in certain sectors and professional groups (Ekberg and Widegren, 2019). This aligns with evidence suggesting that women in Sweden tend to benefit less from transport infrastructure improvements that expand labour market access (Bütikofer et al., 2024).

The interaction of commute time with the child penalty further magnifies its contribution to the GPG. An analysis of American Community Survey data from 2005–2016 found that gender differences in commuting explained 10% of the GPG among heterosexual couples with shared children. Women's shorter commutes were primarily attributed to employment in lower-paying sectors, with commuting explaining 23% of the child wage penalty, as estimated through a conditional OB decomposition (Gutierrez, 2018). Analysis of the same dataset from 2017 estimated that commuting preferences or constraints, such as job location, accounted for 29% of the GPG, an increase from 17.4% in 1990. This trend highlights how decentralised, high-wage job locations interact with gendered commuting preferences to influence wage gaps (Liu and Su, 2024).

Evidence from the UK similarly attributes the impact of commuting on the GPG to the child penalty. A job search model incorporating job differentiation and monopsony power suggested that dependent children increase women's commuting costs, leading to a larger GPG. Women with dependent children were found to experience higher returns to commuting than men, based on LFS and BHPS data (Manning, 2003). Complementary analysis of the QLFS indicated that women with one or two children were 10% less likely to commute over 30 minutes, with this probability rising to 33% for

[18] The validity of these instruments has been questioned. District-level job accessibility may not be fully exogenous if industry and occupation classifications capture wage variation unrelated to commuting.

women with three children by 2008 (McQuaid and Chen, 2012). Job separation data also revealed similar rates for men and women under 30, but higher separation rates for women aged 30-59, suggesting a childcare effect on gendered commuting and wage gaps (Nafilyan, 2020). However, French evidence indicates that children alone do not fully explain gendered commuting preferences. Single, childless women were estimated to be willing to commute 8% less than comparable men, with this difference increasing to 18% for married workers without children and 24% for married parents. Even after adjusting for preferences in working hours, commuting differences remain a significant contributor to the GPG, alongside part-time employment preferences (Le Barbanchon et al., 2021).

The pandemic significantly expanded home and hybrid work arrangements (discussed in Section 4.2.3), with mixed implications for gender differences in labour market outcomes. Evidence from OB decompositions and unconditional quantile regressions using Italy's Participation, Labour and Unemployment Survey suggests that the GPG is larger in occupations with greater work from home feasibility, with older and married women particularly affected (Bonacini et al., 2024). This suggests that as working from home becomes a more established practice, it may inadvertently exacerbate the GPG. Similarly, analysis of the German Socio-Economic Panel between 1997 and 2014 suggests that while working from home reduces gender gaps in working hours and monthly earnings for parents, fathers experience greater increases in hourly wages than mothers, reinforcing persistent inequalities even in flexible work arrangements (Arntz et al., 2022). The GPG also persists on online platforms where employers cannot observe workers' gender, largely due to household responsibilities that disproportionately constrain women's productivity or availability for higher-paying tasks (Adams-Prassl and Berg, 2017). Moreover, working from home appears to have a more pronounced negative correlation with women's earnings than men's, suggesting that while working from home offers flexibility, it may also reinforce traditional gender roles and limit women's career progression and earning potential (Simon and McDonald Way, 2015).

4.4 Data

4.4.1 Quarterly Labour Force Survey

The analysis uses End User Licence data from the QLFS, a nationally representative household survey covering adults residing in private households in the UK (ONS, 2024d; ONS, 2024c).[19,20] The QLFS employs a rotational sampling design, selecting households randomly from the Royal Mail's Postcode Address File. Each selected household is surveyed for five consecutive quarters, with the initial quarter termed 'wave 1' and

[19] The QLFS in Northern Ireland is administered separately but is comparable to the QLFS in the rest of the UK.

[20] Alternative data, such as the ASHE, were considered but deemed impractical due to the lack of direct commuting measures. Analyses of commuting with ASHE data use indirect measures derived from the geometric distances between home and workplace postcodes (Petrongolo and Ronchi, 2020) or estimate commute times with transport planning tools (Nafilyan, 2020) (see discussion in Section 4.2).

subsequent waves labelled sequentially through to 'wave 5'. Interviews are conducted every 13 weeks, so that the fifth interview occurs approximately one year after the first. However, individuals may leave the sample before completing all five waves. A new cohort of addresses are introduced each quarter, ensuring the QLFS maintains a consistent sample size where approximately 20% of households are in each wave at any given quarter. This results in an overlap of about 80% between any two consecutive quarters.

The QLFS is well-suited for exploring the determinants of the CGG and the role of commuting as a driver of the GPG in the UK. It uniquely captures self-reported data on commute time, pay, and home working status - key variables in the context of increased hybrid and home working. The commuting question, a non-core question in the QLFS, is asked annually in the fourth quarter and every quarter every three years to all respondents in employment, except those on government schemes or those working from home or using their home as a working base (discussed below). Previous studies have used this data to examine the relationship between commuting and demographic characteristics (McQuaid and Chen, 2012). It offers a comprehensive understanding of the commuting experience, including aspects such as traffic density and speed (Giménez-Nadal et al., 2018; Van Ommeren and Straaten, 2008). Self-reported pay data in the QLFS has also been extensively used in analyses of the GPG in the UK and across its regions (Jones et al. 2018; Jones and Kaya 2022b; see Chapter 2).

The QLFS also provides detailed information on household composition, including marital status and the presence of dependent children, which are crucial for understanding gendered commuting patterns within specific geographical contexts (Section 4.3.1). These variables, often under-represented or absent in other UK datasets (Section 2.2.4), are essential for analysing the influence of household dynamics on commuting behaviours and labour market outcomes. Given that women disproportionately bear household responsibilities, they often experience a 'dual burden', which significantly affects their commuting behaviour and wages, influencing the respective gender gaps (Johnston-Anumonwo 1992, see Sections 4.3.1 and 2.6).

The research provides 'contemporary' evidence on the CGG and the role of commuting as a driver of the GPG in the UK, using pooled data for individuals from the fourth quarters of 2022 and 2023 (ONS, 2024d; ONS, 2024c). These years are chosen to mitigate potential influences of furlough and lockdown measures, with 2022 representing the first full year post-pandemic. Pooling data across these two years increases the sample size, addressing challenges of declining response rates in the QLFS, particularly pronounced in 2023 (ONS 2023e, Section 2.2.4).[21] The sensitivity of the findings is explored by pooling data from the fourth quarters of 2018 and 2019, and from the first three quarters of 2024. This approach examines potential changes in the relationship between commuting and the GPG since the pandemic (Section 4.8).

[21] While the APS offers a larger sample size than the QLFS due to local sample boosts (Section 5.4), the commuting question is only asked to those in the main QLFS. Thus, APS data does not increase the sample size.

4.4.2 Sample

The sample pools data for individuals from the first and fifth waves of the fourth quarter QLFS in 2022 and the first wave of the fourth quarter QLFS in 2023, creating a contemporary cross-sectional dataset.[22,23] The selection of these waves ensures the availability of pay data, which has been collected only for these waves since 1997, while also avoiding multiple observations of the same individual. This yields an initial sample of 41,809 individuals.

To focus on working-aged individuals, the sample is restricted to those aged 16-65 years, aligning with ONS analyses and other Chapters of this thesis.[24] This age restriction excludes 17,628 individuals, resulting in a sample size of 24,191. The sample is further restricted to individuals who report commuting, working from home, or using their home as a working base. Individuals who report working outside the UK or with hourly pay outside the £0-£99 range are excluded. Self-employed individuals are also excluded due to differences in commuting behaviour (Giménez-Nadal et al., 2024; Reuschke and Houston, 2020), and limited pay data in the QLFS.[25] Conditioning on pay and employees reduces the sample by about half (13,241 individuals), leaving 10,950 employees. Finally, individuals with missing data or who answer '*Don't know*' for any explanatory variable (Table C.2, Appendix C) are dropped, excluding a further 871 individuals. These restrictions result in a final sample of 10,079 employees, comprising 4,668 males and 5,411 females. Of these, 7,161 report that they usually commute and 2,918 indicate that they usually work from home or use their home as a working base.[26]

Proxy responses, where responses are provided on behalf of another resident in the household if that person is unavailable or unable to respond for themselves, are retained to increase sample size and maintain representativeness. However, proxy responses may introduce measurement bias, particularly underreporting commute times, as proxies may lack precise knowledge of other members' schedules. This bias may vary by gender, as highlighted by limited research on proxy responses in travel surveys (Bose and Giesbrecht, 2004). Proxy-reported pay data may suffer similar inaccuracies (Wilkinson, 1998; Skinner et al., 2002). The sample includes 2,640 proxy respondents who usually commute. To mitigate potential biases while preserving sample size, proxy responses are controlled for in all models. The sensitivity analysis explores the extent to which proxy responses may bias the estimated role of commuting as a driver of the GPG in the UK

[22] Commuting data from the fourth quarter (October, November, December) are considered less affected by seasonal factors such as holidays or adverse weather conditions (McQuaid and Chen, 2012).

[23] Larger 'bumper' samples conducted every three years were deemed unsuitable for the analysis, as the most recent bumper sample in 2021 was significantly influenced by pandemic-related disruptions, which altered commuting patterns and pay (see Section 2.2.4). In 2020 and 2021, respondents were asked about their usual commuting arrangements, assuming no coronavirus restrictions, which may differ from actual behaviours. The next bumper sample in 2024 should provide more accurate data on commuting patterns, explored further in Section 4.8.

[24] In the UK, individuals aged 16 years old can legally work under an employment contract, be paid the National Minimum Wage, pay taxes and contribute to National Insurance.

[25] Self-employed individuals often have greater control over workplace location than employees, leading to distinct commuting patterns. Sensitivity analysis examines the CGG among self-employed workers.

[26] This measure is relatively crude and may also include some hybrid workers (discussed below).

(Section 4.8). Finally, as the sample only includes individuals from the first and fifth waves of the fourth quarter of the QLFS, survey weights cannot be applied to align the sample with sub-regional population estimates from the Census. Consequently, all tables report unweighted sample sizes (N).

4.4.3 Variables

Commuting

Since 1997, the QLFS has captured commuting behaviour by asking all employees, self-employed individuals, and unpaid family workers about their primary work location:

(In your main job) do you work mainly ... 1. in your own home, 2. in the same grounds or buildings as your home, 3. in different places using home as a base, or 4. somewhere quite separate from home?

In the fourth quarter annually (or every quarter every three years), those in employment, excluding those on government schemes, and selecting the fourth option are subsequently asked, regardless of wave:[27]

How long in total does it usually take you to travel from home to work?

Responses are recorded in minutes, capped at 180 minutes for commute times exceeding three hours. Individuals working outside the UK are assigned a commute time of zero, though they are ultimately excluded from the sample. Respondents also report their usual mode of travel and whether they commute by car as a driver or passenger.

As a result of these question, the research defines commuters as individuals primarily working at locations separate from home, while non-commuters are those who work mainly in their own home, in the same grounds or buildings as their home, or in different places using their home as a base. This distinction, although pragmatic, cannot distinguish between home workers and hybrid workers who mostly work from home, nor between regular commuters and hybrid workers who primarily commute, potentially misclassifying some hybrid workers as commuters. Despite this, the direct, self-reported measure of commute time may more accurately reflect commuting experiences than distance-based metrics, as it accounts for contextual factors like traffic density, accessibility, and commuting speed (Van Ommeren and Straaten 2008; Giménez-Nadal et al. 2018; see discussion in Section 4.2.1). This measure is widely used in policy contexts, including *Transport Statistics Great Britain* (Transport Statistics Great Britain, 2022) and annual commuting reports (Welsh Government, 2024a). It has been employed to model commute times in the UK (McQuaid and Chen, 2012) and to validate indirect commuting measures derived from the ASHE (ONS, 2019a; Nafilyan, 2020).

[27] The sensitivity of the commuting analysis is explored when the sample consists of all individuals in quarter 4 in 2022, regardless of wave (Section 4.8).

In the pooled data, approximately 70% of respondents are classified as commuters, with a slightly higher proportion of women (72.35%) than men (69.54%) (Table 4.1). This contrasts with commuting data from the Opinions and Lifecycle Survey (ONS, 2023b), likely due to the QLFS's inability to distinguish between commuters and hybrid workers.[28] The mean self-reported one-way commute time for employed commuters is estimated to be 25.83 minutes, with men reporting longer commutes (27.82 minutes) than women (24.19 minutes), resulting in a CGG of 13.07%. This gap may partially reflect gender differences in commuting modes, as women are more likely to use pedestrian methods associated with shorter commutes, whereas men are more likely to use private transport, which tends to involve longer commute times (Table C.3, Appendix C). These estimates are consistent with those derived from indirect measures in 2018 ASHE data, although the ASHE reported slightly longer average commutes for men (32.48 minutes), potentially indicating a greater shift towards homeworking among men with longer commutes since that period (ONS, 2019a).[29]

Table 4.1: Commuting Prevalence, Commute Time, and Hourly Pay by Commuting Status and Gender

		Male	**Female**	**All**	**Gap (%)**
Commute time	Incidence of commuters (%)	69.54	72.35	71.05	-2.81
	Population size	*4,668*	*5,411*	*10,079*	
	N	*3,246*	*3,915*	*7,161*	
	Mean commute time (minutes) (conditional on not working from home nor using home as a working base)	27.82	24.19	25.83	13.07
	N	*3,246*	*3,915*	*7,161*	
Hourly pay	All (£)	20.62	16.67	18.50	19.17
	Population size	*4,668*	*5,411*	*10,079*	
	Commuters (£)	17.69	15.05	16.25	14.90
	N	*3,246*	*3,915*	*7,161*	
	Non-Commuters (£)	27.31	20.89	24.02	23.52
	N	*1,422*	*1,496*	*2,918*	

Note: (i) See text for a description of sample construction and variable definitions. (ii) The gap is measured as a percentage of the relevant male figure in each case.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters.

Hourly Pay

Following the established GPG literature and the analysis of GPGs across areas within Britain (Chapter 3), (log) hourly pay is the main dependent variable in the GPG analysis. The QLFS provides two measures of hourly pay: a direct measure for those paid by the hour and a derived measure based on gross weekly pay in the respondent's main job divided by total usual hours worked, including overtime. Given that the direct measure applies to just over a third of the commuter sample (2,936 individuals), the

[28] The Opinions and Lifestyle Survey captures data on topics of national importance, including commuting habits (mode, time, and shifts in commuting patterns) in response to the impact of the pandemic. While it offers timely insights, its smaller sample size limits its ability to provide detailed demographic breakdowns like those available in the QLFS (ONS, 2023b). For a comparison of commuting data across surveys, see Section 4.2 and Table C.1, Appendix C.

[29] The ASHE estimate may also be longer due to the discrepancy between an employer's PAYE address and an employee's actual work site (Section 4.2.1).

derived measure is preferred, despite potential measurement errors due to non-reporting of pay and hours worked (Bryson, 2017). The analysis also applies the standard ONS filter, excluding individuals with hourly pay above £99.

This derived measure, extensively used in previous analyses of pay and the GPG (e.g., Jones and Kaya 2022b; Jones et al. 2018), includes additions to basic pay, such as overtime and performance-related pay. This contrasts with the ONS's preferred GPG measure, which excludes these components (see Section 2.2 and 3.4). These additions could potentially inflate GPG estimates if men disproportionately receive these additions. Additionally, as the measure is self-reported, with no legal obligations or checks, there may also be potential selection bias and measurement error. Respondents report pay over a chosen sample period, which is then converted into a weekly figure, potentially introducing bias, especially for individuals with irregular or variable pay. Selection bias may also arise from differential response rates by income level (Wood et al., 1993), with evidence suggesting that women, due to greater risk aversion, may understate their income, further influencing GPG estimates (Rizzo and Zeckhauser, 2007; Theurl and Winner, 2011). Despite these concerns, GPG estimates from the QLFS closely align with those from the ASHE, though the latter tends to report slightly higher mean and median figures (Leaker, 2008). Sensitivity analysis explores the results when employees receiving overtime are excluded (Section 4.8).[30]

Table 4.1 presents the mean hourly pay by gender for the total sample and by commuter status. Well-documented gender differences in pay are evident, with a national mean hourly GPG for all employees of 19.17%, exceeding national estimates in ASHE data (14.4% in 2022 and 14.3% in 2023) (ONS, 2023d). Both male and female commuters report lower mean hourly pay than non-commuters, reflecting occupational differences and the types of jobs that can or cannot be done at home. In particular, individuals working in higher-skilled occupations are more likely to work from home, compared to those in manual, service, and frontline jobs (Table C.3, Appendix C). Moreover, the mean hourly pay for male commuters is greater than for female commuters, resulting in a smaller, yet still substantial, GPG of 14.90% for commuters. The larger GPG estimated among non-commuters compared to regular commuters may be driven by job characteristics and labour market changes accelerated by the pandemic. While non-commuting roles are often associated with greater flexibility and remote/hybrid work - a valued amenity for which workers may accept lower pay (Goldin, 2014) - these jobs are also concentrated in higher-paying industries such as education, professional, scientific and technical activities, and the information and communication sector.[31]

Explanatory variables

Relating to the Household Responsibility Hypothesis and Labour Market Structure

[30] It was not possible to repeat the analysis using the direct hourly pay measure, as this reduces the sample.

[31] According to the Business Insights and Conditions Survey (December 2023), 49.6%, 36.6% and 20.8% of workers in these sectors, respectively, report not working from a designated workspace (further discussed in Section 4.8.1).

Hypothesis, the literature identifies four broad determinants of commute time and the CGG: individual characteristics, household variables, job characteristics, and external factors (McQuaid 2009; Giménez-Nadal et al. 2022; Section 4.3). These variables are also well-established determinants of pay and the GPG (Blau and Kahn 1997; Jones and Kaya 2022b; Chapter 2) and are well-captured in the QLFS. Detailed definitions, derivation, and usage of these explanatory variables, as well as commute time and (log) hourly pay as dependent variables, are provided in Table C.2, Appendix C. The explanatory variables in the commuting equation align with those in the wage equation, with the addition of the IV, as defined and discussed in the methodology section (Section 4.5).

The QLFS captures a broader range of individual characteristics than the ASHE, including gender, age, disability, ethnicity, and highest qualification. Disability and ethnicity variables address disparities in transport access and labour market outcomes, while highest qualifications capture differences in job search behaviour and employment opportunities. Household variables (e.g., marital status and the number of dependent children) reflect the joint determination of commuting behaviour and childcare responsibilities within households, which may be particularly relevant for women (Fan, 2017; Sandow and Westin, 2010; MacDonald, 1999; Turner and Niemeier, 1997; Anderson et al., 2001). These household variables extend the analysis from Chapter 3, recognising their influence on pay and human capital accumulation over the life cycle, considered further in Section 4.6.3.

Job characteristics, including employment contract type, public sector employment, and occupation (2020 SOC unit group), account for gendered employment patterns and their influence on willingness to commute. Additional job characteristics, such as workplace size (based on the number of employees, banded as defined by the ONS), tenure (and tenure squared) (measured in months employed at the current organisation), and union membership, are included to capture gender differences in on-the-job human capital accumulation.

Regional controls, defined based on the individual's place of work, account for regional labour market conditions. These regions are defined at the Government Office Region and former Metropolitan County levels, splitting the 12 NUTS 1 regions into further divisions: Scotland is separated into Strathclyde and the Rest of Scotland, Greater London is split into Central, Inner and Outer London, and the six Metropolitan counties (Greater Manchester, Merseyside, South Yorkshire, Tyne and Wear, West Midlands, and West Yorkshire) are separately identified. Due to small sample sizes, the urban regions of Greater Manchester and Merseyside are combined. This approach allows for a more granular examination of urban-rural differences than NUTS regions (Bergantino and Madio, 2015) and aligns with the analysis in Chapter 3 by focusing on where employers are located, and wages are determined.[32] It also better captures factors like

[32]The sensitivity of the analysis is explored without regional controls and with region of residence (Section 4.8).

urbanisation, housing prices, and job density, which are important determinants of commute time (Anderson et al., 2001).

Since the QLFS only asks commuting-related question to a subset of respondents, Table C.3, Appendix C provides summary statistics for all explanatory variables, by gender and commuter status, to examine the composition of commuters and non-commuters in the sample.[33] These confirm well-documented gender gaps: women are more likely to report disabilities, work part-time, belong to trade unions, and be employed in the public sector, regardless of commuter status. Occupational segregation is also evident, with men more frequently employed in lower-skilled occupations, such as the Process, Plant & Machine Operatives and Skilled Trades occupations, while women dominate the Administrative and Sales & Customer Service occupations, regardless of commuter status. These findings are consistent with those in Chapter 3 and align with international evidence on women's higher educational attainment and, on average, stronger productivity-enhancing characteristics (Blau and Kahn, 2017; Jones and Kaya, 2022b). However, this pattern is only evident for commuters, suggesting that highly productive men are more likely to not commute regularly, potentially reflecting differences in home-working feasibility across jobs.

Differences between commuters and non-commuters are also observed (Table C.3, Appendix C). Commuters generally have lower qualifications and are more likely to be trade union members and on temporary contracts. Geographically, commuters are concentrated in regions outside London and the South East, though all employees in Central London are commuters. Female commuters are more likely to work part-time and be employed in the public sector and Caring, Leisure and Other Services occupation than male commuters. In comparison, male commuters are overrepresented in higher-skilled and manual occupations, such as Managers & Senior Officials and Elementary occupations than female commuters. These patterns are consistent with those in the Opinions and Lifestyle Survey (Section 4.2.1).

Building on this, Table C.4, Appendix C compares 'long' and 'short' commuters, defined as those travelling 10 minutes more or less than the average commute within their sectors. The sample includes 1,484 long commuters and 2,841 short commuters, with average commute times of 57 minutes and 10 minutes, respectively. While long commuters are approximately 50% female, the proportion of women is higher among short commuters. Long commuters earn around 47% more per hour and are substantially more likely to hold higher qualifications. Employment characteristics also differ: 84% of long commuters work full-time, compared with 65% of short commuters, and short commuters report longer average tenure. Occupational sorting is also evident, with long commuters disproportionately employed in higher-paying professional and managerial roles, whereas short commuters are more dispersed across lower- and

[33] Some explanatory variables in Table C.3, Appendix C are merged to prevent statistical disclosure for non-commuters. This does not pose an issue for the analysis, as the commuter sample is sufficiently large to mitigate the risk of disclosure.

mid-skill occupations. Finally, long commuters are more likely to be located in London and the South East, reflecting the geographic concentration of high-paying jobs.

4.5 Methodology

The analysis consists of two parts. First, the raw and adjusted CGG and GPG in the UK are estimated using OLS regression. This facilitates the identification of key drivers of both gaps, with a particular focus on assessing the role of commute time as a potential yet often overlooked determinant of the GPG. Given potential endogeneity concerns between commuting and wages (arising, for example, from unobserved job or worker characteristics; see Section 4.3.2), the research further employs a 2SLS regression with an IV approach. This is not intended to deliver a definitive causal estimate, but rather to provide complementary evidence on the robustness of the observed associations between commute time and wages when accounting for possible sources of endogeneity. In this specification, the OLS regression of the CGG serves as the first stage regression, isolating variation in commute time that is plausibly exogenous to wages. Second, the research applies OB decompositions (Blinder, 1973; Oaxaca, 1973) to decompose the mean CGG and GPG and identify the drivers of these gender gaps and the extent to which commuting contributes to the GPG in the UK.

4.5.1 Estimating Raw and Adjusted Gender Gaps in Commuting and Pay

OLS regression

The raw CGG and GPG are first estimated using OLS regression, pooling individuals across genders and years (2022 and 2023):

$$C_{it} = \beta_0 + \alpha F_{it} + \rho Prox_{it} + \phi_t + \varepsilon_{it}; \quad t = 2022, 2023 \tag{4.1}$$

$$\ln W_{it} = \beta_0 + \alpha F_{it} + \rho Prox_{it} + \phi_t + \varepsilon_{it}; \quad t = 2022, 2023 \tag{4.2}$$

where self-reported one way commute time (C_{it}) and the natural logarithm of gross hourly wages ($\ln W_{it}$) for individual i in year t are regressed on a (female) gender indicator F_{it} (equal to one when individual i is female and zero when male), a proxy indicator $Prox_{it}$ (equal to one when individual i is a proxy respondent and zero when not a proxy respondent) and year-specific effects ϕ_t. β_0 is a constant term and ε_i is the random residual term, $\varepsilon_i \sim N(0, \sigma^2)$. The coefficients α in each respective equation quantify the raw CGG in minutes and the raw GPG in log percent.

The models are adjusted to control for individual characteristics, household variables, job characteristics, and workplace region (defined in Table C.2, Appendix C):

$$C_{it} = \beta_0 + \alpha F_{it} + \boldsymbol{\beta}\mathbf{X}_{it} + \rho Prox_{it} + \phi_t + \varepsilon_{it}; \quad t = 2022, 2023 \tag{4.3}$$

$$\ln W_{it} = \beta_0 + \alpha F_{it} + \delta C_{it} + \boldsymbol{\beta}\mathbf{X}_{it} + \rho Prox_{it} + \phi_t + \varepsilon_{it}; \quad t = 2022, 2023 \tag{4.4}$$

where the notation follows from above and $\mathbf{X}_{it}$ is a vector of individual characteristics, household variables, job characteristics, and workplace regions. These are successively introduced across five and six specifications for the CGG and GPG, respectively. The adjusted CGG and GPG are indicated by α, while δ reflects the association between commute time and wages, recognising that this estimate may be influenced by unobserved factors

2SLS regression

The relationship between commuting and wages may suffer from endogeneity due to reverse causality, omitted variable bias, or simultaneity (see discussion in Section 4.3.2). These challenges can lead to biased and inconsistent estimates of commuting as a driver of the GPG.[34] To address this potential endogeneity, the analysis employs an IV approach using a 2SLS regression to provide a more robust estimate of the relationship between commute time and wages. A suitable IV must satisfy two conditions: (i) relevance, meaning it must be strongly correlated with commute time; and (ii) validity, which requires that the instrument affects wages only through its impact on commute time, ensuring no correlation with the error term in the wage equation.[35,36]

Following Bartik (1991), who suggest using industry-level variables as instruments, an individual's commute time is instrumented by the average commute time of other

[34] Common approaches to addressing this endogeneity include fixed effects models (e.g., Manning 2003; Gutiérrez-i-Puigarnau and Van Ommeren 2015; Mulalic et al. 2014; Benito and Oswald 2000; Van Ommeren et al. 1999), sample restrictions (e.g., Gutiérrez-i-Puigarnau et al. 2016), job duration models (e.g., Van Ommeren et al. 2000; Isacsson and Swärdh 2007; Isacsson et al. 2013) and IV approaches (e.g., Farré et al. 2023; Troncoso et al. 2021). See discussion in Section 4.3.2.

[35] Various IVs have been used in the literature, including district of residence, industry, and occupation (Troncoso et al., 2021), city shape (Farré et al., 2023), and the income of other household members in two-earner households (Gutiérrez-i-Puigarnau et al., 2016) (see Section 4.3.2 for an overview). However, many of these instruments face limitations regarding relevance, validity, or data limitations. For example, Gutiérrez-i-Puigarnau and Van Ommeren (2015) attempted to use age and age squared as IVs but found that they failed the relevance criterion due to sample reduction. Similarly, Seltzer and Wadsworth (2024) used the distance between birthplace and the centre of London as an IV in historical data (New Survey of London Life and Labour 1928-1932) to assess the impact of access to public transport on wage returns. However, this IV has limited contemporary application.

[36] Other studies have instrumented wages to explore its impact on commute times, employing IVs such as trade union membership and public sector employment (Benito and Oswald, 2000). However, Manning (2003) highlights that these IVs are sensitive to specification choices. Additional IVs include world export shocks translated into firm-level demand shocks (Aboulkacem and Nedoncelle, 2022). Giménez-Nadal et al. (2024) attempted to use unobservable worker characteristics (e.g., fixed effects for workers, firms, and residence location) as instruments, but these failed due to over-identification issues.

workers within the same industry sector (one-digit SIC code).[37,38] The rationale for using this IV is that commuting patterns tend to be correlated within industries due to geographic clustering or similar operational conditions that affect all workers in the same industry. For instance, industries concentrated in urban centres may have longer average commute times due to congestion, while those in suburban areas may be shorter (Gibbons and Machin, 2006). Crucially, the exclusion restriction assumes that an individual's wage is not directly affected by the industry-average commute time, as this measure primarily reflects external factors such as geographic job distribution and public transport infrastructure rather than individual wage determinants, supporting its use as a valid instrument (Bartik, 1991). While theoretically sound, potential concerns include insufficient relevance if individual commuting decisions are largely driven by personal factors. Additionally, industries with higher wages may require longer commutes, which could compromise the exclusion restriction (Combes and Gobillon, 2015). Unobserved industry characteristics (e.g., job quality) could also correlate with wages, which could bias estimates (Bound et al., 1995). Finally, the assumption that industry-average commuting affects all workers uniformly may not hold if wage structures vary within industries, or if commuting and wages are determined during job search, limiting IV validity.

Statistical tests confirm the relevance of industry-level (one digit SIC) average commute time as a suitable instrument for individual commute time (see Table C.5, Appendix C). The instrument's relevance is confirmed by its coefficient being sizeable and significant at the 0.1% level in both pooled and gender-specific commuting models (Table C.6, Appendix C, discussed in Section 4.6.1). Additionally, the first-stage F-statistics of 54.40, 31.94 and 23.03 in the most comprehensive pooled, male, and female models, respectively, exceed the standard threshold of 10 as well as the Stock-Yogo critical value of 16.38, confirming instrument strength (Stock and Yogo, 2005). While direct tests of the exclusion restriction are infeasible in a single-instrument approach, the theoretical justification first-stage results lend support to the relevance of industry-level commute time as an IV, though concerns about validity cannot be entirely ruled out.

Formally, the IV (Z_i) for the commute time of individual i (C_i) is defined as the average commute time of workers in the same industry (one-digit SIC), excluding individual i ($\overline{C}_{S(i)\setminus\{i\}}$):

[37] This 'group average' IV approach is widely used to address endogeneity. For instance, Altonji and Shakotko (1987) instrument individual tenure with average tenure, Munch et al. (2008) use regional home-ownership rates, and Evans et al. (1992) employ metropolitan area poverty rates to instrument neighbourhood poverty. Similarly, Jones and Kaya (2023) instrument individual participation in performance-related pay jobs using its prevalence in the industry. However, aggregation may also reflect contextual and group-level effects beyond individual characteristics (see Bayer et al. 2008 for a discussion).

[38] Alternative IVs, including the average commute time within occupations, occupational skill groups or region of residence, as well as household status variables like housing tenure (renting status) and household composition, were explored but ultimately rejected due to concerns about relevance and/or validity. For instance, housing tenure may be influenced by income or job stability, which could also affect wages, and reverse causality (where commute time affects housing decisions) could further undermine its validity. Census-level IVs, like public transport usage, were also considered but posed issues due to potential correlations with income beyond commute times (French et al., 2020).

$$Z_i = \overline{C}_{S(i)\setminus\{i\}} \tag{4.5}$$

$$\overline{C}_{S(i)\setminus\{i\}} = \frac{1}{|S(i)| - 1} \sum_{j \in S(i)\setminus\{i\}} C_j \tag{4.6}$$

where $|S(i)|$ is the number of workers in the industry set $S(i)$.

In the first stage of the 2SLS regression, individual commute time (C_i) is regressed on the IV (Z_i) and control variables from the most comprehensive commute equation (Equation 4.3):

$$C_{it} = \beta_0 + \alpha F_{it} + \boldsymbol{\beta}\mathbf{X}_{it} + \gamma Z_i + \rho Prox_{it} + \phi_t + \varepsilon_{it}; \quad t = 2022, 2023 \tag{4.7}$$

where notation follows from above and γ is the coefficient of interest for the IV. A significant positive γ confirms the relevance of the instrument. This is the equivalent of the estimation of the raw and adjusted CGG (Equation 4.3).

In the second stage, the predicted values of commute time from the first stage ($\hat{C}_{it}$) replace actual commute times in the most comprehensive wage equation (Equation 4.4):

$$\ln W_{it} = \beta_0 + \alpha F_{it} + \delta \hat{C}_{it} + \boldsymbol{\beta}\mathbf{X}_{it} + \rho Prox_{it} + \phi_t + \varepsilon_{it}; \quad t = 2022, 2023 \tag{4.8}$$

where notation follows from above and δ provides an estimate of the wage–commuting relationship that accounts for potential endogeneity. A significant positive δ would be consistent with longer commutes being associated with higher wages, suggesting a link between commute time and the GPG, without claiming definitive causality.

4.5.2 Decomposing Gender Gaps

Gender Gap in Commuting

The OB decomposition method (Oaxaca, 1973; Blinder, 1973) is employed to decompose the mean CGG, using estimates from the most comprehensive first-stage regression (Equation 4.7). This approach, commonly employed to decompose wage differences (see Section 2.6 and Chapter 3 for examples), is adapted here to quantify the extent to which the raw CGG can be attributed to differences in observable characteristics (see Fuchs et al. 2024 and Casado-Díaz et al. 2023 for examples). Specifically, the OB decomposition decomposes the observed CGG into: (i) an explained component, which accounts for gender differences in observable characteristics, and (ii) an unexplained component, which captures the portion not accounted for by these characteristics.

The decomposition is based on separate estimations of the first-stage commuting model (Equation 4.7) for each gender $s \in \{\text{male } (M) \text{ and female } (F)\}$:

$$C^s = \beta_0 + \boldsymbol{\beta^s}\mathbf{X}^s + \gamma^s Z^s + \varepsilon^s \tag{4.9}$$

where notation follows from above, and the returns to characteristics (β^s) and commute time (γ^s) vary by gender s.[39] Following Blinder (1973) and using males as the reference group (see Section 2.5.2 for a discussion on reference group selection),[40] the decomposition of the raw CGG ($\overline{C}^M - \overline{C}^F$) is given by:

$$\begin{aligned}
\underbrace{\overline{C}^M - \overline{C}^F}_{\text{Observed CGG}} &= \underbrace{(\overline{X}^M - \overline{X}^F)\widehat{\boldsymbol{\beta}}^M + (\overline{Z}^M - \overline{Z}^F)\widehat{\gamma}^M}_{\text{Explained Gap}} \\
&+ \underbrace{(\widehat{\boldsymbol{\beta}}^M - \widehat{\boldsymbol{\beta}}^F)\overline{\mathbf{X}}^F + (\widehat{\gamma}^M - \widehat{\gamma}^F)\overline{Z}^F + (\widehat{\beta}_0^M - \widehat{\beta}_0^F)}_{\text{Unexplained Gap}}
\end{aligned} \tag{4.10}$$

where a bar above a variable denotes its mean value and $\widehat{\boldsymbol{\beta}}^s$ and $\widehat{\gamma}^s$ are the OLS estimates of $\boldsymbol{\beta}^s$ and γ^s, respectively. The explained gap represents the difference in mean commute times attributable to gender differences in mean characteristics. The unexplained gap captures the influence of unobserved factors, including individual preferences and household responsibilities. The decomposition also allows for a detailed analysis of the contribution of explanatory variables to the explained part of the CGG.

Gender Pay Gap

Similarly, the OB decomposition method is also applied to decompose the mean GPG in the UK (Blinder, 1973; Oaxaca, 1973) to assess the extent to which commuting is associated with the gap. This analysis uses results from the most comprehensive OLS wage model (Equation 4.4) and the second-stage regression, where individual commute time is instrumented by industry-average commute time (Equation 4.8). Specifically, individual commute time C_i is replaced with its predicted value $\widehat{C}_i$ from the first stage regression (Equation 4.7). Allowing returns to characteristics (β^s) and commute time δ^s to vary by gender s, the observed GPG ($\ln \overline{W}^M - \ln \overline{W}^F$) is decomposed as follows, using males as the reference group:[41]

$$\begin{aligned}
\underbrace{\ln \overline{W}^M - \ln \overline{W}^F}_{\text{Observed GPG}} &= \underbrace{(\overline{\mathbf{X}}^M - \overline{\mathbf{X}}^F)\widehat{\boldsymbol{\beta}}^M + (\overline{C}^M - \overline{C}^F)\widehat{\delta}^M}_{\text{Explained Gap}} \\
&+ \underbrace{(\widehat{\boldsymbol{\beta}}^M - \widehat{\boldsymbol{\beta}}^F)\overline{\mathbf{X}}^F + (\widehat{\delta}^M - \widehat{\delta}^F)\overline{C}^F + (\widehat{\beta}_0^M - \widehat{\beta}_0^F)}_{\text{Unexplained Gap}}
\end{aligned} \tag{4.11}$$

[39]For notational simplicity, the subscript i and t, as well as the year-specific effects and proxy indicator are omitted but remain incorporated in the estimation.

[40]The sensitivity of the findings to the choice of reference group is explored in Section 4.8, where the decomposition is re-estimated using female and pooled returns.

[41]The decomposition is also re-estimated using female and pooled returns (Section 4.8.2).

where notation follows from above. The decomposition is formulated to isolate commuting as a potential, though not necessarily causal, factor in the GPG. The explained gap measures the part of the mean hourly GPG attributable to gender differences in observable characteristics, including commute time. The unexplained gap reflects gender differences in the return to these characteristics and is often interpreted as a measure of potential wage discrimination (see Section 3.4 for a discussion).

4.6 The Gender Gap in Commuting

4.6.1 The Raw and Adjusted Gender Gap in Commuting

Table 4.2 presents estimates of the mean self-reported CGG in minutes, measured as the difference in commute time between women and men. These estimates are derived from various specifications of Equation 4.7, which pools individuals across genders and years. In the first specification, self-reported commute time is regressed on a female dummy variable, a constant, and controls for year-specific effects and proxy respondents (Equation 4.1). The coefficient on the female dummy variable provides an estimate of the raw CGG in minutes, unadjusted for characteristics. Specifications (2)-(6) successively control for average industry commute time (the IV), individual characteristics, household variables, job characteristics, and region of workplace. The final specification (6) serves as the first-stage regression in the 2SLS model, which addresses potential endogeneity between commute time and wages. The coefficients on the female dummy variable in these specifications reflect the adjusted CGG in minutes. Table C.6, Appendix C presents the full set of coefficient estimates for all explanatory variables across all specifications.

The raw CGG is estimated at 13.35%, with women commuting, on average, 3.714 minutes less than men (specification (1), Table 4.2). This lower spatial mobility for women is consistent with evidence from other countries (Giménez-Nadal et al., 2022; Fuchs et al., 2024) and the UK, including previous analyses of Understanding Society data, which reported a CGG of 11.7 log percent for employees between 2009-2017 (Reuschke and Houston, 2020).[42] Although slightly smaller than the median CGG based on distance in 2008-2016 ASHE data (ONS, 2019a; Nafilyan, 2020), these findings highlight the persistence of the CGG across datasets and time periods.

Controlling for individual characteristics (specification (3)) widens the CGG to 14.15%, indicating that gender differences in age, disability status, ethnicity, and qualifications contribute to the gap. In contrast, household variables (specification (4)) have minimal

[42] Using Understanding Society data, Reuschke and Houston (2020) find no CGG for the self-employed, suggesting that the self-employed are less constrained by the labour market. However, the sensitivity analysis estimates a larger unadjusted CGG of 6.605 minutes (see specification (9) in Table C.6, Appendix C), consistent with cross-sectional studies (Rosenthal and Strange, 2012). This could reflect self-employed women's preference for working from home to avoid commuting, but may also result from smaller sample sizes. Differences include the insignificance of full-time status, occupations and qualifications.

impact, challenging the Household Responsibility Hypothesis, which suggests that household responsibilities reduce women's commute times (see Section 4.3.1). The results align with prior analyses using Understanding Society data (Reuschke and Houston, 2020),[43] though household dynamics are explored further in Section 4.6.3.

Table 4.2: The Raw and Adjusted Gender Gap in Commuting

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-3.714***	-3.177***	-3.936***	-3.972***	-2.331***	-2.253***
	(0.493)	(0.488)	(0.480)	(0.482)	(0.543)	(0.520)
CGG (%)	13.35%	11.42%	14.15%	14.28%	8.38%	8.10%
Average industry commute time (IV)		0.930***	0.793***	0.793***	0.652***	0.471***
		(0.065)	(0.064)	(0.064)	(0.066)	(0.064)
Year-specific effects	Yes	Yes	Yes	Yes	Yes	Yes
Proxy respondents	Yes	Yes	Yes	Yes	Yes	Yes
Individual characteristics	No	No	Yes	Yes	Yes	Yes
Household variables	No	No	No	Yes	Yes	Yes
Job characteristics	No	No	No	No	Yes	Yes
Region of Workplace	No	No	No	No	No	Yes
Adjusted R^2	0.0076	0.0349	0.0791	0.0791	0.1121	0.1872
N	*7,161*	*7,161*	*7,161*	*7,161*	*7,161*	*7,161*
F-statistic	-	*203.86*	*151.61*	*151.45*	*97.36*	*54.50*
p-value	-	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*

Notes: (i) Estimates are based on an pooled OLS commuting equation. (ii) Males, 2022 and non-proxy respondents are the reference categories. All models include a constant. (iii) Standard errors in parenthesis. (iv) *p<0.05, **p<0.01, ***p<0.001. (v) Estimates in specification (6) form the first stage of the 2SLS model that addresses potential endogeneity between commute time and wages. Figures reported in the final two rows are the test statistics relating to the explanatory power of the instrument within each specification.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters.

The inclusion of job characteristics (specification (5)) significantly narrows the CGG to 8.38%, highlighting the role of labour market constraints, such as full-time employment and occupations, in explaining gender differences in commute times. In the most comprehensive specification (6), which additionally controls for workplace region, the CGG reduces to 8.10%, indicating that men commute 2.253 minutes more than women on average. The relatively low R^2 value (0.1934) is consistent with prior research and potentially highlights the influence of stochastic and/or unobserved factors, such as weather, congestion, or transport infrastructure, on commuting behaviour (Rouwendal and Rietveld, 1994; Benito and Oswald, 2000; Giménez-Nadal et al., 2022).

In terms of specific coefficient estimates, these broadly correspond to previous analyses (e.g., Reuschke and Houston 2020; Fuchs et al. 2021; McQuaid and Lindsay 2005; Giménez-Nadal et al. 2022) and prior expectations. In the most comprehensive model (specification (6)), only qualifications among individual characteristics remain statistically significant, aligning with previous analyses of the UK's CGG (Giménez-Nadal et al., 2022). Lower qualifications are associated with shorter commute times, potentially reflecting limited access to jobs requiring longer travel distances. This

[43]Reuschke and Houston (2020) find that housework is positively associated with women's commute times.

is consistent with the idea that low-skill local labour markets are geographically smaller than high-skill ones, constraining travel options for lower-qualified workers. As previously found, household variables are largely insignificant (Giménez-Nadal et al., 2022; Reuschke and Houston, 2020), challenging the Household Responsibility Hypothesis (Section 4.3.1).

Job characteristics emerge as key determinants of commute time. Managers & Senior Officials and Professional occupations are associated with longer commutes, while part-time roles (more prevalent among women) correspond to shorter commutes, potentially reflecting the geographical scarcity of local high-skilled job opportunities (McQuaid, 2009). Additionally, the inclusion of the average commute time of workers in the same industry sector (the IV) narrows the CGG across all specifications, likely capturing industry-level effects. The coefficient in specification (6) indicates that a one-minute increase in the industry-average commute time is associated with a 0.471-minute increase in individual commute time. The large F-statistics reported in the final two rows of Table 4.2 confirm the IV's relevance, suggesting it is a strong instrument (see discussion in Section 4.5 and Table C.5, Appendix C). Additionally, workplace region also significantly impacts commute time, reflecting geographic disparities, consistent with Fuchs et al. (2024) in Germany. The most comprehensive specification forms the first-stage of the 2SLS wage model.

Table C.6, Appendix C presents gender-specific coefficients from the most comprehensive specification (specifications (7) and (8)). The findings indicate that women's commute times are influenced by part-time employment and qualifications, whereas these factors do not impact men's commute times. This finding aligns with much of the literature (Madden, 1981; McQuaid and Chen, 2012) but contrasts with analysis of Understanding Society data (Reuschke and Houston, 2020). Conversely, lower-skilled occupations are associated with shorter commute times for men but not for women. These results suggest that gender differences in commuting are shaped by both supply-side factors - such as household responsibilities, part-time employment, and qualifications - particularly affect women, and demand-side factors - such as the spatial distribution of jobs and occupational segregation - that predominantly impact men.

4.6.2 Decomposition of the Gender Gap in Commuting

The results of the OB decomposition of the mean CGG are presented in Table 4.3 and Figure 4.2. Of the raw CGG, 1.067 minutes (29.35%) is explained by gender differences in observable characteristics, while 2.568 minutes (70.65%) remain unexplained or the adjusted CGG. This unexplained portion may potentially reflect unobserved preferences, omitted variables, or stochastic factors. The positive explained component indicates that men, on average, possess observable characteristics associated with longer commute times, suggesting that if women had the same observable characteristics as men, the CGG would be 1.067 minutes smaller. The proportion of the CGG that remains unexplained is similar to findings in Germany (Fuchs et al., 2024), indicating that the majority of the raw CGG persists even after controlling for observed characteristics.

The lower panel of Table 4.3 presents the decomposition of the explained gap into the broad determinants of commute time, evaluated using male coefficients.[44] Gender differences in job characteristics make the largest contribution to the explained CGG, explaining 34.11% of the raw CGG and 116.22% of the explained CGG. Full-time employment and public sector employment are the primary drivers (accounting for 61.95% and 38.43% of the explained CGG, respectively), aligning with the analysis of the adjusted CGG (Section 4.6.1). Region of workplace also explains a significant portion (12.97% of the raw CGG and 44.19% of the explained CGG), emphasising the importance of geography (job location and transport availability) in shaping gendered commuting patterns (Fuchs et al., 2024; Rapino and Cooke, 2011).

In comparison, individual characteristics contribute negatively to both the raw and explained CGG (-14.35% and -48.90%, respectively), primarily driven by qualifications, which reduce the raw and explained CGG by -12.10% and -41.24%, respectively. These findings align with evidence from Germany (Fuchs et al., 2024) and research indicating that higher-educated workers have greater regional mobility (McQuaid and Chen, 2012). Occupational differences also contribute negatively to the raw and explained CGG, diverging from German evidence (Fuchs et al., 2024). This discrepancy may be attributable to differences in the aggregation of commuters across various residence-workplace combinations in the German paper. Occupational effects were found to negatively impact the CGG for commuters travelling from urban to rural areas and among inter-rural commuters, potentially reflecting variations in occupational segregation across regions (Fuchs et al., 2024).

The OB decomposition suggests that household variables do not significantly contribute to the CGG. This reflects the estimation of both the raw and adjusted CGG above and prior research (Reuschke and Houston, 2020) and is explored further in Section 4.6.3. In terms of other characteristics, gender differences in firm size significantly increase the CGG, as women are more likely to be employed in smaller firms, while men tend to work in larger firms, which generally offer higher pay and better career prospects (Barth et al., 2016). The contribution of gender differences in firm size explains 6.27% of the raw CGG and 21.37% of the explained CGG, which is comparable to the German context (Fuchs et al., 2024).

In summary, the CGG persists even after controlling for observable differences. Job characteristics, especially full-time employment and public sector employment, are the largest contributor to the explained CGG, while individual characteristics, particularly education, reduce the gap. Gender differences in workplace region also play a role, yet

[44] A similar decomposition of the unexplained gap is not presented, as this depends on the choice of omitted categories for categorical variables. However, Table C.7, Appendix C presents a detailed decomposition of both the explained and unexplained components for all variables, based on normalised effects following (Yun, 2005).

Table 4.3: Decomposition of the mean Gender Gap in Commuting

Raw CGG	-3.635***	[100%]
	(0.500)	
Explained CGG	-1.067*	[29.35%]
	(0.483)	
Unexplained CGG	-2.568***	[70.65%]
	(0.628)	
Explained CGG	-1.067*	[29.35%]
Individual characteristics	0.522***	[-14.35%]
	(0.100)	{-48.90%}
Household variables	0.056	[-1.53%]
	(0.060)	{-5.21%}
Job characteristics	-1.240**	[34.11%]
	(0.439)	{116.22%}
Region of workplace	-0.471**	[12.97%]
	(0.155)	{44.19%}

Notes: (i) The OB method is used to decompose the mean CGG using male coefficients as the baseline. (ii) Specification includes individual characteristics, household variables, job characteristics and region of workplace (20 regions), year and proxy indicators and a constant. (iii) Table C.7, Appendix C provides the detailed decomposition of the explained gap for all variables, as well as the detailed decomposition of the unexplained gap based on normalised effects following Yun (2005). The unexplained component also includes a constant. (iv) Figures in () are standard errors and figures in [] ({}) are a percentage of the raw (explained) CGG. (v) *p<0.05, **p<0.01, ***p<0.001.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters.

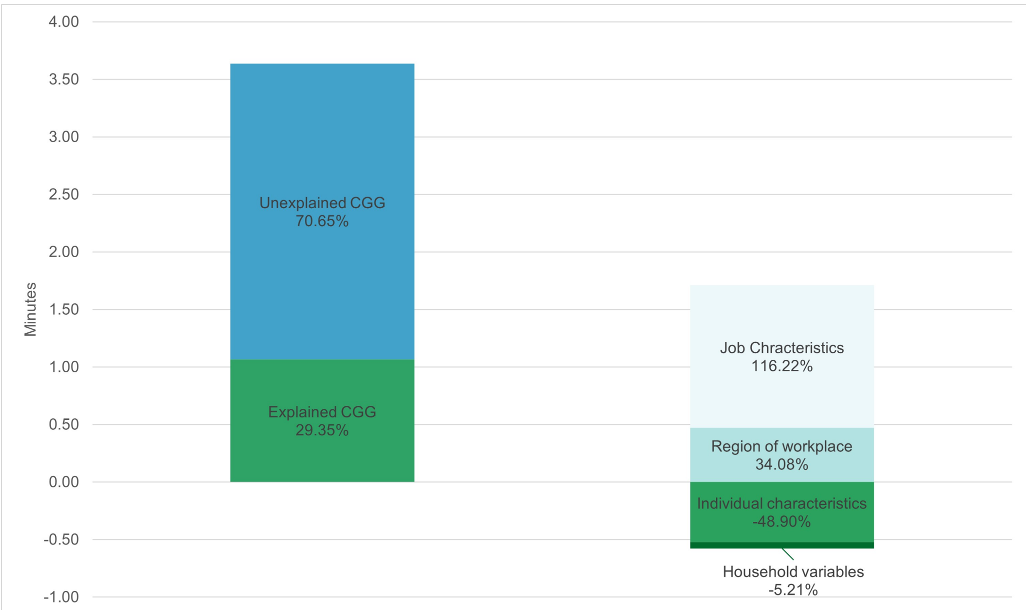


Figure 4.2: Detailed Decomposition of the Raw and Explained Gender Gap in Commuting

Notes: (i) The OB method is used to decompose the mean CGG using male coefficients as the baseline. (ii) Specification includes individual characteristics, household variables, job characteristics and region of workplace (20 regions), year and proxy indicators and a constant. The unexplained component includes the constant. (iii) Table C.7, Appendix C provides the detailed decomposition of the explained gap for all variables. (iv) The totals may not sum to 100% due to rounding.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters.

somewhat smaller, whilst household variables do not contribute significantly to the gap. These findings suggest that labour market constraints are the primary drivers of shorter commute times for women, rather than household responsibilities or inherent commuting preferences. However, household responsibilities may still interact with other factors to influence commute times. Despite this, a large portion of the CGG remains unexplained, potentially reflecting a substantial role of unobserved preferences, omitted variables, or stochastic factors.

4.6.3 Household Composition and Commuting

The analysis provides limited empirical support for the Household Responsibility Hypothesis but acknowledges that household variables may interact with other factors, such as part-time employment and occupational segregation, to shape women's commuting patterns. This contrasts with previous cross-sectional studies (e.g., Gimenez-Nadal and Molina 2016; Fan 2017; Kwon and Akar 2022), which provide evidence of a stronger role for household responsibilities in constraining commute times. However, the findings align with longitudinal analysis of Understanding Society data, which similarly found no significant impact of marital status or the presence of children on commutes times for men or women in the UK (Reuschke and Houston, 2020).

To assess whether the impact of household variables is obscured in the pooled sample, the commuting equation is re-estimated for subsamples by age and household type. This approach reflects expectations that caregiving responsibilities are more likely to affect younger women (aged ≤ 40), who are more likely to have young children, while older individuals (aged > 40) are less constrained. Similarly, the analysis distinguishes between single-earner and dual-earner households to examine intra-household commuting decisions.[45] Single-earner households may face fewer constraints, while dual-earner households may reflect 'tied mover' dynamics for women, whose commuting decisions are secondary to their partner (discussed in Section 4.3.1).

Table 4.4 presents gender-specific commuting patterns by age and family type. For younger men (aged ≤ 40 years), being married is associated with a significant increase in commute time by 3.004 minutes, supporting the hypothesis that married men have longer commutes to access higher-paying jobs as primary earners (Lersch and Kleiner 2018, Section 4.3.1). This effect is absent for older men. In contrast, the presence of school-aged children (aged 5-16 years) significantly reduces women's commute times across both age groups, suggesting that caregiving and school-related constraints disproportionately influence women's commuting patterns. This effect is not observed for men.

[45] The QLFS captures type of family unit (*FUTYPE6*). Single-earner households are defined as those comprising of one individual and lone parents.

Table 4.4: The Adjusted Gender Gap in Commuting by Household Type

	Women		Men		Household Type	
	≤ 40	> 40	≤ 40	>40	Single earner	Dual earner
Female	-	-	-	-	1.126	-3.260***
					(0.983)	(0.620)
Marital status						
Married	0.576	-1.993	3.004*	1.479	0.016	0.644
	(1.146)	(1.051)	(1.486)	(1.403)	(3.943)	(0.786)
Separated, widowed	-0.378	0.984	-5.236	1.872	-0.616	3.469*
or divorced	(2.170)	(1.213)	(3.939)	(1.802)	(1.782)	(1.576)
Children						
Number of children under	-1.621	0.230	1.381	1.237	0.176	-0.502
the age of 5	(0.841)	(2.329)	(1.093)	(2.011)	(1.782)	(0.614)
Number of children aged	-1.338*	-1.174*	-0.872	1.068	-1.156	-0.283
between 5-16 years	(0.601)	(0.598)	(0.830)	(0.736)	(0.743)	(0.355)
Adjusted R^2	0.2007	0.2542	0.1739	0.1879	0.1616	0.2046
N	*1,676*	*2,239*	*1,399*	*1,847*	*1,790*	*5,371*

Notes: (i) Estimates are based on a pooled OLS commuting equation. (ii) All models include individual characteristics, job characteristics, regions of workplaces, a constant and year and proxy indicators term. Males and single, never married are the reference categories. (iii) Standard errors in parenthesis. (iv) *p<0.05, **p<0.01, ***p<0.001.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters.

Decomposition analysis further reflects the impact of caregiving responsibilities (Table C.8, Appendix C). Among younger individuals (aged ≤ 40 years), school-aged children contribute 8.60% to the raw CGG of 3.001 minutes. However, for older individuals, school-aged children are not significant, despite a larger raw CGG of 4.107 minutes. Instead, job characteristics, particularly full-time employment, explain 57.89% of the raw CGG for older individuals, whereas full-time employment is not significant for younger individuals.

Household type analysis reveals distinct gendered commuting patterns (Table 4.4). Women in dual-earner households commute, on average, 3.260 minutes less than men in such households, likely reflecting their greater caregiving and domestic responsibilities or the household's geographic optimisation for men's jobs. Conversely, no significant CGG is observed for individuals in single-earner households, suggesting that women in these households may have greater flexibility to prioritise their own commuting preferences. While these findings suggest an interaction between supply- and demand-side factors, they should be interpreted with some caution given the reduced sample size.

4.7 The Gender Pay Gap and Commuting

4.7.1 The Raw and Adjusted GPG

Table 4.5a and 4.5b present estimates of the mean hourly GPG using OLS and 2SLS regressions, respectively. The 2SLS models aim to account for potential endogeneity between commute time and wages, providing insights into associations that may reflect underlying labour market patterns rather than definitive causal effects. The raw GPG is estimated from Equation 4.2, where log hourly pay is regressed on a female dummy variable, year and proxy indicators, and a constant. The coefficient on the female dummy variable represents the raw GPG in log percent, capturing the difference in hourly pay between women and men without accounting for other characteristics (converted to a percent using Equation 3.2). The adjusted GPG is estimated by progressively controlling for commute time (self-reported in the OLS model and predicted values in the 2SLS model), individual characteristics, household variables, job characteristics, and region of workplace, as specified in Equation 4.4 for the OLS models and Equation 4.8 for the 2SLS models. Full coefficient estimates for all explanatory variables are provided in Table C.9 and C.10, Appendix C for the OLS and 2SLS models, respectively.

The raw GPG is estimated at 16.12%, suggesting substantial gender inequality in the UK labour market. This estimate closely aligns with the national mean hourly GPG in 2022, as estimated in Chapter 3 (15.03%) and the ONS estimates for 2022 and 2023 using ASHE data (14.4% and 14.3%, respectively) (ONS, 2022d), despite different data and time periods.

The results from the OLS models (Table 4.5a) indicate that commute time is positively associated with wages, suggesting that individuals with longer commutes tend to earn more. This finding is consistent across all specifications and aligns with the literature that documents a positive correlation between commuting and wages across various contexts (e.g., Manning 2003 Laird 2006 for UK evidence, further discussed in Section 4.3.2). However, the estimated magnitude of this association is smaller than that found in Scotland, likely reflecting differences in data and control variables (Laird, 2006).

In column (3), controlling for individual characteristics is associated with a widening of the GPG to 16.77%, largely driven by the highest qualification (Table C.9, Appendix C). The inclusion of household variables (column (4)) has minimal influence on the GPG, indicating that household composition is not strongly associated with wage differences between women and men, though indirect mechanisms may exist. Controlling for job characteristics (column (5)) is associated with a substantial reduction in the GPG, with occupation showing a strong association, consistent with previous UK studies (e.g., Jones and Kaya 2022b). The inclusion of workplace region indicators (column (6)) has a small additional effect, resulting in an adjusted mean hourly GPG of 9.78% in the most comprehensive OLS specification.

The coefficient estimates from the OLS models broadly conform to prior analyses of the GPG in Britain (e.g., Chapter 3), the UK (e.g., Olsen et al. 2018), and internationally (e.g., Fuchs et al. 2021; Blau and Kahn 2017) (Table C.9, Appendix C). Among individual characteristics, age and tenure are positively related to wages, with evidence of decreasing returns, suggesting that these variables may proxy for work experience.

Table 4.5: The Raw and Adjusted Gender Pay Gap

(a) OLS

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.149***	-0.124***	-0.155***	-0.153***	-0.093***	-0.093***
	(0.013)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
GPG (%)	16.12%	13.21%	16.77%	16.53%	9.72%	9.78%
(Self-reported) Commute time		0.007***	0.005***	0.005***	0.003***	0.002***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year-specific effects	Yes	Yes	Yes	Yes	Yes	Yes
Proxy respondents	Yes	Yes	Yes	Yes	Yes	Yes
Individual characteristics	No	No	Yes	Yes	Yes	Yes
Household variables	No	No	No	Yes	Yes	Yes
Job characteristics	No	No	No	No	Yes	Yes
Region of Workplace	No	No	No	No	No	Yes
Adjusted R^2	0.0211	0.0901	0.2788	0.2877	0.4283	0.4379
N	*7,161*	*7,161*	*7,161*	*7,161*	*7,161*	*7,161*

(b) 2SLS

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.149***	-0.026	-0.057**	-0.056	-0.048**	-0.040*
	(0.013)	(0.020)	(0.019)	(0.019)	(0.016)	(0.019)
GPG (%)	14.94%	2.59%	5.85%	5.80%	4.96%	4.06%
Predicted commute time		0.033***	0.027***	0.026***	0.020***	0.024***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Year-specific effects	Yes	Yes	Yes	Yes	Yes	Yes
Proxy respondents	Yes	Yes	Yes	Yes	Yes	Yes
Individual characteristics	No	No	Yes	Yes	Yes	Yes
Household variables	No	No	No	Yes	Yes	Yes
Job characteristics	No	No	No	No	Yes	Yes
Region of Workplace	No	No	No	No	No	Yes
Durbin (score) chi2(1)	-	*234.846*	*146.075*	*141.858*	*68.403*	*58.025*
p-value	-	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
N	*7,161*	*7,161*	*7,161*	*7,161*	*7,161*	*7,161*

Notes: (i) Estimates in table (a) are based on a pooled OLS earnings equation. Estimates in table (b) are from the second stage of the IV (two-stage least squares (2SLS)) model. (ii) Males, 2022, and non-proxy respondents are the reference categories. (iii) All models include a constant and year term. (iv) Standard errors in parenthesis. (v) *p<0.05, **p<0.01, ***p<0.001. (vi) Figures reported in the final two rows are the Durbin (score) chi2(1) statistic for endogeneity between commute time and wages within each column.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters.

Regarding household variables, marital status and the presence of young children under five years are associated with higher wages. However, gender-specific models indicate that the number of children under five is only significant for men (Table C.11, Appendix C), consistent with evidence of a 'fatherhood premium' in the UK labour market (as discussed in Section 5.2.1).

Regarding job characteristics, employment in larger firms and full-time employment are associated with higher wages, while public sector employment is associated with lower wages. Occupational dummies confirm that lower-skilled occupations are associated with lower wages, with women overrepresented in them (Table C.3, Appendix C). For example, women are overrepresented in the Sales & Customer Services occupation (the lowest paid occupation) with 9.27% of women compared to 5.36% of men (Table C.3,

Appendix C). Regional workplace indicators are also associated with wage variation, with lower wages in regions outside Central London, particularly in East Anglia, Tyne and Wear, and the Rest of West Midlands, likely reflecting regional differences in occupational structures and commuting patterns.

Gender-specific coefficients in the most comprehensive OLS specification (Table C.11, Appendix C) largely conform to expectations, although there are some differences. For instance, returns to highest qualification and firm size are larger for men, while ethnicity significantly influences wages only for men. These differences suggest that gendered labour market dynamics, where certain characteristics differently impact men and women, contribute to the persistence of the GPG. Despite these differences, the association between commute time and wages is consistent, with a one-minute longer commute linked to approximately a 0.2% higher wage in the most comprehensive model (Table C.11, Appendix C).

In the 2SLS models, predicted commute time, instrumented by the average commute time of workers in the same industry sector, remains positively associated with wages, indicating that longer commutes are linked to higher earnings. The Durbin score chi-squared test and corresponding p-value confirm the instrument's relevance and suggest potential endogeneity between commute time and wages. Accounting for this association increases the estimated effect relative to OLS, implying that simple OLS estimates may understate the relationship between commute length and wages.The magnitude of the association is broadly consistent with findings from Scotland, where commute time elasticity of income was estimated at 0.044 using Scottish Household Survey data and instrumenting with household type and rural/urban classification (Laird, 2006). However, these results contrast with Troncoso et al. (2021), who identified a negative relationship between commute time and wages in Santiago using a 2SLS approach (see Section 4.3.1 for a discussion and critique of their IV). While their analysis similarly found a stronger relationship after accounting for endogeneity, the negative effect in Santiago may reflect distinctive urban labour market characteristics. This includes inequities in job accessibility and spatial mismatches, exacerbated by geographic constraints such as the Andes, which may restrict commuting options and concentrate lower-paying jobs in more accessible areas.

When commute time is treated as endogenous, the estimated GPG is smaller, suggesting that part of the difference in wages observed in OLS models may be associated with labour market constraints, such as geographic location. However, the GPG remains positive and significant in the most comprehensive specification at 4.06% (column (6)). The IV may also partially capture industry-specific patterns, reflecting that women are more likely to work in lower-paying industries with shorter commutes, while men are more concentrated in higher-paying industries often requiring longer commutes.

Gender-specific patterns suggest that the association between commute time and wages may differ by gender (Table C.11, Appendix C). In the 2SLS models, longer commute times are linked to a larger wage association for women than men, in contrast to the broadly similar effects observed in the most comprehensive OLS models. This may reflect household constraints, such as childcare and partner location considerations, or selective labour market participation, where women who undertake longer commutes are more likely to hold higher-skilled or career-oriented positions. These observations align with Anderson et al. (2001), who argue that women's commute times are often shaped by external constraints rather than purely labour market incentives. For men, commuting appears more directly aligned with labour market opportunities, which may explain why OLS estimates understate the association between commute time and wages for men.

The coefficient estimates from the 2SLS models are broadly consistent with those from the OLS models, although there are some differences (Table C.10, Appendix C). Age and tenure remain positively associated with wages, with diminishing returns. Education continues to be positively correlated with wages, while public sector employment and lower-skilled occupations are associated with lower wages. However, in the 2SLS models, full-time employment is no longer significant, and firm size is only significant for men (Table C.11, Appendix C). There is also a reversal of the coefficients for the workplace regions in the 2SLS models. The shift to significantly positive coefficients suggests a spatial wage premium associated with longer commutes to high-wage regions, such as London, where wages compensate for the increased costs and effort of commuting. The strong positive coefficients for Wales and the Rest of Northern workplace regions, which are especially pronounced for women, indicate regional variations in labour market dynamics and gendered wage determination (Table C.11, Appendix C).[46] Overall, these results highlight the role of regional economic structures and the spatial distribution of industries in shaping wage outcomes. Finally, gender-specific coefficients indicate that education is more strongly associated with wages for men than for women in the 2SLS models (Table C.11, Appendix C).

4.7.2 Decomposition of the Gender Pay Gap

Table 4.6 and Figure 4.3 present the OB decomposition of the mean GPG across three models: an OLS model excluding commute time, an OLS model including commute time, and a 2SLS model where commute time is instrumented using the average industry commute time. In the OLS model without commute time, 23.43% of the raw GPG is explained by gender differences in observable characteristics, leaving 76.22% of the gap unexplained. The positive explained component indicates that, on average, men possess more productive observable characteristics. The larger unexplained portion compared to Chapter 3, highlights the persistence of significant gender wage inequality in the UK.

Including commute time in the OLS decomposition increases the portion of the raw

[46] The sensitivity analysis explores the effects of excluding workplace regions and controlling for regions of residence instead (Section 4.8).

Table 4.6: Decomposition of the mean Gender Pay Gap

	No Commute Time		**Commute Time**			
			OLS		**2SLS**	
Raw GPG	-0.143***	[100%]	-0.143***	[100%]	-0.143***	[100%]
	(0.013)		(0.013)		(0.013)	
Explained GPG	-0.034**	[23.43%]	-0.041**	[28.40%]	-0.045***	[31.26%]
	(0.013)		(0.013)		(0.013)	
Unexplained GPG	-0.109***	[76.22%]	-0.102***	[71.60%]	-0.098***	[68.81%]
	(0.014)		(0.014)		(0.014)	
Explained GPG	-0.034**	[23.43%]	-0.041**	[28.40%]	-0.045***	[31.26%]
Commute time	-		-0.009***	[6.22%]	-0.015***	[10.14%]
			(0.002)	{21.91%}	(0.003)	{32.44%}
Individual characteristics	0.010***	[-7.06%]	0.009**	[-6.15%]	0.008**	[-5.84%]
	(0.003)	{-30.15%}	(0.003)	{-21.66%}	(0.003)	{-18.68%}
Household variables	-0.001	[0.82%]	-0.001	[0.91%]	-0.001	[0.70%]
	(0.001)	{3.49%}	(0.001)	{3.20%}	(0.001)	{2.24%}
Job characteristics	-0.038***	[26.29%]	-0.035**	[24.75%]	-0.033**	[23.08%]
	(0.011)	{112.24%}	(0.011)	{87.15%}	(0.011)	{73.83%}
Region of workplace	-0.004*	[2.99%]	-0.003	[2.17%]	-0.004*	[2.57%]
	(0.002)	{12.78%}	(0.002)	{7.66%}	(0.002)	{8.23%}

Notes: (i) The OB method is used to decompose the mean hourly GPG using males as the baseline. (ii) Specification includes individual characteristics, household variables, job characteristics and region of workplace (20 regions), year and proxy indicators and a constant. (iii) Table C.13, Appendix C provides the detailed decomposition of the explained gap for all variables, as well as the detailed decomposition of the unexplained gap based on normalised effects following Yun (2005). The unexplained component also includes a constant. (iv) Figures in () are standard errors and figures in [] ({}) are a percentage of the observed (explained/unexplained) GPG. (iv) *p<0.05, **p<0.01, ***p<0.001.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters.

GPG explained by observable characteristics to 28.40%, reducing the unexplained component to 71.60%. This suggests that commute time is a small but significant correlate of wages and may reflect spatial constraints that disproportionately affect women's wages. In the 2SLS model, which accounts for potential associations between commute time and wages, the explained component rises further to 31.26%. This finding suggests that OLS estimates may underestimate the association between commute time and wages, and that the link between commute time and the GPG is stronger when accounting for this association. The 2SLS model aligns with the theory of compensating wage differentials, in which longer commutes are associated with higher wages. Women, who often face spatial or household constraints, may have limited access to jobs with longer commutes and higher wages, which is reflected in the decomposition results.

The lower panel of Table 4.6 presents the decomposition of the explained gap into broad categories, evaluated at male coefficients.[47] Consistent with previous UK studies (see Chapter 2), individual characteristics, particularly education, contribute negatively to the GPG, reflecting women's higher average qualifications compared to men (Jones and

[47] A decomposition of the unexplained portion is not presented due to its sensitivity to the choice of omitted categories for categorical variables. A detailed decomposition of the explained gap for all variables, along with the decomposition of the unexplained gap based on normalised effects following Yun (2005), is provided in Table C.13, Appendix C.

Kaya, 2022b). However, job characteristics are the largest positive contributors, explaining 112.24%, 87.19%, and 73.83% of the explained component across the three specifications. Public sector employment, full-time employment, and firm size explain the majority of this effect, widening the GPG (Table C.12 and C.13, Appendix C).

Gender differences in commute time also contribute to the explained portion of the raw GPG. In the OLS model, commute time accounts for 6.22% of the raw GPG and 21.91% of the explained component, increasing to 10.14% and 32.44%, respectively, in the 2SLS model. This suggests that women's shorter commute times are associated with a larger portion of the GPG. Relative to other explanatory variables, commute time ranks second only to job characteristics in its contribution to the GPG and is smaller only than full-time employment and public sector employment (Table C.13, Appendix C). Both of these have been extensively analysed (see Chapter 2). In the OLS model, the contribution of commute time is comparable to the mitigating effect of education, while in the 2SLS model, commute time's association is roughly twice as large, suggesting a stronger link when potential associations between commute time and wages are accounted for.

The larger role of commute time in the 2SLS model highlights the potential influence of household responsibilities and intra-household decisions on women's observed commuting patterns and associated wage outcomes. While not strictly causal, these associations suggest that spatial considerations are an important factor in analyses of the GPG and may help explain part of the observed wage differences between men and women.

4.8 Sensitivity Analysis

4.8.1 The Gender Gap in Commuting

The sensitivity of the CGG decomposition is explored through a series of alternative specifications, presented in Table C.14, Appendix C. Given the positively skewed distribution of commute times — where most individuals report short commutes and a minority report longer ones — the decomposition is repeated using the natural logarithm of commute times as the dependent variable (column (2)). This approach, consistent with the main analysis of Fuchs et al. (2024), mitigates the influence of extreme outliers and enables interpretation in terms of elasticities rather than absolute differences, offering insights into proportional gender gaps. The logged model produces findings closely aligned with the primary analysis, confirming the robustness of the initial decomposition.

To better capture daily commuters and differentiate them from hybrid workers - who may commute sporadically or undertake long, infrequent one-way commutes - a maximum commute time of 90 minutes is applied (column (3)), following Fuchs et al.

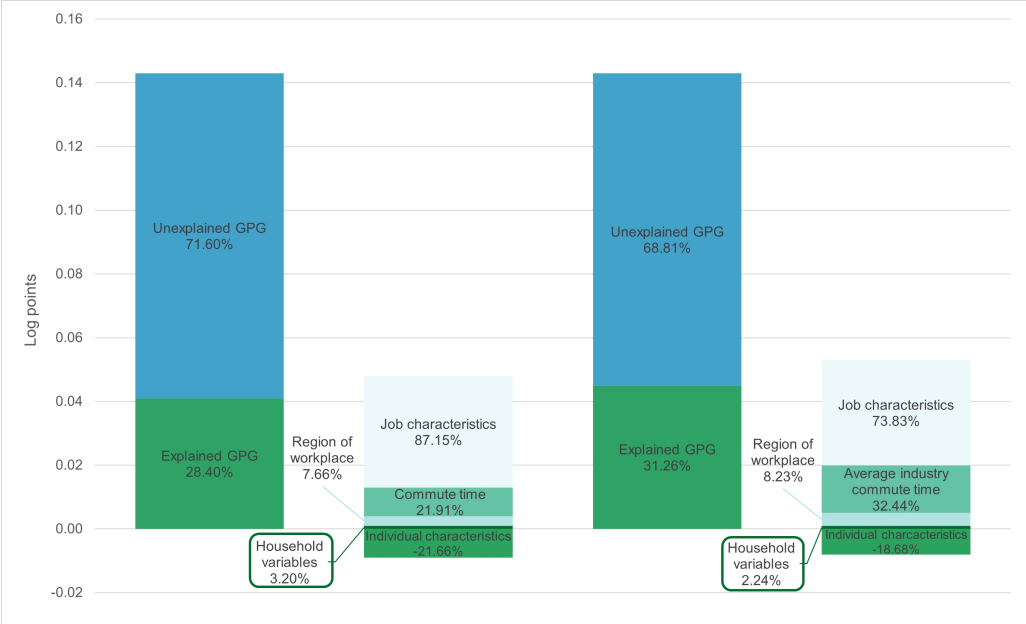


Figure 4.3: Detailed Decomposition of the Raw and Explained Gender Pay Gap

Notes: (i) The OB method is used to decompose the mean hourly GPG using male coefficients as the baseline. (ii) Specification includes individual characteristics, household variables, job characteristics and region of workplace (20 regions), year and proxy indicators and a constant. The unexplained component includes the constant. (iii) Table C.13, Appendix C provides the detailed decomposition of the explained gap for all variables. (iv) The totals may not sum to 100% due to rounding.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters.

(2024). This restriction is intended to filter out individuals whose reported commute times reflect non-daily travel, thereby isolating daily commuters. While commutes longer than 90 minutes are rare (representing only 64 individuals, or less than 1% of the total commuter sample), their exclusion reduces the raw CGG. This suggests that men are more likely than women to engage in very long commutes, which may be infrequent or irregular. Consequently, gender differences in commuting appear more pronounced at the upper end of the commute time distribution. Additionally, the contribution of public sector employment to the CGG diminishes in this restricted sample, suggesting that men with exceptionally long commutes are more concentrated in private sector jobs, which tend to be geographically dispersed.

To further limit biases arising from the research's crude definition of commuters, the sample is restricted to industries where at least 80% of workers report 'working from a designated workspace' in the Business Insights and Conditions Survey (surveyed in December 2023)) (column (4)). This restriction ensures the focus is on industries with high levels of daily commuting, which reduces potential effects from hybrid or remote work patterns, which involve infrequent commuting and gendered uptake of flexible work arrangements. These industries - the accommodation and food service activities, other service activities, transportation and storage, construction and manufacturing - have an estimated average commute time of 24.42 minutes, reflecting more consistent daily commuting patterns. This may be attributed to the rigid spatial and temporal work requirements typical of these sectors, such as fixed workplace locations and scheduled hours.[48] In this restricted sample, the CGG remains similar, with women commuting 3.386 minutes less than men. However, the decomposition analysis suggests that the explained portion of the CGG becomes insignificant, with job characteristics no longer explaining the CGG.

The sensitivity of the results is explored by adapting the sample to account for potential variations in the drivers of the CGG across different employee groups. To address concerns that proxy responses may introduce bias, particularly by under-reporting commute times (see discussion in Section 4.4), these responses are excluded (column (5)). While the raw CGG remains similar to the benchmark, the explained portion increases, with job characteristics and workplace regions accounting for 61.24% and 26.56% of the raw CGG, respectively. This change is primarily driven by the larger role of full-time employment when proxy responses are excluded, suggesting that proxy respondents — who are disproportionately male, younger, less educated, employed in full-time roles, and lower-skilled occupations — may introduce inaccuracies in reporting commute times and other characteristics (Bose and Giesbrecht, 2004). Key travel statistics also differ, with proxy respondents reporting shorter commute times and being more likely to commute using private transport. The analysis also examines the impact of tenure by restricting the sample to employees with more than one year in their current role (column (6)). The findings remain robust, indicating that variations in labour market attachment or employment transitions do not influence the drivers of the CGG.

Given the significant contributions of full-time and public-sector employment to the explained CGG, the analysis is repeated for private-sector employees only and full-time employees only (columns (7) and (8)). The former aligns the analysis with the main analysis of Fuchs et al. (2024), enabling an investigation of the CGG for a more homogeneous group. Among full-time workers, the unadjusted CGG decreases from 3.635 minutes to 1.767 minutes, while the explained portion increases. This suggests that women in full-time roles have characteristics, such as higher educational qualifications and professional occupational roles, which are associated with longer commutes, which partially offset gender differences. In the private sector, the results remain consistent, though workplace regions play a smaller role, possibly due to reduced geographic dispersion in private-sector employment.

Finally, to explore the impact of changing commuting behaviour since the pandemic (discussed in Section 4.2.3), the CGG decomposition is re-estimated using pooled data from the fourth quarters of 2018 and 2019 (columns (9)). Pre-pandemic, the unadjusted CGG was larger at 5.309 minutes, with a greater portion of the mean CGG explained by observable characteristics. The detailed decomposition shows that children account for 1% of the unadjusted CGG in the 2018/2019 data - a factor that is insignificant in the 2022/2023 data. This may indicate that more flexible work patterns, such as increased

[48] Industries with the lowest proportion of workers in designated workspaces include education (49.6%), professional, scientific, and technical activities (36.6%), and information and communication (20.8%).

hybrid working, have reduced the impact of parenthood on gender differences in commuting. This finding aligns with recent evidence highlighting the pronounced benefits of working from home, particularly for women (Alipour et al., 2021; Adams-Prassl et al., 2022; Barrero et al., 2021; Arntz et al., 2022; Nagler et al., 2024; Maestas et al., 2023; Datta, 2019; Aksoy et al., 2022).

The analysis is further repeated using pooled data from all waves in the fourth quarter of 2022 (column (10)) to increase sample size and assess the sensitivity of the results across waves. The findings remain robust, reinforcing that the majority of the CGG remains unexplained, with gender differences in job characteristics continuing to play a significant role in explaining the CGG. Finally, the sensitivity of the analysis to methodological decisions is explored by repeating the decomposition using relevant or pooled coefficient estimates as baseline coefficients (columns (11) and (12)). The results remain robust when using female or pooled coefficients, the latter incorporating a gender dummy as the reference group following Fortin (2008).

4.8.2 The Gender Pay Gap

The sensitivity of the benchmark OB decompositions from the 2SLS regressions is explored in reference to the choice of IV. Specifically, the analysis is repeated using the average commute times of employees within the same two-digit SIC industry (column (2), Table C.15, Appendix C). This IV is theoretically relevant as it captures the geographic clustering of industries and is unlikely to directly affect individual wages. The results remain largely consistent, with minimal differences attributable to the smaller sample size used to ensure the IV is based on averages derived from at least ten individuals.

The remaining columns in Table C.15, Appendix C further demonstrate the robustness of the findings across a wide range of variable definitions, sample restrictions, and model specifications. Column (3) logs commute time to account for its positive skew and provide a measure of commuting elasticity with respect to wages. Column (4) explores the sensitivity of the results by excluding those working overtime, recognising that the baseline hourly pay measure is derived and includes additions to basic pay, such as overtime payments. This differs from the ONS' preferred measure of the GPG, which explicitly excludes overtime (see discussion in Section 2.2). Including overtime may upwardly bias the GPG measure if men, on average, work more overtime than women and disproportionately benefit from overtime premium.[49] The findings remain robust to both the use of logged commute time and the exclusion of overtime workers, reinforcing the importance of commute time as an often overlooked driver of the GPG.

[49] Alternative measures of pay based on hourly rates could not be considered, as such data is available for only approximately a third of the commuter sample (2,936 individuals). Moreover, certain industries (e.g. the distribution, hotels and restaurant industry) and lower-skilled occupations, are overrepresented in this sub-sample, diminishing the relevance of the instrument based on the F-statistic.

The sensitivity of the results is also explored when adapting the sample to account for potential variations in the role of commuting in explaining the mean GPG across different employee groups. Given concerns that proxy responses may introduce bias, particularly through the under-reporting of commute times (see discussion in Section 4.4), these responses are excluded (column (5)). While the contribution of commute time is slightly reduced for non-proxy responses, this is primarily driven by a larger raw GPG for non-proxy individuals. This suggests that concerns about the under-reporting of commute times may be less warranted than initially assumed, although potential biases in pay reporting by proxies may remain. To further assess the impact of tenure on the relationship between commuting and the GPG, given potential biases arising from voluntary and non-voluntary job moves (as discussed in Petrongolo and Ronchi 2020), the sample is restricted to employees who have been in their current job for over a year (column (6)). The findings remain robust, indicating that tenure does not significantly influence the role of commuting in explaining the GPG, nor do differences in labour market attachment or employment transitions substantially alter this relationship.

Given the significant role of the nature of employment characteristics in explaining the CGG, the analysis is conducted separately for employees in the private sector and for full-time employees (column (7) and (8), respectively). In the private sector, the association between commute time and the GPG is consistent with the benchmark. However, for full-time employees, the association is slightly stringer, with commute time accounting for 15.15% of the mean hourly GPG. This likely reflects the more stable labour market attachment and homogeneous employment patterns of full-time workers, where commuting factors are more closely linked to observed wage differences.

To address concerns about the reversal of workplace region coefficients in the 2SLS model (Section 4.7), two alternative specifications are two alternative specifications are explored: excluding workplace regions (column (9)) and controlling for regions based on areas of residence (column (10)). In the OLS model, workplace regions behave as expected, with areas outside Central London associated with lower wages. In the preferred 2SLS specification, however, coefficients are positive, potentially reflecting industry concentration effects. Both adjustments test whether this sign change affects the role of commute time. Defining regions based on residence at a broader geographical level reduces localised industry effects. The results remain broadly robust, with commute time explaining 16.78% and 15.27% of the mean GPG, respectively. This suggests that the observed sign change mainly reflects regional wage variation, which is effectively captured by the IV and its role as a proxy for commute patterns.

The remaining sensitivity analysis confirms that the findings are not sensitive to methodological decisions, the specific choice of QLFS years (column (11)), or the use of female or pooled coefficient estimates as baseline coefficients (column (12) and (13)). When repeating the analysis using pooled data from the fourth quarters of 2018 and

2019, the results remain robust, despite the increasing prevalence of home working. The primary difference is that before the pandemic, a smaller proportion of the mean hourly GPG was explained by commute time (6.37%), likely reflecting a higher proportion of the population commuting regularly in 2018 and 2019, particularly among higher-paid occupations. This is evidenced by the stronger influence of job characteristics, especially occupation, on the mean hourly GPG. The results are also robust when using female and pooled coefficients, where the latter uses a gender dummy as per Fortin 2008. Despite cautions about non-male reference groups (Blau and Kahn, 2017), the findings consistently highlight commuting as an important factor associated with the GPG, underscoring the relevance of spatial considerations in wage disparities between men and women.

4.9 Conclusion

In the context of the majority of GPGs in the UK remaining unexplained (Chapter 3), the literature has increasingly examined the role of non-wage amenities. Despite its potential to affect labour market outcomes, including job accessibility, employment rates, and wages, commuting has been an often overlooked factor in gender wage analyses. Using pooled QLFS data from the fourth quarters of 2022 and 2023, this Chapter provides empirical evidence of substantial gender differences in commute time and its association with the contemporary GPG in the UK. It is the first post-pandemic analysis linking gender differences in commuting to gender differences in pay in the UK.

On average, women in the UK are estimated to commute 3.714 minutes less than men for a one-way journey, corresponding to a raw CGG of 13.35%, consistent with pre-pandemic analyses (e.g., Reuschke and Houston 2020). Key determinants of commute time include education level, occupation, and workplace region, reflecting the geographic concentration of higher-skilled jobs and their associated longer commutes. Despite these differences, an OB decomposition suggests that 70.65% of the mean CGG remains unexplained, likely due to unobserved preferences, unmeasured characteristics, or stochastic variation. Among the explained components, job characteristics - particularly full-time and public sector employment - account for 34.11% of the CGG, while workplace region contributes an additional 12.97%. These findings underscore the spatial dimensions of gendered commuting patterns and the structural factors shaping labour market accessibility and opportunities. Further analysis suggests that household composition has a limited direct impact on the CGG but interacts with other factors, particularly for women under 40 years of age, consistent with the 'child penalty' literature (Kleven et al., 2019).

Commute time is positively associated with wages, consistent with prior UK analyses (e.g., Laird 2006; Manning 2003). When accounting for potential correlations between commute time and unobserved individual characteristics, through the use of an instrument capturing industry-level commuting patterns, this association appears somewhat stronger, particularly for women. Specifically, an additional one minute increase in commute time is associated with a 3.1% and 1.9% increase in wages for women and men, respectively). These results highlight that women's wage outcomes may be more strongly related to spatial and household constraints than men's, rather than asserting a causal effect of commute time on wages (as argued by Anderson et al. 2001).

The OB decomposition of the mean GPG in the UK indicates that commute time is an important factor associated with gender pay differences. In the 2SLS model, the gender difference in commute time is estimated to be associated with 10.14% of the raw GPG and 32.44% of the explained component, aligning with prior international literature that address endogeneity (Caldwell and Danieli, 2024; Gutierrez, 2018; Le Barbanchon et al., 2021; Ekberg and Widegren, 2019; Farré et al., 2023). The estimated association between commuting and the GPG is larger than that obtained from OLS regression, suggesting that OLS may understate the role of commuting in observed wage differences. Among characteristics typically examined in the literature, gender differences in commute time contribute more to the GPG than most factors, and its impact is second only to full-time employment and public sector employment. Its association is also roughly twice as large as that of education in the 2SLS model.

These findings highlight the potential importance of geographic constraints in understanding gendered differences in labour market outcomes. Women's commuting patterns appear closely linked with observed pay differences, potentially reflecting the interaction between household responsibilities and labour market accessibility. The results have clear policy implications: efforts to address the GPG could focus on reducing spatial mobility constraints, improving transport infrastructure, expanding flexible work options, and supporting measures that reduce household responsibilities (e.g., childcare policies). For instance, providing better and more reliable public transport connections from residential areas to higher-paid job locations (particularly outside London) could help reduce commuting-related wage disparities. Future research should further examine the relationship between commuting and the GPG while carefully addressing endogeneity, for instance by focusing on individuals who started their current job 2–5 years ago and did not change residence or household situation after accepting the job. This approach could reduce confounding from job moves or household changes and provide stronger causal evidence on how commuting patterns influence the gender pay gap.

Chapter 5

Evaluating the Childcare Offer for Wales on Employment Rates

5.1 Introduction

Evidence indicates that parenthood significantly contributes to gender inequality in the labour market (Bertrand et al., 2010; Kleven et al., 2019; Schober, 2013). For parents, particularly mothers, balancing work and childcare responsibilities presents considerable challenges, with childcare often acting as a significant barrier to employment.[1] Consequently, many OECD countries, including the UK and its nations, have introduced childcare policies aimed at reducing costs, improving accessibility, and increasing parental, especially maternal, employment rates (Costa Dias et al., 2020; Brewer and Crawford, 2010).

Since 1997, the devolution of childcare policy in the UK has resulted in distinct approaches across its nations. In Wales, childcare policy has been underpinned by the Welsh Government's principles of addressing poverty, promoting social inclusion, and investing in children. The Childcare Offer for Wales (the Offer) reflects these principles, providing working parents of three- and four-year olds with 30 free hours of childcare per week for up to 48 weeks a year. This provision is more generous than the equivalent policy in England (pre-April 2024), which covered up to 38 weeks per year, limited to school terms. Aiming to boost parental, particularly maternal, employment (Coates and Prosser, 2017), this chapter evaluates the Offer's impact on employment, seeking to answer:

1. **How does the Childcare Offer for Wales influence parental employment rates?**

[1] The COVID-19 pandemic has exacerbated these challenges, deepening gender inequalities in the labour market (see Rubery and Tavora 2021 for a detailed discussion on the short-term risks and opportunities surrounding the COVID-19 pandemic and gender inequality).

This analysis builds on international research examining the impact of childcare policies on labour market outcomes. While this evidence suggests that well-designed childcare policies and subsidies can substantially enhance labour market outcomes, the specific impact on parental employment remains ambiguous. These effects appear to largely or entirely depend on the childcare entitlement of the youngest child and vary significantly across demographic groups, including gender, family composition and education level (Fitzpatrick, 2010; Berlinski et al., 2011; Havnes and Mogstad, 2011a; Lundin et al., 2008; Bauernschuster and Schlotter, 2015). For instance, recent research from England, which shares similar childcare policy frameworks with Wales, indicates little impact of part-time childcare on the labour supply of either mothers and fathers, but larger, significant impacts of full-time childcare for mothers whose youngest child becomes eligible (Brewer et al., 2022). By providing empirical evidence from Wales, this study extends the existing literature while complementing the Welsh Government's annual qualitative assessments. Despite Wales' distinct governance structures and demographic characteristics, its policy context shares similarities with other UK nations, making these findings relevant beyond Wales. Additionally, Wales' relatively progressive gender equality policies (O'Hagan and Nesom, 2023; Parken and Ashworth, 2019) offer an opportunity to examine the impact of a generous childcare policy in a context that may differ from other places. The analysis also contributes to the study of GPGs (Chapter 3) by examining the impact of dependent children on labour market outcomes.

The analysis is timely in light of recent policy developments. England plans to extend childcare subsidies to provide 30 hours of free childcare for all under-fives from September 2025, aiming to boost parental workforce participation. In contrast, Welsh Government has not announced plans to expand the Offer but may receive an additional £180 million due to the Barnett formula,[2] which may potentially be used for childcare funding. Instead, Welsh Government is expanding the Flying Start scheme to provide all parents of two-year olds with 12.5 hours of childcare per week, despite evidence suggesting that full-time childcare is more effective in boosting parental employment rates (e.g., Brewer et al. 2022). As childcare policy evolves, understanding the role of publicly funded childcare in facilitating parental employment is crucial.

Using secure data from the person and household APS (ONS, 2024a; ONS, 2023a), which easily identifies eligible parents, provides a larger sample than other UK surveys, and includes detailed labour market information, the evaluation exploits two sources of variation to identify the causal impact of the Offer on parental employment. These variations address the main identification challenge of disentangling the impact of eligibility for free childcare from the independent impact of the child's age on parental labour supply, a common issue in the literature (Brewer et al., 2022; Fitzpatrick, 2010; Goux and Maurin, 2010). The first method employed is a sharp Regression Discontinuity Design (RDD) approach, which exploits the Offer's age eligibility criteria. This compares the employment rates of parents whose children are just eligible for the

[2]The Barnett formula is used by the UK Treasury to determine the annual grants for the devolved governments.

Offer at the start of a school term with those whose children narrowly miss the eligibility cutoff, minimising unobserved differences. The second method is a Difference-in-Differences (DiD) approach, which exploits the phased geographical rollout of the Offer across Welsh wards from July 2017 to April 2019 (see Figure 5.1 and Table D.2, Appendix D for the rollout schedule). The phased introduction, designed to facilitate successful delivery while managing capacity constraints, provides a natural comparison group of parents in areas yet to receive the Offer. By comparing trends in parental employment between those residing in wards that received the Offer earlier and those in wards that received it later, the staggered DiD approach controls for common time trends and unobserved factors that may influence employment outcomes.

The findings from both the RDD and DiD approaches suggest that eligibility for 30 hours free childcare under the Offer has had minimal impact on parental employment rates. This is consistent with findings from studies in Norway (Havnes and Mogstad, 2011a), the US (Fitzpatrick, 2010) and England (Brewer et al., 2022), but contrasts with the significant positive impacts observed in Quebec (Baker et al., 2008), Germany (Bauernschuster and Schlotter, 2015), and Argentina (Berlinski and Galiani, 2007). Despite the small sample sizes in both approaches, the consistency of results across the two approaches strengthens the robustness of the findings and provides confidence in their validity. However, as with other childcare policies, increasing parental employment is not the sole aim of the Offer, meaning that a full evaluation of the Offer should consider its broader impact beyond labour market responses.[3,4]

The Chapter is structured as follows: Section 5.2 provides background on childcare policy in Wales and its connection to broader UK policies. Section 5.3 reviews the current evidence on the impact of childcare policies and subsides in international and UK contexts, as well as the common microeconomics methodologies used by the literature and within this research. Section 5.4 describes the data. Section 5.5 and 5.6 present the methods and results of the RDD and DiD approaches, respectively. Section 5.7 discusses the results in relation to the literature and considers several factors that may explain the minimal impact of the Offer on parental employment rates. Section 5.8 concludes.

5.2 Institutional Background

5.2.1 Childcare Policy in the UK

Comparing childcare policies across countries poses challenges due to differences in definitions, metrics and data (Morgan, 2012; Yerkes and Javornik, 2019). A comparative

[3]For instance, alongside boosting parental employment, the Offer aims to promote child development and school readiness (Coates and Prosser, 2017).

[4]Related research explores the impact of childcare policy in Wales on children's test scores at age five for those who received some form of public childcare between the ages of one and four, highlighting the relationship between socioeconomic background and childcare settings (Welsh Government, 2025).

analysis of six countries identifies the UK, alongside Australia and the Netherlands, as having a market-oriented approach to childcare services, in contrast to the publicly funded models in Iceland, Sweden and Slovenia (Yerkes and Javornik, 2019). This market-based system has implications for childcare accessibility, leading to lower enrolment rates and higher affordability constraints compared to other countries. For instance, dual-earner couples in the UK spend approximately one-third of their net family income on childcare expenses, compared to the OECD average of 12.6% (ibid.).

The UK's childcare system operates within a mixed-market economy, incorporating both for-profit and not-for-profit providers, underpinned by a means-tested funding framework that is often complex and costly. Providers set fees to maximise profitability, resulting in a range of options and competitive pricing. However, this market-driven approach does not necessarily ensure a balanced supply-demand equilibrium, leading to persistent gaps in childcare accessibility (Brennan et al., 2012). Consequently, informal childcare – unpaid care typically provided by relatives or friends – is more prevalent in the UK than in other OECD and EU countries (Figure D.1, Appendix D).

In the UK, there are significant differences in labour market outcomes between individuals with and without dependent children, as evidenced by data from the 2021 LFS, APS and Time Use Survey (ONS, 2022b). Both mothers and fathers report higher employment rates than those without dependent children, with 75.6% of mothers and 92.1% of fathers in employment, compared to 69.1% of women and 71.9% of men without dependent children.[5] Fathers consistently have higher employment rates than men without dependent children, while mothers have surpassed both women without children and men without children since 2007 and 2017, respectively. This disparity may result from factors such as higher inactivity rates among childless individuals due to education or health-related constraints. Childcare policies also contribute to these differences, with evidence suggesting that men may be less likely to adjust their work arrangements in response to childcare responsibilities (ibid.).

Employment rates among parents also vary with the age of the youngest dependent child. In the second quarter LFS 2021, 49.0% of mothers with a child under one-year were in full-time employment, although many may have been on maternity leave, as the LFS considers them as 'in employment'. Full-time employment rates among mothers generally increase with the age of the youngest child, rising from 30.8% for those with a one-year old to 49.2% for those whose youngest child is 18 (ONS 2022b, Figure D.2, Appendix D).

[5] Employment rates among women with dependent children vary by age, with younger mothers being the least likely to be employed. Specifically, in 2021, 54.3% of mothers aged 16 to 24 years were in employment, compared to 69.3% of mothers aged 25 to 34 years and 78.7% among those aged 35 to 49 years. This may reflect the increasing feasibility of labour force participation as children enter education. While mothers aged 25 to 49 years are less likely to be employed than women without dependent children, the opposite is true for those aged 50 years and over. In contrast, fathers are more likely to be in employment than men without dependent children across all age groups, though the difference is largest for younger adults. Among fathers aged 16 to 24 years, 86.6% are in employment, compared to 49.4% of men in the same age group without children (ONS, 2022b).

Mothers in the UK experience a wage penalty beyond the GPG, known as the 'motherhood pay gap' (Costa Dias et al., 2020; Davies and Pierre, 2005). This gap represents the difference in pay between mothers and both women without children and fathers, posing challenges in measurement due to conceptual difficulties, data limitations, and biases, including selection bias (Grimshaw and Rubery, 2015). Using harmonised international data from the first six waves of the ECHP, the unadjusted motherhood pay gap is estimated to be 25% for mothers with two children and 28% for those with three of more children in fixed effects models (Davies and Pierre, 2005). Further, mothers with extended employment interruptions in the 1990s had lower returns to human capital than those with shorter breaks, though this difference was not statistically significant (ibid). Longitudinal data from 1991 to 2015 from the BHPS and Understanding Society suggest that motherhood contributes to a gradual widening of the GPG (Costa Dias et al., 2020). By the time a mother's first child is aged 20, women's hourly wages are estimated to be approximately one-third lower than men's, largely due to the accumulated differences in labour market experience (ibid.). Factors driving the motherhood pay gap include the mother's age at the birth of her first child, marital status, household composition, educational level, length of employment break, full time employment status, and workplace characteristics (Grimshaw and Rubery, 2015).

In contrast, evidence suggests that fathers in the UK earn a wage premium compared to their childless counterparts, although the evidence is inconsistent and often lacks statistical significance (Grimshaw and Rubery, 2015; Mari, 2019). This premium is attributed to factors such as increased work effort, specialisation within couples, and potential employer discrimination (Mari, 2019). An analysis of men initially observed without children in 1991-2016 BHPS data estimates that the wage premium for fathers peaked at 3-4% in fixed effects models, though some estimates were not statistically significant (ibid.). This premium appears to have gradually decreased over time, mirroring trends observed in the US (Blackburn and Korenman, 1994). A comparison between the UK and Australia suggests that the higher wage premium for fathers in the UK may be linked to greater wage inequality (Whitehouse, 2002).

Since 1997, the UK government has implemented a series of childcare policies aimed at supporting families and promoting early childhood development (see Table D.1, Appendix D for a summary of key policies). These policies, mostly applying to England only, emphasise early intervention, a cross-sectoral approach, a play-based early years curriculum, and early education and care (Black et al., 2019). However, these policies operate on a 38-week calendar, which may be challenging for working parents in managing childcare costs outside of term time, potentially increasing reliance on informal care arrangements (Statham et al., 2022). While these policies align with principles of early childhood support, concerns persist about the financial sustainability of the childcare sector and the prevalence of low pay, particularly exacerbated by the pandemic (House of Commons, 2016; Early Years Alliance, 2021). In the March 2023 budget, the UK government announced an expansion of funded childcare entitlement, offering up to 15 hours a week for children aged 9 months to 2 years old from September 2024 and increasing to 30 hours from September 2025. Despite these reforms, it is widely accepted that England's childcare policy remains less progressive than those in other parts of Britain (Statham et al., 2022).

Childcare policy is largely devolved to Scotland, Wales, and Northern Ireland, although key determinants of child development, such as welfare, remain reserved powers. In August 2020, Scotland extended free childcare to 1,140 hours per year (30 hours per week for 38 weeks), with more inclusive eligibility criteria than England's requirement for parents to work a minimum of 16 hours per week. In Wales, initiatives like the Flying Start scheme provide part-time early years education to disadvantaged two- and three-year olds, extended since September 2022 to eventually cover all two-year olds (see below for a full discussion). Additionally, the Offer provides 30 hours of free childcare per week for three- and four-year olds, covering up to 48 weeks annually for working parents, discussed further in Section 5.2.2. In contrast, Northern Ireland lacks a comprehensive childcare policy, offering only basic support, such as grants for upfront childcare costs for parents on Universal Credit. The long-term absence of an Executive or Minister delayed the development of a Childcare Strategy, despite a recent childcare policy review (Purdy and McClelland, 2022). These differences in childcare policies across the UK reflect the varying priorities and powers of devolved governments.

Several UK policies intersect with childcare policies, including Universal Credit, which includes a childcare element covering up to 85% of childcare costs for low-income parents.[6,7,8] However, this support often falls short of actual childcare expenses, especially for full-time care, as maximum limits do not align with costs in most local authorities in England (Jarvie et al., 2021). Additionally, parents face barriers such as high upfront costs, incompatible administrative systems, and unpredictability (Statham et al., 2022). Historically, childcare vouchers and tax credits supported childcare costs, but these schemes have been phased out in favour of Universal Credit, raising concerns about childcare affordability and accessibility for many families. Importantly, Universal Credit did not introduce additional childcare subsidies, which potentially limits its impact on employment incentives, although its exposure is more widespread across areas than childcare policy.

[6] The rollout of Universal Credit in Wales began on 7th April 2014, initially limited to new claims from single job seekers without children in Shotton. From July 2014, eligibility expanded to couples without children, and in January 2015, it was further extended to all families in Shotton. Between February 2015 to March 2016, Universal Credit was gradually introduced across the rest of Wales, initially for new claims from single individuals otherwise eligible for Job Seekers Allowance.

[7] Universal Credit was originally intended to be fully implemented across the UK by 2017. However, due to the suspension of the rollout during the COVID-19 pandemic until May 2022, the government plans to complete the rollout by the end of 2025, although the government has repeatedly delayed the completion date of the rollout. Many job seekers had already transitioned to Universal Credit through new claims or changes in personal circumstances triggering natural migration. Nonetheless, thousands of individuals remain on legacy benefits.

[8] It would be pertinent to separately consider the impact of the Offer on low-income parents, but this is prevented by data limitations. Additionally, there are concerns that the Offer's work requirement may exclude many low-income families who would benefit most from subsidised childcare (Joseph Rowntree Foundation, 2020).

5.2.2 Childcare Policy in Wales

Since devolution, childcare policy in Wales has undergone significant transformations, driven by Welsh Labour's objectives to address poverty, promote social inclusion, and invest in children (Ball and Charles, 2006; Bell, 2013). Beginning with the National Childcare Strategy (1998), subsequent policies have aimed to provide accessible, affordable, and high-quality childcare and early education opportunities, supporting children's holistic development and enabling families to balance work and childcare responsibilities. See Table D.1, Appendix D for a summary of key childcare policies in Wales.

The Offer represents Welsh Labour's commitment to providing 30 hours free childcare per week for working parents of three- and four-year olds, up to 48 weeks a year, as outlined in the party's 2016 Welsh Assembly manifesto, released in January 2016 (Welsh Government, 2017). Anticipated since the announcement of similar changes in England in the Spending Review in November 2015, the Offer serves as the most substantial and financially intensive initiative to support working families and encourage parental employment in Wales. It extends the universal entitlement to early education - initially offering a minimum of 10 hours per week of free education - to 30 hours per week, combining early education and childcare during term time and school holidays. Its primary objective is to alleviate the financial burden of childcare costs for families, with Welsh Government positioning it as the most generous offer across the UK (Welsh Government, 2016), although it bears similarities to the childcare policies in both England and Scotland (Langford et al., 2019). The Offer also aims to enable more parents, especially mothers, to return to work, increase the disposable income of those already employed, address poverty among individuals in low-paid jobs, and promote child development and school readiness (Coates and Prosser, 2017).

Eligibility for the Offer requires a parent to live in Wales, have a child aged three or four, and be employed or self-employed, earning at least the equivalent of 16 hours a week at the National Minimum Wage, up to £100,000 gross per year. Since September 2022, eligibility was extended to parents enrolled in publicly funded tertiary education courses lasting at least 10 weeks and to those on long-term sick leave. The Offer accommodates various family structures, defining a parent as any individual with parental responsibility within a household. For single-parent households, the eligibility criteria apply to the parent, while in two-parent households, both parents must meet the eligibility requirements. In cases of equal custody, one parent is designated as the lead applicant.

The Welsh Government initiated a phased rollout of the Offer across selected trial wards in pilot local authorities in July 2017 to ensure successful integration and delivery, and continuous evaluation of its feasibility and effectiveness (refer to Section 2.1 for the geography of wards). Pilot local authorities chose trial wards based on a variety of data indicators, including demographics, population dynamics, economic factors, employment statistics, housing conditions, income and benefits distribution, community safety, and deprivation levels. Additional considerations included the demographic composition of children in each ward, the proportion of in-work families receiving tax credits, and the availability of childcare facilities. However, these considerations varied among pilot local authorities, and no explicit rationale is given to the selection of pilot local authorities. Section 5.6 considers the challenges with evaluating the Offer given this potential endogenous selection of trial wards and pilot local authorities. Apart from the rollout of Universal Credit (discussed above), there were no other national policy changes during this time.

Full implementation of the Offer across all Welsh wards occurred in April 2019, enabling all eligible parents to access it regardless of their ward of residence.[9] This was facilitated by a controlled expansion of infrastructure, support mechanisms and a comprehensive communication and awareness campaign to inform parents and caregivers about the Offer's availability and benefits. Figure 5.1 depicts the timing of the Offer's phased rollout across Welsh wards by term from July 2017 to April 2019, with detailed ward-level information provided in Table D.2, Appendix D. In most local authorities, the Offer was uniformly introduced across all wards either due to the local authority's size or as part of the initial rollout strategy. In eight local authorities - Cardiff, Conwy, Neath Port Talbot, Newport, Rhondda Cynon Taf, Swansea and Wrexham - a staggered rollout across wards was adopted.

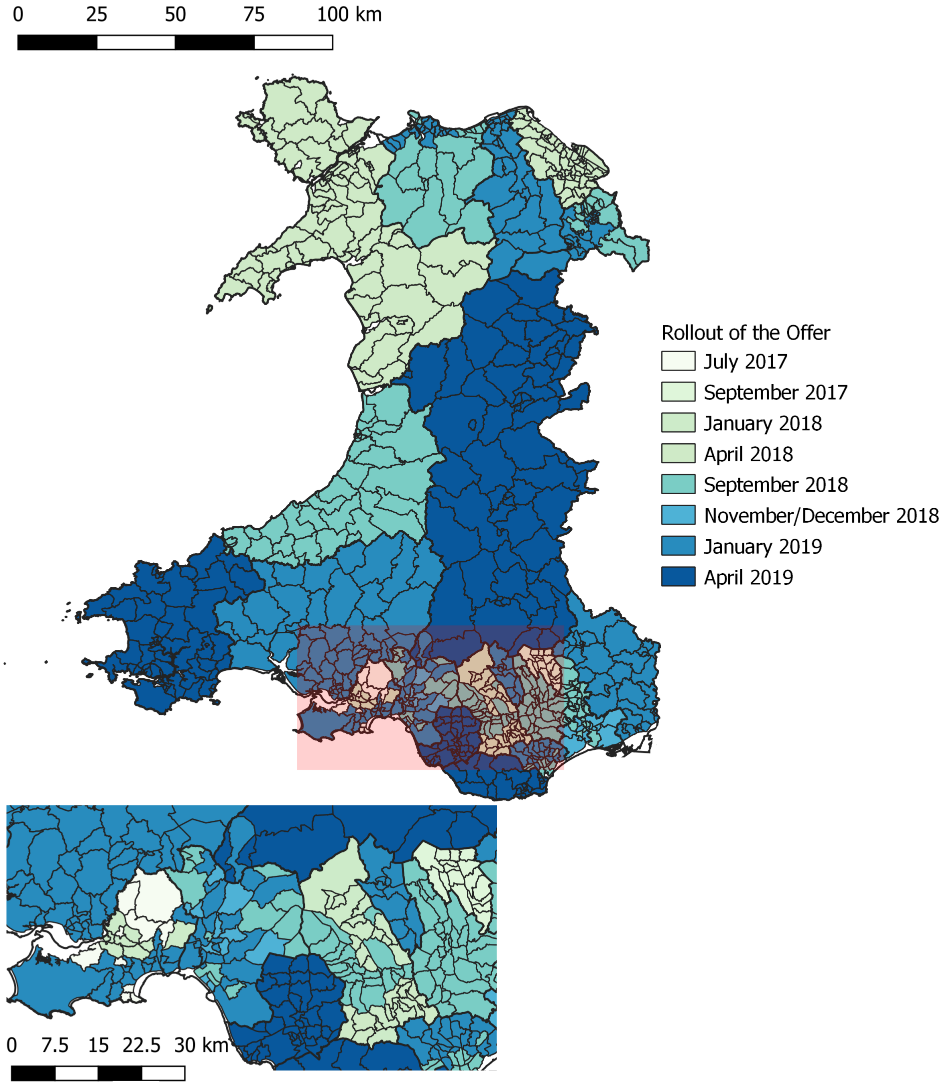
The Offer operates alongside the Flying Start scheme, which aims to formalise the connection between childcare, social class and material disadvantage in Wales. During the Offer's rollout, Flying Start allocated funding to children from birth to three-years in disadvantaged areas, determined by postcodes.[10] Flying Start emphasises early intervention to improve child development outcomes and complements the Offer by encouraging parents to access employment or training opportunities, thereby mitigating the impact of poverty on educational attainment. In addition to childcare support, Flying Start provides a range of additional services for children and families, including intensive health visiting service, parenting support, and assistance for speech, language, and communication development. It also provides parents with 12.5 hours of free childcare per week, distributed as 2.5 hours per day over five days a week for 39 weeks a year. Evidence from parents indicates that while shorter childcare blocks were valuable, they were insufficient for supporting entry into the labour market (Coates and Prosser, 2017).

An Equality Impact Assessment and an Integrated Impact Assessment (Welsh Government, 2018; Welsh Government, 2020) were conducted to ensure the Offer aligned to the Well-being of Future Generations Act and to identify potential

[9] Full implementation of the Offer was initially planned for September 2020.

[10] A list of the 12,554 Flying Start postcodes from 31st March 2016 - September 2022 was provided by Welsh Government's Knowledge and Analytical Services. Since September 2022, Flying Start has been expanding to encompass all families in Wales with children aged two to three, reaching an additional 2,500 children under four (Welsh Government, 2024b).

Figure 5.1: The Phased Rollout of the Childcare Offer for Wales across Wards, July 2017 - April 2019



Source: Data obtained from Freedom of Information requests to Welsh Government and individual Local Authorities

unintended consequences (O'Hagan et al., 2019). These assessments highlighted positive outcomes for children and working parents, as it provided a mechanism to balance career aspirations with childcare responsibilities. However, they also indicated a negative or negligible impact for those ineligible for the Offer. Qualitative research conducted prior to the rollout, with predominantly female parents of one- to five-years in six childcare settings across Wales, found that childcare choices were influenced by family circumstances, work commitments, and geographic accessibility (Coates and Prosser, 2017). Many mothers returning to work reported difficulties balancing career and childcare responsibilities, suggesting the additional hours provided by the Offer could facilitate increased use of formal childcare, enabling job searches or increased work hours without necessitating alternative childcare arrangements (ibid.). Recommendations included designing the Offer for flexible use to accommodate varied work and training schedules and reflect family diversity - considerations that were ultimately incorporated into the policy.

External research explored options for extending childcare support in Wales, evaluating the potential impact of extending the existing 10 free hours of Early Years Education to an additional 20 hours of free childcare, with or without a work requirement (Paull and Xu, 2015).[11] Using the Family Resources Survey (2005-06 to 2013-14) and assuming full uptake, the analysis structurally modelled maternal labour market outcomes. Findings indicated that the additional 20 hours of free childcare, with or without a work requirement, would not substantially impact net income, poverty rates, or work behaviour, given the relatively low proportion of families in the target cohort utilising formal paid childcare. Further, any savings in childcare spending for working parents would be partially offset by reductions in reimbursements under Universal Credit and the Tax Free Childcare scheme. Without a work requirement, the estimated work response to Offer eligibility suggested a marginal decrease in maternal employment rates due to the effect on out-of-work income; with a work requirement, a small positive impact was estimated. The research concluded that the Offer with a work requirement provided better value for promoting parental employment, although both options offered comparable potential for poverty reduction, informing the design and implementation of the Offer (Paull and Xu, 2015).

Since its initial pilot phase, the Offer has been annually evaluated to monitor its progress and assess its impact on eligible families using a mixed methods approach (Welsh Government, 2020; Glover et al., 2018; Glyn et al., 2019; Glyn et al., 2021; Glyn et al., 2022; Harries et al., 2023). Termly monitoring data indicate that the median annual gross salary of individuals accessing the Offer ranges between £20,800 and £25,999, below the Welsh average full-time salary in the ASHE. As a result, the Offer has predominantly benefited lower- to middle-income households (Glyn et al., 2019; Glyn et al., 2022; Harries et al., 2023). However, the Offer's impact on disposable income appears to be modest, with less than a quarter of respondents reporting a substantial increase. A significant proportion noted no significant change in disposable income (Glyn et al., 2019), although later evaluations suggest that the Offer increased earnings of those in lower income brackets (Glyn et al., 2022).

As part of the annual qualitative evaluations, online surveys assess parents' working hours relative to those prior to accessing the Offer. Parents reported limited changes in their working hours, with the majority reporting that they work the same number of hours compared to before accessing the Offer. However, these evaluations also indicate that, without the Offer, lower income parents would be working fewer hours due to unsustainable childcare costs (Glyn et al., 2019; Glyn et al., 2022). Furthermore, women

[11] The work requirement was defined to align with the proposed extension for the Free Early Education Entitlement from 15 to 30 hours in England and for eligibility under the UK Tax Free Childcare scheme, as announced in the Spending Review in November 2015. This work requirement was ultimately adopted to define eligibility for the Offer.

were more likely than men to report increased work hours after accessing the Offer (Glyn et al., 2019). Additionally, over half of the respondents reported greater flexibility in their work arrangements, which facilitated transitions to full-time work or additional hours when needed. For lower-income families, the Offer also provided increased opportunities for in-work training and development (Glyn et al., 2019; Glyn et al., 2021).

The evaluations also assess the financial sustainability and commercial viability of the Offer for childcare providers. In the second year, nearly 80% of providers found the £4.50 per hour rate viable, with a majority reporting a positive impact on profitability and setting sustainability (Glyn et al., 2019). However, concerns emerged about the long-term sustainability of providers, exacerbated by the uneven impact of the pandemic and rising operational costs.[12] Staffing difficulties, further intensified by the pandemic, have persisted, leading some providers to prioritise Offer-funded children due to guaranteed funding and favourable staffing ratios (Glyn et al., 2022; Harries et al., 2023). These factors have raised concerns regarding the expansion of childcare support under Flying Start in Wales.

5.3 Literature Review of Childcare Policies

5.3.1 Microeconomic Approaches to Evaluating Childcare Policies

Various methodological approaches have been employed to evaluate the impact of childcare policies. Macroeconomic approaches typically use reduced-form and structural models to estimate the elasticity of maternal employment relative to the cost of childcare, a key parameter for policy analysis (Brewer and Paull, 2004). For example, a structural first-order Markov model simulating women's life-cycle decisions evaluated the 2013 expansion of subsidised childcare to all working women in Germany, identifying a 1.6% increase in female labour force participation and a 2.4% rise in working hours (Haan and Wrohlich, 2011). Similarly, another structural model focusing on the constrained labour supply of low-educated mothers corroborated these findings (Müller et al., 2019).

Despite their utility, such models often neglect the supply side of the childcare market, ignoring provider responses to demand changes (Brewer and Paull, 2004). A major challenge is disentangling the relationship between childcare price and quality,

[12]The COVID-19 pandemic necessitated adjustments to the delivery of the Offer. In March 2020, Welsh Government imposed restrictions on childcare and education settings, limiting attendance to children of critical workers. During this period, Welsh Government ensured continued payments to providers under the Offer for three months, even during closures or when children couldn't attend. In April 2020, the Offer was temporarily suspended for new entrants, with its budget redirected to support the Coronavirus Childcare Assistance Scheme, which covered the costs for preschool-age children of critical workers and vulnerable children. By June 2020, childcare services were expanded to include children who had accessed the Offer before March 2020, with the Offer reopening to new entrants from 1st September (Glyn et al., 2022). Although a formal evaluation of the impact of these modifications is yet to be conducted, Welsh Government could draw valuable insights from the pandemic experience to address shortcomings in the Offer's delivery and adapt it to evolving family needs and childcare sector dynamics.

particularly when quality-constant prices vary geographically. An ideal structural model would simultaneously estimate a labour supply function, demand for various types of childcare, maternal wages, quality-adjusted childcare prices, the relationship between weekly childcare hours and costs, and the implicit quality and price of informal care (ibid.). However, no study to date has accomplished this due to data and estimation demands. The closest approach combined parent and childcare provider survey data to model demand for quality-related childcare attributes, finding that lower childcare costs led to a shift towards paid care, an increase in paid childcare use, and a decrease demand for quality-related attributes (Blau and Hagy, 1998). While such data are not available in the UK, a simplified structural model of childcare demand and labour supply may be feasible, contingent upon plausible exclusion restrictions. The longitudinal nature of the Families and Children Survey and Understanding Society could account for some unobservable heterogeneity (Brewer and Paull, 2004).

In contrast, microeconomic approaches enable the assessment of causal policy impacts without requiring full structural parameter identification (Spiess and Wrohlich, 2008; Heckman, 2001). They focus on estimating problem-specific parameters associated with the childcare policy ('treatment') and typically employ quasi-experimental econometric techniques to address selection bias, endogeneity in labour supply and childcare decisions, and the challenges of imputing informal childcare costs (Brewer and Paull, 2004). The two main microeconomic approaches commonly used in childcare policy evaluation are variants of the RDD and DiD methodologies. These approaches impose fewer restrictions and assumptions than macroeconomic approaches and aim to establish counterfactuals for estimating policy effects. While a clear distinction between them can be challenging, actual applications often combine these methodologies, collectively contributing to a robust body of evidence.

RDDs evaluate the impact of childcare policies by comparing outcomes for individuals on either side of an 'arbitrary' rule, determined by a continuous variable, such as income or age, used to establish eligibility (Paull et al., 2016). This approach, akin to randomised control trials, identifies a policy's impact at the cutoff point, where discontinuities in outcomes can be attributed to the policy. However, RDDs are limited to estimating local treatment effects for individuals near the threshold and require strict data requirements, as well as the absence of factors influencing outcomes at the cutoff (Hahn et al., 2001; Lee and Lemieux, 2010). Further, RDDs assume no manipulation of eligibility criteria or selective participation (a 'fuzzy' RDD design can partially address such concerns) and rely on the absence of anticipatory behaviour or significant response delays. In the UK, RDDs have assessed the impact of free childcare for three- and four-year olds and disadvantaged two-year olds in England (Brewer et al., 2022), as well as compulsory school entry's effect on lone parent employment and welfare receipts (Brewer and Crawford, 2010). Internationally, RDDs have been used to assess publicly funded universal childcare in Argentina (Berlinski et al., 2011), France (Goux and Maurin, 2010), Germany (Bauernschuster and Schlotter, 2015), and the US (Fitzpatrick, 2010; Fitzpatrick, 2012; Gelbach, 2002), including evaluations of publicly funded universal pre-school on children's educational outcomes (Blanden et al., 2022).

DiDs compare changes in labour market outcomes between eligible and non-eligible parents before and after policy implementation (see Section 2.5.3). This approach can involve matching parents between treatment and control groups or controlling for variables influencing outcome changes, and is applicable to both panel and repeated cross-sectional data. A key strength of DiD is its ability to control for both observed and unobserved time-invariant differences between groups by differencing out fixed characteristics. However, it relies on the assumption of common trends in outcomes in the absence of the policy and the absence of policy-related transitory shocks. With cross-sectional data, it is crucial to ensure no compositional changes in the treatment or control group pre- and post-policy. In the UK, DiDs have been used to evaluate the labour market impact of childcare policy, leveraging variations in policy implementation timing across regions (Blanden et al., 2014; Brewer et al., 2022). International applications include studies from Argentina (Berlinski and Galiani, 2007), Canada (Baker et al., 2008; Lefebvre and Merrigan, 2008), Germany (Bauernschuster and Schlotter, 2015), Israel (Schlosser, 2011), the Netherlands (Bettendorf et al., 2015), Sweden (Lundin et al., 2008), Norway (Havnes and Mogstad, 2011a), Spain (Nollenberger and Rodriguez-Planas, 2015), and the US (Cascio, 2009).

Other microeconomic approaches to evaluating childcare policy include randomised control trials, non-randomised policy evaluations, and statistical matching/regression analysis. These are rarely used due to practical constraints such as high costs, small sample sizes, and the need for detailed data to address confounding variables (Paull et al., 2016; Brewer and Paull, 2004). As a result, their application in UK childcare policy is limited. An example includes a randomised control trial evaluating the Employment, Retention and Advancement demonstration project, though it did not though it did not isolate the impact of the childcare component (Sianesi, 2011).[13] Similarly, the Neighbourhood Nurseries Initiative's evaluation used a non-randomised approach but was limited by small sample sizes in pilot areas, complicating the identification of quantitative impacts (NNI Research Team, 2007).

5.3.2 Evidence of the Impact of Childcare Policies

The extensive and diverse literature on childcare policies and their impact on parental labour market outcomes predominantly explores the effects of increased childcare subsidies and/or universal childcare implementation. The findings, however, are nuanced and contingent on contextual factors and specific policy structures. Economic theory suggests that the labour supply response to such policies is influenced by the interplay between the substitution and income effects (Mincer, 1962). For some, childcare policies

[13]This policy tested a combination of services to support both unemployed individuals entering work and low-paid workers aiming to retain and progress in employment.

act as subsidies that reduce childcare costs, potentially leading to reduced working hours (income effect). For others, these policies may incentivise increased labour supply by raising the returns of additional work hours, thereby increasing the opportunity cost of working fewer hours (substitution effect). Despite the variability in the evidence, both international and UK research consistently indicate that well-designed childcare policies can increase parental labour market participation, hours, and wages. In particular, the evidence points to the heterogeneous impact of these policies based on gender, family structure, maternal education levels, and the eligibility of the youngest child.

International Evidence

International research provides diverse estimates of the impact of childcare subsidies and policies on labour supply, particularly for mothers. This body of work extends the return-to-work post-childbirth literature, suggesting that access to affordable childcare enables mothers to re-enter the workforce, often initially opting for part-time work arrangements (Boeckmann et al., 2015; Datta Gupta et al., 2006a). Childcare policies can ease the transition back to employment by reducing the financial burden of childcare and offering flexibility in working hours, which can shape long-term labour market outcomes for mothers (Brewster and Rindfuss, 2000; Harkness and Waldfogel, 2003). However, most studies focus exclusively on either subsidised part-time or full-time childcare, making it challenging to generalise their findings, as the impact of childcare policies can vary depending on the number of hours children spend in care. In addition, contextual differences between countries further complicate cross-country comparisons, creating ambiguity in understanding the impact of childcare subsidies on labour supply. Nonetheless, the international literature provides valuable insights and considerations.

Given the challenges in generalising findings across diverse contexts and childcare arrangements, recent research increasingly employs causal inference methods to better estimate the effects of childcare policies on labour supply. To address potential bias in OLS regressions (Section 5.3), studies have increasingly used RDDs, which exploit eligibility discontinuities based on children's date of birth. For example, using quarter of birth as an instrument in US Census data from 1980, Gelbach (2002) evaluates the impact of public school enrolment in kindergarten on maternal labour supply. The findings suggest that labour supply increased by 6-24% for married and lone mothers whose youngest child was five. However, these estimates may be biased as they assume that children born in the same quarter are of the same age at the time of observation. If maternal labour supply is influenced by a child's exact age - independent of public school enrolment - then quarter of birth becomes an invalid instrument. Subsequent analyses using more precise birth dates from 2010 revealed varying effects, highlighting the sensitivity of results to methodological choices (Fitzpatrick, 2012).

The RDD approach has also been applied to assess the impact of universal pre-kindergarten availability for four-year olds on maternal labour supply in Georgia and Oklahoma with Census data (Fitzpatrick, 2010). No significant impact on maternal labour supply was found when comparing children born just before and after the eligibility cutoff, except for minor changes in rural areas. These null effects are attributed to the possibility of a lower elasticity of female labour supply in recent years (ibid.). In France, an RDD approach is used to estimate the impact of pre-elementary school eligibility on maternal labour supply by exploiting a strict cutoff based on children's exact dates of birth, using data from the 1999 French Population Census (Goux and Maurin, 2010). No significant impact on labour market participation is identified for dual parent families, but significant discontinuities are estimated among single mothers, particularly for those with lower education. However, the use of Census data, which captures labour supply at specific points, limits the comprehensiveness of these findings (Brewer and Crawford, 2010).

Date-of-birth eligibility cutoffs are also leveraged in other contexts using household survey data. In Argentina, pooled data from the Encuesta Permanent de Hogares (1995-2001) are used to administrative cutoffs in preschool eligibility to estimate the impact of preschool attendance on maternal labour supply (Berlinski et al., 2011). The findings estimate that, on average, 13 mothers start work for every 100 youngest children that start preschool, although this estimate is not consistently statistically significant. Moreover, mothers were 19.1 percentage points more likely to work for more than 20 hours a week, with an average increase of 7.8 hours per week due to pre-school attendance of the youngest child (ibid.). Similar positive effects of childcare policies are also identified in research that employs an RDD approach to exploit date-of-birth cutoffs from a German public childcare reform introduced in 1996, using data from the German Socio-Economic Panel (Bauernschuster and Schlotter, 2015). The estimates suggest that eligibility for public childcare increased maternal labour supply by 6 percentage points and by 35 percentage points if the youngest child attended public childcare as a result of the cutoff. However, the relevance of the cutoff diminished over time and was negligible in East Germany, where public childcare capacity was not constrained. The positive effects were more pronounced among more educated mothers, those with older children, and those with a greater age gap between their children (ibid.).

International evidence employing a DiD approach to evaluate the impact of childcare policies on labour supply also yield varied results. While some studies report minimal effects on parental labour supply, especially for mothers (Lundin et al., 2008; Havnes and Mogstad, 2011a), others identify significant impacts (Bettendorf et al., 2015; Schlosser, 2011; Lefebvre and Merrigan, 2008; Baker et al., 2008; Berlinski and Galiani, 2007). These discrepancies are largely attributed to variations in policies and pre-policy childcare usage and maternal employment.

In Sweden, the introduction of maximum childcare prices, analysed through a DiD approach with 2001 and 2003 survey data from Statistics Sweden, estimated negligible effects on maternal labour supply (Lundin et al., 2008). Similarly, a large-scale expansion of subsidised childcare in Norway in 1975, using administrative data covering the entire resident population, was estimated to have had minimal impact on the employment rate of married mothers (Havnes and Mogstad, 2011a). This might be a result of the high pre-policy maternal employment rate in these contexts, resulting in subsidised childcare primarily crowding out informal care rather than significantly increasing maternal employment (Bettendorf et al., 2015).

Conversely, in contexts with lower pre-policy maternal employment, DiD approaches often report positive effects on maternal labour supply. In Quebec, using data from the National Longitudinal Survey of Children and Youth, the introduction of highly subsidised childcare is estimated to have led to a 14 percentage point increase in childcare usage (approximately one-third above the baseline) and a 7.7 percentage point increase in employment for married women (14.5 percent above the baseline) (Baker et al., 2008). These large positive impacts are also replicated in another DiD study in Quebec, using better measures of labour supply from the Survey of Labour and Income Dynamics (Lefebvre and Merrigan, 2008). However, critiques of these studies emphasise concurrent changes in family and child benefits in Quebec and Canada around the time of the childcare reform, raising concerns about the attribution of these effects solely to childcare reforms (Havnes and Mogstad, 2011a; Bettendorf et al., 2015).

Similarly, a policy leading to a substantial increase in public schooling in the US from the mid-1960s to the mid-1970s is estimated to have had large positive impacts on maternal labour force participation, with four mothers estimated to enter the workforce for every ten children enrolled in public school (Cascio, 2009). However, caution is needed in interpreting these treatment effects as causal, given potential issues with state-time variation, likely unobserved compositional changes over a 40-year period, and the lack of controls for important characteristics, including parental education. The estimates may also provide an upper bound estimate on the likely employment responses to recent expansions of public schooling in the US.

More recent studies reveal smaller yet significant impacts of childcare policies on parental labour market outcomes. A Dutch study, employing a DiD approach and using LFS data from 1995-2009, compares labour market outcomes for parents aged 20-50 whose youngest child is under 12 with those whose youngest child is aged 12-17 (Bettendorf et al., 2015). The study suggests that a childcare subsidy reform increased women's labour force participation and average weekly hours worked, though the effects were smaller than American and Canadian studies, due to the higher pre-reform participation rates among Dutch mothers. However, the impacts are larger than those in Sweden and Norway, as only working single parents and two-earner couples are eligible for childcare subsidies in the Netherlands (ibid.). Similarly, studies in Germany and Spain indicate modest yet notable impacts. In Germany, using Micro Census data, a 10 percentage point increase in public childcare coverage for three- and four-year olds is estimated to have increased maternal employment by 3.4 percentage points - reassuringly similar to their RDD estimates of 6 percentage points (discussed above)

(Bauernschuster and Schlotter, 2015). In Spain, using LFS data from 1987-1997, publicly subsidised childcare for three-year olds is estimated to have substantially and persistently increased maternal employment and hours worked whose youngest child is affected by the reform (Nollenberger and Rodriguez-Planas, 2015).

These studies emphasise that the impact of childcare policies vary across parental sub-group, with larger and more persistent effects estimated for mothers with higher education levels. An analysis of the introduction of free public preschool for children aged three- and four-years in Israel using LFS data from 1998-2003 estimates that labour force participation increased by seven percentage points among educated women, but was negligible for less educated mothers (Schlosser, 2011). In Spain, the benefits of publicly subsidised childcare for three-year olds were sustained for mothers with at least a high school diploma, while the impact diminished for those without (Nollenberger and Rodriguez-Planas, 2015). This pattern suggests that more educated mothers, who are better positioned to capitalise on childcare policies due to their prior investment in human capital and existing labour market attachment, experience more significant benefits. Conversely, college-educated mothers in Spain showed no substantial increase in labour participation, likely due to their pre-existing strong attachment to the labour market and ability to afford childcare independently (ibid.).

Evidence from the UK

Despite substantial investment in childcare policies in the UK and their explicit objectives (see Section 5.2.2 for the aims of the Offer), empirical evaluations remain limited. Existing studies predominantly employ RDD and DiD approaches to form plausible counterfactual groups and address potential unobserved differences between working and non-working parents. The findings underscore the importance of timing and the extent of childcare entitlements, particularly for mothers. They also emphasise the need for ongoing evaluation mechanisms to comprehensively capture the dynamic impacts of these policies.

Two prominent UK studies employ an RDD approach to evaluate the impact of childcare policies, exploiting strict age eligibility criteria for part-time childcare and full-time education in England (Brewer and Crawford, 2010; Brewer et al., 2022). Brewer and Crawford (2010) use data from the Work and Pensions Longitudinal Study to estimate the causal impact of a three-year-old age eligibility criterion on lone parent's benefits and employment outcomes, recognising that childcare is a significant barrier to work for this group. By comparing the labour market outcomes of two similar groups of lone parents, one with children eligible for nursery or school and the other without, the research estimates that eligibility for full-time primary education increased the proportion of lone parents leaving welfare and entering work by approximately two percentage points, with the impact peaking around eight to nine months after eligibility. However, the impact of part-time nursery education on lone parent's labour supply was less pronounced. Despite the precision in estimating the timing of impact (as the data capture exact date-of-births), the study only estimates the intention to treat effect of living in an area in which the Local Authority allows children to start part-time or full-time education, as direct enrolment data is not observed (ibid.).

Brewer et al. (2022) build on this by evaluating the impact of offering free, half-day childcare to pre-school children and its extension to the whole school day upon formal schooling in England. Utilising an RDD approach and 2011 UK Census data, the study estimates a small, statistically insignificant, positive effect of free part-time childcare for the youngest child on maternal labour force participation. In contrast, eligibility for free full-time childcare results in a significant increase of approximately 3.5 percentage points in maternal labour force participation and 1.5 percentage points in maternal employment, observed seven months after entitlement. The study is only able to estimate the impact of free part-time childcare by duration of exposure, due to children becoming entitled to free part-time childcare each term, rather than every year, despite evidence from Brewer and Crawford (2010) finding that this matters for our understanding of the impact of childcare policies. Consistent with international findings, the policy's impact on paternal labour market outcomes is negligible. While these results are robust to a number of sensitivity analyses, including the choice of bandwidth and the way children's age is controlled for, they are specific to parents of children born at particular times of the year and for outcomes observed at one point in time (e.g. the Census date in 2011) (Brewer et al., 2022).

Their RDD approach is supplemented with a panel data approach, resembling a fixed effect DiD model where the child's month of birth serves as the group dimension and age as the time dimension (Brewer et al., 2022). This method mitigates limitations of RDD approaches by addressing differences in observed and unobserved factors, such as family background or preferences regarding family and work (Clarke et al., 2019). Using LFS data to leverage repeat observations, Brewer et al. (2022) introduce parent-level fixed effects to the DiD specification to assess the impact of entitlement to free full-time and part-time childcare by duration of exposure and across all birth months. The findings indicate nuanced effects on maternal labour force participation. Entitlement to free part-time childcare for the youngest child is associated with a modest increase in labour force participation by 2.1 percentage points for eligible mothers in the third term of part-time entitlement, with similar effects estimated in the fourth and fifth terms (ibid.). Similar results are reflected in another DiD study examining the impact of free part-time pre-school education by exploiting the geographical availability of free places (Blanden et al., 2014). Using 2002-2007 LFS data and focusing on mothers with three-year old children, a 10 percentage point increase in coverage is estimated to have had insignificant effects on all measures of maternal labour market behaviour (ibid.).

In contrast, significant effects are observed for mothers whose youngest child become entitled to free full-time care. Labour force participation is estimated to increase by 5.1 percentage points in the first term of entitlement, rising to 7.8 percentage points by the third term (Brewer et al., 2022). Consistent with the international literature, no effects are estimated for fathers concerning the youngest child's eligibility for part-time or full-time childcare on labour market participation or employment. Full-time childcare is found to increase the probability of mothers being in the labour force by 3.1 percentage points, with a third of these mothers finding work. Additionally, full-time childcare is estimated to increase the hours of work for mothers already in the labour market. Heterogeneity analysis indicates smaller effects for less educated mothers and the labour market participation effects are lower (but employment effects are higher) for mothers with partners, although these differences are not statistically significant. Further, offering free full-time childcare is estimated to have had a significantly greater impact on maternal labour supply in areas with lower unemployment rates (ibid.).

5.3.3 Potential Impacts of the Offer on Parental Employment Rates

The literature indicates that the demand for childcare is influenced by a range of economic and non-economics factors, including wages, work preferences and the characteristics of childcare options such as price, quality, and convenience. Childcare policies can impact parental demand, specifically by reducing the price of formal childcare, which may influence both childcare choices and labour supply decisions (see Blau and Hagy 1998 and Mumford et al. 2020 for theoretical discussions of models jointly estimating labour supply and childcare decisions in response to different childcare subsidies).

Under the Offer, the price of formal childcare for 30 hours a week is effectively zero from the start of the school term after a child turns three until they start full-time schooling, normally the September after their fourth birthday, provided the parent works at least 16 hours a week (see Section 5.2.2). To put this in context, the average hourly rate charged for formal childcare for three- and four-year olds in Wales in 2023 was £7.60 (Oxtoby, 2023).[14] This equates to an implicit subsidy of approximately £228 per week, compared to the median weekly earnings for full-time adults in Wales of £598.10, based on ASHE 2022 data (Welsh Government, 2022). This aligns with findings from England indicating that the Offer can influence parental labour supply decisions at the margin but is unlikely to affect broader factors such as fertility or partnership status, despite surpassing estimated costs in England from 2019 (Brewer et al., 2022).

An important consideration is the potential for the Offer to act as a substitute for informal childcare arrangements rather than inducing additional labour supply. Data from the 2015-2016 Family Resources Survey suggests that a high proportion of families in Wales rely on informal childcare to balance work and caregiving responsibilities (Crocker et al., 2018). By fully subsidising formal childcare for eligible families, the Offer may lead to a reallocation of childcare arrangements rather than a meaningful

[14] Oxtoby (2023) indicates a £2.60 per hour shortfall in funding for the Offer, raising concerns regarding its long-term financial sustainability.

increase in parental labour supply or working hours. For example, evidence from Norway indicates that the introduction of subsidised childcare primarily crowded out informal care arrangements rather than increasing maternal employment (Havnes and Mogstad, 2011a). If a similar dynamic applies in Wales, the principal benefit of the Offer may lie in reducing childcare costs for parents who are already employed, rather than significantly altering labour supply behaviour.

Parental responses to the Offer can be categorised into three groups (Brewer et al., 2022). First, parents not currently using childcare may be incentivised to start, potentially increasing labour force participation. Second, parents already paying for part-time childcare may experience conflicting income and substitution effects, leading to ambiguous labour supply outcomes. Third, parents who were already paying for 30 or more hours of childcare per week may experience a predominant income effect, likely reducing their labour supply (ibid.). However, these predictions rely on static assumptions and may not fully capture anticipatory decision-making. Given the long-standing nature of childcare policies, forward-looking parents may factor childcare entitlements into their decisions from birth. Conversely, short-sighted or constrained parents may respond more significantly upon eligibility or gradually over time. While this analysis acknowledges such heterogeneity in responses, it follows the standard assumption in econometric studies exploiting birthday-based eligibility thresholds that parents do not fully anticipate future entitlements (Berlinski et al., 2011; Fitzpatrick, 2010; Goux and Maurin, 2010).

5.4 Data

5.4.1 Annual Population Survey

The evaluation of the Offer is based on secure data from the person and household APS, a comprehensive and nationally representative household survey in the UK (ONS, 2024a; ONS, 2023a).[15] Both the secure versions of the household and person APS are used to identify eligible and not yet eligible children and their parents based on full dates of birth and wards of residence, crucial variables not available in End User Licence APS data. The household and person APS differ only in their handling of non-respondents; the household APS retains them to establish relationships between household members and derive relevant variables. Proxy responses, where one household member responds on behalf of an absent respondent (usually a partner or parent), are included to reduce non-response bias. Although proxy responses may introduce accuracy concerns, especially for variables like pay, these concerns are minimal for the key

[15] As the data for this project are confidential and potentially disclosive, the APS is accessed through the SDS for projects where the researchers are accredited and where there is clear public benefit. This project was approved for the use of these data and all outputs have been subject to disclosure control. Full details are available via the SDS, which collates data for individuals in Britain. APS data for Northern Ireland is collected by the Northern Ireland Statistics and Research Agency.

outcome variable, employment status. Therefore, proxy responses are included to increase the sample size for both the RDD and DiD approaches.[16,17]

The APS offers several advantages for evaluating the Offer, primarily due to its larger sample size compared to other UK surveys. This is achieved by combining individuals from waves 1 and 5 across four consecutive quarters of the main LFS with individuals in waves 1 to 4 of the Enhanced sample of the English, Welsh, and Scottish Local Labour Force Survey (Section 2.2.4). Table 5.1 details this construction process for the pooled April 2019 to March 2020 APS, which corresponds to the Offer's first full year of implementation and the period analysed in the RDD approach (Section 5.5). Since each quarterly LFS sample comprises five waves (Section 4.4), constructing the APS by selecting waves 1 and 5 from four successive quarters guarantees that each household appears only once in annual data (Section 4.4; as demonstrated by the orange cells in Table 5.1). By preventing duplication while maintaining a sufficiently large sample size to generate reliable data at smaller geographical levels. Despite declining response rates in the post-pandemic period (Section 2.2.4), the APS maintains a sample size of approximately 320,000 respondents and 120,000 households. This large sample size help mitigate sampling errors, which is particularly important given that both estimation approaches focus on a narrowly defined population subgroup. However, even within the APS, the subgroup of interest remains relatively small (see Tables 5.2, 5.6 and 5.7).

Table 5.1: Structure of pooled April 2019 to March 2020 APS data

		Q2 2019	**Q3 2019**	**Q4 2019**	**Q1 2020**
LFS	Cohort 1 (First sampled Q2 2018)	Wave 5			
	Cohort 2 (First sampled Q3 2018)	Wave 4	Wave 5		
	Cohort 3 (First sampled Q4 2018)	Wave 3	Wave 4	Wave 5	
	Cohort 4 (First sampled Q1 2019)	Wave 2	Wave 3	Wave 4	Wave 5
	Cohort 5 (First sampled Q2 2019)	Wave 1	Wave 2	Wave 3	Wave 4
	Cohort 6 (First sampled Q3 2019)		Wave 1	Wave 2	Wave 3
	Cohort 7 (First sampled Q4 2019)			Wave 1	Wave 2
	Cohort 8 (First sampled Q1 2020)				Wave 1
Local Sample Boosts	Cohort 1 (First Sampled Apr 2016 - Mar 2017)	Wave 4			
	Cohort 2 (First Sampled Apr 2017 - Mar 2018)	Wave 3			
	Cohort 3 (First Sampled Apr 2018 - Mar 2019)	Wave 2			
	Cohort 4 (First Sampled Apr 2019 - Mar 2020)	Wave 1			

Source: Adapted from ONS (2012).

Beyond its sample size, the APS is a suitable choice for the evaluation of the Offer as it is the recommended source for local employment-related statistics in the UK, including parental employment rates. Alongside ward of residence and detailed information on children, the APS collects a comprehensive range of socio-economic characteristics, including education level and partnership status, which are known to influence employment dynamics (e.g., Brewer et al. 2022; see discussion in Section 5.3). These variables are crucial for both the RDD and DiD approaches, as they help mitigate concerns related to the relatively small sample sizes by ensuring that key identifying

[16] The household APS uniformly weights individuals within the same household to ensure consistency in weighted estimates. For further details on the household and person APS differences and weighting procedures, refer to the Labour Force Survey User Guide Volume 6 (ONS, 2022f).

[17] In the RDD sample, 75 parents (35.71%) are proxy responses, while in the staggered DiD sample, 192 parents (33.10%) are proxy responses. Sensitivity analyses examine the effect of including proxy responses (see Sections 5.5 for the RDD approach and 5.6 for the DiD approach.

assumptions, such as the similarity of parents across the eligibility cutoff in the RDD approach and the common trends assumption in the DiD approach, hold (see Section 5.5 and 5.6, respectively). Furthermore, the APS captures local labour market conditions across small geographical areas, enhancing its suitability for evaluating the Offer during its phased geographical rollout across Welsh wards.

The APS' data collection throughout the year offers significant advantages for evaluating the Offer. It enables an evaluation of the Offer throughout the school year in Wales, which starts in September and is divided into three terms: Autumn (September to December), Spring (January to March/April, depending on Easter), and Summer (April to July). Eligibility for the Offer begins on the first day of the first month of each school term following a child's third birthday, allowing for the estimation of its impact at specific cutoff points throughout the year in the RDD approach. This approach addresses concerns regarding variations in parental conception timing (Clarke et al., 2019) and potential differential impacts of Offer eligibility across school terms, which may be influenced by varying term lengths and probabilities of accessing publicly funded places (Brewer et al., 2022). Moreover, the APS' continuous data collection overcomes limitations of point-in-time data like Census records, which only estimate policy effectiveness for children born at specific times of the year (see Section 5.3). It also enables real-time monitoring of the Offer between Censuses, crucial due to the phased rollout and initial implementation occurring between the 2011 and 2021 Censuses. This is in contrast to the analysis of English childcare policy, where 2011 Census data provided sufficient coverage for the relevant timeframe (Brewer et al., 2022). Similarly, the DiD approach utilises the APS' temporal dimension to exploit the Offer's phased rollout across Welsh wards by term (Figure 5.1).

The sample for each approach is detailed in their respective methodology sections. In both cases, the sample is restricted to working-age parents aged between 16-64 years, with children falling within specified age ranges, and who report their employment status. Individuals with missing values for any of the explanatory variables (Table D.3, Appendix D) are excluded from the analysis.

5.4.2 Identifying Eligible and Not Yet Eligible Children and Parents

Both the secure household and person APS are used to identify eligible and not yet eligible children and their parents in each approach. These provide comprehensive data for each individual, including full date of births and household relationships. This information, coupled with the Offer's predefined eligibility criteria, facilitates the identification of eligible and not yet eligible children within specific time periods. Eligibility for the Offer commences at the start of a term (defined as the 1st of April, 1st September, 1st January) following a child's third birthday, and extends until the child enters formal schooling, typically the September after their fourth birthday. Exceptions may arise in cases where schools have multiple intakes per year (rare in Wales) or when parents defer their child's entry to Reception until later in the same school year. Given the importance of accurately defining eligibility periods for estimating the impact of the Offer, exact age criteria are detailed in each approach. Children not yet eligible are defined as those who have not reached the age of three by the start of a term.

Identifying eligible and not yet eligible children based on full dates of birth and wards of residence allows for straightforward identification of their parents in the household APS, as relationships between household members and the head of household, regardless of age, are recorded.[18] Given the Offer's broad and inclusive definition of a parent, which includes partners, carers, and grandparents (Section 5.2.2), parents are defined following Brewer et al. (2022) as the head of household or the spouse or partner of the head of the household in households containing children or step-children of the head of household. However, it is not possible to discern whether these parents are the biological or legal guardian of the relevant child in the data.

5.4.3 Dependent and Explanatory Variables

The main dependent variable is the self-reported employment status of parents, defined according to the ILO definition of employment. Parents are defined as employed if they report being employed, self-employed, in government employment and training programmes, or an unpaid family worker, provided they have worked in a job for at least one hour or are temporarily absent from a job. Non-employed individuals encompass those who are ILO unemployed or economically inactive.[19]

The evaluation also considers the impact of Offer eligibility on hours worked, recognising that the literature suggests that childcare policies tend to induce modest changes in labour supply at the intensive margin (e.g. Brewer et al. 2022; Lefebvre and Merrigan 2008; Lundin et al. 2008, see discussion in Section 5.3). In this analysis, the dependent variable is usual hours worked (excluding overtime), aligning with the Offer's eligibility criteria. Following Brewer et al. (2022), non-employed parents are assigned a value of zero to prevent unnecessary sample size reduction.[20,21] A limitation of this approach is

[18] The head of household is defined as the household member who owns the accommodation; is legally responsible for the rent; or occupies the accommodation as reward of their employment, or through some relationship to its owner who is not a member of the household. If there are joint householders, the one with the highest income is the head of household. If their income is the same, then the eldest one is the head of household (ONS, 2023c).

[19] The APS includes additional variables that could refine the definition of employment, particularly in relation to the Offer's objective of increasing working hours. These variables relate to individuals actively seeking additional employment, exploring alternative employment with more hours, or aiming to increase hours in their current job. However, employing these as the primary dependent variable would result in smaller sample sizes, insufficient for robust analysis.

[20] An alternative approach of restricting the sample to employed parents was considered but was ultimately not pursued due to the substantial reduction in sample size for each approach.

[21] The research initially planned on using three binary indicators for parents working 1-15 hours, 16-29 hours, and 30 or more hours per week as outcome variables, reflecting thresholds for UK in-work support eligibility (Brewer et al., 2022). However, small sample sizes for some groups would compromise the robustness of the analysis and potentially risk statistical disclosure.

that the dependent variable captures both extensive-margin and intensive-margin effects, meaning that observed impacts may reflect changes in overall employment rates as well as changes in hours worked, rather than isolating intensive-margin effects exclusively.

For each approach, various specifications, both without and with controls for parental characteristics, local authority of residence, and calendar month, are estimated. These controls are necessary to ensure the validity of both approaches in evaluating the impact of Offer eligibility on parental employment (discussed fully in the methodology sections). The parental characteristics, outlined in Table D.3, Appendix D, include the parent's age (and age squared), an indicator for a parent's low education (defined as the highest educational qualification being below A-levels), a cohabitation dummy indicating the presence of a spouse or partner in the household, and the number of dependent children under 16-years old. Such controls are standard in the evaluation of childcare policies, as they ensure the validity of identification approaches, and are recognised as influential in parental employment rates and the effectiveness of childcare policies in increasing employment rates (e.g., Brewer et al. 2022; Section 5.3). Additionally, these controls do not suffer from issues related to small sample sizes. Controlling for local authority of residence and calendar month addresses potential variations in local labour market conditions and seasonality in employment rates, further ensuring the validity of each approach.

5.5 Sharp Regression Discontinuity Design Approach

The sharp RDD method is commonly employed in situations where an individual's assignment to a treatment is determined by a cutoff point on a single quantitative assignment variable, typically defined by an arbitrary rule. Assuming that individuals just below and above the cutoff are similar in characteristics, the (local) treatment effect can be estimated by comparing outcomes for individuals just on either side of the cutoff.

Given date-of-birth rules, the RDD approach is widely used to evaluate the impact of childcare policies on parental labour market outcomes (see Section 5.3 for a comprehensive review of this evidence). The approach adopted here is similar, insofar as it exploits the Offer's strict date-of-birth eligibility criteria to estimate the impact of the Offer during its first full year of implementation (April 2019 - March 2020).

5.5.1 Sample

The RDD approach uses pooled APS data from April 2019 to March 2020 (ONS, 2024a; ONS, 2023a) to evaluate the Offer's impact on parental employment rates. This period captures the initial impact of the Offer during its first full year of implementation, post-trial period. It ensures that all parents with children of the relevant age are eligible for the Offer regardless of ward of residence, while also avoiding the period when the

Offer was suspended due to the COVID-19 pandemic (refer to Section 5.2.2 for a detailed timeline). Moreover, this timeframe minimises anticipation effects, where parents might adjust labour market decisions based on expected future childcare eligibility. Unlike Brewer et al. (2022), who use a balanced panel by excluding parents who appear only once in the sample, utilising one year of data also prevents the presence of multiple observations for some parents, as it prevents further reduction of an already limited sample size.

During this year, parents became eligible to access the Offer at three distinct cutoff points, aligned to the first day of the first month of school terms in Wales: 1st April 2019, 1st September 2019, and 1st January 2020. Accordingly, three distinct samples are constructed based on the Offer's strict date-of-birth criteria (as outlined in Table 5.2). To be eligible for the Offer at the start of each term, parents must have a child who is at least three-years old and has not yet commenced full-time schooling, typically the September after the child's fourth birthday. Unlike much of the related literature (except Lundin et al. 2008), where the sample is limited to eligibility of the youngest child, the research considers eligibility of any child meeting the age criteria to avoid further reduction in sample sizes, although potential variation in the impact of Offer eligibility is explored in the heterogeneity analysis (Section 5.5).

To reduce bias in estimating the impact of the Offer, the sample is restricted to parents within a narrow bandwidth around each term's cutoff. The choice of bandwidth is crucial; wider bandwidths can improve precision but risk introducing bias due to potentially large differences between parents with children born near term cutoffs and those with children born further away (Gelman and Imbens, 2019). Balancing precision and bias is nuanced (Lee and Lemieux, 2010), as the RDD relies on the assumption that parents just eligible for the Offer and those not yet eligible are comparable in observable characteristics. While minimal differences are more plausible between parents whose children are born one day apart, compared to those born up to six months apart, a larger bandwidth would increase the sample size.[22] Following Brewer et al. (2022), the research employs a 90-day bandwidth on either side of term cutoffs, consistent with the 100-day bandwidth in Fitzpatrick (2010). This choice reflects a trade-off due to sample size constraints; narrower bandwidths may limit robustness, while a wider bandwidth would include parents in their second term of Offer eligibility or those not yet eligible for at least two terms, given the shortest term related to the Offer is approximately 90 days (1st January - 31st March). To limit potential observable differences in characteristics among eligible and not yet eligible parents, the most comprehensive specification controls for parental characteristics, local authority and calendar month fixed effects. In robustness checks, the analysis is rerun with a 60-day bandwidth and an optimal bandwidth selected via a data-driven, non-parametric approach as proposed by Calonico et al. (2020) (see Section 5.5).

[22]See McCrary (2008) and McCrary and Royer (2011) for discussions on differences across quarters of birth.

Given this 90-day bandwidth, Table 5.2 outlines the birth dates of eligible and not yet eligible children for each term, along with parental sample sizes by term, gender, and eligibility status. The sample sizes by term are modest, with the gender breakdown for the not yet eligible group by term suppressed to prevent statistical disclosure. Pooling term samples yields a total sample of 210 parents, with 96 not yet eligible and 114 eligible. Table D.4, Appendix D presents the average characteristics by eligibility status and gender in the pooled data, further discussed in relation to the validity of the assumptions underlying the RDD approach (Section 5.5).

Table 5.2: RDD Sample Size by Gender, Term Cohort and Eligibility Status (April 2019 - March 2020)

Term cohort	**APS**	**Eligibility status**	**Birth dates of children** (90-day bandwidth)	**Sample of parents**		
				All	**Mothers**	**Fathers**
Pooled sample	Apr 2019 - Mar 2020	Eligible		114	65	49
		Not yet eligible		96	56	37
April 2019	Apr - Jun 2019	Eligible	1st Jan 2016 - 31st Mar 2016	33	17	16
		Not yet eligible	1st Apr 2016 - 29th Jun 2016	23	-	-
September 2019	Sep - Dec 2019	Eligible	2nd Jun 2016 - 31st Aug 2016	47	26	21
		Not yet eligible	1st Sep 2016 - 29th Nov 2016	36	-	-
January 2020	Jan - Mar 2020	Eligible	2nd Oct 2016 - 31st Dec 2016	34	22	12
		Not yet eligible	1st Jan 2017 - 31st Mar 2017	37	-	-

5.5.2 Methodology

The sharp RDD approach is commonly employed in evaluating childcare policies, leveraging somewhat ‘arbitrary’ but strict date-of birth rules for eligibility criteria (Section 5.3, Hahn et al. 2001).[23] The approach relies on several assumptions, including a smooth relationship between the running variable and the outcome, individuals’ inability to manipulate their treatment status, and demographic similarity at the cutoff, except for treatment assignment. These assumptions align the RDD approach with the principles of a randomised controlled trial (Imbens and Lemieux, 2008), although the estimated (local) average treatment effect may lack generalisability beyond the cutoff without additional assumptions.

Under these assumptions, estimating the (local) average effect of a childcare policy is often conducted through a variant of the generic sharp RDD model:

$$Y_i = \alpha + \tau Treat_i + f(\chi_i) + \varepsilon_i \tag{5.1}$$

where Y_i is the outcome of interest for individual i and $Treat_i$ is a treatment indicator variable equal to one when individual i accesses the policy and zero when they do not. This assignment is determined by a continuous running variable, χ_i, such that $Treat_i = 1\{\chi_i \geq 0\}$, meaning the probability of treatment assignment experiences a discontinuity at the cutoff, jumping from zero to one in the sharp case. $f(\cdot)$ represents a flexible function of the running variable, potentially incorporating an interaction between

[23] The sharp RDD relies on a clear cutoff that determines treatment eligibility. In contrast, the fuzzy RDD relaxes the strict assignment rule, allowing eligibility near the cutoff to deviate from the rule (Hahn et al., 2001).

the running variable and the treatment variable to account for shifts in intercepts across treatment assignment. It can also take the form of any polynomial order, though linear and quadratic specifications are preferred to avoid 'overfitting' the data (Gelman and Imbens, 2019; Lee and Lemieux, 2010). α is a constant and $\varepsilon_i \sim N(0, \sigma^2)$ is the random error term. The (local) average treatment effect of the childcare policy is measured by τ, representing the discontinuity in outcomes at the cutoff.

In the case where the Offer is the treatment, parental eligibility is determined by their child's age relative to the start of a term, establishing a cutoff criterion. To be eligible, a parent must have a child at least three-years old and not yet enrolled in full-time schooling, typically by the September following the child's fourth birthday (Table 5.2). Consequently, the treatment indicator $Offer_i^c$ for parent i in term cohort $c \in \{Apr, Sep, Jan\}$ equals one if their child meets the eligibility criteria and zero if their child does not. Given this age eligibility criterion, the relevant running variable $Days_i^c$ represents the age difference in days between the child's birthdate and the relevant start date for each term c, a common approach in the childcare literature (e.g. Brewer et al. 2022; Fitzpatrick 2010).

The literature recommends estimating the Offer's impact separately for each term due to potential heterogeneity in the impact of Offer eligibility across term cohorts. Such variation may arise from differences in term lengths and the differential probabilities of securing a publicly funded childcare place. Evidence from England suggests that children due to start nursery in September have a higher probability of placement upon eligibility (Brewer et al., 2022).

Given these considerations, Equation 5.1 is adapted to estimate the Offer's impact on parent i's employment status in term cohort c (Y_i^c):

$$Y_i^c = \alpha^c + \pi^c Offer_i^c + g(Days_i^c) + \varepsilon_i^c \tag{5.2}$$

where α^c is a constant, and $g(Days_i^c)$ follows Brewer et al. (2022) and Fitzpatrick (2010) as a local polynomial (quadratic) function that interacts with the treatment variable $Offer_i^c$, such that $g(Days_i^c) = \sum_{j=1}^{2} \gamma^j Days_i^{cj} + \sum_{j=1}^{2} \psi^j (Offer_i^c \cdot Days_i^{cj})$, where j indicates the polynomial order. While restricting the sample to parents within a 90-day bandwidth on either side of term cutoffs reduces bias and limits sensitivity to the choice of functional form for $g(\cdot)$, the functional form remains important. A linear specification is explored in the sensitivity analysis (Section 5.5). Given the absence of data on actual Offer utilisation in the APS, π^c captures the Offer's intention-to-treat (hereinafter, ITT) effect for term cohort c, rather than the (local) average treatment effect. This approach, common in the childcare literature (e.g. Brewer et al. 2022; Fitzpatrick 2010), distributes the average impact across all parents intended to benefit from the Offer, effectively capturing the impact of eligibility rather than actual utilisation.

While estimating the model separately by each term cohort is preferable, the modest sample sizes by term cohort (Table 5.2) raise concerns about the sensitivity of ITT estimates to the choice of functional form. In such cases, a common approach is to pool data across multiple cutoffs. This requires re-centering the running variable at each cutoff so that all units are aligned to a common reference point, where the cutoff is normalised to zero. The data are then pooled, treating all observations as if they share a single cutoff at zero. This approach has been widely used in RDD analyses with multiple cutoffs (Garibaldi et al., 2012; Zimmerman, 2019; Fort et al., 2020). However, the pooled ITT estimate may obscure valuable treatment effect heterogeneity, producing a weighted average that assumes identical effects across cutoffs and disregards weighting schemes (Cattaneo et al., 2016; Bertanha, 2020). To address this, the pooled model is adapted to capture the Offer's impact for each term cohort c by including term cohort-specific effects c^c and their interaction with the treatment variable $Offer_i^c$:

$$Y_i^c = \alpha^c + \pi Offer_i^c + g(Days_i^c) + \sum_{c \neq Apr} [\nu_1^c c_i^c + \nu_2(c_i^c \cdot Offer_i^c)] + \varepsilon_i^c \tag{5.3}$$

where notation follows from above, the April ITT effect is given by π, the difference in employment rates across terms c is given by ν_1^c, and ν_2^c measures the difference in ITT effects across terms c.

Sharp RDDs rely on the assumption of demographic similarity across the cutoff, meaning that parents just below and above the cutoff should be comparable in all respects except for Offer eligibility (see discussion in Section 5.5.3). This implies it is not strictly necessary to control for parental characteristics, although doing so can improve precision. As fully discussed in Section 5.5, even with a narrow 90-day bandwidth, some discontinuities in characteristics persist, likely due to the small sample size (see Table 5.2). Consequently, to address these discontinuities and ensure the validity of the RDD approach, parental characteristics (Table D.3, Appendix D), and calendar month and local authority fixed effects are successively controlled for, adapting Equation 5.3 to:

$$Y_{ilm}^c = \alpha^c + \boldsymbol{\beta^c} \mathbf{X}_i^c + \pi Offer_i^c + g(Days_i^c) + \sum_{c \neq Apr} [\nu_1^c c_i^c + \nu_2(c_i^c \cdot Offer_i^c)] + \phi_m + \mu_l + \varepsilon_{ilm}^c \tag{5.4}$$

where notation follows from above, $\mathbf{X}_i^c$ is a vector of parental characteristics, m indicates the month of observation, l signifies the local authority of residence, and ϕ_m and μ_l are calendar month and local authority fixed effects, respectively.

While this specification controls for differences in characteristics across eligible and not yet eligible parents, it assumes a homogeneous impact of Offer eligibility across all parents. This is despite potential variation across parental subgroups in constraints surrounding childcare and employment decision and the likely heterogeneity in the benefits derived from selecting into childcare and the labour market (Cornelissen et al., 2018; Kottelenberg and Lehrer, 2017). For example, childcare policies are more likely to influence maternal employment decisions, given that women predominantly bear the burden of childcare, due to cultural norms, work-family policies and/or the lower average earnings of women. Similarly, the impact may vary by eligibility of the youngest child in the household, as older children are typically in full-time schooling (Berlinski et al. 2011; Brewer et al. 2022; Goux and Maurin 2010; see Section 5.3 for an overview). Moreover, the staggered geographical rollout of the Offer (Figure 5.1) suggests that its impact may differ across Welsh wards, particularly if there are anticipation effects and variation over time. This is because parents residing in non-trial wards would have only just become eligible at the start of the sample period (April 2019). Understanding these heterogeneous impacts is crucial for evaluating the Offer in relation to its aims of supporting maternal employment, increasing the incomes of families, and reducing the risk of poverty.

Consequently, to explore these potential heterogeneous impacts, the analysis focuses on the following parental subgroups: mothers, parents whose youngest child is eligible, and parents residing in non-trial wards.[24,25] Conventional methods typically involve separate analyses for different parental subgroups (e.g., Fitzpatrick 2010; Finseraas et al. 2017), but this is impractical due to small sample sizes. Instead, the analysis uses the pooled sample and adapts the most comprehensive RDD specification (Equation 5.4) to include interactions between the treatment variable $Offer_i$ and dummy variables for parental subgroup G, differing only from not allowing the impact of characteristics to vary across subgroups. To maintain statistical power and focus on the potential heterogeneous impact across parental subgroups, the specification pools across term cohorts but excludes term interactions:[26]

$$Y_{ilm} = \alpha + \boldsymbol{\beta}\mathbf{X}_i + \pi Offer_i + [\omega_1 G_i \cdot \omega_2 (G_i \cdot Offer_i)] + g(Days_i) + \phi_m + \mu_l + \varepsilon_{ilm} \qquad (5.5)$$

where notation follows from above and ω_2, as the interaction coefficient between parental subgroup G and the treatment dummy, indicates whether the impact of Offer eligibility differs systematically for parents in subgroup G compared with the overall sample of parents.[27]

[24] Non-trial wards would have only just become eligible at the start of the sample period.

[25] While it would have been intriguing to further consider the heterogeneous impact of Offer eligibility by ethnicity, educational attainment and lone parent status, the sample size for each parental subgroup is too small for robust analysis. The research had also initially aimed to explore the potential heterogeneous impact of Offer eligibility by Flying Start area, given that these areas could already access some free childcare (Section 5.2.2 details the interaction between the Offer and Flying Start). However, this was not possible due to challenges in coding the 12,554 postcodes that were Flying Start areas in the Offer's first full year of implementation.

[26] The sensitivity of the heterogeneity analysis is tested by re-estimating the model with term-specific impacts (Table D.7, Appendix D).

[27] Local authority fixed effects are included in the non-trial areas specification, as trial areas are based on wards, rather than local authorities.

5.5.3 Results

Exploration of the Assumptions Underlying the RDD approach

To validly assess the impact of Offer eligibility on parental employment rates using the outlined RDD approach, all potentially relevant variables, except for eligibility and employment rates, must remain continuous at the cutoff. This continuity ensures comparability between parents just above and below the cutoff, implying that eligibility is effectively randomly assigned (Lee and Card, 2008). While it is not possible to definitively test these continuities, several tests can support the validity of the RDD approach. It is common practice to explore these assumptions before presenting the ITT estimates of Offer eligibility.

To verify continuity and detect any potential manipulation in birth timing, density tests are conducted to examine the distribution of parents with children born within a 180-day window relative to the pooled cutoff (McCrary 2008, Figure 5.2). This graphical depiction is crucial, as manipulation could result in an increased number of parents with children born just before the cutoff. Such manipulation might arise if parents strategically time their child's birth to maximise eligibility for publicly funded childcare, either due to prior knowledge or experienced with the childcare system from having older children. This would invalidate the RDD approach, as the child's age (in days, relative to the cutoff) would correlate with outcomes for reasons other than eligibility (see Section 5.5).

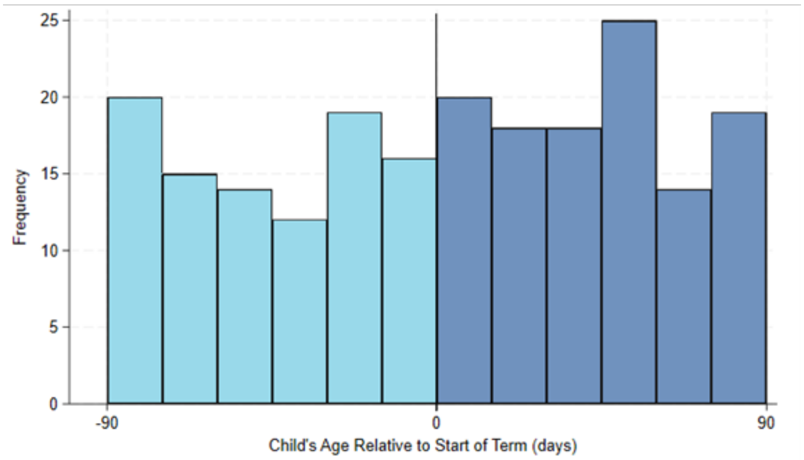
Unlike other analyses, the distribution of parents around the cutoff is presented as a histogram, with each bar representing a 15-day interval (approximately half a month), ensuring a minimum of ten parents per interval to avoid statistical disclosure (Figure 5.2).[28] The histogram shows minimal differences in the number of parents with children born just before and after the pooled cutoff, suggesting no significant evidence of manipulation. While there are marginally more eligible parents than not yet eligible at the pooled cutoff, this disparity is minor relative to the overall variation in birth rates. This pattern aligns with Brewer and Crawford (2010), who observed similar trends using administrative data for the September 2004 term and attributed the discrepancy to strategic birth timing for school enrolment.

To further ensure that any observed discontinuity in parental employment rates at term cutoffs is due to Offer eligibility rather than differences in parental characteristics, it is essential to verify that observed characteristics are not correlated with eligibility status. Significant differences in characteristics between eligible and not yet eligible parents would undermine the assumption of random assignment around the cutoff. However, given the small sample size, minor differences may occur due to random variation.

Figures D.3a-d, Appendix D illustrate how key observable characteristics vary by

[28] The distribution of parents with children born within a 180-day window relative to each term's cutoff is not presented to prevent statistical disclosure.

Figure 5.2: Distribution of Parents around the Pooled Cutoff



Notes: (i) Underlying N=210. (ii) Width of bars is 15 days.

Source:Author calculations based on pooled April 2019 - March 2020 APS.

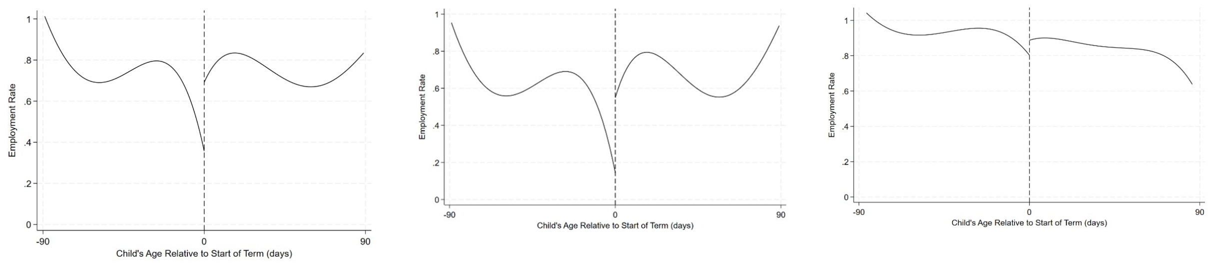
eligibility status around the cutoff. These are presented as histograms with 30-day intervals (approximately one month) to ensure no statistical disclosure. Table D.4, Appendix D presents the average of these characteristics by eligibility status and gender. The analysis reveals some discontinuities around the cutoff, particularly regarding age.[29] The variation in parental age by eligibility status is consistent with previous studies on childcare policy in England (Brewer and Crawford, 2010), though the discrepancy is larger than expected. While eligible children are, on average, three months older than those not yet eligible, this does not fully explain the four-year average age difference between eligible and not yet eligible parents. Additionally, a slightly higher proportion of not yet eligible parents report lower educational attainment (below A-levels) and non-cohabitation with a partner.

To formally test for discontinuities in these observed characteristics, the RDD is re-estimated for the pooled sample, using these characteristics as outcomes without controls (following Equation 5.2). The results, presented in Table D.5, Appendix D, indicate no significant discontinuities at the cutoff in parental age or number of dependent children. This suggests that changes in parental employment rates at the cutoff are not driven by these characteristics. However, significant discontinuities are observed in low education and cohabitation status for the September and January terms. Since the sharp RDD approach relies on the assumption that eligible and not yet eligible parents are similar in all respects except for eligibility status, the most comprehensive and preferred specification includes controls for these parental characteristics. Additionally, local authority fixed effects and calendar month fixed effects are included to account for potential temporal and local labour market variations (Equation 5.4). These adjustments ensure that the assumptions underlying the RDD approach hold,

[29]The age distribution of parents ranges from 17 to 66 at the time of observation.

Figure 5.3: Parental Employment Rates around the Pooled Cutoff

(a) All parents (b) Mothers (c) Fathers



Notes: (i) Underlying N for a=210, b=124, c=86. (ii) The lines are estimates of local polynomial regressions of the employment rate (on the y-axis) on the age of the relevant child (in days) relative to the pooled cutoff.

Source: Author calculations based on pooled April 2019 - March 2020 APS.

validating its use in evaluating the Offer's impact on parental employment rates.

Impact of Offer Eligibility on Parental Employment Rates

The average employment rates for parents who are not yet eligible and those who are eligible for the Offer appear similar in the pooled data (75.00% and 74.56%, respectively, Table D.4, Appendix D). This suggests minimal overall impact of Offer eligibility during its first full year of implementation. However, the graphical depiction of the empirical relationship between parental employment rates and the age of the child (in days) relative to the pooled cutoff indicates a discontinuity (Figure 5.3a). This discrepancy arises because descriptive statistics average employment rates over the entire bandwidths on either side of the pooled cutoff, while the graphical discontinuity reflects a sharp fall in parental employment rates approaching the cutoff. Equivalent graphical depictions by gender suggest that this discontinuity at the pooled cutoff is primarily driven by a dramatic decline in maternal employment, rather than paternal employment (Figure 5.3b, 5.3c). This is also evident in the descriptive statistics (Table D.4, Appendix D). These findings align with existing literature, which suggests that mothers are more sensitive to childcare policy changes than fathers (e.g. Brewer et al. 2022; Bettendorf et al. 2015, Section 5.3).[30]

Table 5.3 provides the ITT estimates of the impact of Offer eligibility on parental employment rates across four RDD specifications (Section 5.5). These estimates are based on a 90-day bandwidth either side of the cutoffs and a flexible quadratic function of the child's age (in days). Term cohort-specific ITT estimates without controls (specifications (1a), (1b), (1c)) indicate no significant impact of Offer eligibility on parental employment rates for any term cohort. Nonetheless, the positive point estimates are consistent with the analysis conducted in England (Brewer et al., 2022).

Given the small sample sizes for each term cohort, specification (2) pools the data across

[30]These patterns persist when applying a quadratic functional form in child's age (in days), as in the RDD approach, as shown in Figure D.4, Appendix D,

Table 5.3: RDD Estimates of the Impact of Offer Eligibility on Parental Employment Rates

	(1)			(2)	(3)	(4)
	(a) April	(b) September	(c) January	Pooled data across terms		
Offer	0.144	0.243	0.207	0.195	0.105	0.345
	(0.385)	(0.347)	(0.297)	(0.211)	(0.184)	(0.235)
Days	0.016	-0.013	-0.005	-0.001	-0.004	-0.001
	(0.016)	(0.017)	(0.010)	(0.007)	(0.007)	(0.008)
Days^2	0.000	-0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Offer x Days	-0.024	0.010	0.002	-0.004	0.002	-0.005
	(0.021)	(0.019)	(0.015)	(0.010)	(0.008)	(0.010)
Offer x Days^2	-0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
September cohort				0.202*	0.076	0.163
				(0.116)	(0.104)	(0.158)
September cohort x Offer				-0.073	0.033	-0.123
				(0.153)	(0.135)	(0.156)
January cohort				0.169	0.085	0.111
				(0.116)	(0.104)	(0.166)
January cohort x Offer				0.012	0.115	-0.018
				(0.158)	(0.143)	(0.170)
Mother					-0.142**	-0.150***
					(0.058)	(0.057)
Age					0.053***	0.074***
					(0.020)	(0.022)
Age^2					-0.001***	-0.001***
					(0.000)	(0.000)
Low education					-0.195***	-0.204***
					(0.057)	(0.059)
Cohabition					0.330***	0.318***
					(0.081)	(0.092)
Number of Dependent children					-0.059**	-0.071**
					(0.028)	(0.030)
Calendar month fixed effects	No	No	No	No	No	Yes
Local authority fixed effects	No	No	No	No	No	Yes
R^2	0.0632	0.0224	0.0186	0.0433	0.3130	0.4322
N	56	83	71	210	210	210

Notes: (i) This table reports ITT estimates from RDD regressions using a 90-day bandwidth either side of the cutoffs and a flexible quadratic function in the age of the child (in days). (ii) The first month of the term, the Cardiff local authority and the April term cohort are the reference categories. (iii) Figures in () are standard errors. (iv) *p<0.10, **p<0.05, ***p<0.01.

Source: Author calculations based on pooled April 2019 - March 2020 APS.

terms. However, even with pooled data, the ITT estimates remain statistically insignificant. Specifications (3) and (4) refine the analysis by sequentially controlling for parental characteristics, and calendar month and local authority fixed effects to account for observed differences between eligible and not yet eligible parents (Table D.4, Appendix D). Despite these controls, the ITT estimates, while positive, remain statistically insignificant across all specifications.[31] The small sample size in the pooled data likely limits the statistical power of the RDD approach, raising concerns about its capacity to detect meaningful effects and, consequently, limiting the robustness of the conclusions drawn from this analysis.

In terms of parental characteristics, the analysis confirms established patterns. Mothers and parents with lower education exhibit significantly lower employment rates. Conversely, older parents are more likely to be employed, though this diminishes at older ages. Cohabiting parents also demonstrate higher employment rates, while an

[31] Controlling for parental characteristics, calendar month and local authority fixed effects to term-specific models (specifications (1a), (1b) and (1c)) similarly yields insignificant estimates.

Table 5.4: RDD Estimates of the Heterogeneous Impact of Offer Eligibility by Parental Subgroups

	(1) Mothers	(2) Youngest child	(3) Non-trial areas
Eligible in subgroup N	65	86	23
Not yet eligible in subgroup N	59	74	30
Offer	0.226	0.309	0.275
	(0.209)	(0.235)	(0.197)
Mother	-0.193***	-0.149***	-0.152***
	(0.082)	(0.057)	(0.057)
Mother x Offer	0.075		
	(0.107)		
Youngest		-0.045	
		(0.116)	
Youngest x Offer		-0.076	
		(0.153)	
Non-trial area			0.013
			(0.160)
Non-trial area x Offer			-0.077
			(0.155)
Calendar month fixed effects	Yes	Yes	Yes
Local authority fixed effects	Yes	Yes	Yes
R^2	0.4308	0.4347	0.4299
N	210	210	210

Notes: (i) The table reports ITT estimates based on the April 2019-March 2020 from RDD regressions using a 90-day bandwidth either side of the cutoffs. (ii) The regressions control for a second order polynomial in the difference between the age of the child and the relevant cutoff, an interaction between this polynomial and the cutoff, as well as the age and age squared of the parent, dummies for low education and cohabitation status and the number of dependent children. (iii) The first month of the term, the Cardiff local authority and the April term cohort are the reference categories. (iv) Figures in () are standard errors. (v) *p<0.10, **p<0.05, ***p<0.01.

Source: Author calculations based on pooled April 2019 - March 2020 APS.

extra dependent child lowers the likelihood of employment. These findings are as expected and align with the broader literature on parental labour market outcomes (Section 2.6, 5.3). This may suggest that the sample size does not limit statistical power.

Heterogeneous Impact of Offer Eligibility across Parental Subgroups

Variations in childcare constraints and employment decisions across different parental subgroups may contribute to the overall insignificance of the estimated impact of Offer eligibility on parental employment rates in the baseline RDD results. Aggregating across diverse parental groups could obscure differential effects, particularly if certain subgroups respond more strongly to the policy. The significant and expected coefficients for some covariates in the baseline analysis support this interpretation. ITT estimates for different parental subgroups and their interactions with the treatment variable are presented in Table 5.4, with the full set of RDD estimates presented in Table D.6, Appendix D.

Despite indications from the literature that the overall insignificant impact of Offer eligibility may obscure differential employment responses among mothers and fathers, as well as among parents whose eligible child is the youngest and non-youngest, specifications (1) and (2) in Table 5.4 reveal no significant differences in the impact of

Offer eligibility across these subgroups. However, the point estimates suggest a more favourable impact on maternal employment rates, consistent with previous research findings (Brewer et al., 2022) and Figure 5.3b. The unexpected negative point estimate for the youngest child suggests the possibility that the Offer's impact may be larger for parents with younger, not yet eligible children. Nevertheless, these estimates lack statistical significance, preventing rejection of the null hypothesis that the impact of Offer eligibility is consistent across these parental groups. While this may in part reflect limited statistical power, it is also possible that the absence of a clear impact across parental subgroups may reflect the complex nature of employment decisions, which are shaped not only by childcare availability and cost but also by factors such as identity, traditional gender roles, and attitudes toward parental employment. These broader influences are discussed further in Section 5.7.

Specification (3) assesses whether the impact of Offer eligibility differs for parents residing in non-trial wards compared to those in trial wards. Non-trial wards refer to wards where residents became eligible to access the Offer for the first time in April 2019, during national rollout (refer to Section 5.2.2 for a discussion and Figure 5.1 for an illustration). It might be expected that Offer eligibility would have a greater impact on parental employment rates for those residing in non-trial wards, as they only became eligible at the start of the sample period. However, if there was non-random selection of trial wards, the impact of Offer eligibility in trial wards may be different than that in non-trial wards. As it is, the coefficient for the interaction between non-trial area and Offer eligibility remains insignificant, indicating a uniform impact regardless of whether parents reside in trial or non-trial wards. The results of the heterogeneity analysis do not change when the Offer's impact is allowed to vary across terms (Table D.7, Appendix D).

Overall, there is no evidence of heterogeneity in the impact of Offer eligibility by gender, the eligibility status of the youngest child, or residency in non-trial wards. This lack of significance and apparent uniformity may imply a homogeneous parental response to Offer eligibility, though this is likely attributable to the small sample size and limited statistical power of the sample during the first full year of implementation.

Impact of Offer Eligibility on Usual Hours Worked

Alongside potential increases in parental employment rates, childcare policies are found to induce modest changes in labour supply at the intensive margin and even smaller changes in earnings (Section 5.3, Brewer et al. 2022; Lefebvre and Merrigan 2008; Lundin et al. 2008). This analysis extends the most comprehensive RDD specification (Equation 5.4) to evaluate the impact of Offer eligibility on usual hours worked (excluding overtime), assigning a value of zero to non-employed parents. The results, presented in column (4) of Table D.6, Appendix D, indicate that the impact on usual hours worked is statistically insignificant. This may be attributed to the limited sample size (197 parents) and the corresponding lack of statistical power, although the presence of significant coefficients for some covariates suggests otherwise. This finding aligns with Brewer et al. (2022) in England, highlighting the importance of examining the long-term effects of childcare policies on labour supply, particularly at the intensive margin.

Due to reductions in the sample size, the RDD analysis could not be extended to hourly pay, which would have complemented the analysis of GPGs across areas within Britain (Chapter 3). The sample size for parents reporting hourly pay was 95, limiting the statistical power necessary for meaningful analysis.

5.5.4 Sensitivity Analysis

The sensitivity of the ITT estimates is explored with respect to the choice of bandwidth and functional form of the running variable (age of the child in days). These choices are crucial, as there is a trade-off between a wider bandwidth, which increases sample size, and a narrower bandwidth, which enhances comparability between eligible and not yet eligible parents (Section 5.5). For example, it is easier to argue that parents of children born one day apart are more similar than parents of children born six months apart, as in the baseline analysis. A narrower bandwidth reduces sensitivity to the functional form of the running variable but may affect the reliability of the ITT estimates (Gelman and Imbens, 2019).

Table D.8, Appendix D presents the RDD estimates with a 60-day bandwidth, using both linear and quadratic controls for the child's age, and a 90-day bandwidth with a linear functional form. Exploration with narrower or wider bandwidths is limited by sample constraints; a 30-day bandwidth reduces the sample to 74 parents, compromising robustness, while a wider bandwidth results in overlapping term cutoffs and could dilute the comparability of eligible and not yet eligible parents, undermining the RDD approach. The 60-day bandwidth (approximately two months) yields a statistically significant impact of Offer eligibility on employment rates at the 5% level, suggesting a potential increase of approximately 70 percentage points, irrespective of the functional form used. This suggests that narrowing the bandwidth has enhanced comparability between eligible and not yet eligible parents, reducing bias and resulting in more precise and significant ITT estimates, despite the smaller sample size. However, it is essential to balance the trade-off between bias and variance; overly narrow bandwidths can lead to imprecise estimates due to small sample sizes, while overly wide bandwidths can introduce bias from less comparable groups.

The sensitivity of the results to the inclusion of proxy responses is also examined, given potential concerns about data accuracy (Section 5.4). Presented in Table D.8, Appendix D, the Offer's impact remains statistically insignificant, indicating that the presence of proxy responses does not significantly alter the findings on employment status.

The sensitivity of the baseline results is further explored using the method by Calonico et al. (2020), which optimally determines the bandwidth to minimise the mean squared error. The resulting optimal bandwidths, ranging from 34 to 48 days, yield sample sizes that are insufficient for robust analysis. This methodology also allows for the application of different kernel functions, which differentially weight observations based on their proximity to the cutoff. Kernel weighting is particularly relevant in RDD approaches, as it affects the extent to which parents further from the cutoff contribute to the estimated ITT effect.

Using a 90-day bandwidth and a flexible second-order polynomial, the results indicate a significant increase in employment rates of 26.33 percentage points with a triangular kernel and 27.30 percentage points with an Epanechnikov kernel.[32] These findings contrast with the baseline estimates, which, while positive, were statistically insignificant. This shift in significance suggests that the lack of statistical significance in the baseline results may be attributable to the inclusion of parents further from the cutoff, who may be systematically different from those just above and just below the cutoff. This concern is supported by the exploration of the RDD assumptions (Section 5.5. By applying kernel weighting, the estimation assigns greater influence to parents closest to the cutoff, thereby improving comparability and reducing potential bias arising from heterogeneity in the sample. The resulting significant estimates indicate a potentially positive and significant impact of the Offer on parental employment rates for parents whose children are just eligible, underscoring the importance of bandwidth selection and weighting strategies in RDD approaches to ensure valid causal inference.

Given the limitations associated with sample size and comparability in the RDD approach, the analysis is conducted using a DiD approach to exploit the phased geographical rollout of the Offer across Welsh wards.

5.6 Difference-in-Differences Approach

The DiD method identifies the causal effects of broadly applied policies and non-random interventions by comparing changes in outcomes over time between individuals who receive a treatment (treatment group) and those who do not (control group). The method relies on the common trends assumption, which asserts that, in the absence of treatment, differences in trends between the treatment and control group would remain constant over time.[33]

[32] While the methodology proposed by Calonico et al. (2020) adjusts ITT estimates for explanatory variables, efficiency constraints require that these coefficients remain restricted (Calonico et al., 2019). As a result, this method estimates ITT effects under the assumption of homogeneity across term cohorts, without providing separate coefficients for covariates, and is therefore not presented here.

[33] In the staggered DiD approach, several variants of the common trends assumption have been considered. For example, Callaway and Sant'Anna (2021) and Sun and Abraham (2021) propose approaches where the assumption holds only after some groups are treated, or for eventually treated groups, but not for the never-treated. These trade-offs are discussed further in Section 5.6 (Roth et al., 2023).

By leveraging geographic and temporal variation in policies, the DiD method is frequently employed to evaluate the impact of childcare policies on various parental labour market outcomes (see Section 5.3 for an overview). The approach adopted here exploits the phased geographic rollout of the Offer across Welsh wards to estimate the impact of Offer eligibility during its trial period (July 2017 - March 2019).[34]

5.6.1 Sample

The DiD approach uses pooled secure APS data from January 2016 to March 2019 (ONS, 2024a; ONS, 2023a) to evaluate the impact of Offer eligibility on parental employment rates. This period encompasses both the phased geographic rollout of the Offer across Welsh wards from July 2017 to March 2019 and a substantial pre-rollout period, aligned with the announcement in the Welsh Labour manifesto for the 2016 Welsh Assembly election (Section 5.2).[35] This allows for the examination of the common trends assumption and potential anticipation effects, where parents may adjust their labour market decisions based on expected future childcare eligibility (Blanden et al., 2022; Brewer et al., 2022). Data post-March 2019 are excluded, as the national rollout of the Offer in April 2019 eliminated an effective control group for the DiD approach. Instead, the RDD approach evaluates the Offer's impact during its first full year of implementation (April 2019 - March 2020, Section 5.5).

The sample comprises of all parents with children aged three- or four-years by the start of each school term (1st April, 1st September and 1st January) who have not yet commenced full-time schooling (assumed to be the September after the child's fourth birthday) and are in the first wave of either the main LFS or the Enhanced sample during the sample period. This pooling approach creates a cross-sectional dataset that mitigates the risk of multiple observations for some parents (see Table 5.1 for the formation of annual APS data).[36] Table 5.6 details the date-of-birth criteria for the sample period, which includes all children who were eligible at the time of observation. Unlike most related literature - except Lundin et al. (2008), and the RDD approach (Section 5.5) - the DiD approach includes all parents with children meeting the age criteria, rather than restricting the sample to those whose youngest child is eligible, in order to avoid reducing the sample size.. The heterogeneous impact of Offer eligibility across parental subgroup is explored in both the static and staggered DiD analysis.

Parents are grouped based on the rollout of the Offer in their ward of residence, resulting in eight groups: July 2017 (10 wards), September 2017 (26 wards), January 2018 (30 wards), April 2018 (149 wards), September 2018 (181 wards),

[34] It is not possible to evaluate the period after the national rollout using the DiD approach, as the analysis requires a control group that remains not yet eligible for the Offer throughout the sample period.

[35] A longer time period is considered in the sensitivity analysis (Section 5.6).

[36] The APS has a rotational panel design, combining individuals in waves 1 and 5 across four consecutive quarters of the main LFS with individuals in waves 1 to 4 of the Enhanced sample of the English, Welsh and Scottish Local Labour Force Survey (Section 5.4).

November/December 2018 (24 wards), January 2019 (250 wards), and April 2019 (194 wards) (Figure 5.1 and Table D.2, Appendix D). The DiD approach requires a control group that remains not yet treated throughout the sample period. Thus, parents residing in wards that received the Offer at the point of national rollout (April 2019) serve as an effective control group, as they remain not yet treated across the sample period. This group of parents forms an appropriate control group under the assumptions of no anticipation and common trends (though these can be relaxed in the staggered DiD approach), meaning that differences in parental employment rate trends between treatment and control groups would remain constant over time in the absence of the Offer (Callaway and Sant'Anna, 2021; Baker et al., 2022).

Table 5.5: Birth Dates of Children of Eligible Age, January 2016 - March 2019 pooled APS data

Pooled APS data	**Born**
1st January 2016 - 31st March 2016	1st September 2011 - 31st December 2012
1st April 2016 - 31st August 2016	1st September 2011 - 31st March 2013
1st September 2016 - 31st December 2016	1st September 2012 - 31st August 2013
1st January 2017 - 31st March 2017	1st September 2012 - 31st December 2013
1st April 2017 - 31st August 2017	1st September 2012 - 31st March 2014
1st September 2017 - 31st December 2017	1st September 2013 - 31st August 2014
1st January 2018 - 31st March 2018	1st September 2013 - 31st December 2014
1st April 2018 - 31st August 2018	1st September 2013 - 31st March 2015
1st September 2018 - 31st December 2018	1st September 2014 - 31st August 2015
1st January 2019 - 31st March 2019	1st September 2014 - 31st December 2015

Static and Dynamic DiD Approach

Due to the small number of wards in some groups (e.g., July 2017, September 2017), the static and dynamic DiD approaches condition on treatment groups and their respective control groups with at least 30 parents in both the pre- and post-Offer periods to prevent statistical disclosure.[37] Table 5.6 provides the sample size for the April 2018 and September 2018 treatment groups, along with their respective control groups, in both the pre- and post-Offer periods, defined relative to the rollout for each treatment group, by gender. While the April 2018 and September 2018 treatment groups have larger sample sizes than the not yet eligible and eligible parental groups in the pooled RDD specification, the modest sample sizes, may still limit statistical power.

The full set of summary statistics for employment rates and explanatory variables for the April 2018 and September 2018 treatment groups, as well as their respective control groups, are provided in Table D.9, Appendix D. These statistics, presented for both the pre-Offer and post-Offer periods, provide insights into the potential impact of Offer eligibility on parental employment rates. For the April 2018 treatment group, parental employment rates decreased in the post-Offer period, whereas they increased for the September 2018 group. The control group had a higher parental employment rate in the post-Offer period compared to the April 2018 treatment group but was comparable to

[37] It was initially hoped that parents receiving the Offer in January 2019 could be included as a treatment group in the static and dynamic DiD approach. However, in the post-Offer period (January 2019-March 2019), only 21 parents were in this treatment group and a potentially disclosive sample size for their respective April 2019 control group.

Table 5.6: Static and Dynamic DiD Sample Sizes by Treatment Group, Rollout of the Offer, and Gender

(a) April 2018 Treatment Group

	Time period	Treatment group All	Mothers	Fathers	Control group All	Mothers	Fathers
Pre-Offer	January 2016 - March 2018	77	41	36	168	94	74
Post-Offer	April 2018 - March 2019	45	26	19	65	39	26

(b) September 2018 Treatment Group

	Time period	Treatment group All	Mothers	Fathers	Control group All	Mothers	Fathers
Pre-Offer	January 2016 - March 2018	174	97	77	203	115	88
Post-Offer	April 2018 - March 2019	45	27	18	30	18	12

Notes: (i) The pre-Offer period is defined relative to the rollout of the Offer for each treatment group, which in turn defines each April 2019 control group.

Source: Author calculations based on pooled January 2016 - March 2019 APS.

the pre-Offer period relative to the September 2018 treatment group. These descriptive statistics suggest a minimal impact of Offer eligibility on parental employment rates, a finding further illustrated in Figure 5.4. This figure presents parental employment rates over the sample period by term for the April 2018 and September 2018 treatment groups and the April 2019 control group, with the a and b markers indicating the timing of the Offer's rollout, respectively. While the figure presents parental employment rates by term to avoid statistical disclosure, the employment rates over time are not smooth, as expected, suggesting potential small sample bias. For example, the dramatic drop in parental employment rates for the April 2018 wards are likely attributable to small sample biases.

In both the static and dynamic DiD approaches, substantial changes in observable characteristics between each treatment group and their respective control group may indicate unobserved compositional changes, potentially undermining the validity of the DiD estimates. Tables D.9a and D.9b, Appendix D show that the treatment groups and their respective control groups exhibit broadly similar characteristics, with only slightly lower education levels in the treatment groups. Importantly, there is little change over time in the relative characteristics of both treatment groups and their control groups, supporting the credibility of the DiD assumptions.

Staggered DiD Approach

To address the potential limitations posed by small sample sizes in the static and dynamic DiD analyses, the staggered DiD approach pools data across all treatment groups that received the Offer at the start of a term. This increases statistical power by incorporating the September 2017 and January 2018 treatment groups, which were previously excluded for not meeting the threshold of 30 parents in both the pre- and post-Offer periods. However, the staggered DiD approach is limited to data up to December 2018, as the sample size of the April 2019 treatment group as the control

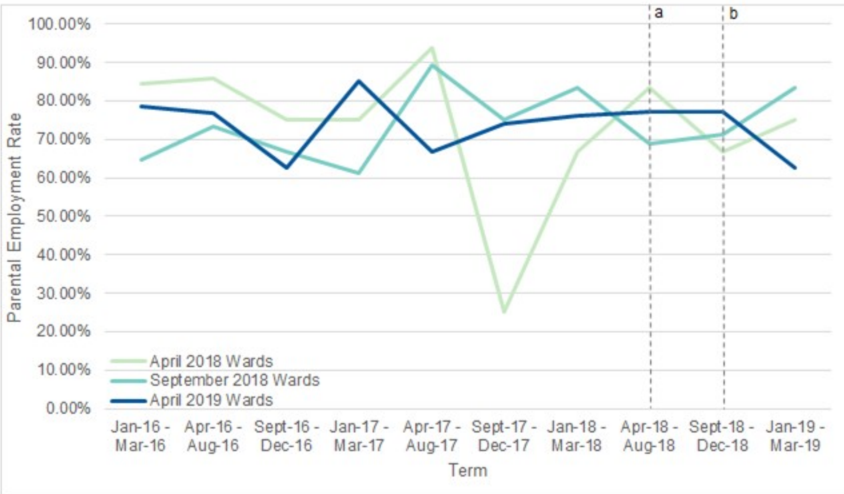


Figure 5.4: Parental Employment Rates by Term, grouped by Ward according to the Offer's Rollout

Notes: (i) a and b indicate the rollout of the Offer in wards that first received the Offer in April 2018 and September 2018, respectively. (ii) Underlying N for April 2018 wards is 122, September 2018 is 316 and April 2019 is 233.

Source: Author calculations based on pooled January 2016 - March 2019 APS.

group in the January 2019 term is potentially disclosive. Table 5.7 reports the number of parents in each treatment group by Offer rollout, as well as in the control group, which includes parents residing in wards who received the Offer in April 2019.

Table 5.7: Number of Parents by Treatment Group and Offer Rollout (Staggered DiD Sample)

	Treatment Groups					**Control Group**
	Sep-17	Jan-18	Apr-18	Sep-18	All	
All	17	33	110	195	355	225
Pre-Offer	-	-	77	174	280	-
Post-Offer	-	-	33	21	75	-

Notes: (i) The pre-Offer period is defined relative to the rollout of the Offer for each treatment group. (ii) The control group consists of parents residing in wards that received the Offer in April 2019. (iii) The sample size of the September 2017 treatment group is omitted to avoid potential statistical disclosure.

Source: Author calculations based on pooled January 2016 - December 2018 APS.

Table D.9c, Appendix D presents summary statistics for employment rates and explanatory variables for both the treatment groups (by pre- and post-Offer periods) and the control group. Consistent with findings from the static and dynamic DiD samples, these results show minimal impact of Offer eligibility on parental employment rates. While the characteristics of the treatment and control groups are broadly comparable, the treatment groups tend to have slightly lower levels of education, are younger, and have fewer children than the control group. Additionally, parents in the treatment groups during the post-Offer period exhibit a lower rate of cohabitation. These differences justify the inclusion of parental characteristics in the preferred model specification, to control for observable heterogeneity in the analysis.

5.6.2 Methodology

The DiD method is a common approach used to evaluate childcare policies, exploiting temporal and spatial variations in policy implementation (Section 5.3, Paull et al. 2016). It relies on two key identifying assumptions: no anticipation, where individuals do not change their behaviour in anticipation of becoming eligible for the policy; and a common trend assumption, whereby in the absence of the policy, the average change in outcomes over time would have been the same for both treatment and control groups. Under these assumptions, the average treatment effect or ITT effect can be interpreted as the differential change in the outcome between the treated and control groups before and after policy implementation.[38]

Assuming two groups ($g = [0, 1]$) and two time periods ($t = [0, 1]$), where group 0 remains ineligible for the policy in both periods and group 1 becomes eligible in period 1, the ITT effect of a childcare policy, δ, can be estimated using a simple DiD approach:

$$\delta = E[(Y_{i1}^1(1) - Y_{i0}^1(0)) - (Y_{i1}^0(0) - Y_{i0}^0(0))] \tag{5.6}$$

where $Y_{it}^g(1)$ represents the outcome of parent i in group g in time period t when eligible for the policy, and $Y_{it}^g(0)$ represents the outcome when ineligible. The no anticipation assumption implies $E[Y_{it}^g(1) - Y_{it}^g(0)] = 0$, and the common trends assumption suggests $E[Y_{i1}^1(0) - Y_{i0}^1(0)] = E[Y_{i1}^0(0) - Y_{i0}^0(0)]$.

Static DiD Approach

To estimate the impact of Offer eligibility on parental employment rates, a static DiD approach is first employed, which assumes constant treatment effects overtime. Two separate specifications are estimated for each treatment group (April 2018 and September 2018) compared to their respective April 2019 control group, as the group that remained not yet treated in the sample period. The static DiD model for each treatment group is specified as follows:

$$Y_{it} = \alpha + \lambda_1 Treat_i + \lambda_2 Post_t + \delta(Treat_i \cdot Post_t) + \varepsilon_{it} \tag{5.7}$$

where Y_{it} is the employment status of parent i in time period t. $Treat_i$ is a treatment indicator, equal to one when parent i is in the treatment group and zero when parent i is in the control group. Similarly, $Post_t$ is a time period indicator, equal to one in the post-Offer period and zero in the pre-Offer period, defined relative to the rollout of the Offer for each treatment group (Table 5.6). The interaction term $Treat_i \cdot Post_t$ captures the effect of being in the treatment group in the post-Offer period, with the coefficient δ representing the ITT effect of the Offer on parental employment rates.

[38] The ITT effect is typically estimated in the childcare literature, as data often do not capture actual policy utilisation (see Section 5.6 for further discussion).

$\varepsilon_{it} \sim N(0, \sigma^2)$ is the random error term.

For δ to accurately estimate the Offer's ITT effect for each treatment group, both the no anticipation and common trends assumptions must hold. Consistent with standard practice in the literature (e.g., Lundin et al. 2008), controlling for parental characteristics helps ensure that observed changes in employment rates are attributable to Offer eligibility, rather than changes in parental characteristics. This is particularly important given the modest sample size for each treatment group. Consequently, five specifications are estimated for each treatment and respective control group. The first specification is the basic model with no controls (Equation 5.7). The second controls for parental characteristics (as defined in Table D.3, Appendix D, consistent with the RDD analysis). The third and fourth specifications control for parental characteristics and local authority fixed effects or calendar month fixed effects (rather than year-month fixed effects), to control for seasonal and local labour market condition variations, respectively. Finally, the most comprehensive specification controls for parental characteristics, local authority fixed effects, and calendar month fixed effects, adapting Equation 5.7 to:

$$Y_{ilmt} = \alpha + \boldsymbol{\beta}\mathbf{X}_i + \lambda_1 Treat_i + \lambda_2 Post_t + \delta(Treat_i \cdot Post_t) + \mu_l + \phi_m + \varepsilon_{ilmt} \tag{5.8}$$

where Y_{ilmt} is the employment status of parent i residing in local authority l during month m in time period t. $\mathbf{X}_i$ is a vector of parental characteristics, with $\boldsymbol{\beta}$ representing the estimated returns. μ_l and ϕ_m denote local authority fixed effects and calendar month fixed effects, respectively.

As in the RDD, the research explores whether the impact of Offer eligibility varies across different parental subgroups, by adapting the baseline model (Equation 5.7) to allow the ITT effect to differ by parental subgroup G, as specified below:

$$\begin{aligned} Y_{ilmt} =& \alpha + \boldsymbol{\beta}\mathbf{X}_i + \lambda_1 Treat_i + \lambda_2 Post_t + \delta(Treat_i \cdot Post_t) \\ &+ \omega_1 G_i + \omega_2(G_i \cdot Treat_i) + \omega_3(G \cdot Post_t) + \omega_4(G \cdot Treat_i \cdot Post_t) \\ &+ \phi_m + \mu_l + \varepsilon_{ilmt} \end{aligned} \tag{5.9}$$

where notation follows from above, G_i is a dummy variable equal to one if parent i is in subgroup G and zero when they are not. The coefficient ω_4 on the triple interaction term $(G \cdot Treat_i \cdot Post_t)$ captures whether the impact of Offer eligibility on parental employment rates differs systematically by subgroup G. As with the RDD analysis, heterogeneity is explored by gender and eligibility of the youngest child. Variation across trial group is inherently addressed by estimating the separate models for each treatment group.

Even with controls, the common trends assumption may not hold due to unobserved differences associated with both treatment status and parental employment rates. This could introduce omitted variable bias, leading to incorrect attribution of changes in employment rates to the Offer rather than to these unobserved factors. While the static DiD model cannot directly test the common trends assumption, a dynamic DiD approach can examine how the impact evolves over time and test for anticipatory effects.[39] If the common trends assumption holds, there should be no significant differences in employment trends between each treatment and respective control groups prior to the Offer's rollout.

Dynamic DiD Approach

The dynamic DiD approach (event study framework) extends the static approach by allowing the treatment effects to vary over time, providing insights into the evolution of the Offer's impact on parental employment rates. It also provides a formal test of the common trends assumption by examining pre-Offer periods for anticipatory effects.

The dynamic DiD replaces the single post-Offer indicator ($Post_t$ in Equation 5.8) with a series of indicators for each term relative to the Offer's rollout for each treatment group, centred around the term immediately preceding the Offer's rollout for each treatment group:[40]

$$Y_{ilmt} = \alpha + \boldsymbol{\beta}\mathbf{X}_i + \lambda_1 Treat_i + \sum_{k=\underline{k}}^{\bar{k}} \lambda_{2k} Post_{tk} + \sum_{k=\underline{k}}^{\bar{k}} \delta_k (Treat_i \cdot Post_{tk}) + \phi_m + \mu_l + \varepsilon_{ilmt} \tag{5.10}$$

where notation follows from above, and δ_k captures the Offer's ITT effect in each term k for each treatment group, accounting for $\underline{k}$ leads $(\delta_{\underline{k}}, ..., \delta_{-2})$ (anticipatory effects) and $\overline{k}$ lags (post-Offer effects) $(\delta_0, ..., \delta_{\overline{k}})$. The term immediately before the Offer rollout for each treatment group serves as the baseline and is the first lead $k = 1$. If the common trends assumption holds, the lead coefficients δ_k should be close to zero and statistically insignificant, indicating no anticipatory effects. Significant changes in δ_k for $k \geq 0$ would indicate an impact of Offer eligibility on parental employment rates. An immediate effect on parental employment rates will be evident when $k = 0$, while estimates for $k > 0$ will reveal potential dynamic ITT effects. The same five specifications as in the static DiD are estimated for each treatment group and respective control group to ensure that changes in parental employment rates are attributable to Offer eligibility rather than compositional changes in the sample.

Staggered DiD Approach

[39] The ability to explore temporal dynamics is somewhat constrained by the limited post-Offer period before national implementation.

[40] Event periods are aligned with school terms to match the phased rollout of the Offer (see Figure 5.1). While an alternative approach could define event periods using calendar months for more granular temporal analysis, this would necessitate the exclusion of calendar month fixed effects and could lead to less robust estimates due to modest sample sizes.

The relatively small sample sizes in the static and dynamic DiD models for each treatment group and relative control group (Table 5.6) may limit statistical power, potentially obscuring significant impacts. To address this, pooling across treatment groups to exploit the full phased rollout of the Offer across Welsh wards increases the sample size. However, directly extending the static and dynamic approaches to this staggered rollout can introduce bias, complicating causal inference even with natural extensions of the common trends and no anticipation assumptions (Goodman-Bacon, 2021; Roth and Sant'Anna, 2023; Baker et al., 2022).

The static DiD model assumes homogeneous treatment effects across groups and terms, implying that all treatment groups experience the same impact of the Offer and that the impact is constant regardless of when the Offer was introduced. These assumptions are unlikely to hold in the Offer's staggered rollout, given factors like the endogenous selection of trial wards, learning effects over time, and local adaptations. Such heterogeneity in treatment effects across groups and terms can bias static DiD estimates. Specifically, the overall ITT effect can become a convex weighted average of treatment effects, sometimes assigning negative weights, especially for long-term effects (Goodman-Bacon, 2021; Borusyak et al., 2024; Chaisemartin and D'Haultfoeille, 2023). The Goodman-Bacon decomposition illustrates how these biases arise by aggregating DiD comparisons, including instances where earlier-treated groups act as controls for later-treated groups (Goodman-Bacon, 2021). These "forbidden comparisons" can introduce negative weights that distort estimates when treatment effects are heterogeneous.[41]

The dynamic DiD model, while allowing for time-varying treatment effects, also faces challenges with treatment heterogeneity across groups (Borusyak et al., 2024; Sun and Abraham, 2021). Like the static DiD model, the dynamic DiD approach in staggered settings can assign negative weights to certain ITT estimates post-Offer rollout, leading to biased ITT estimates when aggregating across groups and terms. Further, when treatment heterogeneity is present, lead coefficients in the dynamic DiD model may not equal zero, even if common trends hold in every period. This complicates the assessment of pre-treatment trends and misrepresent the validity of the common trends assumption (Sun and Abraham, 2021).

To address these limitations of the static and dynamic approaches, the analysis adopts the Callaway and Sant'Anna (hereinafter, CS) staggered DiD approach, which offers two advantages. First, it avoids negative weighting by assigning weights proportionally to treatment group size, rather than relying on OLS-based weights influenced by treatment effect variance. Second, it explicitly defines control groups, preventing "forbidden comparisons" and improving transparency. Table D.10, Appendix D provides a

[41]See Goodman-Bacon (2021) for a demonstration of this decomposition with three groups: early-treated, later-treated, and never treated. Roth and Sant'Anna (2023) provide further mathematical intuition behind how these weighting problems arise when treatment effects evolve over time.

comparison of the CS staggered DiD approach with alternative staggered approaches.[42]

The CS staggered DiD approach estimates group-time ITT effects as follows:

$$ITT(g,t) = \mathbb{E}[Y_{it}^{g}(g) - Y_{it}(0)|G_i = g] \tag{5.11}$$

which estimates the ITT effect for the treatment group first receiving the Offer in term g (the group-specific treatment period) by comparing changes in outcomes for this group between the pre-treatment period $g-1$ and a post-treatment period $t > g$, relative to a control group C:

$$ITT(g,t) = \mathbb{E}[Y_{it} - Y_{ig-1}|G_i = g] - \mathbb{E}[Y_{it} - Y_{ig-1}|G_i = C] \tag{5.12}$$

which extends Equation 5.6 to account for multiple groups and terms.

Ideally, the analysis would consider the five treatment groups receiving the Offer at the start of terms (September 2017, January 2018, April 2018, September 2018 and January 2019) and use the April 2019 group as the control group, as they remain not yet treated during the sample period.[43,44] However, due to the small sample size of the April 2019 control group in January 2019, that term and group are excluded from the analysis.

Unlike the static and dynamic DiD approaches, the preferred staggered DiD specification controls only for parental characteristics. This addresses observable heterogeneity between treatment and control groups (Table D.9c, Appendix D) while avoiding over-identification issues. The CS staggered approach also relaxes the common trends assumption to allow for group-specific pre-Offer trends. This flexibility accommodates the possibility that each treatment group follows its own counterfactual trend in the absence of the Offer, reducing the risk of bias from pre-existing differences. Furthermore, common trends are allowed to hold after conditioning on covariates, enhancing robustness.

Dynamic estimates are also presented, using the term prior to the Offer's rollout in each group as the reference term. This results in eight leads and one lag, with post-Offer estimates covering up to two terms post-Offer introduction. To ensure robustness, each event term includes a minimum of 10 parents per treatment group. To estimate the

[42] Imputation based approaches (e.g., Athey and Imbens 2022; Borusyak et al. 2024) construct counterfactual outcomes but are less suitable for studies focusing on treatment heterogeneity. Another approach is the Sun and Abraham (2021) method, which estimates dynamic effects for each group separately but requires larger sample sizes.

[43] Two groups, those where the Offer was rolled out in July 2017 and November 2018/December 2018, are excluded due to misalignment with the start of school terms. Using school terms as evert periods aligns with the dynamic DiD approach and mitigates issues arising from small sample sizes in some calendar months for some groups.

[44] The CS staggered DiD approach allows for two control group options: those who are never-treated (or in the analysis, those who remain not-yet treated in the sample period), and those not yet treated in each term. Sensitivity analyses in Section 5.6 examine how results vary based on the chosen control group.

overall ITT effect of Offer eligibility on parental employment, group-time specific ITT effects are aggregated as follows:

$$\theta = \sum_{g=1}^{G} \sum_{t=0}^{T} w_t^g \cdot ITT(g,t) \tag{5.13}$$

where w_t^g are weights assigned to each $ITT(g,t)$.[45]

Finally, heterogeneity in the impact of Offer eligibility across parental subgroups is explored by conditioning on gender and the eligibility status of the youngest child. Heterogeneity across trial groups is addressed through the staggered DiD framework.

5.6.3 Static DiD Results

Impact of Offer Eligibility on Parental Employment Rates

To evaluate the impact of Offer eligibility on parental employment rates, separate static DiD models are employed for the April 2018 and September 2018 treatment groups, using their respective April 2019 control groups. These treatment groups are chosen due to their larger sample sizes compared to other groups, and are analysed separately because eligibility timing differs and the Offer's impact may change over time, which could introduce bias in pooled estimates (see Goodman-Bacon 2021, Section 5.6.2). These static DiD estimates provide a benchmark average ITT effect on the extensive margin of employment. Given that baseline parental employment for each group is already high (see Figure 5.4), substantial overall changes are not necessarily expected, even if the policy has important impacts for specific subgroups or on margins other than employment. The results therefore serve primarily to establish whether there is any large, immediate average effect of Offer eligibility.

The ITT effect of the Offer is captured by the interaction term $(Treat_i \cdot Post_t)$ in Equation 5.7, where δ represents the impact of Offer eligibility on parents residing in a trial ward post-Offer rollout. For each treatment group, five specifications are estimated: without controls (1); with parental characteristics (2); with parental controls and local authority fixed effects (3); with parental controls and calendar month fixed effects (4); and with parental controls and local authority and calendar month fixed effects (5).[46] These estimates are presented in Table 5.8a and b for the April 2018 and September 2018 treatment groups, respectively.

Across all specifications, there is no statistically significant evidence that Offer eligibility impacted parental employment rates, as the coefficient on the interaction term remains

[45] Callaway and Sant'Anna (2021) discuss various weighting schemes, including equal weighting and weighting based on group frequency in the treated sample.

[46] Calendar month and local authority fixed effects control for seasonal variations in employment rates and local labour market conditions, respectively.

Table 5.8: Static DiD Estimates of the Impact of Offer Eligibility on Parental Employment Rates

(a) April 2018 Treatment Group

	(1)	(2)	(3)	(4)	(5)
Treatment group (yes=1, no=0)	0.047	-0.014	-0.099	-0.042	-0.110
	(0.060)	(0.055)	(0.153)	(0.057)	(0.156)
Post-Offer (Post-Apr/Sept 2018=1,	0.022	0.046	0.049	0.028	0.029
Pre-Apr/Sept 2018=0)	(0.064)	(0.057)	(0.057)	(0.060)	(0.060)
Treatment group*Post-Offer	-0.045	-0.029	-0.028	0.019	0.017
	(0.104)	(0.093)	(0.094)	(0.096)	(0.096)
Mother		-0.256***	-0.258***	-0.257***	-0.259***
		(0.044)	(0.044)	(0.044)	(0.044)
Age		0.059***	0.051***	0.058***	0.049***
		(0.017)	(0.017)	(0.017)	(0.018)
Age^2		-0.001***	-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)
Low education		-0.117***	-0.127***	-0.113**	-0.124***
		(0.045)	(0.045)	(0.046)	(0.045)
Cohabiting		0.153**	0.141**	0.174**	0.165**
		(0.069)	(0.069)	(0.070)	(0.070)
Number of dependent children in family		-0.080***	-0.079***	-0.086***	-0.083***
aged under 16 years old		(0.023)	(0.024)	(0.024)	(0.025)
Parental characteristics	No	Yes	Yes	Yes	Yes
Local authority fixed effects	No	No	Yes	No	Yes
Calendar month fixed effects	No	No	No	Yes	Yes
R^2	0.0018	0.2191	0.24477	0.2462	0.2701
N	*355*	*355*	*355*	*355*	*355*

(b) September 2018 Treatment Group

	(1)	(2)	(3)	(4)	(5)
Treatment group (yes=1, no=0)	0.002	-0.002	-0.155	-0.014	-0.149
	(0.045)	(0.041)	(0.094)	(0.042)	(0.095)
Post-Offer (Post-Apr/Sept 2018=1,	-0.006	0.015	0.015	0.032	0.031
Pre-Apr/Sept 2018=0)	(0.086)	(0.077)	(0.077)	(0.084)	(0.084)
Treatment group*Post-Offer	0.042	0.002	-0.030	0.019	-0.008
	(0.113)	(0.101)	(0.101)	(0.104)	(0.105)
Mother		-0.236***	-0.233***	-0.234***	-0.232***
		(0.040)	(0.039)	(0.040)	(0.039)
Age		0.064***	0.061***	0.061***	0.056***
		(0.014)	(0.014)	(0.014)	(0.015)
Age^2		-0.001***	-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)
Low education		-0.202***	-0.203***	-0.209***	-0.211***
		(0.039)	(0.040)	(0.040)	(0.040)
Cohabiting		0.097*	0.077	0.098	0.084
		(0.058)	(0.058)	(0.060)	(0.060)
Number of dependent children in family		-0.067***	-0.051***	-0.063***	-0.058**
aged under 16 years old		(0.021)	(0.021)	(0.022)	(0.023)
Parental characteristics	No	Yes	Yes	Yes	Yes
Local authority fixed effects	No	No	Yes	No	Yes
Calendar month fixed effects	No	No	No	Yes	Yes
R^2	0.0007	0.2215	0.2615	0.2433	0.2835
N	*452*	*452*	*452*	*452*	*452*

Notes: (i) This table reports static DiD estimates based on pooled January 2016 - March 2019 APS. (ii) The pre-Offer period is defined relative to the rollout of the Offer for each treatment group, which in turn defines each April 2019 control group. (iii) January, 2016 and the Cardiff local authority are the reference categories. (iv) Figures in () are standard errors. (v) *p<0.10, **p<0.05, ***p<0.01.

Source: Author calculations based on pooled January 2016 - March 2019 APS.

insignificant across the specifications. The insignificance of both the time and treatment group indicators further suggests an absence of systematic differences in employment trends between each treatment group and respective control group prior to the Offer's rollout, suggesting the validity of the common trends assumption. This finding contrasts with studies reporting significant positive impacts of childcare subsidies on parental employment rates (e.g. Bauernschuster and Schlotter 2015 for Germany; Brewer et al. 2022 for England; Berlinski and Galiani 2007 for Argentina; and Bousselin 2022 for Luxembourg), but aligns with findings from the US (Fitzpatrick, 2010) and Norway (Havnes and Mogstad, 2011a) (see Section 5.3 for an overview of the evidence). These results are consistent with the RDD approach (Section 5.5) and the descriptive statistics (Table D.9, Appendix D). However, the lack of significant effects may be partially attributed to limited statistical power, potentially resulting from the relatively small sample sizes of each treatment group.

Heterogeneous Impact of Offer Eligibility across Parental Subgroups

The estimates in Table 5.8 do not account for potential differences in the impact of Offer eligibility on parental employment rates across different parental subgroups. From a policy perspective, the groups most likely to be affected are those for whom the additional childcare provision reduces a key constraint on labour market participation - typically mothers and parents whose youngest child is eligible for the Offer (see Section 5.3). Such parents face higher opportunity costs of employment and may respond more strongly to reduced childcare costs or increased availability. Prior research suggests that gender and family structure significantly influence labour market outcomes (Lundin et al. 2008, Section 5.3).

To assess this potential heterogeneity, the analysis compares the impact of Offer eligibility between mothers and fathers, and between parents whose youngest child is eligible and those whose youngest child is not. An overview of the subgroup results is presented in Table 5.9, with full estimates presented in Table D.11, Appendix D.

Consistent with the RDD estimates, the results indicate no statistically significant differences in the impact of Offer eligibility across these parental subgroups in either treatment group. Despite the theoretical expectation of variation, there is no evidence of differential effects between mothers and fathers or by the eligibility status of the youngest child. This apparent homogeneity is likely due to the small sample sizes within each subgroup, which limit statistical power and the ability to detect meaningful differences.

Impact of Offer Eligibility on Usual Hours Worked

In line with the RDD approach and the stated aims of the Offer, static DiD models are employed to evaluate the impact of Offer eligibility on usual hours worked (excluding overtime) for the April 2018 and September 2018 treatment groups. The hours worked measure matches the definition used to determine Offer eligibility and, following Brewer

Table 5.9: Static DiD Estimates of the Impact of Offer Eligibility by Mother and Youngest Child Eligibility

(a) April 2018 Treatment Group

	Mothers	Youngest child
Treatment group*Post-Offer	0.082	-0.017
	(0.144)	(0.203)
Mother*Treatment group*Post-Offer	-0.109	
	(0.187)	
Youngest*Treatment group*Post-Offer		0.074
		(0.237)
Parental characteristics	Yes	Yes
Local authority fixed effects	Yes	Yes
Calendar month fixed effects	Yes	Yes
R^2	0.2760	0.2744
N	*355*	*355*

(b) September 2018 Treatment Group

	Mothers	Youngest child
Treatment group*Post-Offer	0.016	-0.210
	(0.162)	(0.192)
Mother*Treatment group*Post-Offer	-0.048	
	(0.203)	
Youngest*Treatment group*Post-Offer		0.298
		(0.228)
Parental characteristics	Yes	Yes
Local authority fixed effects	Yes	Yes
Calendar month fixed effects	Yes	Yes
R^2	0.2876	0.2954
N	*452*	*452*

Notes: (i) This table reports static DiD estimates based on pooled January 2016 - March 2019 APS. (ii) The pre-Offer period is defined relative to the rollout of the Offer for each treatment group, which in turn defines each control group. (iii) The specifications control for Offer period, treatment group indicator, their interaction, age and age squared of the parent, dummies for low education and cohabitation status, and the number of dependent children in the household, as well as local authority and calendar month fixed effects. (iv) For the April 2018 treatment group, there are 200 mothers (41 and 26 in the treated group in the pre- and post-Offer period, respectively, and 94 and 39 in the control group in the pre- and post-Offer period, respectively) and 240 parents whose youngest child is eligible (50 and 39 in the treated group in the pre- and post-Offer period, respectively, and 117 and 34 in the control group in the pre-and post-Offer period, respectively). In the September 2018 treatment group, there are 257 mothers (97 and 27 in the treated group in the pre- and post-Offer period, respectively and 115 and 18 in the control group in the pre- and post-Offer period, respectively) and 301 parents whose youngest child is eligible (115 and 35 in the treated group in the pre- and post-Offer period, respectively, and 133 and 18 in the control group in the pre- and post-Offer period, respectively). (v) January, 2016 and the Cardiff local authority are the reference categories. (vi) Figures in () are standard errors. (vi) *p<0.10, **p<0.05, ***p<0.01.

Source: Author calculations based on pooled January 2016 - March 2019 APS.

et al. (2022) assigns a value of zero to non-employed parents. This approach prevents sample size reductions and maintains consistency across analyses.[47] As the analysis conditions on parents reporting usual hours worked, the sample sizes are smaller than in the main static DiD models - 259 parents in the April 2018 treatment group and 326 in the September 2018.

[47] As discussed in Section 5.4.3, this measure does not exclusively capture changes on the intensive margin.

Table 5.10 presents the average usual hours worked per week for each treatment group and their respective April 2019 control group across different Offer periods. These descriptive statistics suggest that the Offer did not significantly affect the usual hours worked for either treatment group. This is confirmed by the static DiD estimates in Table D.12, Appendix D, which show statistically insignificant impacts for both the April 2018 and September 2018 treatment groups. Given that many eligible parents were already working close to full-time hours (35 hours per week) prior to the Offer, there may have been limited scope for further increases, which could explain the absence of significant effects on this margin.

Table 5.10: Average Usual Hours Worked per Week by Treatment and Control Groups and Time Period

	April 2018		September 2018	
	Treatment group	Control group	Treatment group	Control group
All	33.63	34.10	34.66	34.10
N	*93*	*166*	*160*	*166*
Pre-Offer	32.75	35.14	34.51	34.50
N	*59*	*119*	*126*	*145*
Post-Offer	35.18	31.45	35.21	31.33
N	*34*	*47*	*34*	*21*

Source: Author calculations based on pooled January 2016 - March 2019 APS.

5.6.4 Dynamic DiD Results

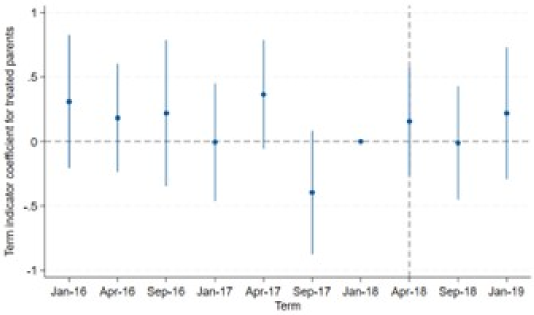
Impact of Offer Eligibility on Parental Employment Rates

The validity of the static DiD approach relies on the common trends assumption between each treatment group and their respective April 2019 control group in the terms prior to the Offer's introduction in each treatment group. This assumption may be challenged by factors such as the non-random selection of trial wards in pilot local authorities, anticipation effects, self-selection from parents moving to trial wards to access the Offer earlier, or the influence of concurrent policies like Universal Credit and Flying Start (see Section 5.2.2 for a discussion of their interaction with the Offer). While trial wards in pilot local authorities were selected based on various data indicators (e.g. demographics, economic factors), the differing selection criteria across local authorities introduced an element of randomisation. Nonetheless, selection bias may still arise if wards were chosen based on initial employment rates, potentially correlating with post-Offer trends.

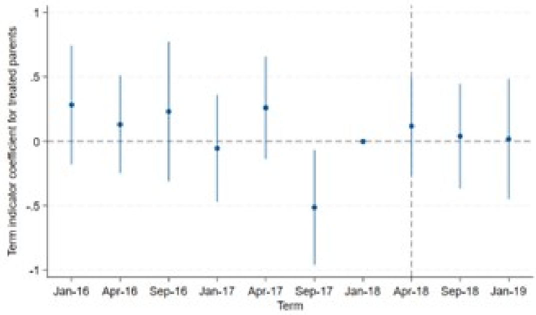
To assess the common trends assumption and explore the temporal dynamics of the Offer's impact, a dynamic DiD approach is employed (as specified in Equation 5.10). This specification normalises the time period to the term preceding the Offer's introduction for each treatment group (January 2018 for the April 2018 group; April 2018 for September 2018 group) and traces the differential impact of Offer eligibility over time. The model controls for parental characteristics and local authority and calendar month fixed effects. Comprehensive results are presented in Table D.13

Figure 5.5: Dynamic DiD Event Study Graphs of the Impact of Offer Eligibility on Parental Employment Rates

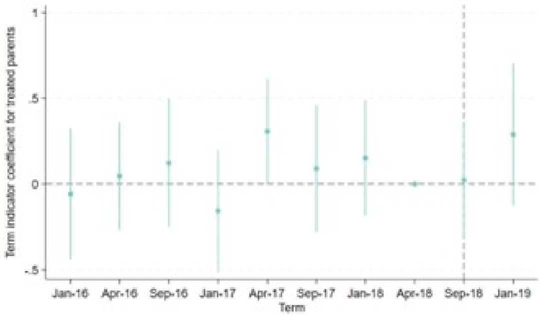
(a) April 2018 Treatment group, no controls



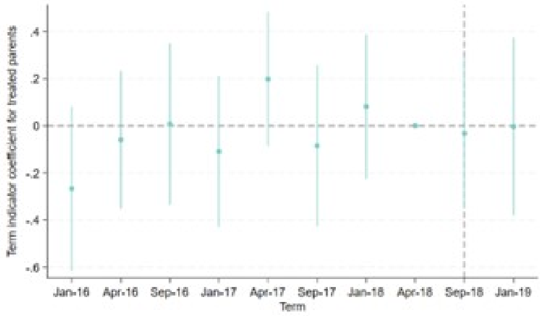
(b) April 2018 Treatment group, with controls



(c) September 2018 Treatment group, no controls



(d) September 2018 Treatment group, with controls



Notes: (i) These graphs plot the coefficients and their 95% confidence intervals of the termly indicators interacted with the treatment group indicators to demonstrate the impact of Offer eligibility in wards that received the Offer in April 2018 (Figures (a) and (b)) and September 2018 (Figures (c) and (d)). (ii) Underlying N for April 2018 (Figures (a) and (b)) is 355 and for September 2018 (Figure (c) and (d)) is 452. (iii) The coefficients for Figures (a) and (c) are estimated in regressions of parental employment rates on indicators for terms, an indicator for treatment group, and their interactions. The coefficients for Figures (b) and (d) are estimated in regressions of parental employment rates on indicators for terms, an indicator for treatment group, and their interactions, age and age squared of the parent, dummies for low education and cohabitation status, and the number of dependent children in the household, as well as local authority and calendar month fixed effects. (iv) January, the Cardiff local authority and the term before the Offer introduction for each treatment group are the reference categories. (v) Corresponding estimates can be found in Table D.13 and Table D.14, Appendix D.

Source: Author calculations based on pooled January 2016 - March 2019 APS.

and D.14, Appendix D, across the five specifications used in the static DiD approach for the April 2018 and September 2018 treatment groups, respectively.

Figures 5.5a and 5.5b visually present the coefficients and 95% confidence intervals of the termly indicators interacted with the April 2018 treatment group indicator. These figures correspond to the most basic specification (without controls) and the most comprehensive specification (with controls for parental characteristics, and local authority and calendar month fixed effects - column (1) and (5) in Tables D.13 and D.14, Appendix D, respectively). Similarly, Figures 5.5c and 5.5d provide equivalent graphs for the September 2018 treatment group.

The DiD dynamic event study graphs largely support the common trends assumption for each treatment group and their respective April 2019 control group, as pre-Offer estimates are generally insignificantly different from zero. This suggests that parental employment rates followed similar pre-Offer trends across groups. The main exception is the September 2017 coefficient for the April 2018 treatment group in the most comprehensive specification (column (5) in Table D.13, Appendix D). The significance of this coefficient points to a potential pre-existing difference in employment rates between the April 2018 treatment group and its April 2019 control group, which could indicate a violation of the common trends assumption.

However, several factors mitigate this concern. First, the significance of this coefficient is not consistent across specifications. Second, the April 2018 treatment group experiences an unusually large drop in employment rates - from over 90% in April 2017 to 25% in September 2017 (Figure 5.4) - suggesting that the result may be driven by small-sample bias rather than a systematic difference in trends. Finally, the post-Offer coefficients for the April 2018 treatment group are consistently insignificant across all specifications, indicating no significant impact of Offer eligibility on parental employment rates.

Overall, the analysis finds no short-term impact of Offer eligibility on parental employment rates for either treatment group, as all post-Offer coefficients are statistically insignificant. This is consistent with the evidence, which suggests that the immediate effects of childcare policies on parental employment - particularly in English-speaking countries - are often limited, with more substantial impacts emerging over time (Kleven et al., 2019). For example, in England, the impact of full-time childcare eligibility on maternal employment grew stronger over time: by the end of the first year of full-time entitlement, the effect was significantly larger than in the first term (Brewer et al., 2022). Such findings suggest that mothers may require time to re-enter the labour market and secure suitable employment after becoming eligible for full-time childcare. The delayed response underscores the importance of considering medium- to long-term effects when evaluating childcare policies. Consequently, the absence of significant employment effects immediately after the Offer's introduction should not be interpreted as evidence of no impact; rather, it may reflect that the effects materialise gradually. Unfortunately, longer-term impacts cannot be assessed here, as the April 2019 control groups are no longer valid comparators after the Offer's full rollout across Wales in April 2019.

5.6.5 Staggered DiD Results

Impact of Offer Eligibility on Parental Employment Rates

To fully exploit the staggered rollout of the Offer across Welsh wards and school terms, a more sophisticated approach than the static and dynamic DiD models is required. As discussed in Section 5.6, static and dynamic DiD models can introduce biases in staggered settings, which is why the effects for the two largest treatment groups were presented separately above. To address this limitation, the CS staggered DiD approach is employed, which increases the sample size by incorporating all treatment groups receiving the Offer at the start of school terms (September 2017, January 2018, April 2018 and September 2018). Due to the small sample size of the April 2019 control group during the January 2019 term, this term and treatment group are excluded, focusing the analysis on the trial period up to December 2018. This approach helps mitigate concerns that small sample sizes in individual treatment groups contributed to the previously insignificant results.

Table 5.11 presents baseline ITT estimates of Offer eligibility on parental employment rates, using parents residing in wards that received the Offer in April 2019 as the control group, as they remain not yet treated during the sample period. Five specifications are presented to maintain consistency with the static and dynamic DiD approaches: (1) no controls, (2) parental characteristics, (3) parental characteristics and local authority fixed effects, (4) parental characteristics and calendar month fixed effects, and (5) parental characteristics with both local authority and calendar month fixed effects. The preferred specification is column (2), which controls for parental characteristics to address observable heterogeneity between treatment and control groups (Table D.9, Appendix D). While local authority and calendar month fixed effects are preferred in the static and dynamic DiD approaches, their inclusion in the staggered DiD approach risks over-identifying ITT effects by potentially absorbing the variation in treatment groups. For example, the September 2017 treatment group consists solely of parents residing in wards in the Blaenau Gwent local authority (see Table D.2, Appendix D). To address small sample bias, post-Offer estimates are pooled across one and two terms post-introduction, ensuring at least 10 parents per treatment group in each term.

Across all five specifications, the overall ITT effect, calculated by aggregating weighted group-term ITT effects across all treatment groups and terms, is statistically insignificant, indicating that Offer eligibility had no significant impact on parental employment rates. Event study estimates similarly show no significant changes in employment rates post-Offer. Pre-Offer trends, represented by coefficients for periods "8 to 2 terms pre-Offer", are largely insignificant, supporting the relaxed common trends assumption in this staggered setting. Joint tests of pre-Offer coefficients further confirm the absence of significant pre-trends, reinforcing the validity of this assumption.[48]

Figures 5.6a and 5.6b visualise the dynamic ITT effect estimates of Offer eligibility on parental employment rates, without and with parental controls, respectively. The x-axis shows terms relative to the Offer rollout, with negative values indicating pre-Offer terms and positive values indicating post-Offer terms. The y-axis represents the ITT effects on parental employment rates. Both figures include 95% confidence intervals - blue for

[48]To verify that smaller treatment groups do not introduce bias and to align more closely with the static and dynamic analyses, the staggered DiD is repeated using only the April 2018 and September 2018 treatment groups. Results, presented in panel B of Table D.17, Appendix D, with and without parental controls, show no significant impact of Offer eligibility. Dynamic effects for these groups, visualised in Figures D.6a and D.6b, Appendix D, confirm these findings.

Table 5.11: Staggered DiD Estimates of the Impact of Offer Eligibility on Parental Employment Rates

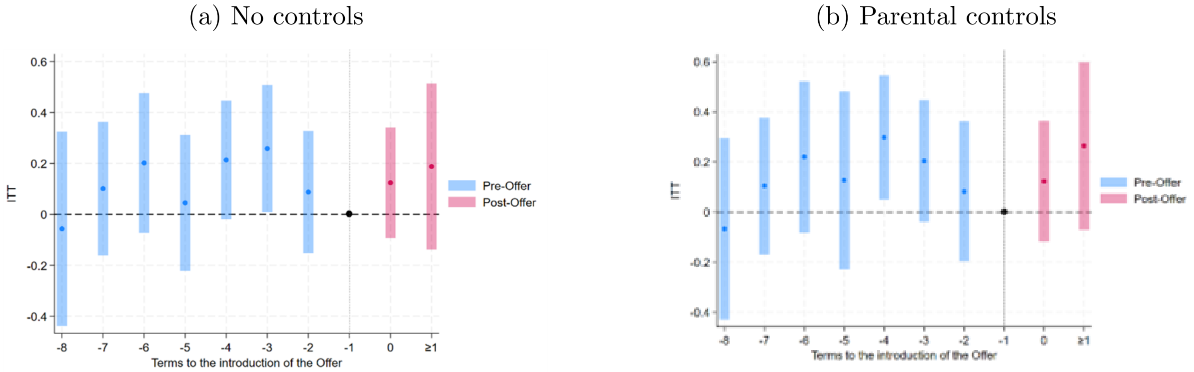
		(1)	(2)	(3)	(4)	(5)
Overall ITT on Treated		0.143	0.166	-0.004	0.228	0.322
		(0.111)	(0.117)	(0.706)	(0.712)	(1.422)
Dynamic effects	Pre-Offer average	0.121	0.138	0.163	0.056	0.017
(event study		(0.098)	(0.102)	(0.939)	(0.323)	(0.780)
estimates)	Post-Offer average	0.156	0.193	0.010	0.259	0.351
		(0.120)	(0.123)	(0.763)	(0.667)	(1.530)
	8 terms pre-Offer	-0.057	-0.067	0.107	-0.456	-0.465
		(0.195)	(0.184)	(1.483)	(0.521)	(0.788)
	7 terms pre-Offer	0.101	0.103	-0.178	0.092	-0.246
		(0.134)	(0.139)	(1.102)	(0.203)	(1.051)
	6 terms pre-Offer	0.202	0.220	0.233	0.228	0.364
		(0.140)	(0.154)	(2.150)	(0.927)	(2.371)
	5 terms pre-Offer	0.045	0.126	0.387	0.075	0.353
		(0.136)	(0.181)	(1.031)	(0.476)	(1.040)
	4 terms pre-Offer	0.214*	0.297**	0.200	0.267*	0.003
		(0.119)	(0.126)	(1.230)	(0.146)	(1.472)
	3 terms pre-Offer	0.258**	0.203	0.153	0.259	0.165
		(0.127)	(0.124)	(1.192)	(0.283)	(1.782)
	2 terms pre-Offer	0.087	0.082	0.242	-0.072	-0.058
		(0.122)	(0.142)	(1.308)	(0.446)	(2.114)
	1 term pre-Offer	-	-	-	-	-
	Term of Offer introduction	0.124	0.122	-0.026	0.177	0.277
		(0.111)	(0.123)	(0.650)	(0.790)	(1.264)
	$\geq$ 1 term post-Offer	0.188	0.264	0.045	0.341	0.424
		(0.166)	(0.170)	(0.966)	(0.571)	(1.835)
	Leads / Lags	-8 / $\geq$ 1	-8 / $\geq$ 1	-8 / $\geq$ 1	-8 / $\geq$ 1	-8 / $\geq$ 1
	N	*580*	*580*	*580*	*580*	*580*
Pre-trend test	Chi-squared	507.320	204.752	79.431	86.822	52.341
	p-value	0.000	0.000	0.000	0.000	0.000
Parental characteristics		No	Yes	Yes	Yes	Yes
Local authority fixed effects		No	No	Yes	No	Yes
Calendar month fixed effects		No	No	No	Yes	Yes

Notes: (i) This table reports the overall ITT effects of Offer eligibility on parental employment rates, estimated using the Callaway and Sant'Anna (2021) staggered DiD approach, with the April 2019 treatment group as the control group. The overall ITT effect captures the average effect for all eligible parents across treatment groups and terms, regardless of whether the Offer was actually accessed. (ii) Dynamic effects reflect time-varying impacts, using the term before Offer introduction as the reference term (event time -1), using the 'long2' option, so that pre-Offer estimates are constructed symmetrically to post-Offer estimates and are comparable to traditional dynamic DiD estimators (Roth, 2024). (iii) The underlying *N* for the control group is 225 across all terms and for the September 2017, January 2018, April 2018 and September 2018 treatment groups is 17, 33, 110 and 195, respectively across all terms. (iv) Parental characteristics include age and age squared of the parent, dummies for low education and cohabitation status and the number of dependent children in the household. (v) Figures in () are standard errors. (vi) *p<0.10, **p<0.05, ***p<0.01. (vii) The chi-squared statistics tests whether all pre-Offer estimates are equal to zero.

Source: Author calculations based on pooled April 2019 - March 2020 APS.

pre-Offer and red for post-Offer terms. In both specifications, the post-Offer confidence intervals cross zero, indicating no statistically significant impact of Offer eligibility on parental employment. Although some pre-Offer coefficients are significant, potentially raising concerns about the common trends assumption, the CS staggered DiD approach mitigates this by accommodating group-specific dynamics and conditioning on parallel trends only where appropriate.

Figure 5.6: Staggered DiD Event Study Graphs of the Impact of Offer Eligibility on Parental Employment Rates



Notes: (i) These graphs plot the estimates of the ITT effect of Offer eligibility on parental employment rates by event period (defined as terms to the introduction of the Offer) and their 95% confidence intervals, derived using the Callaway and Sant'Anna (2021) DiD estimator with an event-study specification. (ii) ITT estimates represent the average effect of the Offer for eligible parents in each event period relative to the term the Offer was introduced, regardless of whether the Offer was actually accessed. (iii) Dynamic effects show the time-varying impacts of Offer eligibility relative to the term before the Offer's introduction. Term 0 indicates the term the Offer was introduced. (iv) Plotted points represent ITT estimates, with error bars indicating 95% confidence intervals. (v) Underlying N for both graphs is 580, for the control group is 225 and for the September 2017, January 2018, April 2018 and September 2018 treatment groups is 17, 33, 110 and 195, respectively across all terms. (vi) Figure (b) controls for the age and age squared of the parent, dummies for low education and cohabitation status, and the number of dependent children in the household. (vii) Corresponding estimates can be found in Table 5.11.

Source: Author calculations based on pooled January 2016 - December 2018 APS.

Heterogeneous Impact of Offer Eligibility Across Parental Subgroups

Consistent with the RDD and static DiD approaches, the staggered DiD analysis examines whether the impact of Offer eligibility differs across key parental subgroups: mothers and parents whose youngest child is eligible for the Offer. These groups are of particular policy interest, as gender and family structure are known to influence labour market behaviour (Lundin et al., 2008). However, due to insufficient numbers of parents in each subgroup with certain key characteristics (e.g., low education) across treatment and control groups, these analyses are estimated without parental characteristic controls to preserve statistical power. The estimates are presented in Table D.15, Appendix D, with dynamic estimates visualised in Figure D.5a and D.5b, Appendix D.

Contrary to expectations, the results show no statistically significant effect of Offer eligibility for either subgroup. For mothers, the absence of measurable effects mirrors the overall findings, suggesting limited short-term labour market adjustments. Similarly, parents whose youngest child is eligible display no significant response, despite theoretical and empirical evidence pointing to potentially greater flexibility in labour supply for this group. Taken together, these results suggest that any subgroup-specific effects (if present) are either small in magnitude or require a longer post-policy period to materialise.

Impact of Offer Eligibility on Usual Hours Worked

Given the Offer's aims, the analysis extends beyond employment rates to consider its impact on usual hours worked (excluding overtime). This captures potential changes in labour supply intensity, as parents might increase working hours even if overall employment rates remain unchanged. Such effects are particularly relevant for mothers, for whom childcare provision can ease constraints on full-time or extended working patterns. Following Brewer et al. (2022) and the preceding analyses, non-employed parents are assigned a value of zero for usual hours worked. This ensures sample consistency and avoids sample size reductions, maintaining a minimum of 10 parents per treatment group in each term. The results, presented in Table D.16, Appendix D and visualised in Figure D.5c and d, Appendix D, indicate no statistically significant impact of Offer eligibility on hours worked, even after controlling for parental characteristics.

These results align with the RDD and static DiD estimates, as well as with survey evidence indicating that the Offer has had minimal overall impact on total hours worked (Glyn et al., 2019; Glyn et al., 2022). However, this survey evidence also suggests a relatively larger effect for mothers. The absence of statistically significant results here may reflect the limited statistical power of the staggered DiD approach - while it has a larger sample size than the RDD and static DiD models, it remains relatively small. In addition, prior evaluations in England suggest that impacts on the intensive margin often take time to emerge, strengthening over the medium term rather than immediately after policy introduction (Brewer et al., 2022).

Finally, as with the RDD approach, the staggered DiD analysis cannot be extended to hourly pay. Although the total sample size would be 298, the distribution across treatment groups and terms would fall below the 10-parent threshold in some cells, undermining the reliability of wage effect estimates.

5.6.6 Sensitivity Analysis

The research explores the sensitivity of the baseline staggered DiD results to alternative samples and control groups, and additional parental controls. This analysis addresses potential biases related to control group selection and omitted variables. The results are presented in Table D.17, Appendix D, with dynamic effects visualised in Figures D.6a-h, Appendix D, for both the specifications without controls and the preferred specification with parental controls.

Panel A of Table D.17, Appendix D, examines the sensitivity of the staggered DiD results to the inclusion of proxy responses. Excluding proxy responses reduces the sample by approximately one-third. Despite this reduction, the impact of the Offer on parental employment remains statistically insignificant, suggesting that proxy responses do not significantly alter the findings. Panel B further assesses whether the small sizes of certain treatment groups introduce bias. The analysis confirms that the results remain insignificant, indicating that limited sample sizes within specific treatment groups do not distort the overall conclusions.

Panel C of Table D.17, Appendix D examines the sensitivity of the results to the choice of control group, as this can significantly affect estimates (Roth and Sant'Anna, 2023). The baseline analysis uses parents residing in wards that received the Offer in April 2019 as the control group, selected for its clean comparison and consistency with static and dynamic DiD analyses. To evaluate the robustness of this choice, two alternative control groups are considered. First, the control group is expanded to include all parents residing in wards not yet treated during the sample period. The larger sample size enhances statistical power and allows for broader comparisons, helping to identify any potential anticipatory effects of the Offer. Second, the control group is redefined to consist of parents from the January 2019 and April 2019 treatment groups, both of which remain not yet treated throughout the sample period. This specification tests whether the timing of treatment impacts the results. In both cases, the results remain statistically insignificant, confirming that the baseline findings are not sensitive to the specific characteristics of the April 2019 control group.

Panel D of Table D.17, Appendix D expands the set of parental controls to include dummies for white ethnicity and disability status, to address concerns about unobserved heterogeneity. Census 2021 data show that demographic characteristics, including ethnicity and disability, significantly affect employment rates (ONS, 2024e). Failure to account for these may introduce omitted variable bias, especially if these characteristics correlate with treatment assignment or employment outcomes. After excluding parents with missing data on ethnicity and disability (leaving 95 parents who identify as disabled and 27 non-white parents), the results remain unchanged, with no significant impact of Offer eligibility on parental employment rates. This suggests that unobserved heterogeneity related to ethnicity and disability does not drive the null results.

The sensitivity of the results is also explored to potential anticipation effects, given the Offer's announcement in January 2016 in Welsh Labour's manifesto for the 2016 Welsh Assembly election and its implementation beginning in July 2017. While parents might have adjusted their employment in anticipation of future eligibility, given the short time frame between announcement and eligibility, and the costs associated with interim childcare, such effects are unlikely. Any anticipation effects would likely be more pronounced in the control group, but immediate childcare expenses reduce this risk. Additionally, strategic behaviour to secure childcare slots is not an issue, as childcare spaces were universally available for eligible children. The acceleration of the national rollout by 18 months further limits potential anticipation effects. There may have also been anticipation effects from the announcement of a similar policy in England in the Spending Review in November 2015. To empirically test for anticipation effects from both announcements, the staggered DiD analysis is re-estimated starting from January

2014 (two years before the first announcement in Wales). These results, presented in Table D.18 and Figure D.7, Appendix D indicate that there is no evidence of anticipation effects, verifying the robustness of the baseline findings.

Across all specifications, results remain consistent and statistically insignificant. These findings underscore the robustness of the main estimates, suggesting that the Offer had no measurable impact on parental employment rates. The persistent insignificance of the estimates across different model specifications and control groups strengthens the broader conclusion that the Offer had limited or no effect on parental employment, consistent with the RDD and static and dynamic DiD approaches.

5.7 Discussion of results

The results indicate that eligibility for 30 hours of free childcare under the Offer has had minimal impact on parental employment rates and usual hours worked. In the RDD approach (Section 5.5), any significant positive effects are sensitive to the choice of bandwidth and thus to the sample size, suggesting that limited statistical power may have prevented the detection of smaller but potentially meaningful impacts. These finding align with estimates from childcare policy evaluations in Norway (Havnes and Mogstad, 2011a) and the US (Fitzpatrick, 2010), but contrast with the significant positive impacts observed in Quebec (Baker et al., 2008), Germany (Bauernschuster and Schlotter, 2015), and Argentina (Berlinski and Galiani, 2007). They are also consistent with evidence from England, where a similar childcare subsidy did not substantially transform parental labour market outcomes, except for a significant increase in the labour supply of mothers whose youngest child was eligible (Brewer et al., 2022).

Several factors could explain the minimal impact of the Offer on parental employment rates, beyond the possibility that modest sample sizes in the RDD and DiD approaches limited statistical power. First, parental employment rates in Wales were already high before the Offer's introduction, with paternal and maternal employment rates at 91.4% and 74.5%, respectively, just before the Offer's phased geographic rollout in LFS April-June 2017 data (ONS, 2022c). In contrast, when childcare subsidies or reforms were introduced in Argentina and Germany, the employment rates of mothers with three- and four-years olds were around 40% and 50%, respectively. Such high pre-Offer employment rates in Wales may have left limited room for the Offer to have influenced parental employment decisions at the margin.

Second, the timing of eligibility may have dampened the Offer's potential impact. Parental eligibility for the Offer begins at the start of the term following a child's third birthday, which may be too late to prevent some parents from leaving the labour force following childbirth. In contrast, Quebec provides subsidised full-time childcare from birth to age five, allowing parents to maintain continuous employment. While some parents in Wales received part-time childcare through the Flying Start scheme when their child was two-years old, the scheme's limited provision (2.5 hours per day) is unlikely to incentivise a full return to work, particularly for low-income families (Blundell et al., 2016). The planned extension of childcare subsidies in England to all children under five from September 2025 will offer an important test of whether earlier support yields stronger labour market impacts.

Third, the Offer may not be sufficiently generous or flexible to enable parents to return to work. In Quebec, parents can access up to 10 hours of subsidised childcare per day, while the Offer provides up to six hours per day, which can only be taken at set times. Although more generous than its equivalent in England by covering periods outside of school term time, it still excludes four weeks per year. This limitation may constrain the Offer's ability to remove financial barriers to employment, especially for lone parents or those with lower levels of education. Qualitative evaluations have also identified relatively low take-up rates in certain areas, particularly in the Valleys, despite high awareness of the Offer due to national promotional campaigns (Harries et al., 2023).

Fourth, Wales already had a well-established private childcare market prior to the Offer's introduction, with high levels of both formal and informal childcare use among working families with at least one child aged three or four. The 2015–2016 Family Resources Survey estimated formal childcare use at 70.77% and informal childcare at 30.77%.[49] This pre-existing infrastructure may have reduced the marginal effect of the Offer, unlike in countries such as Canada, the US, Israel, and Argentina, where subsidised childcare entered previously unsubsidised markets. Concerns have also been raised in annual qualitative evaluations of the Welsh Government about the sustainability of providing enough childcare places through the Offer (Glyn et al., 2022; Harries et al., 2023). Disparities in take-up rates may also reflect regional variations in the capacity to deliver the promised childcare hours (Harries et al., 2023).

An evaluation of the Offer cannot overlook its potential to impact outcomes beyond labour market responses, particularly given that the Offer's aim of encouraging more parents to return to work, sits alongside the aims of encouraging child development and school readiness (Coates and Prosser, 2017). Evidence consistently shows that early childhood investments have high returns, especially for disadvantaged children (Knudsen et al., 2006). This supports the argument that governments should focus on equalising initial endowments through early interventions, rather than compensating for differences in outcomes later in life (Currie, 2001). For instance, while Norway's childcare reform had minimal causal effects on the employment rates of married mothers (Havnes and Mogstad, 2011a), it significantly improved children's educational attainment (Havnes and Mogstad, 2015; Havnes and Mogstad, 2011b). These findings align with evidence

[49]In the Family Resources Survey, formal childcare includes playgroup or pre-school, day nursery or crèche, nursery school, infant's school (reception or nursery), primary school (reception or nursery), out of school club, holiday scheme, family/combined centre, boarding school, childminder, and other formal arrangements. Informal childcare includes grandparents, non-resident parent/ex-spouse/ex-partner, siblings, other relatives, nanny/au pair, friends or neighbours, and other non-relatives (including babysitter).

from intensive early intervention programs in the US (Karoly et al., 2005). This evidence suggests that the benefits of childcare policies extend beyond labour market impacts, potentially influencing long-term effects on child outcomes. However, this research does not examine the impact of the Offer on childhood outcomes or equality of opportunity due to data limitations, despite these being core priorities for Welsh Government, as outlined in the Government of Wales Act. Consequently, it is not possible to rule out significant impacts in these areas, and future work should aim to fill this evidence gap.

Other potential issues include self-selection, where families might move to trial wards to access the Offer earlier, and concurrent policies implemented at the national level, such as Universal Credit.[50] However, the high costs associated with moving likely outweigh the financial benefits of free childcare, making widespread self-selection unlikely. While the data cannot directly control for induced mobility, such effects are considered part of the overall impact and do not undermine the validity of the research design. Additionally, the rollout of Universal Credit during the same period could have influenced parental employment incentives. However, because Universal Credit was implemented on a broader scale than the Offer, exposure was similar across treatment and control groups, limiting the potential for differential effects. Further, Universal Credit did not introduce additional childcare subsidies, limiting its direct impact on parental employment decisions. Aside from the rollout of Universal Credit, no other major national policy changes occurred during this period that might confound the analysis.

Finally, the analysis focuses solely on parental labour market activities and does not address the Offer's impact on unpaid activities, the distribution of household responsibilities, or child development.

5.8 Conclusion

In the context of many countries increasing the number of hours of free or highly subsidised childcare for pre-school children, and with the extension of childcare subsidies to all under-fives by September 2025 in England, it is important to understand the likely labour supply effects of such policies, particularly as increasing parental employment is often a stated aim. Using comprehensive and nationally representative data from both the secure version of the person and household APS (ONS, 2024a; ONS, 2023a), the research contributes to the literature by evaluating the impact of the Offer on parental

[50] Universal Credit was rolled out in Shotton, Flint, and Mold in April 2017; Cwmbran and Pontypool in July 2017; Wrexham, Neath, and Port Talbot in October 2017; Newport Gwent in November 2017; Gorseinon, Morriston, and Swansea in December 2017; Cardiff Alexandra House and Cardiff Charles Street in February 2018; Rhyl in April 2018; Colwyn Bay, Llandudno, Bridgend, Maesteg, and Porthcawl, Abergavenny, Caldicot, Chepstow, and Merthyr Tydfil in June 2018; Abertillery and Ebbw Vale in July 2018; Bargoed, Blackwood, Caerphilly, Haverfordwest, Milford Haven, and Pembroke Dock in September 2018; Brecon, Llandrindod Wells, Machynlleth, Newtown, Welshpool, Ystradgynlais, Barry, and Penarth in October 2018; Aberdare, Llantrisant, Pontypridd, Porth, Tonypandy, and Treorchy in November 2018; and Amlwch, Holyhead, Llangefni, Aberystwyth, Cardigan, Bangor, Caernarfon, Dolgellau, Porthmadog, Pwllheli, Ammanford, Carmarthen, and Llanelli in December 2018.

employment rates. It employs multiple identification approaches - a sharp RDD, static and dynamic DiDs, and a staggered DiD approach proposed by Callaway and Sant'Anna (2021). In doing so, it provides the first quantitative evaluation of the policy, complementing Welsh Government's annual qualitative evaluations (Glover et al., 2018; Glyn et al., 2019; Glyn et al., 2021; Glyn et al., 2022; Harries et al., 2023).

Across these approaches, the results consistently show no significant impact of Offer eligibility on parental employment rates, hours worked, or heterogeneous impacts across demographic groups. These findings contribute to the growing body of evidence suggesting that even well-designed and generous childcare policies do not always lead to substantial shifts in labour market outcomes. While this contrasts with international evidence from Quebec (Baker et al., 2008), Germany (Bauernschuster and Schlotter, 2015), and Argentina (Berlinski and Galiani, 2007), it is more consistent with recent findings from England and elsewhere showing similarly modest impacts (e.g., Brewer et al. 2022; Havnes and Mogstad 2011a; Fitzpatrick 2010. Unlike the evaluation in England (Brewer et al., 2022), there is no evidence of a positive impact for mothers whose youngest child was eligible, possibly reflecting the specific labour market dynamics, demographic profile, and multi-objective nature of the Offer in Wales. Limited statistical power in the available data may also contribute to the absence of significant effects.

Several factors could explain the minimal impact observed. First, parental employment in Wales was already relatively high before the Offer, leaving less scope for growth.Second, many parents may have secured informal or paid childcare before eligibility began, meaning the Offer primarily reduced costs for families already working rather than drawing new entrants into the labour force. Third, prior research suggests that impacts on hours worked often emerge gradually, so effects may be stronger in the medium term. Fourth, there may simply be little scope for increasing hours if parents are already working as much as they can, a possibility supported by Wales' relatively high rates of formal childcare use before the Offer's introduction, as suggested by external research that explored options for extending childcare support in Wales prior to the Offer's introduction (Paull and Xu, 2015).

In addition, access and eligibility constraints may limit the Offer's reach. Qualitative evaluations report lower take-up in some areas, particularly in the Valleys, despite high awareness (Glyn et al., 2022). The work requirement may exclude lower-income families who could benefit most, while supply-side constraints — such as the finding that only 23% of local authorities provide sufficient childcare to meet demand (Joseph Rowntree Foundation, 2020) — may restrict actual access even among eligible families. Without administrative data on participation, it is difficult to distinguish between low uptake and low impact, underscoring the need for better monitoring.

While increasing parental employment is an important policy goal, it is not the sole purpose of the Offer (Coates and Prosser, 2017). International evidence from Norway

(Havnes and Mogstad, 2011a; Havnes and Mogstad, 2015) and the US (Karoly et al., 2005) shows that childcare reforms can generate long-term gains in child outcomes even when labour market effects are small. The Offer may therefore still deliver substantial benefits in child development, family well-being, and gender equality that this study cannot assess due to data limitations but that remain central to the policy's aims.

In conclusion, the findings suggest that the Offer has had a limited effect on parental employment and usual hours worked in Wales. This highlights the need for policymakers to carefully consider the design and objectives of childcare policies and underscores the importance of developing comprehensive data infrastructure to systematically collect data on childcare policy uptake, participation rates, and broader socio-economic outcomes — such as parental well-being, child development, and school readiness — would enable more precise assessments of policy effectiveness and whether the Offer meets its original aims.

Chapter 6

Conclusion

This thesis provides empirical evidence on the magnitude, spatial variation, and drivers of gender inequality across labour markets in the UK, with a particular focus on the policy implications. It makes a novel contribution to the literature by examining spatial variation within the UK - a context that, despite ongoing devolution and decentralisation, maintains relatively uniform institutional, economic, and policy frameworks. This approach addresses key challenges associated with cross-country comparisons, including data harmonisation, institutional heterogeneity, and cultural differences. The findings highlight the importance of local labour market structures, the spatial allocation of employees, and potential spatial constraints that vary by gender. Further, by exploiting the unique implementation of a devolved childcare policy and applying quasi-experimental approaches, this thesis provides evidence on the effectiveness of a policy aimed at reducing gender gaps, particularly those arising from having children. This concluding chapter synthesises the key findings of each empirical Chapter, assesses their broader academic and policy implications, outlines their main limitations, and identifies avenues for future research.

The first empirical Chapter of this thesis (Chapter 3) explores the magnitude and determinants of spatial variation in GPGs across areas at both the regional (NUTS 1) and local (NUTS 3) levels within Britain. Using secure data from the 2022 ASHE, which provides comprehensive and reliable information on the structure and distribution of earnings in the UK, the analysis enable analysis at smaller geographical levels and represents the first full post-pandemic year unaffected by furlough policies.

The findings reveal substantial spatial variation in GPGs across areas within Britain. While the national raw GPG stands at 15.03%, regional estimates range from 10.19% in Wales to 16.88% in London. At the local level, the variation is even more pronounced, with the raw GPG varying from -0.40% in Enfield to 28.92% in Solihull. This degree of variation mirrors differences observed across European countries (Kaya, 2023) and across areas within Spain (Murillo Huertas et al., 2017) and Germany (Fuchs et al., 2021). These findings highlight that national-level GPG estimates obscure significant spatial disparities by aggregating data across diverse labour markets. The analysis identifies key drivers of this variation, including occupational segregation and public sector employment, consistent with cross-country evidence demonstrating that both gender differences in observable characteristics and their returns contribute to the magnitude of national GPGs and the international variation (Blau and Kahn, 1992; Blau and Kahn, 1996b). These findings also align with prior research on the determinants of the GPG in the UK (e.g. Olsen et al. 2018), which emphasises the role of productivity-related characteristics in shaping GPGs. However, given the study's focus on relative measures, there is a risk that what appears to be a female advantage in certain areas may instead reflect male disadvantage, particularly in less prosperous regions (Fuchs et al., 2021; Jones and Kaya, 2022b; Longhi, 2020). Future research should further explore the relationship between spatial variation in GPGs and overall wage levels to better understand these dynamics.

OB decompositions of GPGs across areas at the regional and local levels within Britain indicate that gender differences in observable characteristics explain less than a third of raw GPGs at the regional level and under half at the local level. This leaves the majority of raw GPGs unexplained, a component often interpreted as an upper-bound estimate of discrimination, though this interpretation requires caution due to potential omitted variable bias. The findings suggest that much of the spatial variation in GPGs arises from differences in the spatial allocation of employees. This is consistent with cross-country comparisons (Kaya, 2023) and UK-specific research showing that the smaller GPG in Northern Ireland is largely attributable to occupational allocation and the returns to occupations (Jones and Kaya, 2022b). For example, Wales and 55 local areas are estimated to have a negative explained component, indicating that women working in these areas have, on average, more productivity-enhancing characteristics than men. However, since these areas are predominantly located at the lower end of the GPG spatial distribution, this raises concerns that smaller GPGs may obscure underlying inequalities, consistent with findings from Germany (Fuchs et al., 2021) and Spain (Murillo Huertas et al., 2017).

The unexplained component of the GPG, which consistently favours men, remains relatively stable across areas but exhibits greater variation at the local level. This suggests that areas with smaller GPGs do not necessarily reflect greater gender equality, reinforcing the need to distinguish between the GPG and 'discrimination'. These findings align with evidence from Northern Ireland (Jones and Kaya, 2022b) and Germany (Fuchs et al., 2021), as well as long-term trends in the UK, which demonstrate the persistence of large unexplained GPGs despite overall GPG narrowing (Jones et al., 2018; Jones and Kaya, 2022b). Recognising the potential influence of broader contextual factors, the unexplained GPG is found to vary on the basis of local area characteristics, including industrial composition, unemployment rates, and the degree of rurality. Specifically, areas with a high proportion of employees in the Manufacturing and Construction industries tend to have larger unexplained GPGs, whereas those with a greater share of employees in the Public administration, education, and social work industry tend to have smaller unexplained GPGs. These findings are consistent with evidence from Germany, where male-dominated industries have been associated with larger unexplained gaps, potentially reflecting economic opportunities within these industries (Fuchs et al., 2021). This may indicate the potential effectiveness of equality duties in reducing unexplained GPGs in the public sector, as suggested by national-level evidence (Blackaby et al., 2012a; Jones et al., 2018). Similar policy interventions could be explored for industries with persistently large unexplained GPGs, such as Manufacturing and Construction.

Given the continued prominence of the unexplained GPG across areas, a natural extension of the Chapter would involve utilising data with richer individual-level information, such as the QLFS. However, due to its smaller sample size, the QLFS is unsuitable for analysis at smaller geographical levels. Alternatively, the linked ASHE-2011 Census dataset could provide a more comprehensive wage specification by integrating detailed individual characteristics with reliable earnings data at the local level. However, given that this data predates the COVID-19 pandemic, it does not capture recent shifts in labour market dynamics, gender inequality, or spatial employment patterns (Blundell et al., 2022). While further research is required to fully understand the unexplained component of the GPG, this study underscores the need for policymakers to look beyond national headline figures and implement policies that address structural gender inequality in the labour market.

An additional avenue for future research involves using the longitudinal aspect of the ASHE to analyse the evolution of spatial variation in the GPG within Britain following the introduction of policies such as the PSED and GPG reporting requirements. With additional post-pandemic data now available, a temporal analysis of GPG trends across Britain would provide further insights into the spatial drivers of these trends and the role of differential policies, particularly given the increasing regional disparities since 1997 (Figure 3.2). Such an analysis would determine whether this observed divergence is primarily driven by London due to its industrial composition.

Building on the findings of the first empirical Chapter, the second empirical Chapter (Chapter 4) shifts focus to the CGG and its potential role as a driver of the mean GPG in the UK. Using pooled data from the QLFS for the fourth quarters of 2022 and 2023, this Chapter examines the post-pandemic CGG within the context of widespread adoption of home and hybrid working, which has significantly altered commuting behaviours. The transition towards home working has the potential to mitigate the CGG and other related labour market outcomes by reducing the time and stress associated with commuting, a shift that has been identified as particularly beneficial for women (Alipour et al., 2021; Adams-Prassl et al., 2022; Barrero et al., 2021; Arntz et al., 2022; Nagler et al., 2024; Maestas et al., 2023; Datta, 2019; Aksoy et al., 2022). By focusing on the period following the COVID-19 pandemic, the analysis contributes to the ongoing debate on gender inequality in the post-pandemic labour market by presenting evidence of the impact of commuting in a context where the majority of GPGs across Britain remain unexplained (Chapter 3).

Despite the potential mitigating effects of increased home working, the estimated CGG remains substantial at 13.35%, a figure consistent with prior UK-based estimates using Understanding Society data (Reuschke and Houston, 2020) and comparable to estimates from other European countries (Giménez-Nadal et al., 2022), including Germany (Fuchs et al., 2024). This estimate is derived from employees who primarily work at locations separate from their homes, a group more likely to have lower qualifications and be concentrated in regions outside London and the South East. However, given London's greater reliance on public transport, commuting patterns in these regions likely differ substantially (Nafilyan, 2020). The OB decomposition of the CGG suggests that the majority of the CGG remains unexplained even after controlling for individual and household characteristics not considered in the first empirical Chapter. This may be attributed to unobserved factors such as personal preferences, unmeasured characteristics, or stochastic variables like weather, congestion, or communications infrastructure, as highlighted in other research (Rouwendal and Rietveld, 1994; Benito and Oswald, 2000; Giménez-Nadal et al., 2022). Among the explained components, job characteristics - particularly full-time and public sector employment - emerge as the largest contributors, emphasising the importance of the spatial distribution of high-skilled job opportunities. These findings align with research on the commuting behaviour of parents in Scotland, where similar patterns have been observed (McQuaid, 2009). Further, the role of workplace regions as a significant driver of the CGG highlights the importance of spatial variations in job accessibility and labour market opportunities, consistent with findings on commuting behaviour in Germany (Fuchs et al., 2024). While household composition has a comparatively smaller effect on commute times, the presence of school-aged children appears to influence the commuting patterns of women under the age of 40, consistent with the broader literature on the gendered impacts of parenthood on employment decisions (e.g., Kleven et al. 2018; Kleven et al. 2019).

To address potential endogeneity between commuting and wages, the analysis employs a 2SLS regression model, using the average commute time of workers within the same industry sector (one-digit SIC) as an IV for self-reported commute times. This approach represents a methodological contribution to the literature, as identifying suitable instruments for commuting is inherently challenging (Manning, 2003). The chosen IV is justified by the argument that industry-level variables serve as effective instruments (Bartik, 1991), as commuting patterns are often correlated within industries due to geographic clustering and similar operational conditions affecting all workers in the same industry, including congestion (Gibbons and Machin, 2006). This methodology complements previous research using alternative IVs, such as district of residence, industry and occupation in Chile (Troncoso et al., 2021) and city shape in the US (Farré et al., 2023), neither of which are applicable in the UK context. Additionally, the research contributes to the broader literature addressing endogeneity concerns, through sample constraints and job duration models (Caldwell and Danieli, 2024; Gutierrez, 2018; Le Barbanchon et al., 2021; Ekberg and Widegren, 2019).

The analysis estimates a raw mean GPG of 16.2%, with the majority remaining unexplained even after controlling for an extensive set of individual characteristics, household variables, and commute time. However, an OB decomposition using the 2SLS specification finds that gender differences in commute time explain 10.14% of the raw GPG. While this estimate is on the lower end of the international range, it aligns with evidence suggesting that commuting explains between 10-25% of the raw GPG (e.g., Le Barbanchon et al. 2021; Farré et al. 2023; Caldwell and Danieli 2024; Gutierrez 2018; Ekberg and Widegren 2019). This contribution is substantial and comparable to other work-related characteristics typically explored in the literature, such as public sector employment (Jones et al., 2018). These findings suggest that commuting plays a crucial role in shaping the mean GPG and that spatial factors should be systematically incorporated into GPG analyses. The results also emphasise the influence of non-wage amenities, which influence job accessibility, labour market participation, and employment choices (Goldin, 2014; Mas and Pallais, 2017; Wiswall and Zafar, 2018; Clark et al., 2020).

The research illustrates how constraints on spatial mobility — whether driven by household responsibilities, labour market structures, or broader socioeconomic factors — contribute to gender inequalities in the labour market. Policies aimed at increasing women's mobility could include the expansion of safe and reliable public transport infrastructure, initiatives to reduce gendered household responsibilities, and measures to promote flexible work arrangements. Additionally, raising employer awareness of gendered commuting differences could encourage workplace policies that accommodate employees with caregiving responsibilities, such as designated parking spaces for individuals engaging in 'trip-chaining' behaviours (e.g., dropping children off at school before commuting to work). Future research could further explore regional variations in gendered commuting to inform targeted policy interventions, particularly in relation to public transport accessibility.

Despite its empirical and methodological contributions, this analysis has several limitations. First, the QLFS collects commuting data only in the fourth quarter, restricting the temporal scope of the analysis. However, future research could replicate this analysis using the most recent 2024 bumper sample, which includes commuting data across all quarters. Additionally, the data does not distinguish between hybrid workers who regularly commute and those who commute infrequently, nor does it differentiate between hybrid and fully remote workers. These distinctions are particularly relevant in the post-COVID-19 context, where evolving work arrangements continue to reshape commuting patterns. Future research could also address potential selection biases in the

QLFS, which may affect the representativeness of the commuter subsample. Furthermore, declining response rates since 2023 pose challenges to the robustness of the data, and the relatively small sample size may limit the generalisability of the findings. These limitations highlight the need for further research to address data gaps and better capture the changing nature of commuting behaviours. Analysing post-pandemic commuting trends over time using repeated cross-sectional data from the QLFS, could provide additional insights into whether evolving commuting behaviours mitigate gender inequality in the labour market. Nevertheless, this Chapter makes an important contribution by demonstrating that spatial considerations are important factors in explaining wage differences, underscoring the need for further investigation into the intersection of commuting and gender inequality.

Building on the spatial analysis of gender gaps across labour markets in the UK in the first two empirical Chapters, the third empirical Chapter (Chapter 5) provides the first quantitative evaluation of the Welsh Government's childcare policy, the Offer, on parental employment rates. Given that time out of the labour force due to childcare responsibilities is a significant driver of the child wage penalty and long-term gender gaps (Bertrand, 2011; Kleven et al., 2018; Kleven et al., 2019; Schober, 2013), the Offer represents a key policy intervention aimed at mitigating gender gaps in the labour market. The policy provides working parents of three- and four-year olds with 30 hours of free childcare per week for up to 48 weeks a year.

In contrast to much of the existing literature, which primarily focuses on maternal employment, the research evaluates the Offer's impact on both mothers and fathers. In doing so, it aligns with recent studies in England (Brewer et al., 2022), Switzerland (Felfe et al., 2016), and Norway (Andresen and Havnes, 2019), which take a broader perspective on parental labour market outcomes. By examining Wales, where childcare provision differs from other parts of the UK, the evaluation offers insights into the effectiveness of targeted childcare subsidies in a devolved policy setting, complementing the evaluation of England's childcare policy. These findings contribute to the broader policy debate on the sustainability, accessibility, and long-term impact of early childhood education and care provision in Wales (Thomas, 2024). Moreover, the evaluation is particularly timely given the planned expansion of childcare subsidies in England from 2025, and the Welsh Government's extension of its Flying Start scheme, both of which underscore the increasing policy focus on early years provision.

The evaluation employs nationally representative secure data from the household and person APS and applies two quasi-experimental approaches to estimate the causal impact of the Offer on parental employment rates. The first approach applies a sharp RDD approach to exploit the strict age-based eligibility criteria of the Offer during its first full year of implementation (April 2019 - March 2020, i.e. post-trial period). This methodology is widely used in the evaluation of childcare policies, including in England (Brewer et al., 2022; Brewer and Crawford, 2010; Blanden et al., 2022), Argentina

(Berlinski et al., 2011), France (Goux and Maurin, 2010), Germany (Bauernschuster and Schlotter, 2015), and the US (Fitzpatrick, 2010; Fitzpatrick, 2012; Gelbach, 2002). The second approach employs a DiD framework to exploit the phased geographical rollout of the Offer across Welsh wards, covering both the trial period (July 2017 - April 2019) and a substantial pre-Offer period (January 2016 - June 2017). While the DiD approach has been extensively used in childcare policy evaluations in England (Brewer et al., 2022), Argentina (Berlinski and Galiani, 2007), Canada (Baker et al., 2008; Lefebvre and Merrigan, 2008), Germany (Bauernschuster and Schlotter, 2015), Israel (Schlosser, 2011), the Netherlands (Bettendorf et al., 2015), Sweden (Lundin et al., 2008), Norway (Havnes and Mogstad, 2011a), Spain (Nollenberger and Rodriguez-Planas, 2015), and the US (Cascio, 2009), the staggered DiD approach adopted here is novel in the context of childcare policy evaluation. This methodological innovation is only enabled by the unique phased implementation of the Offer, designed to ensure feasibility, effective delivery, and continuous assessment.

The findings indicate that the Offer has had no significant impact on parental employment rates or hours worked. These results align with a growing body of evidence suggesting that even relatively generous childcare policies do not always translate into measurable changes in labour market outcomes (Brewer et al., 2022; Havnes and Mogstad, 2011a; Fitzpatrick, 2010). This contrasts with findings from Quebec, Germany, and Argentina, where similar policies have been associated with significant increases in parental (mostly maternal) employment (Bauernschuster and Schlotter, 2015; Baker et al., 2008; Berlinski and Galiani, 2007). Although prior research suggests that the impact of childcare policy may vary across demographic groups (Berlinski et al., 2011; Bauernschuster and Schlotter, 2015; Havnes and Mogstad, 2011a; Lundin et al., 2008), the research finds no differential impacts across parental subgroups, including mothers and parents whose youngest child is eligible for the Offer. These findings differ from the evaluation of England's childcare policy, which found little overall impacts on parental employment but identified positive employment effects for mothers whose youngest child was eligible (Brewer et al., 2022).

Several factors may explain these findings. First, Wales' relatively high maternal employment rate may have constrained the potential for further increases in labour supply, in contrast to countries with lower baseline maternal employment rates, such as Germany and Argentina, where policy impacts were more pronounced (Bauernschuster and Schlotter, 2015; Berlinski et al., 2011). Second, many parents may have already relied on informal or paid childcare arrangements before becoming eligible for the Offer, limiting its effect on employment decisions. Rather than acting as a labour market incentive, the policy may primarily serve as a financial support mechanism for parents already in employment. Third, limited reliance on formal childcare services among families in the target age group may have further contributed to the lack of observed employment effects. These factors are compounded by the relatively small sample sizes available for each estimation approach, despite the use of the largest available dataset for Wales with sufficiently detailed information on childcare eligibility. These sample size constraints may reduce statistical power, making it difficult to determine whether the absence of a significant effect reflects genuine policy ineffectiveness or data limitations. While both the RDD and DiD approaches offer robust identification strategies, they rely on assumptions that may not fully hold, such as the comparability of parents on either side of the RDD eligibility cutoff and the common trends assumption in the DiD approach. Although the staggered policy rollout mitigates some of these concerns, methodological challenges remain inherent in evaluating the labour market impacts of childcare policies.

Low policy uptake may also have influenced the findings. Qualitative evidence suggests substantial regional variation in Offer participation, with lower engagement in certain areas potentially reducing its overall effectiveness (Glyn et al., 2022). Moreover, the Offer's work requirement may exclude many low-income families who would benefit most from subsidised childcare, further limiting its impact on employment. This issue is further compounded by evidence indicating that only 23% of local authorities in Wales currently provide sufficient childcare to meet demand (Joseph Rowntree Foundation, 2020), raising concerns about accessibility and supply-side constraints. The absence of centralised administrative data on individual Offer participation complicates the ability to distinguish between low uptake and genuine policy ineffectiveness, underscoring the need for enhanced data collection and centralised monitoring.

As childcare policy continues to evolve in both Wales and England, integrating evaluation mechanisms from the outset will be essential for evidence-based policymaking. Developing a comprehensive data infrastructure to systematically collect data on childcare policy uptake, participation rates, and broader socio-economic outcomes — such as parental well-being, child development, and school readiness — would enable more precise assessments of policy effectiveness and whether the Offer meets its original aims (Coates and Prosser, 2017). Furthermore, future research should explore the interactions between childcare policies and other welfare programs, such as Universal Credit, to provide a more holistic understanding of the factors influencing parental employment decisions. Expanding the scope of analysis to include unpaid household labour, gendered caregiving responsibilities, and child outcomes could further strengthen the evidence base for childcare policymaking. These considerations are particularly pertinent as the Welsh Government assesses the relative benefits of extending the Offer versus expanding the Flying Start scheme, particularly given concerns over the financial sustainability of childcare provision under devolved funding arrangements.

Ultimately, this thesis underscores the need for more comprehensive and accessible data to analyse gender inequality across labour markets in the UK. Given the UK's comparatively slow progress in narrowing gender gaps relative to other OECD nations and growing regional divergences, a stronger empirical foundation is necessary to inform the development of evidence-based policies that address drivers of gender inequality.

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Appendix A

Table A.1: Key Policies in Britain affecting Gender Inequality across Labour Markets

Policy	Summary
Equal Pay Act, 1970 (implemented in January 1976)	Established the principle of equal pay for women and men engaged in the same or equivalent work.
Sex Discrimination Act, 1975	Prohibited discrimination on the basis of sex or marital status in employment, education, and the provision of goods and services.
Equal Value Directive, 1983	Reinforced the principle of equal pay for work of equal value, extending legal protections beyond identical job roles.
National Childcare Strategy, 1999	Introduced measures to improve childcare accessibility, including free nursery education for four-year-olds, later extended to three-year-olds. Aimed to support parental employment, particularly for mothers.
Part-time Workers' Regulations, 2000	Prohibited less favourable treatment of part-time workers compared to full-time employees in terms of pay, working conditions, and benefits.
Right to Request Flexible Working, 2003	Granted working parents the right to request flexible work arrangements for childcare reasons, with employers required to consider these applications seriously.
Equality Act, 2010	Harmonised existing equality legislation, providing legal protection to nine protected characteristics: age, gender, race, disability, religion, pregnancy and maternity, sexual orientation, gender reassignment, and marriage and civil partnership). Initially included provisions to for GPG reporting, but these were later implemented through separate regulations.
Shared Parental Leave, 2015	Allowed eligible parents to share maternity leave entitlement and pay.
30 Hours Free Childcare Policy, 2017	Provided 30 hours free childcare per week for children aged 3-4 in England (and later devolved nations), available to working parents earning under £100K and at least £167 per week.
Equality Act 2010 (Gender Pay Gap Information) Regulations, 2017	Mandated employers with 250 or more employees to annually report six measures of the GPG within their organisations. Reporting regulations were temporarily suspended during the COVID-19 pandemic.

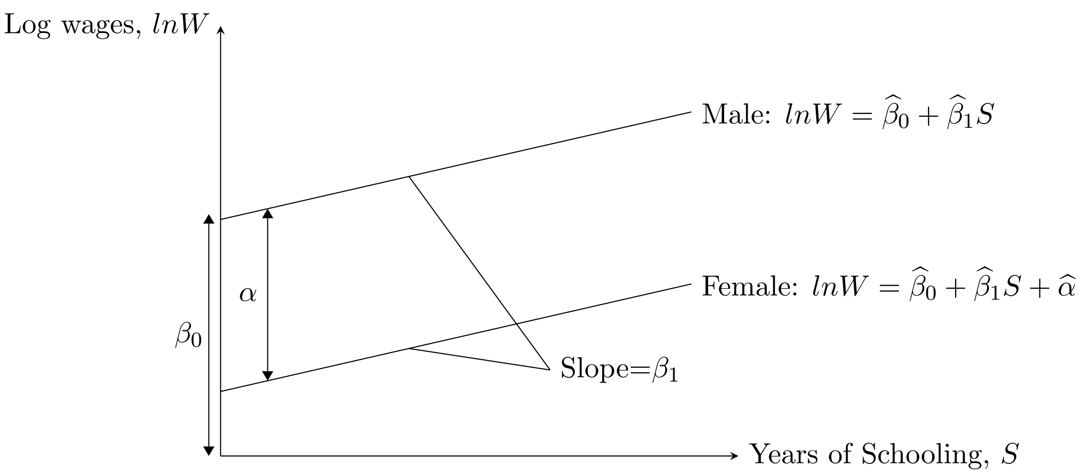
Source: Adapted from Bryson et al. 2020)

Table A.2: Summary of Devolved Powers

Northern Ireland, Scotland and Wales	**Also devolved in Northern Ireland**
Health and social services Education, training and skills Local government Housing Economic development Agriculture, forestry and fisheries Environment and planning Transport Tourism, sport, culture and heritage	Justice and policing Charity law Energy Employment law Social security, child support, pensions NI Civil Service Equal opportunities Time Long haul Air Passenger Duty
Also devolved in Scotland	**Also devolved in Wales**
Justice and policing Charity law Drink-drive limit Stamp Duty Licensing of onshore oil and gas extraction Some income tax (inc. ability to set rates and thresholds) Regulate air weapons Abortion Tax on carriage of passengers by air Management of Crown Estate assets in Scotland Equal Opportunities in relation to public bodies in Scotland Fire and rescue services Water and flood defences Landfill tax Some social security elements Consumer advocacy and advice Scottish Parliament and local government elections Policing of railways in Scotland Road signs and speed limits	Welsh language Some income tax Stamp duty Landfill tax Road signs and speed limits Equal Opportunities in relation to public bodies in Wales Licensing of onshore oil and gas extraction Assembly and local government elections

Source: UK Government (n.d.)

Figure A.1: Estimation of the Adjusted GPG using a Mincerian Wage Equation



Notes: (i) Estimation of the Mincerian wage equation yields two separate regressions lines for males and females. The vertical distance between the two regression lines represents α as the GPG adjusted for years of schooling. (ii) A hat above the variable indicates its OLS estimate.

Table A.3: Public Sector Equality Duties in Wales, Scotland and England

Specific Duties	**Specific Duties relating to the GPG**
Equality Act 2010 (Statutory Duties)(Wales) Regulations 2011	Requires public bodies to: • Publish objectives to meet the general PSED; • Provide a statement on steps taken or intended to achieve each objective; • Monitor progress towards meeting objectives; • Consider equality information when setting objectives; • Publish annual workforce pay data disaggregated by protected characteristics, job, grade, pay, working pattern, and contract type; and • Publish an action plan addressing gender pay differences.
Equality Act 2010 (Specific Duties)(Scotland) Regulations 2012	Public bodies in Scotland have a duty to: • Report progress on mainstreaming the equality duty; • Publish equality outcomes and report progress; • Gather and use employee equality data; • Consider equality criteria in public procurement; and • Publish information in an accessible format. Scottish Ministers must also publish proposals to enable better performance. Public bodies with 20 (since 2016) or more employees must publish a statement an equal pay statement every four years, containing policies on equal pay and occupational segregation. The first report may focus solely on gender but later reports must include additional protected characteristics.
Equality Act 2010 (Specific Duties and Public Authorities) Regulations 2017	Public bodies in England are required to: • Publish annual information demonstrating compliance with the general PSED; • Publish one or more specific and measurable equality objectives every four years. Since 2017, public bodies with 250 or more employees must publish six annual measures of the (mean and median) GPG, although reporting was temporarily suspended during the COVID-19 pandemic.

Appendix B

Table B.1: Overview of Empirical Research on Spatial Variation in the Gender Pay Gap

Study	**Summary**
Jones and Kaya (2022b)	Using QLFS data from 2016 to 2019, the analysis explores the smaller, and sometimes negative, GPG in Northern Ireland compared to the rest of the UK, employing OB and JMP decompositions. The smaller GPG in Northern Ireland is predominantly attributed to women possessing, on average, more productive characteristics and lower wage inequality, which partially mitigates the impact of gender differences in returns to characteristics. Occupational allocation and non-gender specific factors account for a substantial portion of the cross-country GPG differential.
Stewart (2014)	Using ASHE data from 2012, the research examines the median GPG in London compared to the rest of Britain across the wage distribution employing OB decompositions. The analysis estimates a larger GPG in London, especially in the upper half of the wage distribution. At the median, the regional GPG difference is due to differences in individual and work-related characteristics; however, in the top third of the wage distribution, the higher GPG in London is not driven by characteristics.
Fuchs et al. (2021)	Using administrative data for all full-time employees in Germany, the research documents substantial spatial heterogeneity in the GPG across local areas, employing OB decompositions. The results indicate that high GPG local areas are driven by gendered differences in job-related characteristics, whereas low-GPG areas reflect gender differences in individual characteristics. The industrial composition of local areas is also an important driver of the spatial variation in GPGs across local areas.
Murillo Huertas et al. (2017)	Using matched employer-employee microdata from Spain, the research analyses the regional variation in the GPG through a JMP decomposition, supported by panel data techniques. The research identifies significant regional variations in the GPG, comparable to cross-country disparities in Europe. These gaps are partially explained by gender differences in characteristics, but institutional, economic, and demographic factors (minimum wage levels, female labour force participation, and fertility rates) also contribute meaningfully to regional heterogeneity.

Table B.2: Unweighted Sample Size across Areas in Britain, by Gender and Geographical Level

Area	Total	Males	Females
National	124,963	58,525	66,438
Regional			
North East	5,069	2,290	2,779
North West	14,105	6,566	7,539
Yorkshire and the Humber	11,358	5,381	5,977
East Midlands	8,943	4,238	4,705
West Midlands	11,190	5,401	5,789
East of England	11,595	5,520	6,075
London	17,173	8,262	8,911
South East	16,723	7,833	8,890
South West	10,805	5,171	5,634
Wales	6,011	2,680	3,331
Scotland	11,991	5,183	6,808
Local - North East (England)			
Hartlepool and Stockton on Tees	508	224	284
South Teeside	398	203	195
Darlington	234	108	126
County Durham	851	394	457
Northumberland	503	207	296
Tyneside	1,955	856	1,099
Sunderland	620	298	322
Local - North West (England)			
West Cumbria	465	262	203
East Cumbria	553	262	291
Manchester	1,736	785	951
Greater Manchester South West	1,076	506	570
Greater Manchester South East	730	337	393
Greater Manchester North West	915	416	499
Greater Manchester North East	1,008	467	541
Blackburn with Darwen	266	101	165
Blackpool	325	134	191
Lancaster and Wyre	403	199	204
Mid Lancashire	1,057	507	550
East Lancashire	507	234	273
Chorley and West Lancashire	358	169	189
Warrington	535	291	244
Cheshire East	835	401	434
Cheshire West and Chester	666	307	359
East Merseyside	798	405	393
Liverpool	1,056	456	600
Sefton	429	162	267
Wirral	387	165	222
Local - Yorkshire and the Humber			
Kingston upon Hull	550	251	299
East Riding of Yorkshire	614	279	335
North and North East Lincolnshire	573	279	294
York	490	237	253
North Yorkshire County Council	1,260	616	644
Barnsley, Doncaster and Rotherham	1,319	616	703
Sheffield	1,057	514	543
Bradford	847	374	473
Leeds	2,914	1,384	1,530
Calderdale and Kirklees	1,027	511	516
Wakefield	707	320	387
Local - East Midlands (England)			
Derby	634	289	345
East Derbyshire	501	238	263
South and West Derbyshire	752	378	374
Nottingham	724	327	397

North Nottinghamshire	971	445	526
South Nottinghamshire	483	216	267
Leicester	657	302	355
Leicestershire County Council and Rutland	1,432	730	702
West Northamptonshire	839	432	407
North Northamptonshire	619	312	307
Lincolnshire County Council	1,331	569	762
Local - West Midlands (England)			
Herefordshire	381	176	205
Worcestershire County Council	1,071	517	554
Warwickshire County Council	1,228	620	608
Telford and Wrekin	409	192	217
Shropshire	602	327	275
Stoke-on-Trent	666	295	371
Staffordshire County Council	1,552	724	828
Birmingham	2,051	987	1,064
Solihull	641	410	231
Coventry	733	293	440
Dudley	478	228	250
Sandwell	485	248	237
Walsall	448	212	236
Wolverhampton	445	224	221
Local - East of England			
Peterborough	521	260	261
Cambridgeshire County Council	1,482	729	753
Suffolk	1,519	773	746
Norwich and East Norfolk	773	370	403
North and West Norfolk	383	187	196
Breckland and South Norfolk	426	225	201
Luton	358	147	211
Hertfordshire	2,598	1,141	1,457
Bedford	385	169	216
Central Bedfordshire	457	200	257
Southend-on-Sea	247	113	134
Thurrock	239	136	103
Essex Haven Gateway	730	343	387
West Essex	466	225	241
Heart of Essex	572	282	290
Essex Thames Gateway	439	220	219
Local - London			
Camden and City of London	3,001	1,535	1,466
Westminster	1,992	971	1,021
Kensington & Chelsea and Hammersmith and Fulham	749	338	441
Wandsworth	367	174	193
Hackney and Tower Hamlets	820	388	432
Tower Hamlets	1,089	589	500
Haringey and Islington	904	459	445
Lewisham and Southwark	1,282	571	711
Lambeth	495	219	276
Bexley and Greenwich	544	234	310
Barking & Dagenham and Havering	468	205	263
Redbridge and Waltham Forest	425	190	235
Enfield	370	159	211
Bromley	410	156	254
Croydon	432	203	229
Merton, Kingston upon Thames and Sutton	828	368	460
Barnet	406	185	221
Brent	695	388	307
Ealing	431	222	209
Harrow and Hillingdon	805	391	414

Hounslow and Richmond upon Thames	660	317	343
Local - South East (England)			
Berkshire	1,872	918	954
Milton Keynes	703	348	355
Buckingham County Council	803	380	423
Oxfordshire	1,544	764	780
Brighton and Hove	609	243	366
East Sussex County Council	752	328	424
West Surrey	1,362	620	742
East Surrey	625	291	334
West Sussex (South West)	754	350	404
West Sussex (North East)	668	372	296
Portsmouth and Isle of Wight	716	324	392
Southampton	529	234	295
South Hampshire	756	335	421
Central Hampshire	1,200	529	671
North Hampshire	659	301	358
Medway	386	184	202
Kent Thames Gateway	650	315	335
East Kent	769	328	441
Mid Kent	644	324	320
West Kent	722	345	377
Local - South West (England)			
Bristol, City of	1,308	626	682
Bath and North East Somerset, North Somerset and South Gloucestershire	1,466	733	733
Gloucestershire	1,048	527	521
Swindon	514	248	266
Wiltshire County Council	861	416	445
Bournemouth and Poole	659	329	330
Dorset County Council	737	357	380
Somerset	974	440	534
Cornwall and Isles of Scilly	916	446	470
Plymouth	560	246	314
Torbay	212	100	112
Devon County Council	1,550	703	847
Local - Wales			
Isle of Anglesey and Gwynedd	329	154	175
Conway and Denbighshire	397	162	235
South West and Mid Wales	846	339	507
Central Valleys	516	199	317
Gwent Valleys	511	225	286
Bridgend and Neath Port Talbot	444	222	222
Swansea	574	223	351
Monmouthshire and Newport	524	219	305
Cardiff and Vale of Glamorgan	1,275	614	661
Flintshire and Wrexham	595	323	272
Local - Scotland			
Aberdeen City and Aberdeenshire	1,134	465	669
Highlands and Islands	461	197	264
Inverness & Nairn and Moray, Badenoch & Starthspey	464	194	270
Angus and Dundee City	547	238	309
Clackmannanshire and Fife	767	307	460
East Lothian and Midlothian	250	125	125
Edinburgh, City of	1,756	812	944
Falkirk	314	121	193
Perth & Kinross and Stirling	545	246	299
West Lothian	336	139	197
East Dunbartonshire, West Dunbartonshire, Helensburgh and Lomond	333	133	200

Glasgow City	2,080	957	1,123
Inverclyde, East Renfrewshire and Renfrewshire	569	247	322
North Lanarkshire	657	315	342
Scottish Borders	225	101	124
Dumfries and Galloway	299	111	188
Ayrshire	674	246	428
South Lanarkshire	580	229	351

Source: Author calculations based on weighted ASHE 2022 data.

Table B.3: Variable Definitions

Variables	ASHE Variable	Definition
Dependent Variables		
(Log) hourly wages	*hexo*, derived from *gpox/bhr*	Log of hourly earnings for the reference period, excluding overtime, derived from gross pay excluding overtime and basic paid hours
Individual Characteristics		
Age (and age^2)	*age*	Age (in years)
Tenure (and tenure^2)	Derived from *empsta*	Months in present job
Full-/Part-time	*ft*	Dummy variable equals 1 if employed part-time, 0 if employed full-time
Permanent/Temporary contract	*pt*	Dummy variable, equals 1 if temporary/casual contract, 0 if permanent contract
Workplace Characteristics		
Firm size	Derived from	
Small $\leq$50 employees	*idbrnemp*	Dummy variable, equal 1 if place of work has 50 or less employees, 0 if place of work has 51 employees or more.
Medium (51-250 employees)		Dummy variable if place of work has 51-250 employees, 0 if place of work has 50 or less employees or 251 or more employees.
Large (251-1000 employees)		Dummy variable if place of work has 251-1000 employees, 0 if place of work has 250 or less employees or 1001 or more employees
Enterprise (1001+ employees)		Dummy variable if place of work has 1001 or more employees, 0 if place of work has 1000 or less employees
Collective agreement	Derived from *colag*	Dummy variable, equals 1 if an individual's wage is set by any type of collective agreement, 0 if an individual's wage is not set by any type of agreement
Occupations		
Managers & Senior Officials	Derived from *occ20*	Dummy variable, equals 1 if current occupation is managers and senior officials, 0 if current occupation is not managers and senior officials
Professional	Derived from *occ20*	Dummy variable, equals 1 if current occupation is professional, 0 if current occupation is not professional
Associate professional	Derived from *occ20*	Dummy variable, equals 1 if current occupation is associate professional, 0 if current occupation is not associate professional
Administrative	Derived from *occ20*	Dummy variable, equals 1 if current occupation is administrative and secretarial, 0 if current occupation is not administrative and secretarial

Skilled trades	Derived from *occ20*	Dummy variable, equals 1 if current occupation is skilled trades, 0 if current occupation is not skilled trades
Personal service	Derived from *occ20*	Dummy variable, equals 1 if current occupation is personal service, 0 if current occupation is not personal service
Sales & customer service	Derived from *occ20*	Dummy variable, equals 1 if current occupation is sales and customer service, 0 if current occupation is not sales and customer service
Process, plant & machine operatives	Derived from *occ20*	Dummy variable, equals 1 if current occupation is process, plant and machine operatives, 0 if current occupation is not process, plant and machine operatives
Elementary occupations	Derived from *occ20*	Dummy variable, equals 1 if current occupation is elementary occupations, 0 if current occupation is not elementary occupations
Public sector employment	*pubpriv*	Dummy variable, equals 1 if in public sector employment (legal status 4,5 and 6), 0 if private sector employment (legal status 1,2 and 3) or not for profit employment (legal status 7)
Occupational skill groups		
High-skilled occupations	Derived from *occ20*	Dummy variable, equals 1 if current occupation is professional, associate professional or managers and senior officials, 0 if current occupation is not professional, associate professional or managers and senior officials
Medium-skilled occupations	Derived from *occ20*	Dummy variable, equals 1 if current occupation is process, plant and machine operatives, skilled trades or elementary occupations, 0 if current occupation is not process, plant and machine operatives, skilled trades or elementary occupations
Low-skilled occupations	Derived from *occ20*	Dummy variable, equals 1 if current occupation is Sales & customer service, Personal Service or Administrative, 0 if current occupation is not Sales & customer service, Personal Service or Administrative

Table B.4: Hourly Wages by Gender in Selected Areas, by Full-Time Status

	Full-time employees				**Part-time employees**			
	All	Men	Women	Gap (%)	All	Men	Women	Gap (%)
National	£19.61	£20.58	£18.15	11.81	£14.59	£14.50	£14.62	-0.83
N	*87,049*	*48,967*	*38,082*		*37,914*	*9,558*	*28,356*	
Regional								
North East (England)	£16.96	£17.40	£16.32	6.21	£13.77	£14.15	£13.66	3.46
N	*3,409*	*1,915*	*1,494*		*1,660*	*375*	*1,285*	
North West (England)	£18.05	£18.89	£16.86	10.75	£14.06	£13.98	£14.09	-0.79
N	*9,999*	*5,538*	*4,461*		*4,106*	*1,028*	*3,078*	
Yorkshire and the Humber	£17.39	£18.25	£16.02	12.22	£13.30	£13.80	£13.12	4.93
N	*7,556*	*4,380*	*3,176*		*3,802*	*1,001*	*2,801*	
East Midlands (England)	£17.40	£18.14	£16.20	10.69	£13.53	£13.16	£13.63	-3.57
N	*6,158*	*3,625*	*2,533*		*2,785*	*613*	*2,172*	
West Midlands (England)	£18.17	£19.07	£16.73	12.27	£14.07	£13.38	£14.30	-6.88
N	*7,818*	*4,554*	*3,264*		*3,372*	*847*	*2,525*	
East of England	£18.70	£19.59	£17.23	12.05	£14.77	£14.41	£14.88	-3.26
N	*7,806*	*4,601*	*3,205*		*3,789*	*919*	*2,870*	
London	£25.93	£27.92	£23.17	17.01	£17.08	£16.12	£17.56	-8.93
N	*13,081*	*6,959*	*6,122*		*4,092*	*1,303*	*2,789*	
South East (England)	£19.81	£20.91	£18.11	13.39	£15.21	£15.21	£15.21	0.04
N	*11,583*	*6,525*	*5,058*		*5,140*	*1,308*	*3,832*	
South West (England)	£18.03	£18.76	£16.82	10.34	£14.52	£15.06	£14.37	4.58
N	*7,303*	*4,303*	*3,000*		*3,502*	*868*	*2,634*	
Wales	£17.20	£17.67	£16.57	6.23	£13.89	£13.72	£13.95	1.68
N	*4,127*	*2,228*	*1,899*		*1,884*	*452*	*1,432*	
Scotland	£19.06	£19.76	£18.13	8.25	£14.44	£14.11	£14.53	-2.98
N	*8,209*	*4,339*	*3,870*		*3,782*	*844*	*2,938*	
Local								
Minimum: Torbay	£14.99	£15.67	£13.93	11.10	£11.82	£10.52	£12.46	-18.44
N	*125*	*72*	*53*		*87*	*28*	*59*	
25th percentile: Kingston upon Hull	£16.92	£17.59	£15.92	9.49	£13.68	£14.38	£13.41	6.75
N	*367*	*204*	*163*		*183*	*47*	*136*	
Median: Northumberland	£17.98	£19.87	£15.47	22.14	£14.22	£15.04	£13.98	7.05
N	*309*	*165*	*144*		*194*	*42*	*152*	
75th percentile: Warwickshire Country Council	£19.40	£20.84	£16.46	21.02	£15.47	£14.70	£15.69	-6.73
N	*861*	*541*	*320*		*367*	*79*	*288*	
Maximum: Tower Hamlets	£34.54	£37.08	£30.27	18.37	£21.09	£13.94	£24.42	-75.18
N	*943*	*540*	*403*		*146*	*49*	*97*	

Notes: (i) Mean hourly earnings relate to the respective estimation sample, defined according to ASHE guidance. (ii) The gap is measured as a percentage of the relevant male figure in each case.

Source: Author calculations based on weighted ASHE 2022 data.

Table B.5: Summary Statistics for all Variables by Gender in Selected Areas at each Geographical Level

	National			**Regional**								
				Smallest: North East			*Median*: North West			*Largest*: London		
	All	Men	Women	All	Men	Women	All	Men	Women	All	Men	Women
(Log) Hourly wages	7.39	7.46	7.32	7.28	7.34	7.23	7.33	7.40	7.27	7.63	7.70	7.54
N	*124,963*	*58,525*	*66,438*	*5,069*	*2,290*	*2,779*	*14,105*	*6,566*	*7,539*	*17,173*	*8,262*	*8,911*
Individual Characteristics												
Age (years)	40.94	40.81	41.07	41.18	40.94	41.41	40.76	40.55	40.97	39.31	39.59	39.00
N	*124,963*	*58,525*	*66,438*	*5,069*	*2,290*	*2,779*	*14,105*	*6,566*	*7,539*	*17,173*	*8,262*	*8,911*
Tenure (months)	94.80	98.19	91.35	103.36	101.77	104.84	97.08	98.89	95.31	83.06	86.43	79.30
N	*124,963*	*58,525*	*66,438*	*5,069*	*2,290*	*2,779*	*14,105*	*6,566*	*7,539*	*17,173*	*8,262*	*8,911*
Full-time employment (%)	73.45	85.93	60.71	70.58	85.46	56.65	74.06	86.22	62.08	80.24	87.32	72.35
N	*87,049*	*48,967*	*38,082*	*3,409*	*1,915*	*1,494*	*9,999*	*5,538*	*4,461*	*13,081*	*6,959*	*6,122*
Permanent contract (%)	92.19	93.56	90.79	92.31	93.03	91.64	92.69	93.24	92.14	92.21	93.58	90.69
N	*115,002*	*54,692*	*60,310*	*4,678*	*2,128*	*2,550*	*13,066*	*6,122*	*6,944*	*15,773*	*7,700*	*8,073*
Workplace Characteristics												
Firm size (%)												
Small ($\leq$ 50) employees	22.76	24.13	21.36	20.67	22.87	18.61	21.18	22.26	20.12	20.68	21.05	20.28
N	*26,485*	*13,255*	*13,230*	*960*	*482*	*478*	*2,734*	*1,359*	*1,375*	*3,353*	*1,628*	*1,725*
Medium (51-250 employees)	14.79	15.89	13.67	12.36	15.58	9.34	15.47	16.86	14.09	14.50	14.29	14.73
N	*16,628*	*8,456*	*8,163*	*552*	*321*	*231*	*1,978*	*1,009*	*969*	*2,191*	*1,008*	*1,183*
Large (251-1000 employees)	13.11	13.92	12.30	13.50	15.42	11.71	13.83	15.24	12.43	12.18	12.20	12.16
N	*14,655*	*7,376*	*7,279*	*604*	*317*	*287*	*1,752*	*918*	*834*	*1,892*	*904*	*988*
Enterprise (1001+ employees)	49.34	46.06	52.68	53.47	46.13	60.34	49.53	45.64	53.35	52.64	52.46	52.84
N	*67,195*	*29,429*	*37,766*	*2,953*	*1,170*	*1,783*	*7,641*	*3,280*	*4,361*	*9,737*	*4,722*	*5,015*
Collective agreement (%)	40.29	35.45	45.22	44.83	38.36	50.89	43.15	38.38	47.84	34.85	33.25	36.65
N	*53,078*	*21,913*	*31,165*	*2,372*	*913*	*1,459*	*6,346*	*2,598*	*3,748*	*6,204*	*2,915*	*3,289*
Occupation variables (%)												
Managers & Senior officials	10.06	12.45	7.62	7.22	8.85	5.69	9.12	10.91	7.36	13.92	16.70	10.80
N	*11,643*	*7,069*	*4,574*	*330*	*191*	*139*	*1,183*	*693*	*490*	*2,394*	*1,428*	*966*
Professional	28.16	28.54	27.77	23.45	24.06	22.89	25.88	26.86	24.92	36.98	37.79	36.08
N	*26,956*	*11,506*	*15,450*	*937*	*378*	*559*	*2,899*	*1,238*	*1,661*	*4,671*	*2,171*	*2,500*
Associate professional	15.09	14.92	15.26	15.68	14.39	16.90	14.39	12.73	16.02	15.76	15.94	15.56
N	*14,151*	*7,327*	*6,824*	*582*	*273*	*309*	*1,488*	*702*	*786*	*2,180*	*1,137*	*1,043*
Administrative	10.98	5.64	16.42	11.91	6.92	16.58	11.82	6.59	16.97	9.94	6.15	14.16
N	*16,862*	*4,310*	*12,552*	*734*	*209*	*525*	*2,038*	*569*	*1,469*	*2,201*	*669*	*1,532*
Skilled trades	6.15	10.68	1.52	7.08	12.61	1.91	6.37	11.40	1.42	3.27	5.21	1.10
N	*7,042*	*6,210*	*832*	*322*	*279*	*43*	*811*	*725*	*86*	*529*	*444*	*85*
Personal service	7.80	3.68	12.02	8.19	4.02	12.09	8.50	3.99	12.95	5.98	3.45	8.80
N	*11,941*	*2,427*	*9,514*	*481*	*100*	*381*	*1,431*	*284*	*1,147*	*1,350*	*342*	*1,008*
Sales & customer service	6.71	5.07	8.38	8.04	5.81	10.12	6.97	5.49	8.42	5.40	4.45	6.47
N	*12,847*	*4,928*	*7,919*	*606*	*215*	*391*	*1,465*	*581*	*884*	*1,484*	*645*	*839*
Process, plant & machine ops.	5.01	8.54	1.42	5.83	11.03	0.97	5.37	9.26	1.54	2.35	3.96	0.56

N	*7,667*	*6,542*	*1,125*	*334*	*304*	*30*	*867*	*740*	*127*	*632*	*551*	*81*
Elementary occupations	10.04	10.48	9.60	12.60	12.32	12.86	11.58	12.76	10.41	6.40	6.34	6.46
N	*15,854*	*8,206*	*7,648*	*743*	*341*	*402*	*1,923*	*1,034*	*889*	*1,732*	*875*	*857*
Public sector employment (%)	24.42	16.80	32.21	28.84	19.09	37.97	25.26	17.12	33.27	23.72	19.33	28.61
N	*31,044*	*9,498*	*21,546*	*1,510*	*447*	*1,063*	*3,648*	*1,065*	*2,583*	*4,032*	*1,553*	*2,479*
				Local								
				Smallest: Torbay			*Median*: Northumberland			*Largest*: Tower Hamlets		
				All	Men	Women	All	Men	Women	All	Men	Women
(Log) Hourly wages				7.17	7.20	7.13	7.30	7.40	7.22	7.90	7.97	7.81
N				*212*	*100*	*112*	*503*	*207*	*296*	*1,089*	*589*	*500*
Individual Characteristics												
Age (years)				41.30	40.00	42.59	41.75	42.73	40.94	38.15	38.37	37.82
N				*212*	*100*	*112*	*503*	*207*	*296*	*1,089*	*589*	*500*
Tenure (months)				91.65	82.91	100.25	98.92	110.20	89.64	84.58	87.21	80.77
N				*212*	*100*	*112*	*503*	*207*	*296*	*1,089*	*589*	*500*
Full-time employment (%)				62.62	75.16	50.27	65.03	80.76	52.10	89.36	93.86	82.83
N				*125*	*72*	*53*	*309*	*165*	*144*	*943*	*540*	*403*
Permanent contract (%)				94.87	96.03	93.73	92.10	93.93	90.60	93.16	94.64	91.01
N				*201*	*96*	*105*	*464*	*196*	*268*	*1,018*	*559*	*459*
Workplace Characteristics												
Firm size (%)												
Small (≤50 employees)				26.27	27.56	25.00	27.91	34.21	22.73	11.64	12.21	10.82
N				*52*	*25*	*27*	*132*	*68*	*64*	*117*	*64*	*53*
Medium (51-250 employees)				19.94	13.18	26.60	13.19	18.77	8.60	8.27	6.73	10.51
N				*40*	*12*	*28*	*58*	*35*	*23*	*80*	*33*	*47*
Large (251-1000 employees)				15.98	18.53	13.46	16.21	16.43	16.03	8.27	9.01	7.19
N				*29*	*16*	*13*	*74*	*31*	*43*	*78*	*47*	*31*
Enterprise (1001+ employees)				37.81	40.74	34.94	42.69	30.58	52.64	71.82	72.05	71.48
N				*91*	*47*	*44*	*239*	*73*	*166*	*814*	*445*	*369*
Collective agreement (%)				38.82	40.83	36.85	49.81	39.93	57.93	26.96	26.17	28.12
N				*80*	*40*	*40*	*265*	*86*	*179*	*317*	*169*	*148*
Occupational Skill Group												
High Skilled				36.92	38.44	35.41	39.68	43.37	36.66	78.54	82.44	72.90
N				*60*	*29*	*31*	*155*	*71*	*84*	*755*	*432*	*323*
Medium Skilled				28.92	23.63	34.14	31.64	27.47	35.07	13.93	10.04	19.57
N				*64*	*23*	*41*	*170*	*60*	*110*	*200*	*78*	*122*
Low Skilled				34.16	37.93	30.44	28.67	29.16	28.27	7.53	7.52	7.53
N				*88*	*48*	*40*	*178*	*76*	*102*	*134*	*79*	*55*
Public sector employment (%)				20.95	20.20	21.70	31.32	23.08	38.10	17.23	12.03	24.78
N				*80*	*40*	*40*	*159*	*47*	*112*	*194*	*71*	*123*

Notes: (i) All variables are binary (unless otherwise stated). (ii) Variable means are constructed on the basis of the estimation sample and are rounded to two decimal places. (iii) Positive case sample sizes are provided in italics after each estimation, with sample size for areas provided in Appendix B, Table B.2.

Source: Author calculations based on weighted ASHE 2022 data.

Table B.6: Full Coefficient Estimates for Wage Equations across Areas, National and Regional Levels

	National *N: 124,963*					**Regional** *Minimum*: **Wales** (*N: 6,011*)				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Female	-0.140***	-0.080***	-0.088***	-0.094***	-0.093***	-0.097***	-0.056***	-0.077***	-0.083***	-0.086***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)
Age		0.060***	0.059***	0.037***	0.037***		0.058***	0.058***	0.036***	0.035***
		(0.001)	(0.001)	(0.001)	(0.001)		(0.003)	(0.003)	(0.002)	(0.002)
Age^2		-0.001***	-0.001***	-0.000***	-0.000***		-0.001***	-0.001***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Tenure		0.001***	0.001***	0.001***	0.001***		0.001***	0.001***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Tenure^2		-0.000***	-0.000***	-0.000***	-0.000***		-0.000	-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Full-/Part-time		-0.220***	-0.208***	-0.068***	-0.068***		-0.165***	-0.156***	0.029**	-0.030***
		(0.003)	(0.003)	(0.003)	(0.003)		(0.013)	(0.012)	(0.011)	(0.011)
Permanent/Temporary contract		0.051***	0.031***	-0.008*	-0.007*		0.066***	0.030	0.006	0.006
		(0.005)	(0.005)	(0.004)	(0.004)		(0.016)	(0.016)	(0.014)	(0.014)
Medium firm size			0.090***	0.084***	0.084***			0.049**	0.066***	0.066***
			(0.004)	(0.004)	(0.004)			(0.018)	(0.015)	(0.015)
Large firm size			0.118***	0.108***	0.108***			0.066**	0.103***	0.105***
			(0.004)	(0.004)	(0.004)			(0.020)	(0.017)	(0.017)
Enterprise firm size			0.130***	0.121***	0.122***			0.132***	0.110***	0.100***
			(0.003)	(0.003)	(0.003)			(0.014)	(0.013)	(0.013)
Collective agreement			0.010***	-0.007**	-0.004			0.085***	0.051***	0.037***
			(0.003)	(0.002)	(0.003)			(0.012)	(0.010)	(0.011)
Managers & Senior Officials				0.456***	0.456***				0.358***	0.361***
				(0.006)	(0.006)				(0.025)	(0.025)
Professional				0.433***	0.433***				0.400***	0.396***
				(0.004)	(0.004)				(0.015)	(0.015)
Associate professional				0.154***	0.154***				0.124***	0.125***
				(0.004)	(0.004)				(0.018)	(0.018)
Skilled trades				-0.023***	-0.023***				0.048**	0.053**
				(0.005)	(0.005)				(0.019)	(0.020)
Personal service				-0.134***	-0.133***				-0.101***	-0.102***

	National (continued)					**Regional (continued)**				
				(0.003)	(0.003)				(0.014)	(0.014)
Sales & customer services				-0.161***	-0.163***				-0.140***	-0.128***
				(0.004)	(0.004)				(0.015)	(0.015)
Process, plant & machine operatives				-0.116***	-0.117***				-0.099***	-0.094***
				(0.004)	(0.004)				(0.017)	(0.017)
Elementary occupations				-0.209***	-0.210***				-0.182***	-0.177***
				(0.003)	(0.003)				(0.014)	(0.014)
Public					-0.008***					0.035**
					(0.003)					(0.013)
Adjusted R^2	0.022	0.182	0.120	0.460	0.460	0.014	0.180	0.221	0.474	0.475
	Regional *Median*: **South West** (*N: 10,805*)					**Regional** *Maximum*: **London** (*N: 17,173*)				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Female	-0.129***	-0.078***	-0.089***	-0.085***	0.085***	-0.156***	-0.087***	-0.091***	-0.080***	-0.075***
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)
Age		0.060***	0.058***	0.035***	0.035***		0.071***	0.071***	0.050***	0.050***
		(0.002)	(0.002)	(0.002)	(0.002)		(0.002)	(0.002)	(0.002)	(0.002)
Age^2		-0.001***	-0.001***	-0.000***	-0.000***		-0.001***	-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Tenure		0.001***	0.001***	0.001***	0.001***		0.002***	0.002***	0.001***	0.001***
		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
$Tenure^2$		-0.000***	-0.000***	-0.000***	-0.000		-0.000***	-0.000***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Full-/Part-time		-0.146***	-0.137***	-0.037***	-0.037***		-0.350***	-0.327***	-0.118***	-0.120***
		(0.009)	(0.009)	(0.008)	(0.008)		(0.010)	(0.010)	(0.009)	(0.009)
Permanent/Temporary contract		0.048***	0.017	0.002	0.002		-0.037**	-0.048***	-0.047***	-0.044***
		(0.014)	(0.014)	(0.012)	(0.012)		(0.013)	(0.013)	(0.011)	(0.011)
Medium firm size			0.076***	0.066***	0.066***			0.138***	0.120***	0.124***
			(0.13)	(0.011)	(0.011)			(0.014)	(0.012)	(0.012)
Large firm size			0.116***	0.086***	0.086***			0.146***	0.140***	0.144***
			(0.013)	(0.012)	(0.012)			(0.015)	(0.013)	(0.013)
Enterprise firm size			0.125***	0.105***	0.105***			0.178***	0.175***	0.186***
			(0.010)	(0.009)	(0.010)			(0.011)	(0.010)	(0.010)
Collective agreement			0.048*	0.007	0.008			-0.026**	-0.020**	0.005
			(0.009)	(0.008)	(0.009)			(0.009)	(0.008)	(0.009)
Managers & Senior officials				0.389***	0.388***				0.541***	0.535***
				(0.016)	(0.016)				(0.015)	(0.015)

	National (continued)					Regional (continued)				
Professional				0.417***	0.417***				0.409***	0.412***
				(0.011)	(0.011)				(0.011)	(0.011)
Associate professional				0.166***	0.166***				0.150***	0.152***
				(0.012)	(0.012)				(0.012)	(0.012)
Skilled trades				0.011	0.011				-0.127***	-0.131***
				(0.013)	(0.013)				(0.017)	(0.017)
Personal service				-0.094***	-0.094***				-0.232***	-0.227***
				(0.012)	(0.012)				(0.011)	(0.011)
Sales & customer service				-0.141***	-0.141***				-0.222***	-0.233***
				(0.012)	(0.012)				(0.012)	(0.013)
Process, plant & machine operatives				-0.084***	-0.085***				-0.140***	-0.153***
				(0.013)	(0.013)				(0.016)	(0.017)
Elementary occupations				-0.166***	-0.167***				-0.285***	-0.291***
				(0.010)	(0.010)				(0.012)	(0.012)
Public					0.002					-0.061***
					(0.010)					(0.009)
Adjusted R^2	0.022	0.194	0.216	0.461	0.461	0.020	0.200	0.214	0.443	0.444

Notes: (i) Estimates are based on a pooled OLS earnings equation. (ii) Males, small firm size and the Administrative occupation are the reference categories. (iii) All models include a constant term. (iv) Standard errors in parenthesis. (v) $^{*}< 0.05$, $^{**}< 0.01$, $^{***}< 0.001$.

Source: Author calculations based on weighted ASHE 2022 data.

Table B.7: Adjusted Gender Pay Gaps across Areas for All Employees, Local Level

	(1)	(2)	(3)	(4)	(5)
North East (England)					
Hartlepool and Stockton on Tees	-0.165***	-0.091*	-0.111**	-0.100**	-0.096*
N: 508	(0.039)	(0.040)	(0.042)	(0.038)	(0.039)
South Teeside	-0.123**	-0.060	-0.055	-0.083*	-0.084*
N: 398	(0.041)	(0.038)	(0.038)	(0.036)	(0.036)
Darlington	-0.141*	-0.052	-0.064	-0.062*	-0.060
N: 234	(0.058)	(0.052)	(0.050)	(0.041)	(0.042)
County Durham	-0.107***	-0.081**	-0.094***	-0.118***	-0.120***
N: 851	(0.031)	(0.028)	(0.028)	(0.025)	(0.025)
Northumberland	-0.178***	-0.115**	-0.146***	-0.144***	-0.149***
N: 503	(0.044)	(0.041)	(0.044)	(0.037)	(0.036)
Tyneside	-0.092***	-0.044*	-0.058**	-0.087***	-0.088***
N: 1,955	(0.020)	(0.019)	(0.019)	(0.017)	(0.017)
Sunderland	-0.042	-0.028	-0.050	-0.100**	-0.101**
N: 620	(0.033)	(0.034)	(0.035)	(0.034)	(0.036)
North West (England)					
West Cumbria	-0.177***	-0.107**	-0.100**	-0.119***	-0.138***
N: 465	(0.043)	(0.035)	(0.033)	(0.030)	(0.031)
East Cumbria	-0.122***	-0.080*	-0.082**	-0.102***	-0.107***
N: 553	(0.032)	(0.031)	(0.030)	(0.026)	(0.027)
Manchester	-0.101***	-0.054*	-0.067***	-0.087***	-0.083***
N: 1,735	(0.024)	(0.021)	(0.021)	(0.019)	(0.019)
Greater Manchester South West	-0.167***	-0.119***	-0.124***	-0.152***	-0.153***
N: 1,076	(0.029)	(0.027)	(0.027)	(0.025)	(0.025)
Greater Manchester South East	-0.138***	-0.079*	-0.085**	-0.117***	-0.121***
N: 730	(0.033)	(0.032)	(0.031)	(0.028)	(0.029)
Greater Manchester North West	-0.049	-0.016	-0.032	-0.091***	-0.097***
N: 915	(0.030)	(0.029)	(0.029)	(0.024)	(0.024)
Greater Manchester North East	-0.083**	-0.033	-0.050	-0.117***	-0.128***
N: 1,008	(0.029)	(0.028)	(0.028)	(0.025)	(0.025)
Blackburn with Darwen	-0.050	-0.031	-0.043	-0.074	-0.106*
N: 266	(0.061)	(0.058)	(0.062)	(0.049)	(0.048)
Blackpool	-0.020	-0.014	-0.039	-0.071*	-0.064
N: 325	(0.045)	(0.039)	(0.037)	(0.036)	(0.035)
Lancaster and Wyre	-0.136**	-0.056	-0.064	-0.126***	-0.128***
N: 403	(0.043)	(0.039)	(0.039)	(0.033)	(0.034)
Mid Lancashire	-0.152***	-0.066**	-0.082***	-0.114***	-0.109***
N: 1,057	(0.026)	(0.024)	(0.023)	(0.021)	(0.021)
East Lancashire	-0.101*	-0.056	-0.071	-0.120***	-0.116**
N: 507	(0.041)	(0.039)	(0.039)	(0.035)	(0.037)
Chorley and West Lancashire	-0.139**	-0.126**	-0.131**	-0.157***	-0.162***
N: 358	(0.050)	(0.049)	(0.047)	(0.042)	(0.042)
Warrington	-0.113**	-0.040	-0.052	-0.103***	-0.109***
N: 535	(0.039)	(0.036)	(0.036)	(0.031)	(0.031)
Cheshire East	-0.203***	-0.115***	-0.111***	-0.128***	-0.121***
N: 835	(0.033)	(0.030)	(0.030)	(0.026)	(0.027)
Cheshire West and Chester	-0.108**	-0.088*	-0.087*	-0.102**	-0.103**
N: 666	(0.036)	(0.036)	(0.037)	(0.033)	(0.033)
East Merseyside	-0.182***	-0.146***	-0.156***	-0.170***	-0.180***
N: 798	(0.033)	(0.035)	(0.036)	(0.030)	(0.030)
Liverpool	-0.126***	-0.077**	-0.085***	-0.078***	-0.081***

	(1)	(2)	(3)	(4)	(5)
N: 1,056	(0.028)	(0.025)	(0.024)	(0.022)	(0.022)
Sefton	-0.109*	-0.099*	-0.137**	-0.152***	-0.161***
N: 429	(0.051)	(0.050)	(0.050)	(0.044)	(0.045)
Wirral	-0.135**	-0.072	-0.085*	-0.083*	-0.088*
N: 387	(0.046)	(0.043)	(0.043)	(0.036)	(0.036)
Yorkshire and the Humber					
Kingston upon Hull	-0.101**	-0.073*	-0.090**	-0.089**	-0.096**
N: 550	(0.036)	(0.035)	(0.034)	(0.028)	(0.030)
East Riding of Yorkshire	-0.132***	-0.097**	-0.100**	-0.154***	-0.153***
N:614	(0.036)	(0.035)	(0.035)	(0.032)	(0.032)
North and North East Lincolnshire	-0.212***	-0.155***	-0.160***	-0.192***	-0.201***
N: 573	(0.034)	(0.035)	(0.035)	(0.032)	(0.033)
York	-0.204***	-0.116**	-0.117**	-0.124***	-0.127***
N: 490	(0.041)	(0.039)	(0.039)	(0.035)	(0.036)
North Yorkshire County Council	-0.108***	-0.047*	-0.054*	-0.084***	-0.082***
N: 1,260	(0.024)	(0.023)	(0.023)	(0.021)	(0.021)
Barnsley, Doncaster and Rotherham	-0.158***	-0.084***	-0.097***	-0.148***	-0.146***
N: 1,319	(0.023)	(0.023)	(0.023)	(0.021)	(0.021)
Sheffield	-0.101***	-0.064*	-0.070**	-0.080***	-0.080***
N: 1,057	(0.027)	(0.025)	(0.024)	(0.021)	(0.021)
Bradford	-0.143***	-0.070*	-0.081**	-0.115***	-0.120***
N: 847	(0.032)	(0.030)	(0.029)	(0.026)	(0.026)
Leeds	-0.175***	-0.109***	-0.103***	-0.122***	-0.123***
N: 2,914	(0.017)	(0.016)	(0.016)	(0.014)	(0.013)
Calderdale and Kirklees	-0.164***	-0.105***	-0.121***	-0.127***	-0.117***
N: 1,027	(0.028)	(0.027)	(0.026)	(0.023)	(0.023)
Wakefield	-0.170***	-0.107**	-0.110**	-0.135***	-0.150***
N: 707	(0.035)	(0.034)	(0.034)	(0.030)	(0.030)
East Midlands (England)					
Derby	-0.232***	-0.136***	-0.125***	-0.149***	-0.143***
N: 634	(0.038)	(0.033)	(0.032)	(0.030)	(0.030)
East Derbyshire	-0.157***	-0.091*	-0.095**	-0.124***	-0.125***
N: 501	(0.035)	(0.037)	(0.036)	(0.032)	(0.032)
South and West Derbyshire	-0.138***	-0.084*	-0.094**	-0.095***	-0.106***
N: 752	(0.028)	(0.033)	(0.033)	(0.027)	(0.027)
Nottingham	-0.038	0.005	0.006	-0.038	-0.039
N: 724	(0.033)	(0.031)	(0.031)	(0.027)	(0.027)
North Nottinghamshire	-0.150***	-0.116***	-0.131***	-0.160***	-0.157***
N: 971	(0.028)	(0.029)	(0.029)	(0.025)	(0.026)
South Nottinghamshire	-0.196***	-0.152***	-0.156***	-0.148***	-0.149***
N: 483	(0.042)	(0.042)	(0.042)	(0.036)	(0.036)
Leicester	-0.093**	-0.069*	-0.085**	-0.100***	-0.101***
N: 657	(0.034)	(0.032)	(0.032)	(0.029)	(0.030)
Leicestershire County Council	-0.152***	-0.079***	-0.080***	-0.087***	-0.084***
N: 1,432	(0.024)	(0.022)	(0.022)	(0.019)	(0.019)
West Northamptonshire	-0.150***	-0.111***	-0.117***	-0.128***	-0.123***
N: 839	(0.032)	(0.031)	(0.030)	(0.027)	(0.027)
North Northamptonshire	-0.162***	-0.104**	-0.105**	-0.100***	-0.108***
N: 619	(0.035)	(0.034)	(0.034)	(0.029)	(0.030)
Lincolnshire County Council	-0.091***	-0.049*	-0.069**	-0.073***	-0.083***
N: 1,331	(0.023)	(0.023)	(0.023)	(0.021)	(0.021)
West Midlands (England)					
Herefordshire	-0.048	-0.105*	-0.108*	-0.130**	-0.137**

	(1)	(2)	(3)	(4)	(5)
N: 381	(0.043)	(0.049)	(0.050)	(0.042)	(0.042)
Worcestershire County Council	-0.121***	-0.091***	-0.102***	-0.106***	-0.110***
N: 1,071	(0.026)	(0.025)	(0.024)	(0.022)	(0.022)
Warwickshire County Council	-0.196***	-0.134***	-0.138***	-0.137***	-0.134***
N: 1,228	(0.026)	(0.025)	(0.025)	(0.023)	(0.023)
Telford and Wrekin	-0.160***	-0.074	-0.088*	-0.104**	-0.099*
N: 409	(0.042)	(0.042)	(0.044)	(0.039)	(0.039)
Shropshire	-0.127***	-0.082*	-0.107**	-0.144***	-0.148***
N: 602	(0.038)	(0.034)	(0.034)	(0.032)	(0.032)
Stoke-on-Trent	-0.105**	-0.066*	-0.092**	-0.120***	-0.126***
N: 666	(0.033)	(0.031)	(0.031)	(0.027)	(0.028)
Staffordshire County Council	-0.124***	-0.072**	-0.081**	-0.108***	-0.111***
N: 1,552	(0.023)	(0.025)	(0.025)	(0.023)	(0.024)
Birmingham	-0.150***	-0.080***	-0.084***	-0.090***	-0.088***
N: 2,051	(0.021)	(0.019)	(0.019)	(0.017)	(0.017)
Solihull	-0.254***	-0.144***	-0.110**	-0.148***	-0.131***
N: 641	(0.037)	(0.034)	(0.034)	(0.031)	(0.031)
Coventry	-0.176***	-0.145***	-0.151***	-0.138***	-0.130***
N: 733	(0.037)	(0.034)	(0.034)	(0.032)	(0.032)
Dudley	-0.097*	-0.053	-0.061	-0.087**	-0.089**
N: 478	(0.041)	(0.040)	(0.039)	(0.034)	(0.034)
Sandwell	-0.032	0.012	-0.006	-0.104**	-0.109**
N: 485	(0.037)	(0.036)	(0.036)	(0.032)	(0.033)
Walsall	-0.066	-0.012	-0.061	-0.078*	-0.101**
N: 448	(0.040)	(0.037)	(0.038)	(0.033)	(0.034)
Wolverhampton	-0.019	-0.005	-0.009	-0.054	-0.062
N: 445	(0.040)	(0.037)	(0.038)	(0.034)	(0.035)
East of England					
Peterborough	-0.089*	-0.038	-0.037	-0.071*	-0.068*
N: 521	(0.038)	(0.037)	(0.038)	(0.032)	(0.033)
Cambridge County Council	-0.149***	-0.094***	-0.095***	-0.116***	-0.111***
N: 1,482	(0.025)	(0.024)	(0.024)	(0.021)	(0.021)
Suffolk	-0.150***	-0.087***	-0.102***	-0.114***	-0.117***
N: 1,519	(0.022)	(0.021)	(0.021)	(0.019)	(0.019)
Norwich and East Norfolk	-0.115***	-0.046	-0.050	-0.074**	-0.082**
N: 772	(0.032)	(0.032)	(0.032)	(0.028)	(0.028)
North and West Norfolk	-0.093*	-0.014	-0.031	-0.069	-0.083*
N: 383	(0.041)	(0.040)	(0.039)	(0.035)	(0.035)
Breckland and South Norfolk	-0.147***	-0.096*	-0.111**	-0.101**	-0.112***
N: 426	(0.038)	(0.037)	(0.036)	(0.033)	(0.032)
Luton	-0.209***	-0.129*	-0.157**	-0.180***	-0.179***
N: 358	(0.054)	(0.052)	(0.053)	(0.049)	(0.050)
Hertfordshire	-0.116***	-0.072***	-0.083***	-0.090***	-0.092***
N: 2,598	(0.019)	(0.019)	(0.019)	(0.017)	(0.017)
Bedford	-0.022	0.023	0.002	-0.036	-0.036
N: 385	(0.047)	(0.043)	(0.045)	(0.041)	(0.041)
Central Bedfordshire	-0.181***	-0.131**	-0.133**	-0.131***	-0.132**
N: 457	(0.044)	(0.041)	(0.042)	(0.037)	(0.037)
Southend-on-Sea	-0.083	-0.060	-0.068	-0.083	-0.091
N: 247	(0.058)	(0.054)	(0.052)	(0.048)	(0.047)
Thurrock	-0.213***	-0.081	-0.093	-0.135**	-0.141***
N: 239	(0.057)	(0.052)	(0.049)	(0.044)	(0.042)
Essex Haven Gateway	-0.161***	-0.092**	-0.105***	-0.120***	-0.130***

	(1)	(2)	(3)	(4)	(5)
N: 730	(0.033)	(0.030)	(0.031)	(0.028)	(0.028)
West Essex	-0.101*	-0.041	-0.046	-0.058	-0.065
N: 466	(0.044)	(0.039)	(0.038)	(0.033)	(0.034)
Heart of Essex	-0.139***	-0.083*	-0.087*	-0.110**	-0.109**
N: 572	(0.039)	(0.039)	(0.038)	(0.033)	(0.034)
Essex Thames Gateway	-0.203***	-0.128**	-0.140***	-0.131***	-0.142***
N: 439	(0.044)	(0.041)	(0.040)	(0.038)	(0.038)
London					
Camden and City of London	-0.212***	-0.170***	-0.168***	-0.150***	-0.140***
N: 3,001	(0.021)	(0.019)	(0.018)	(0.018)	(0.018)
Westminster	-0.169***	-0.120***	-0.116***	-0.084***	-0.084***
N: 1,992	(0.024)	(0.022)	(0.022)	(0.020)	(0.020)
Kensington & Chelsea and	-0.098***	-0.052	-0.059	-0.055	-0.058
Hammersmith & Fulham *N: 749*	(0.038)	(0.035)	(0.034)	(0.031)	(0.032)
Wandsworth	-0.083	-0.020	-0.016	-0.001	-0.002
N: 367	(0.049)	(0.043)	(0.042)	(0.036)	(0.036)
Hackney and Newham	-0.078*	-0.011	-0.019	-0.045	-0.048
N: 820	(0.037)	(0.032)	(0.031)	(0.028)	(0.029)
Tower Hamlets	-0.165***	-0.088**	-0.086**	-0.075*	-0.042**
N: 1,089	(0.037)	(0.032)	(0.031)	(0.030)	(0.029)
Haringey and Islington	-0.135***	-0.083**	-0.080**	-0.086**	-0.076**
N: 904	(0.034)	(0.031)	(0.030)	(0.028)	(0.028)
Lewisham and Southwark	-0.090**	-0.039	-0.041	-0.059*	-0.055*
N: 1,282	(0.029)	(0.026)	(0.025)	(0.023)	(0.023)
Lambeth	-0.136**	-0.108**	-0.111**	-0.122***	-0.122***
N: 495	(0.046)	(0.040)	(0.040)	(0.036)	(0.036)
Bexley and Greenwich	-0.081*	0.006	-0.019	-0.031	-0.040
N: 544	(0.039)	(0.036)	(0.034)	(0.030)	(0.029)
Barking & Dagenham and Havering	-0.175***	-0.126**	-0.151***	-0.156***	-0.180***
N: 468	(0.048)	(0.045)	(0.043)	(0.040)	(0.038)
Redbridge and Waltham Forest	-0.134**	-0.074	-0.088*	-0.099*	-0.118**
N: 425	(0.048)	(0.045)	(0.043)	(0.039)	(0.037)
Enfield	0.004	0.028	-0.001	-0.006	-0.091*
N: 370	(0.054)	(0.048)	(0.046)	(0.044)	(0.043)
Bromley	-0.158***	-0.089*	-0.102**	-0.076*	-0.088*
N: 410	(0.046)	(0.039)	(0.039)	(0.036)	(0.035)
Croydon	-0.214***	-0.116*	-0.128**	-0.113**	-0.118**
N: 432	(0.044)	(0.046)	(0.045)	(0.036)	(0.036)
Merton, Kingston upon Thames	-0.131***	-0.056	-0.070*	-0.072**	-0.077**
and Sutton *N: 828*	(0.035)	(0.033)	(0.032)	(0.027)	(0.027)
Barnet	-0.068	-0.035	-0.043	-0.028	-0.034
N: 406	(0.050)	(0.046)	(0.046)	(0.040)	(0.040)
Brent	-0.132***	-0.066*	-0.062*	-0.054*	-0.054*
N: 695	(0.028)	(0.027)	(0.026)	(0.024)	(0.024)
Ealing	0.003	0.057	0.041	0.037	0.023
N: 431	(0.049)	(0.046)	(0.045)	(0.040)	(0.040)
Harrow and Hillingdon	-0.024	0.032	0.004	-0.018	-0.036
N: 805	(0.035)	(0.032)	(0.031)	(0.028)	(0.028)
Hounslow and Richmond upon	-0.122***	-0.045	-0.052	-0.044	-0.038
Thames *N: 660*	(0.041)	(0.039)	(0.038)	(0.033)	(0.034)
South East (England)					
Berkshire	-0.211***	-0.133***	-0.135***	-0.128***	-0.120***
N: 1,872	(0.023)	(0.021)	(0.020)	(0.018)	(0.019)

	(1)	(2)	(3)	(4)	(5)
Milton Keynes	-0.086*	-0.072*	-0.091**	-0.092**	-0.095**
N: 703	(0.036)	(0.033)	(0.033)	(0.031)	(0.031)
Buckingham County Council	-0.237***	-0.142***	-0.148***	-0.144***	-0.147***
N: 803	(0.038)	(0.035)	(0.035)	(0.031)	(0.031)
Oxfordshire	-0.151***	-0.097***	-0.097***	-0.098***	-0.093***
N: 1,544	(0.024)	(0.023)	(0.023)	(0.021)	(0.021)
Brighton and Hove	-0.143***	-0.114**	-0.117***	-0.116***	-0.113***
N: 609	(0.036)	(0.035)	(0.035)	(0.030)	(0.030)
East Sussex County Council	-0.044	0.015	0.011	-0.032	-0.036
N: 752	(0.031)	(0.028)	(0.028)	(0.025)	(0.025)
West Surrey	-0.188***	-0.127***	-0.133***	-0.116***	-0.113***
N: 1,362	(0.027)	(0.025)	(0.024)	(0.023)	(0.023)
East Surrey	-0.164***	-0.101**	-0.105**	-0.088**	-0.087**
N: 625	(0.041)	(0.037)	(0.037)	(0.033)	(0.033)
West Sussex (South West)	-0.022	-0.023	-0.039	-0.060*	-0.068*
N: 754	(0.033)	(0.031)	(0.031)	(0.028)	(0.028)
West Sussex (North East)	-0.136***	-0.070	-0.079*	-0.103**	-0.100**
N: 668	(0.040)	(0.037)	(0.036)	(0.032)	(0.032)
Portsmouth and Isle of Wight	-0.150***	-0.096**	-0.098**	-0.108***	-0.110***
N: 716	(0.035)	(0.034)	(0.034)	(0.029)	(0.030)
Southampton	-0.070	-0.040	-0.073	-0.094**	-0.081*
N: 529	(0.041)	(0.039)	(0.039)	(0.036)	(0.035)
South Hampshire	-0.116***	-0.051	-0.045	-0.052	-0.053
N: 756	(0.034)	(0.030)	(0.031)	(0.027)	(0.028)
Central Hampshire	-0.164***	-0.103***	-0.103***	-0.109***	-0.106***
N: 1,200	(0.028)	(0.026)	(0.026)	(0.023)	(0.023)
North Hampshire	-0.244***	-0.171***	-0.151***	-0.141***	-0.144***
N: 659	(0.038)	(0.041)	(0.040)	(0.037)	(0.037)
Medway	-0.189***	-0.116**	-0.122**	-0.164***	-0.170***
N: 386	(0.045)	(0.043)	(0.042)	(0.038)	(0.038)
Kent Thames Gateway	-0.245***	-0.167***	-0.170***	-0.179***	-0.187***
N: 650	(0.039)	(0.038)	(0.037)	(0.036)	(0.037)
East Kent	-0.067*	-0.026	-0.038	-0.041	-0.039
N: 769	(0.033)	(0.030)	(0.030)	(0.026)	(0.026)
Mid Kent	-0.091**	-0.041	-0.061*	-0.081**	-0.084**
N: 644	(0.032)	(0.030)	(0.030)	(0.028)	(0.028)
West Kent	-0.094**	-0.041	-0.049	-0.072*	-0.075*
N: 722	(0.033)	(0.031)	(0.030)	(0.029)	(0.029)
South West (England)					
Bristol, City of	-0.123***	-0.064**	-0.069**	-0.092***	-0.076***
N: 1,308	(0.026)	(0.024)	(0.023)	(0.021)	(0.022)
Bath and North East Somerset, North Somerset and South Gloucestershire *N: 1,466*	-0.177*** (0.023)	-0.109*** (0.023)	-0.120*** (0.022)	-0.108*** (0.020)	-0.105*** (0.021)
Gloucestershire	-0.116***	-0.076*	-0.074*	-0.061*	-0.067*
N: 1,048	(0.029)	(0.031)	(0.030)	(0.027)	(0.027)
Swindon	-0.208***	-0.146***	-0.152***	-0.119***	-0.132***
N: 514	(0.043)	(0.041)	(0.040)	(0.034)	(0.035)
Wiltshire County Council	-0.173***	-0.113***	-0.122***	-0.110***	-0.110***
N: 861	(0.029)	(0.028)	(0.028)	(0.025)	(0.026)
Bournemouth and Poole	-0.131***	-0.076*	-0.075*	-0.085**	-0.085**
N: 659	(0.037)	(0.033)	(0.033)	(0.030)	(0.030)
Dorset County Council	-0.135***	-0.131***	-0.155***	-0.161***	-0.165***

	(1)	(2)	(3)	(4)	(5)
N: 737	(0.034)	(0.033)	(0.031)	(0.026)	(0.026)
Somerset	-0.096***	-0.059*	-0.071*	-0.112***	-0.124***
N: 974	(0.027)	(0.028)	(0.028)	(0.025)	(0.024)
Cornwall and Isles of Scilly	-0.083**	-0.049	-0.066*	-0.083***	-0.081***
N: 916	(0.027)	(0.027)	(0.026)	(0.024)	(0.024)
Plymouth	-0.026	-0.020	-0.005	-0.060*	-0.048
N: 560	(0.033)	(0.031)	(0.030)	(0.028)	(0.030)
Torbay	-0.075	-0.042	-0.038	-0.043	-0.048
N: 212	(0.052)	(0.042)	(0.039)	(0.034)	(0.033)
Devon County Council	-0.115***	-0.078***	-0.097***	-0.112***	-0.116***
N: 1,550	(0.021)	(0.021)	(0.020)	(0.018)	(0.019)
Wales					
Anglesey and Gwynedd	-0.097*	-0.024	-0.056	-0.097*	-0.089*
N: 329	(0.048)	(0.050)	(0.047)	(0.039)	(0.038)
Conwy and Denbighshire	-0.073*	-0.036	-0.072*	-0.088***	-0.096**
N: 397	(0.042)	(0.036)	(0.034)	(0.029)	(0.030)
South West and Mid Wales	-0.056	-0.024	-0.057*	-0.078**	-0.086***
N: 846	(0.031)	(0.028)	(0.027)	(0.026)	(0.026)
Central Valleys	-0.103*	-0.076	-0.117*	-0.112**	-0.119**
N: 516	(0.041)	(0.044)	(0.046)	(0.041)	(0.042)
Gwent Valleys	-0.127***	-0.085*	-0.111**	-0.125***	-0.130**
N: 511	(0.038)	(0.041)	(0.041)	(0.037)	(0.040)
Bridgend and Neath Port Talbot	-0.159***	-0.108**	-0.134***	-0.149***	-0.169***
N: 444	(0.038)	(0.036)	(0.036)	(0.033)	(0.035)
Swansea	-0.016	-0.022	-0.033	-0.053	-0.056
N: 574	(0.037)	(0.035)	(0.035)	(0.031)	(0.031)
Monmouthshire and Newport	-0.103**	-0.051	-0.057	-0.083*	-0.081*
N: 524	(0.037)	(0.036)	(0.037)	(0.033)	(0.033)
Cardiff and Vale of Glamorgan	-0.103***	-0.049*	-0.057**	-0.084***	-0.086***
N: 1,275	(0.024)	(0.022)	(0.022)	(0.020)	(0.020)
Flintshire and Wrexham	-0.123***	-0.116***	-0.139***	-0.168***	-0.176***
N: 595	(0.034)	(0.035)	(0.033)	(0.030)	(0.031)
Scotland					
Aberdeen City and Aberdeenshire	-0.117***	-0.067*	-0.063*	-0.112***	-0.116***
N: 1,134	(0.030)	(0.028)	(0.028)	(0.024)	(0.024)
Highlands and Islands	-0.103**	-0.070	-0.085*	-0.109**	-0.110**
N:461	(0.039)	(0.040)	(0.038)	(0.033)	(0.033)
Inverness & Nairn and Moray,	-0.056	-0.004	-0.022	-0.065	-0.078*
Badenoch & Strathspey *N: 464*	(0.039)	(0.038)	(0.036)	(0.034)	(0.033)
Angus and Dundee City	-0.050	-0.028	-0.050	-0.053*	-0.060*
N: 547	(0.034)	(0.031)	(0.030)	(0.025)	(0.025)
Clackmannanshire and Fife	-0.098**	-0.064*	-0.090**	-0.095***	-0.098***
N: 767	(0.030)	(0.030)	(0.029)	(0.024)	(0.024)
East Lothian and Midlothian	-0.186***	-0.149***	-0.147***	-0.132***	-0.131***
N: 250	(0.050)	(0.043)	(0.044)	(0.037)	(0.037)
Edinburgh, City of	-0.147***	-0.092***	-0.093***	-0.102***	-0.096***
N: 1,756	(0.023)	(0.020)	(0.020)	(0.018)	(0.018)
Falkirk	-0.172**	-0.138**	-0.140**	-0.163***	-0.166***
N: 314	(0.053)	(0.051)	(0.051)	(0.044)	(0.045)
Perth & Kinross and Stirling	-0.099**	-0.052	-0.084*	-0.106***	-0.106***
N: 545	(0.037)	(0.034)	(0.034)	(0.029)	(0.029)
West Lothian	-0.106*	-0.043	-0.044	-0.081*	-0.079*
N: 336	(0.043)	(0.042)	(0.043)	(0.036)	(0.036)

	(1)	(2)	(3)	(4)	(5)
East Dunbartonshire, West Dunbartonshire, Helensburgh and Lomond *N: 333*	-0.235***	-0.146***	-0.179***	-0.156***	-0.159***
	(0.048)	(0.044)	(0.044)	(0.037)	(0.037)
Glasgow City	-0.129***	-0.081***	-0.089***	-0.106***	-0.105***
N: 2,080	(0.020)	(0.018)	(0.018)	(0.016)	(0.016)
Inverclyde, East Renfrewshire	-0.079*	-0.007	-0.034	-0.070*	-0.074*
and Renfrewshire *N: 569*	(0.037)	(0.034)	(0.034)	(0.028)	(0.029)
North Lanarkshire	-0.121***	-0.082*	-0.100**	-0.128***	-0.138***
N: 657	(0.034)	(0.033)	(0.033)	(0.027)	(0.028)
Scottish Borders	-0.045	-0.028	-0.035	-0.050	-0.076
N: 225	(0.059)	(0.059)	(0.064)	(0.052)	(0.051)
Dumfries and Galloway	-0.002	0.061	-0.023	-0.057	-0.057
N: 299	(0.043)	(0.050)	(0.047)	(0.039)	(0.041)
Ayrshire	-0.078*	-0.037	-0.071*	-0.092**	-0.099***
N: 674	(0.039)	(0.034)	(0.032)	(0.029)	(0.029)
South Lanarkshire	-0.081*	-0.021	-0.049	-0.063*	-0.071*
N: 580	(0.038)	(0.036)	(0.036)	(0.032)	(0.032)
Individual characteristics	No	Yes	Yes	Yes	Yes
Workplace characteristics	No	No	Yes	Yes	Yes
Occupation	No	No	No	Yes	Yes
Sector	No	No	No	No	Yes

Notes: (i) Estimates are based on a pooled OLS earnings equation. (ii) Males, small firm size and low skilled occupations are the reference categories. (iii) All models include a constant term. (iv) Standard errors are in parenthesis. (v) $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Source: Author calculations based on weighted ASHE 2022 data.

Table B.8: Full Coefficient Estimates for Wage Equations across Areas, Local Level

	Local *Minimum*: **Enfield** (*N: 370*)					**Local** *Median*: **South Teeside** (*N: 398*)				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Female	0.004	0.028	-0.001	-0.060	-0.091*	-0.123**	-0.060	-0.055	-0.083*	-0.084*
	(0.054)	(0.048)	(0.046)	(0.044)	(0.043)	(0.041)	(0.038)	(0.038)	(0.036)	(0.036)
Age		0.017	0.014	0.015	0.015		0.049***	0.042***	0.042***	0.042***
		(0.012)	(0.012)	(0.011)	(0.010)		(0.009)	(0.009)	(0.009)	(0.009)
Age^2		-0.000	-0.000	-0.000	-0.000		-0.001***	-0.001***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Tenure		0.002**	0.002*	0.002*	0.002*		0.001*	0.001*	0.000	0.000
		(0.000)	(0.001)	(0.001)	(0.001)		(0.000)	(0.000)	(0.000)	(0.000)
Tenure^2		-0.000	-0.000	-0.000	-0.000		-0.000	-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Full/Part-time		-0.290***	-0.273***	-0.098	-0.084		-0.276***	-0.252***	-0.162***	-0.162***
		(0.053)	(0.064)	(0.060)	(0.057)		(0.036)	(0.037)	(0.037)	(0.037)
Permanent/ Temporary contracts		-0.041	-0.041	-0.108	-0.077		0.005	0.019	-0.045	-0.045
		(0.067)	(0.067)	(0.071)	(0.069)		(0.062)	(0.063)	(0.059)	(0.059)
Medium			-0.001	0.017	-0.054			-0.117*	0.059	0.059
			(0.098)	(0.078)	(0.077)			(0.058)	(0.051)	(0.051)
Large			-0.191*	-0.121	0.169*			0.177**	0.115*	0.115*
			(0.093)	(0.082)	(0.083)			(0.055)	(0.052)	(0.052)
Enterprise			-0.069	0.006	-0.051			0.129**	0.080	0.079
			(0.075)	(0.067)	(0.067)			(0.043)	(0.052)	(0.045)
Collective agreement			0.204***	0.063	-0.048			0.054	-0.053	0.052
			(0.057)	(0.053)	(0.059)			(0.041)	(0.038)	(0.038)
High Skilled				0.546***	0.476***				0.351***	0.350***
				(0.058)	(0.061)				(0.040)	(0.041)
Medium Skill				0.126***	0.076				0.082*	0.081*
				(0.055)	(0.054)				(0.034)	(0.035)
Public					0.243***					0.004
					(0.062)					(0.051)
Adjusted R^2	0.000	0.194	0.235	0.437	0.463	0.026	0.260	0.293	0.439	0.439
	Local *Maximum*: **Solihull** (*N: 641*)									
	(1)	(2)	(3)	(4)	(5)					
Female	-0.254***	-0.144***	-0.110**	-0.148***	-0.131***					
	(0.037)	(0.034)	(0.034)	(0.031)	(0.031)					

	Local (continued)					Local (continued)
Age		0.067***	0.064***	0.056***	0.055***	
		(0.009)	(0.009)	(0.008)	(0.008)	
Age^2		-0.001***	-0.001***	-0.001***	-0.001***	
		(0.000)	(0.000)	(0.000)	(0.000)	
Tenure		0.002**	0.001	0.001	0.001	
		(0.001)	(0.001)	(0.001)	(0.001)	
Tenure^2		-0.000*	-0.000	-0.000	-0.000	
		(0.000)	(0.000)	(0.000)	(0.000)	
Full-/Part-time		-0.303***	-0.284***	-0.157***	-0.134***	
		(0.038)	(0.039)	(0.036)	(0.036)	
Permanent/Temporary contract		0.022	0.014	0.026	0.016*	
		(0.114)	(0.105)	(0.098)	(0.095)	
Medium			0.101	0.062	0.073*	
			(0.065)	(0.059)	(0.059)	
Large			0.127	0.084	0.103	
			(0.070)	(0.063)	(0.062)	
Enterprise			0.206***	0.156**	0.155**	
			(0.052)	(0.049)	(0.048)	
Collective agreement			0.084*	0.122***	0.169***	
			(0.041)	(0.036)	(0.037)	
High Skilled occupations				0.310***	0.338***	
				(0.030)	(0.030)	
Medium Skilled occupations				-0.026	0.000	
				(0.034)	(0.033)	
Public					-0.277***	
					(0.060)	
Adjusted R^2	0.073	0.321	0.363	0.475	0.491	

Notes: i) Estimates are obtained from an OLS earnings equation of weighted ASHE 2022 data. (ii) Males, small firm size and the low-skilled occupation are the reference categories. (iii) All models include a constant term. (iv) Standard errors in parenthesis. (v) $^{*}< 0.05$, $^{**}< 0.01$, $^{***}< 0.001$.

Source: Author calculations based on weighted ASHE 2022 data.

Table B.9: Decomposition of GPGs across Areas, by geographical level

Area	**Explained GPG**	**Unexplained GPG**	**Area**	**Explained GPG**	**Unexplained GPG**
National					
Britain	-0.033***	-0.107***			
N: 124,963	(0.002)	(0.003)			
	[23.6%]	[76.4%]			
Regional					
North East	-0.011	-0.095***	London	-0.067***	-0.089***
N: 5,069	(0.011)	(0.012)	*N: 17,173*	(0.006)	(0.008)
	[10.3%]	[89.7%]		[43.1%]	[56.9%]
North West	-0.019***	-0.106***	South East	-0.047***	-0.107***
N: 14,105	(0.006)	(0.007)	*N: 16,723*	(0.006)	(0.007)
	[15.1%]	[84.9%]		[30.4%]	[69.6%]
Yorkshire and the Humber	-0.024***	-0.127***	South West	-0.030***	-0.100***
N: 11,358	(0.007)	(0.008)	*N: 10,805*	(0.007)	(0.008)
	[16.0%]	[84.0%]		[22.9%]	[77.1%]
East Midlands	-0.029***	-0.110***	Wales	0.007	-0.104***
N: 8,943	(0.008)	(0.009)	*N: 6,011*	(0.009)	(0.010)
	[20.6%]	[79.4%]		[-7.2%]	[107.2%]
West Midlands	-0.019**	-0.120***	Scotland	-0.006	-0.111***
N: 11,190	(0.007)	(0.008)	*N: 11,991*	(0.007)	(0.008)
	[13.4%]	[86.6%]		[4.7%]	[95.3%]
East of England	-0.018*	-0.111***			
N: 11,595	(0.007)	(0.008)			
	[14.0%]	[86.0%]			
North East					
Hartlepool and Stockton on Tees	-0.060*	-0.105**	Northumberland	-0.010	-0.168***
N: 508	(0.029)	(0.040)	*N: 503*	(0.030)	(0.040)
	[36.2%]	[63.8%]		[5.6%]	[94.4%]
South Teeside	-0.040	-0.083*	Tyneside	-0.003	-0.088***
N: 398	(0.028)	(0.039)	*N: 1,955*	(0.015)	(0.018)
	[32.8%]	[67.2%]		[3.8%]	[96.2%]
Darlington	-0.074	-0.066	Sunderland	0.045	-0.086**
N: 234	(0.049)	(0.048)	*N: 620*	(0.025)	(0.032)
	[52.8%]	[47.2%]		[-107.7%]	[207.7%]
County Durham	0.019	-0.126***			
N: 851	(0.024)	(0.027)			

Area	Explained	Unexplained	Area	Explained	Unexplained
	[-18.1%]	[118.1%]			
North West					
West Cumbria	-0.043	-0.134***	Mid Lancashire	-0.011	-0.141***
N: 465	(0.035)	(0.035)	*N: 1,057*	(0.020)	(0.023)
	[24.1%]	[75.9%]		[7.0%]	[93.0%]
East Cumbria	0.000	-0.123***	East Lancashire	0.041	-0.141***
N: 553	(0.029)	(0.028)	*N: 507*	(0.030)	(0.037)
	[-0.4%]	[100.4%]		[-40.7%]	[140.7%]
Manchester	-0.016	-0.085***	Chorley and West Lancashire	0.005	-0.143***
N: 1,736	(0.016)	(0.020)	*N: 358*	(0.035)	(0.042)
	[16.0%]	[84.0%]		[-3.5%]	[103.5%]
Greater Manchester South West	-0.003	-0.164***	Warrington	-0.003	-0.110***
N: 1,076	(0.020)	(0.026)	*N: 535*	(0.033)	(0.033)
	[1.5%]	[98.5%]		[2.3%]	[97.7%]
Greater Manchester South East	-0.015	-0.123***	Cheshire East	-0.092***	-0.111***
N: 730	(0.021)	(0.028)	*N: 835*	(0.024)	(0.030)
	[11.1%]	[88.9%]		[45.4%]	[54.6%]
Greater Manchester North West	0.056*	-0.105***	Cheshire West and Chester	-0.014	-0.093**
N: 915	(0.024)	(0.025)	*N: 666*	(0.025)	(0.031)
	[-115.6%]	[215.6%]		[13.3%]	[86.7%]
Greater Manchester North East	0.034	-0.117***	East Merseyside	-0.012	-0.170***
N: 1,008	(0.022)	(0.024)	*N: 798*	(0.025)	(0.030)
	[-41.0%]	[141.0%]		[6.4%]	[93.6%]
Blackburn with Darwen	0.036	-0.087	Liverpool	-0.045*	-0.081***
N: 266	(0.043)	(0.048)	*N: 1,056*	(0.020)	(0.024)
	[-72.4%]	[172.4%]		[35.8%]	[64.2%]
Blackpool	0.028	-0.048	Sefton	0.050	-0.159***
N: 325	(0.034)	(0.038)	*N: 429*	(0.032)	(0.045)
	[-140.0%]	[240.0%]		[-45.2%]	[145.2%]
Lancaster and Wyre	-0.010	-0.126***	Wirral	-0.048	-0.087*
N: 403	(0.036)	(0.037)	*N: 387*	(0.033)	(0.041)
	[7.5%]	[92.5%]		[35.3%]	[64.7%]
Yorkshire and the Humber					
Kingston upon Hull	0.003	-0.103**	Sheffield	-0.005	-0.096***
N: 550	(0.029)	(0.033)	*N: 1,057*	(0.019)	(0.023)
	[-2.7%]	[102.7%]		[5.1%]	[94.9%]
East Riding of Yorkshire	0.024	-0.156***	Bradford	-0.024	-0.120***
N: 614	(0.027)	(0.031)	*N: 847*	(0.020)	(0.026)

Area	**Explained**	**Unexplained**	**Area**	**Explained**	**Unexplained**
	[-18.3%]	[118.3%]		[16.6%]	[83.4%]
North and North East Lincolnshire	-0.016	-0.197***	Leeds	-0.046***	-0.129***
N: 573	(0.026)	(0.034)	*N: 2,914*	(0.012)	(0.015)
	[7.3%]	[92.7%]		[26.2%]	[73.8%]
York	-0.084**	-0.120**	Calderdale and Kirklees	-0.037	-0.127***
N: 490	(0.027)	(0.038)	*N: 1,027*	(0.021)	(0.024)
	[41.1%]	[58.9%]		[22.6%]	[77.4%]
North Yorkshire County Council	-0.022	-0.086***	Wakefield	-0.014	-0.184***
N: 1,260	(0.016)	(0.021)	*N: 707*	(0.028)	(0.033)
	[20.3%]	[79.7%]		[-8.4%]	[108.4%]
Barnsley, Doncaster and Rotherham	0.005	-0.162***			
N: 1,319	(0.018)	(0.021)			
	[-3.0%]	[103.0%]			
East Midlands					
Derby	-0.054	-0.177***	Leicester	0.002	-0.095**
N: 634	(0.030)	(0.032)	*N: 657*	(0.023)	(0.030)
	[23.4%]	[76.6%]		[-1.6%]	[101.6%]
East Derbyshire	-0.016	-0.141***	Leicestershire County Council	-0.053**	-0.099***
N: 501	(0.025)	(0.033)	*N: 1,432*	(0.018)	(0.021)
	[10.2%]	[89.8%]		[35.1%]	[64.9%]
South and West Derbyshire	-0.003	-0.135***	West Northamptonshire	-0.005	-0.145***
N: 752	(0.023)	(0.028)	*N: 839*	(0.023)	(0.028)
	[2.1%]	[97.9%]		[3.3%]	[96.7%]
Nottingham	0.005	-0.043***	North Northamptonshire	-0.060*	-0.103**
N: 724	(0.024)	(0.029)	*N:619*	(0.025)	(0.033)
	[-12.2%]	[112.2%]		[36.8%]	[63.2%]
North Nottinghamshire	0.009	-0.159***	Lincolnshire County Council	-0.009	-0.082***
N: 971	(0.022)	(0.025)	*N: 1,331*	(0.018)	(0.021)
	[-6.0%]	[106.0%]		[9.9%]	[90.1%]
South Nottinghamshire	-0.058	-0.138***			
N: 483	(0.030)	(0.040)			
	[29.6%]	[70.4%]			
West Midlands					
Herefordshire	0.042	-0.090*	Birmingham	-0.038**	-0.111***
N: 381	(0.029)	(0.038)	*N: 2,051*	(0.013)	(0.018)
	[-87.1%]	[-187.1%]		[25.7%]	[74.3%]
Worcestershire County Council	-0.007	-0.114***	Solihull	-0.097**	-0.157***
N: 1,071	(0.019)	(0.022)	*N: 641*	(0.037)	(0.037)

Area	Explained	Unexplained	Area	Explained	Unexplained
	[6.0%]	[94.0%]		[38.2%]	[61.8%]
Warwickshire County Council	-0.042*	-0.154***	Coventry	-0.037	-0.139***
N: 1,228	(0.018)	(0.024)	*N: 733*	(0.025)	(0.034)
	[21.4%]	[78.6%]		[21.0%]	[79.0%]
Telford and Wrekin	-0.076*	-0.084*	Dudley	0.002	-0.099**
N: 409	(0.034)	(0.041)	*N: 478*	(0.031)	(0.038)
	[47.7%]	[52.3%]		[-2.4%]	[102.4%]
Shropshire	0.029	-0.156***	Sandwell	0.088**	-0.120***
N: 602	(0.030)	(0.035)	*N: 485*	(0.032)	(0.034)
	[-23.2%]	[123.2%]		[-272.7%]	[372.7%]
Stoke-on-Trent	0.026	-0.132***	Walsall	0.054	-0.121***
N: 666	(0.025)	(0.029)	*N: 448*	(0.036)	(0.038)
	[-24.9%]	[124.9%]		[-82.0%]	[182.0%]
Staffordshire County Council	-0.007	-0.117***	Wolverhampton	0.046	-0.065**
N: 1,552	(0.015)	(0.020)	*N: 445*	(0.029)	(0.039)
	[5.7%]	[94.3%]		[-236.6%]	[336.6%]
East of England					
Peterborough	0.007	-0.096**	Bedford	0.035	-0.057
N: 521	(0.028)	(0.034)	*N: 385*	(0.043)	(0.047)
	[-8.1%]	[108.1%]		[-155.6%]	[255.6%]
Cambridge County Council	-0.028	-0.121***	Central Bedfordshire	-0.054	-0.127**
N: 1,482	(0.017)	(0.022)	*N: 457*	(0.032)	(0.042)
	[19.0%]	[81.0%]		[29.8%]	[70.2%]
Suffolk	-0.020	-0.130***	Southend-on-Sea	0.004	-0.087
N: 1,519	(0.017)	(0.020)	*N: 247*	(0.043)	(0.052)
	[13.3%]	[86.7%]		[-5.4%]	[105.4%]
Norwich and East Norfolk	-0.021	-0.095***	Thurrock	-0.075	-0.138**
N: 773	(0.012)	(0.029)	*N: 239*	(0.054)	(0.047)
	[17.8%]	[82.2%]		[35.3%]	[64.7%]
North and West Norfolk	0.004	-0.096*	Essex Haven Gateway	-0.023	-0.137***
N: 383	(0.031)	(0.038)	*N: 730*	(0.027)	(0.032)
	[-4.0%]	[104.0%]		[14.5%]	[85.5%]
Breckland and South Norfolk	-0.036	-0.110**	West Essex	-0.025	-0.076*
N: 426	(0.029)	(0.035)	*N: 466*	(0.036)	(0.037)
	[24.7%]	[75.3%]		[25.0%]	[75.0%]
Luton	-0.033	-0.175***	Heart of Essex	-0.036	-0.102**
N: 358	(0.043)	(0.050)	*N: 572*	(0.031)	(0.038)
	[16.0%]	[84.0%]		[26.2%]	[73.8%]

Area	Explained	Unexplained	Area	Explained	Unexplained
Hertfordshire	-0.016	-0.100***	Essex Thames Gateway	-0.034	-0.169***
N: 2,598	(0.014)	(0.018)	*N: 439*	(0.033)	(0.046)
	[13.8%]	[86.2%]		[16.6%]	[83.4%]
London					
Camden and City of London	-0.065***	-0.147***	Redbridge and Waltham Forest	-0.007	-0.127**
N: 3,001	(0.012)	(0.018)	*N: 425*	(0.030)	(0.040)
	[30.5%]	[69.5%]		[5.5%]	[94.5%]
Westminster	-0.071***	-0.098***	Enfield	0.120**	-0.116*
N: 1,992	(0.013)	(0.022)	*N: 370*	(0.040)	(0.047)
	[42.1%]	[57.9%]		[3000.0%]	[-2900.0%]
Kensington & Chelsea and Hammersmith	-0.033	-0.065	Bromley	-0.053	-0.105*
& Fulham *N: 749*	(0.022)	(0.035)	*N: 410*	(0.037)	(0.043)
	[33.8%]	[66.2%]		[33.7%]	[66.3%]
Wandsworth	-0.063	-0.020	Croydon	-0.097**	-0.117**
N: 367	(0.035)	(0.041)	*N: 432*	(0.033)	(0.038)
	[75.9%]	[24.1%]		[45.3%]	[54.7%]
Hackney and Newham	-0.035	-0.043	Merton, Kingston upon Thames and	-0.053*	-0.077**
N:820	(0.025)	(0.031)	Sutton*N: 828*	(0.025)	(0.030)
	[44.9%]	[55.1%]		[40.8%]	[59.2%]
Tower Hamlets	-0.113***	-0.051	Barnet	-0.036	-0.032
N: 1,089	(0.025)	(0.032)	*N: 406*	(0.036)	(0.041)
	[68.7%]	[31.3%]		[53.1%]	[46.9%]
Haringey and Islington	-0.046***	-0.089**	Brent	-0.074**	-0.059*
N:904	(0.021)	(0.030)	*N: 695*	(0.023)	(0.025)
	[34.0%]	[66.0%]		[55.6%]	[44.4%]
Lewisham and Southwark	-0.030	-0.060*	Ealing	0.038	-0.035
N: 1,282	(0.018)	(0.025)	*N: 431*	(0.039)	(0.043)
	[32.9%]	[67.1%]		[1184.4%]	[-1084.4%]
Lambeth	-0.021	-0.116**	Harrow and Hillingdon	0.025	-0.049
N: 495	(0.027)	(0.038)	*N:805*	(0.025)	(0.028)
	[15.1%]	[84.9%]		[-108.1%]	[208.1%]
Bexley and Greenwich	-0.030	-0.051	Hounslow and Richmon upon Thames	-0.088**	-0.033
N:544	(0.031)	(0.031)	*N: 660*	(0.029)	(0.038)
	[37.1%]	[62.9%]		[72.6%]	[27.4%]
Barking & Dagenham and Havering	0.038	-0.212***			
N:468	(0.037)	(0.043)			
	[-21.8%]	[121.8%]			
South East					

Area	**Explained**	**Unexplained**	**Area**	**Explained**	**Unexplained**
Berkshire	-0.092***	-0.119***	Portsmouth and Isle of Wight	-0.031	-0.118***
N: 1,872	(0.016)	(0.020)	*N: 716*	(0.028)	(0.034)
	[43.5%]	[56.5%]		[21.0%]	[79.0%]
Milton Keynes	0.020	-0.106***	Southampton	0.025	-0.095*
N:703	(0.023)	(0.032)	*N:529*	(0.029)	(0.039)
	[-23.1%]	[123.1%]		[-35.9%]	[139.5%]
Buckingham County Council	-0.094***	-0.143***	South Hampshire	-0.055*	-0.062*
N:803	(0.027)	(0.034)	*N:756*	(0.026)	(0.030)
	[39.6%]	[60.4%]		[46.9%]	[53.1%]
Oxfordshire	-0.065***	-0.087***	Central Hampshire	-0.056**	-0.108***
N: 1,544	(0.018)	(0.023)	*N: 1,200*	(0.020)	(0.024)
	[42.7%]	[57.3%]		[34.1%]	[65.9%]
Brighton and Hove	-0.047	-0.097**	North Hampshire	-0.115***	-0.129***
N: 609	(0.025)	(0.033)	*N: 659*	(0.028)	(0.038)
	[32.6%]	[67.4%]		[47.1%]	[52.9%]
East Sussex County Council	-0.005	-0.038	Medway	-0.002	-0.187***
N: 752	(0.024)	(0.027)	*N: 386*	(0.032)	(0.039)
	[12.3%]	[87.7%]		[0.9%]	[99.1%]
West Surrey	-0.080***	-0.108***	Kent Thames Gateway	-0.034	-0.211***
N: 1,362	(0.019)	(0.024)	*N: 650*	(0.029)	(0.038)
	[42.5%]	[57.5%]		[13.9%]	[86.1%]
East Surrey	-0.044	-0.120**	East Kent	-0.007	-0.060*
N: 625	(0.026)	(0.037)	*N: 769*	(0.024)	(0.029)
	[26.6%]	[73.4%]		[10.7%]	[89.3%]
West Sussex (South West)	0.038	-0.060*	Mid Kent	-0.006	-0.085**
N: 754	(0.022)	(0.029)	*N: 644*	(0.024)	(0.030)
	[-176.4%]	[276.4%]		[6.3%]	[93.7%]
West Sussex (North East)	-0.030	-0.106**	West Kent	-0.010	-0.084**
N: 668	(0.028)	(0.034)	*N: 722*	(0.026)	(0.030)
	[22.3%]	[77.7%]		[10.2%]	[89.8%]
South West					
Bristol, City of	-0.044*	-0.079***	Dorset County Council	0.032	-0.167***
N: 1,308	(0.018)	(0.023)	*N: 737*	(0.025)	(0.029)
	[36.0%]	[64.0%]		[-23.9%]	[123.9%]
Bath and North East Somerset, North	-0.071***	-0.107***	Somerset	0.037	-0.133***
Somerset and South Gloucestershire	(0.016)	(0.021)	*N: 974*	(0.021)	(0.023)
N: 1,466	[39.9%]	[60.1%]		[-38.0%]	[138.0%]
Gloucestershire	-0.056*	-0.061*	Cornwall and Isles of Scilly	0.010	-0.093***

Area	**Explained**	**Unexplained**	**Area**	**Explained**	**Unexplained**
N: 1,048	(0.022)	(0.029)	*N:916*	(0.020)	(0.024)
	[48.0%]	[52.0%]		[-11.9%]	[111.9%]
Swindon	-0.048	-0.160***	Plymouth	0.037	-0.063*
N: 514	(0.032)	(0.040)	*N: 560*	(0.029)	(0.032)
	[23.0%]	[77.0%]		[-141.1%]	[241.1%]
Wiltshire County Council	-0.053*	-0.121***	Torbay	0.018	-0.093*
N: 861	(0.021)	(0.027)	*N: 212*	(0.045)	(0.041)
	[30.2%]	[69.8%]		[-23.7%]	[123.7%]
Bournemouth and Poole	-0.042	-0.089**	Devon County Council	-0.002	-0.114***
N: 659	(0.024)	(0.032)	*N: 1,550*	(0.016)	(0.019)
	[32.3%]	[67.7%]		[1.5%]	[98.5%]
Wales					
Anglesey and Gwynedd	-0.020	-0.077*	Bridgend and Neath Port Talbot	0.025	-0.184***
N: 329	(0.035)	(0.038)	*N: 444*	(0.030)	(0.036)
	[21.0%]	[79.0%]		[-15.6%]	[115.6%]
Conwy and Denbighshire	0.018	-0.092**	Swansea	0.031	-0.047
N: 397	(0.031)	(0.032)	*N: 574*	(0.028)	(0.032)
	[-24.7%]	[124.7%]		[-193.2%]	[293.2%]
South West and Mid Wales	0.041	-0.097***	Monmouthshire and Newport	-0.024	-0.078*
N: 846	(0.022)	(0.026)	*N: 524*	(0.031)	(0.035)
	[-73.1%]	[173.1%]		[23.6%]	[76.4%]
Central Valleys	0.009	-0.112**	Cardiff and Vale of Glamorgan	-0.012	-0.092***
N: 516	(0.028)	(0.036)	*N: 1,275*	(0.016)	(0.020)
	[-8.4%]	[108.4%]		[11.3%]	[88.7%]
Gwent Valleys	0.005	-0.132***	Flintshire and Wrexham	0.042	-0.165***
N: 511	(0.029)	(0.037)	Wrexham *N: 595*	(0.026)	(0.028)
	[-3.8%]	[103.8%]		[-33.9%]	[133.9%]
Scotland					
Aberdeen City and Aberdeenshire	0.013	-0.130***	West Lothian	-0.035	-0.071
N: 1,134	(0.023)	(0.027)	*N: 336*	(0.035)	(0.045)
	[-11.0%]	[111.0%]		[33.0%]	[67.0%]
Highlands and Islands	0.006	-0.109***	East Dunbartonshire, West	-0.066*	-0.169***
N: 461	(0.031)	(0.033)	Dunbartonshire, Helensburgh and	(0.031)	(0.040)
	[-6.1%]	[106.1%]	Lomond *N: 333*	[28.2%]	[71.8%]
Inverness & Nairn and Moray, Badenoch	0.039	-0.095**	Glasgow City	-0.018	-0.111***
& Strathspey *N: 464*	(0.031)	(0.033)	*N: 2,080*	(0.013)	(0.017)
	[-69.9%]	[169.9%]		[14.2%]	[85.8%]
Angus and Dundee City	0.020	-0.070*	Inverclyde, East Renfrewshire and	-0.014	-0.065*

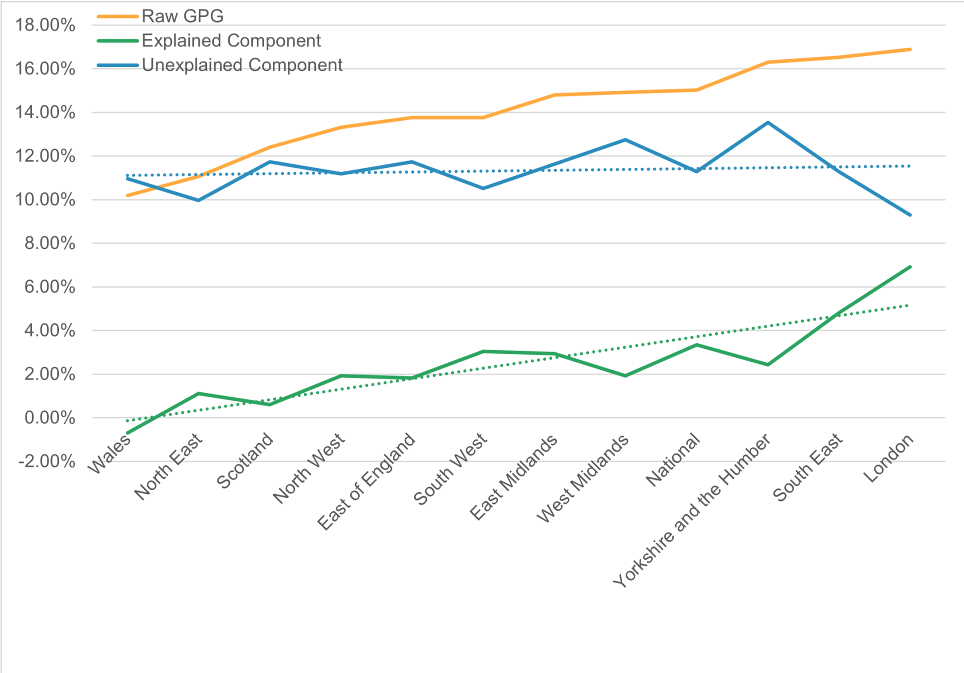
Area	Explained	Unexplained	Area	Explained	Unexplained
547	(0.024)	(0.028)	Renfrewshire *N: 569*	(0.027)	(0.031)
	[-40.4%]	[140.4%]		[17.7%]	[82.3%]
Clackmannanshire and Fife	0.015	-0.113***	North Lanarkshire	0.033	-0.154***
N: 767	(0.023)	(0.026)	*N: 657*	(0.026)	(0.030)
	[-15.3%]	[115.3%]		[-26.9%]	[126.9%]
East Lothian and Mid-lothian	-0.027	-0.159***	Scottish Borders	-0.001	-0.044
N: 250	(0.039)	(0.040)	*N: 225*	(0.064)	(0.066)
	[14.5%]	[85.5%]		[2.3%]	[97.7%]
Edinburgh, City of	-0.045**	-0.102***	Dumfries and Galloway	0.062	-0.064
N: 1,756	(0.015)	(0.019)	*N: 299*	(0.039)	(0.036)
	[30.4%]	[69.6%]		[-3868.7%]	[3968.7%]
Falkirk	0.019	-0.191***	Ayrshire	0.022	-0.100**
N: 314	(0.036)	(0.049)	*N:674*	(0.026)	(0.033)
	[-10.9%]	[110.9%]		[-27.9%]	[127.9%]
Perth & Kinross and Stirling	0.004	-0.103***	South Lanarkshire	-0.006	-0.075*
N: 545	(0.029)	(0.031)	*N: 580*	(0.030)	(0.034)
	[-4.2%]	[104.2%]		[7.7%]	[92.3%]

Notes: i) Estimates are based on an OB decomposition of mean hourly GPGs across areas using relevant male coefficients as the baseline. (ii) The specification includes individual characteristics (age, age-squared, tenure, tenure-squared and a part-time and a temporary contract indicator), workplace characteristics (firm size and a collective agreement indicator), occupations, and public sector employment. (iii) Figures in [] are proportions of the raw GPG. (iv) Standard errors in parenthesis. (v) $^{*}< 0.05$, $^{**}< 0.01$, $^{***}< 0.001$.

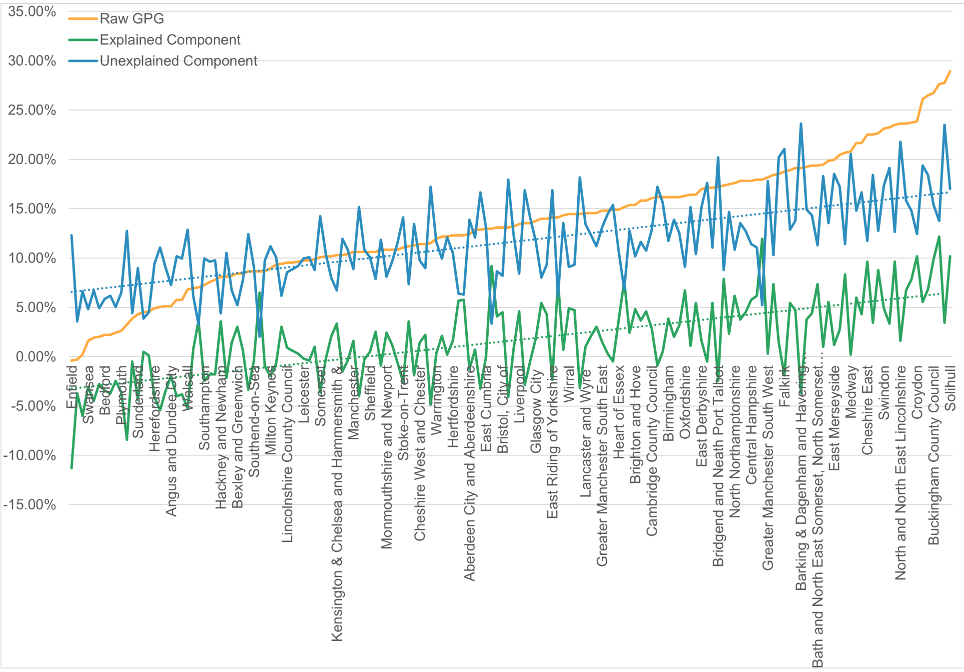
Source: Author calculations based on weighted ASHE 2022 data.

Figure B.1: Explained and Unexplained Component of Gender Pay Gaps across Areas, by Geographical Level

(a) Regional Level



(b) Local Level



Notes: (i) Estimates are based on an OB decompositions of mean hourly GPGs across areas using relevant male coefficients as the baseline. (ii) The specification includes individual characteristics (age, age-squared, tenure, tenure-squared and a part-time and a temporary contract indicator), workplace characteristics (firm size and a collective agreement indicator), occupations, and public sector employment. (iii) Areas are sorted in increasing order of their raw GPG. (iv) The linear trend lines depict the generalised magnitude of the explained and unexplained part in the sorted areas. (v) Small discrepancies between the sum of the explained and unexplained components and raw GPG s are a result of rounding.

Source: Author calculations based on weighted ASHE 2022 data.

Table B.10: Detailed Decomposition of Gender Pay Gaps across Areas, National and Regional Level

	National (*N: 124,963*)		**Regional** *Minimum*: **Wales** (*N: 6,011*)		*Maximum*: **London** (*N: 17,173*)	
Raw GPG	-0.140***	[100%]	-0.097***	[100%]	-0.156***	[100%]
Explained Component	-0.033***	[23.4%]	0.007	[-7.2%]	-0.067***	[43.1%]
Unexplained Component	-0.107***	[76.6%]	-0.104***	[107.2%]	-0.089***	[56.9%]
Explained Component	-0.033***	[100%]	0.007	[100%]	-0.067***	[100%]
Age	0.009**	[-26.2%]	0.029**	[410.6%]	-0.025**	[37.7%]
Age^2	-0.010***	[30.3%]	-0.029**	[-410.6%]	0.019*	[-28.4%]
Tenure	-0.005***	[15.2%]	-0.000	[-0.5%]	-0.009***	[13.4%]
Tenure^2	0.003***	[-9.1%]	-0.000	[-0.0%]	0.005***	[-7.5%]
Full-/Part-time	-0.015***	[45.5%]	-0.009***	[-128.6%]	-0.014***	[20.9%]
Permanent/Temporary contract	-0.000	[0.1%]	0.000	[0.2%]	-0.001*	[1.5%]
Medium firm size	-0.001***	[3.0%]	-0.002*	[-28.6%]	0.000	[-0.3%]
Large firm size	-0.001***	[3.0%]	-0.003**	[-42.9%]	-0.000	[0.0%]
Enterprise firm size	0.006***	[-18.2%]	0.009***	[128.6%]	0.001	[-1.5%]
Collective agreement	-0.001*	[0.6%]	0.001	[14.3%]	0.000	[-0.2%]
Manager & Senior Officials	-0.021***	[63.6%]	-0.014***	[-200.0%]	-0.031***	[46.3%]
Professional	-0.003**	[9.1%]	0.002	[28.6%]	-0.007*	[10.4%]
Associate professional	0.000	[-0.3%]	0.000	[0.1%]	-0.001	[1.5%]
Skilled trades	0.009***	[-27.3%]	0.004	[57.1%]	0.008***	[-11.9%]
Personal service	-0.010***	[30.3%]	-0.010***	[-142.9%]	-0.012***	[17.9%]
Sales & customer service	-0.005***	[15.2%]	-0.003***	[-42.9%]	-0.005***	[7.5%]
Process, plant & machine operatives	0.012***	[-36.4%]	0.013***	[185.7%]	0.007***	[-10.4%]
Elementary occupations	0.002***	[-6.1%]	0.005***	[71.4%]	-0.000	[0.2%]
Public sector	-0.000	[0.2%]	0.014***	[200.0%]	-0.004***	[6.0%]

Notes: (i) Estimates are based on an OB decompositions of mean hourly GPGs across areas using relevant male coefficients as the baseline. (ii) The specification includes individual characteristics (age, age-squared, tenure, tenure-squared and a part-time and a temporary contract indicator), workplace characteristics (firm size and a collective agreement indicator), occupations, and public sector employment. (iii) Figures in [] are proportions of the raw GPG in the top panel and proportions of the explained GPG in the bottom panel. (iv) $^{*}< 0.05$, $^{**}< 0.01$, $^{***}< 0.001$.

Source: Author calculations based on weighted ASHE 2022 data.

Table B.11: Detailed Decomposition of Gender Pay Gaps across Areas, Local Level

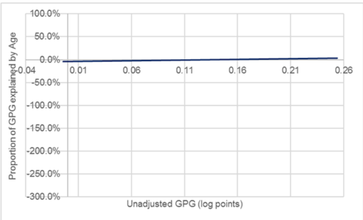
	Local			
	Minimum: **Enfield** (*N: 370*)		*Maximum*: **Solihull** (*N: 641*)	
Raw GPG	0.004	[100%]	-0.254***	[100%]
Explained	0.120**	[3000.0%]	-0.097**	[38.2%]
Unexplained	-0.116*	[-2900.0%]	-0.157***	[61.8%]
Explained Component	0.120**	[100%]	-0.097**	[100%]
Age	0.027	[22.4%]	-0.032	[33.2%]
Age^2	-0.025	[-20.8%]	0.020	[-20.6%]
Tenure	0.005	[4.2%]	0.004	[-4.1%]
Tenure^2	0.001	[0.8%]	-0.009	[9.3%]
Full-/Part-time	0.000	[0.0%]	-0.028*	[28.9%]
Permanent/Temporary contract	-0.001	[-0.8%]	0.001	[-1.0%]
Medium firm size	0.000	[0.0%]	-0.005	[5.28%]
Large firm size	-0.001	[-0.8%]	0.003	[-3.1%]
Enterprise firm size	-0.005	[-4.2%]	-0.019	[19.6%]
Collective agreement	-0.009	[-7.5%]	-0.035*	[36.1%]
High-Skilled Occupations	0.038	[31.7%]	0.010	[-10.3%]
Medium-Skilled Occupations	0.005	[4.2%]	0.006	[-6.2%]
Public sector	0.085**	[70.8%]	-0.012	[12.4%]

Notes: (i) Estimates are based on an OB decompositions of mean hourly GPGs across areas using relevant male coefficients as the baseline. (ii) The specification includes individual characteristics (age, age-squared, tenure, tenure-squared and a part-time and a temporary contract indicator), workplace characteristics (firm size and a collective agreement indicator), occupational skill group, and public sector employment. (iii) Figures in [] are proportions of the raw GPG in the top panel and proportions of the explained GPG in the bottom panel. (iv) $^{*}< 0.05$, $^{**}< 0.01$, $^{***}< 0.001$.

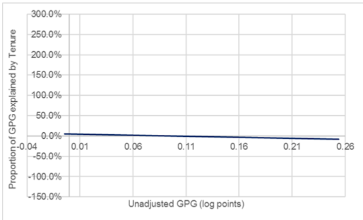
Source: Author calculations based on weighted ASHE 2022 data.

Figure B.2: Contribution of Explanatory Variables to the Gender Pay Gap Across Areas

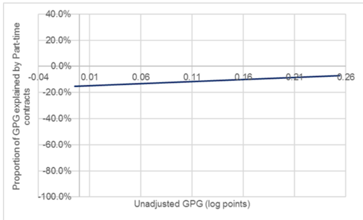
(a) Age and age^2



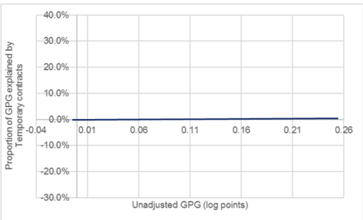
(b) Tenure and tenure^2



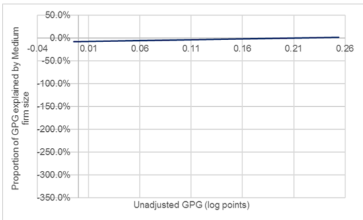
(c) Part-time work



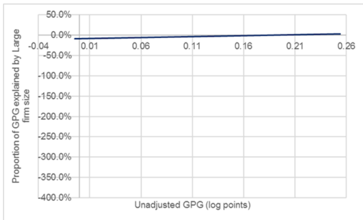
(d) Temporary contracts



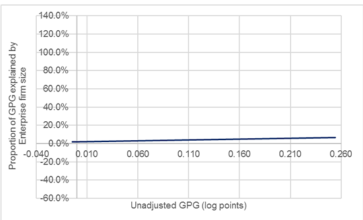
(e) Medium firm size



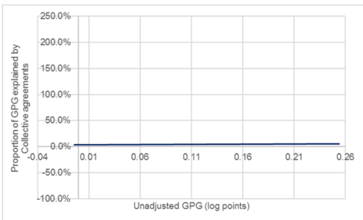
(f) Large firm size



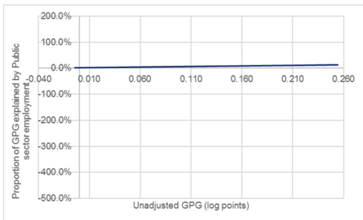
(g) Enterprise firm size



(h) Collective agreements



(i) Public sector



Notes: (i) Estimates are based on OB decompositions of mean GPGs across areas within Britain using relevant male coefficients as the reference. (ii) All areas are included, regardless of the geographical level, and are sorted in increasing order of their raw GPG. Dumfries and Galloway is excluded from the analysis of part-time, Enterprise firm size and collective agreements and Enfield is excluded in the public sector analysis, as the proportion explained exceeds 1000%. (iii) Linear trend lines illustrate spatial variations in the contribution of each explanatory variable to the GPG across ranked areas.

Source: Author calculations based on weighted ASHE 2022 data.

Table B.12: Detailed Decomposition of the raw Gender Pay Gap across Selected Areas, by Geographical Level, Sensitivity to Pooled Coefficients

	National		**Regional**				**Local**			
	(*N: 124,963*)		**Wales** (*N: 6,011*)		**London** (*N: 17,173*)		**Enfield** (*N: 370*)		**Solihull** (*N: 641*)	
Raw GPG	-0.140***	[100%]	-0.097***	[100%]	-0.156***	[100%]	0.004	[100%]	-0.254***	[100%]
Explained Component	-0.047***	[33.6%]	-0.011	[11.0%]	-0.081***	[51.7%]	0.096*	[2190.9%]	-0.123***	[48.3%]
Unexplained Component	-0.093***	[66.4%]	-0.086***	[89.0%]	-0.075***	[48.3%]	-0.091*	[-2090.9%]	-0.131***	[51.7%]
Explained Component	-0.047***	[100%]	-0.011	[100%]	-0.081***	[100%]	0.096*	[100%]	-0.123***	[100%]
Age	0.010***	[-20.3%]	0.033**	[-309.7%]	-0.029**	[36.3%]	0.018	[18.3%]	-0.049	[39.8%]
Age^2	-0.011***	[22.9%]	-0.033**	[303.3%]	0.022*	[-26.7%]	-0.011	[-11.6%]	0.035	[-28.3%]
Tenure	-0.005***	[11.0%]	-0.001	[6.4%]	-0.010***	[12.4%]	0.004	[4.6%]	-0.023	[19.0%]
Tenure^2	0.003***	[-6.1%]	0.000	[-1.0%]	0.006***	[-7.9%]	0.000	[0.5%]	0.014	[-11.2%]
Full-/Part-time	-0.017***	[36.5%]	-0.007**	[69.3%]	-0.018***	[22.2%]	-0.011	[-11.3%]	-0.032***	[25.6%]
Temporary contract	-0.000**	[0.4%]	0.000	[-1.8%]	0.001***	[-1.6%]	0.002	[1.8%]	0.001	[-0.9%]
Medium firm size	-0.002***	[4.0%]	-0.003***	[32.3%]	0.001	[-0.7%]	0.000	[0.3%]	0.004	[-3.3%]
Large firm size	-0.002***	[3.7%]	-0.003***	[31.3%]	-0.000	[0.1%]	-0.001	[-0.6%]	0.003	[-2.8%]
Enterprise firm size	0.008***	[-17.2%]	0.011***	[-100.7%]	0.001	[-0.9%]	-0.004	[-4.7%]	-0.032**	[25.6%]
Collective agreement	-0.000	[0.8%]	0.004**	[-39.0%]	0.000	[-0.2%]	-0.008	[-8.4%]	-0.035***	[28.5%]
Manager & Senior Officials	-0.022***	[46.7%]	-0.014***	[128.9%]	-0.032***	[39.0%]				
Professional	-0.003**	[7.1%]	0.003	[-24.0%]	-0.007*	[8.7%]				
Associate professional	0.001	[-1.1%]	0.000	[-1.7%]	-0.001	[0.7%]				
Skilled trades	0.002***	[-4.5%]	-0.006**	[54.1%]	0.005***	[-6.7%]				
Personal service	-0.011***	[23.6%]	-0.011***	[107.2%]	-0.012***	[15.1%]				
Sales & customer service	-0.005***	[11.4%]	-0.004***	[34.6%]	-0.005***	[5.8%]				
Process, plant & machine ops	0.008***	[-17.7%]	0.008***	[-73.9%]	0.005***	[-6.4%]				
Elementary occupations	0.002***	[-3.9%]	0.005***	[-47.9%]	-0.000	[0.4%]				
High-Skilled Occupations							0.039	[40.4%]	0.007	[-5.6%]
Medium-Skilled Occupations							0.005	[4.9%]	0.000	[0.0%]
Public sector	-0.001	[2.8%]	0.007**	[-67.9%]	-0.006***	[7.0%]	0.063**	[65.9%]	-0.017*	[13.5%]

Notes: (i) Estimates are based on an OB decompositions of mean hourly GPGs across areas using relevant pooled coefficients as the baseline. (ii) The specification includes individual characteristics (age, age-squared, tenure, tenure-squared and a part-time and a temporary contract indicator), workplace characteristics (firm size and a collective agreement indicator), occupations, and public sector employment. (iii) Figures in [] are proportions of the raw GPG in the top panel and proportions of the explained GPG in the bottom panel. (iv) $^{*}< 0.05$, $^{**}< 0.01$, $^{***}< 0.001$.

Source: Author calculations based on weighted ASHE 2022 data.

Table B.13: Detailed Decomposition of the raw Gender Pay Gap across Selected Areas, by Geographical Level, Sensitivity to Female Coefficients

	National		**Regional**				**Local**			
	(*N: 124,963*)		**Wales** (*N: 6,011*)		**London** (*N: 17,173*)		**Enfield** (*N: 370*)		**Solihull** (*N: 641*)	
Raw GPG	-0.140***	[100%]	0.097***	[100%]	0.156***	[100%]	0.004	[100%]	0.254***	[100%]
Explained Component	0.058***	[41.2%]	-0.016	[16.5%]	-0.094***	[59.9%]	0.086	[1973.2%]	-0.150***	[58.8%]
Unexplained Component	0.082***	[58.8%]	-0.081***	[83.5%]	0.063***	[40.1%]	-0.082	[-1873.2%]	-0.105**	[51.2%]
Explained Component	0.058***	[100%]	-0.016	[100%]	-0.094***	[100%]	0.086	[100%]	-0.150***	[100%]
Age	0.011***	[-18.2%]	0.039**	[-241.8%]	-0.033**	[35.3%]	0.002	[2.3%]	-0.053	[35.6%]
Age^2	-0.012***	[20.0%]	-0.037**	[230.3%]	0.024*	[-25.9%]	0.010	[11.3%]	0.038	[-25.7%]
Tenure	-0.005***	[9.3%]	-0.001	[6.0%]	-0.011***	[11.6%]	0.002	[1.9%]	-0.034	[22.6%]
Tenure^2	0.003***	[-5.5%]	0.000	[-1.9%]	0.007***	[-7.6%]	-0.000	[-0.2%]	0.021	[-13.9%]
Full-/Part-time	-0.021***	[36.8%]	-0.000	[1.1%]	-0.024***	[25.8%]	-0.021	[-23.9%]	-0.036**	[24.1%]
Temporary contract	-0.001**	[0.9%]	0.000	[-0.8%]	-0.002**	[1.6%]	-0.013***	[84.2%]	-0.032***	[34.4%]
Medium firm size	-0.002***	[4.0%]	-0.005***	[28.7%]	0.001	[-0.6%]	0.001	[0.9%]	0.013	[-8.4%]
Large firm size	-0.002***	[3.6%]	-0.004***	[25.2%]	-0.000	[0.1%]	-0.001	[-1.0%]	0.005	[-3.6%]
Enterprise firm size	0.010***	[-17.2%]	0.013***	[-80.0%]	0.001	[-0.8%]	-0.003	[-3.7%]	-0.051**	[34.3%]
Collective agreement	0.000	[-0.1%]	0.007***	[-43.0%]	0.000	[0.0%]	-0.002	[-1.8%]	-0.030**	[19.8%]
Manager & Senior Officials	-0.023***	[40.0%]	-0.013***	[84.2%]	-0.032***	[34.4%]				
Professional	-0.003**	[5.8%]	0.002	[-15.5%]	-0.007*	[7.9%]				
Associate professional	0.001	[-1.8%]	0.000	[-1.40%]	-0.001	[0.7%]				
Skilled trades	-0.000	[0.6%]	-0.006*	[40.6%]	0.004***	[-4.8%]				
Personal service	-0.015***	[25.5%]	-0.019***	[120.6%]	-0.013***	[14.2%]				
Sales & customer service	-0.005***	[9.1%]	-0.005***	[31.0%]	-0.004***	[4.7%]				
Process, plant & machine ops	0.007***	[-12.6%]	0.008***	[-47.8%]	0.005***	[-4.9%]				
Elementary occupations	0.002***	[-3.2%]	0.005**	[-31.8%]	-0.000	[0.4%]				
High-Skilled Occupations							0.042	[48.7%]	0.006	[-3.9%]
Medium-Skilled Occupations							0.006	[6.6%]	-0.001	[0.5%]
Public sector	-0.001	[2.2%]	0.001	[-3.7%]	-0.008***	[8.0%]	0.047	[54.1%]	-0.022*	[14.7%]

Notes: (i) Estimates are based on an OB decompositions of mean hourly GPGs across areas using relevant female coefficients as the baseline. (ii) The specification includes individual characteristics (age, age-squared, tenure, tenure-squared and a part-time and a temporary contract indicator), workplace characteristics (firm size and a collective agreement indicator), occupations, and public sector employment. (iii) Figures in [] are proportions of the raw GPG in the top panel and proportions of the explained GPG in the bottom panel. (iv) *< 0.05, **< 0.01, ***< 0.001.

Source: Author calculations based on weighted ASHE 2022 data.

Table B.14: Decomposition of the raw Gender Pay Gap across Selected Areas, Sensitivity Analysis

		National		**Regional**				**Local**			
				Wales		**London**		**Enfield**		**Solihull**	
(1) Pooled Coefficients	Raw GPG	-0.140***	[100%]	-0.097***	[100%]	-0.156***	[100%]	0.004	[100%]	-0.254***	[100%]
	Explained	-0.047***	[33.6%]	-0.011	[11.0%]	-0.081***	[51.7%]	0.096*	[2190.9%]	-0.123***	[48.3%]
	Unexplained	-0.093***	[66.4%]	-0.086***	[89.0%]	-0.075***	[48.3%]	-0.091*	[-2090.9%]	-0.131***	[51.7%]
	N	*124,963*		*6,011*		*17,173*		*370*		*641*	
(2) Female Coefficients	Raw GPG	-0.140***	[100%]	-0.097***	[100%]	-0.156***	[100%]	0.004	[100%]	-0.254***	[100%]
	Explained	-0.058***	[41.2%]	-0.016	[16.5%]	-0.094***	[59.9%]	0.086	[1973.2%]	-0.150***	[58.8%]
	Unexplained	-0.082***	[58.8%]	0.081***	[83.5%]	-0.063***	[40.1%]	-0.082	[-1873.2%]	-0.105**	[41.2%]
	N	*124,963*		*6,011*		*17,173*		*370*		*641*	
(3) Unweighted ASHE 2022	Raw GPG	-0.120***	[100%]	-0.079***	[100%]	-0.141***	[100%]	0.017	[100%]	-0.258***	[100%]
	Explained	-0.013***	[11.1%]	0.026***	[-32.5%]	-0.054***	[38.2%]	0.133***	[782.5%]	-0.086*	[33.4%]
	Unexplained	-0.107***	[88.9%]	-0.104***	[132.5%]	-0.087***	[61.8%]	-0.116**	[-682.5%]	-0.172***	[66.3%]
	N	*124,963*		*6,011*		*17,173*		*370*		*641*	
(4) 2019 data	Raw GPG	-0.165***	[100%]	-0.121***	[100%]	-0.199***	[100%]	-0.135**	[100%]	-0.205***	[100%]
	Explained	-0.036***	[21.8%]	0.001	[-0.8%]	-0.084***	[42.2%]	-0.013	[9.6%]	-0.114***	[55.6%]
	Unexplained	-0.129***	[78.2%]	-0.122***	[100.8%]	-0.115***	[57.8%]	-0.122**	[90.4%]	-0.091*	[44.4%]
	N	*157,868*		*7,290*		*23,122*		*456*		*735*	
(5) Full-time employees	Raw GPG	-0.099***	[100%]	-0.054***	[100%]	-0.134***	[100%]	0.011	[100%]	-0.183***	[100%]
	Explained	0.012***	[-12.0%]	0.038***	[-69.6%]	-0.038***	[28.3%]	0.136**	[1230.0%]	-0.036	[19.7%]
	Unexplained	-0.111***	[112.0%]	-0.092***	[169.6%]	-0.096***	[71.7%]	-0.125*	[-1130.0%]	-0.147***	[80.3%]
	N	*87,049*		*4.127*		*13,081*		*230*		*517*	
(6) Exclude those working overtime	Raw GPG	-0.154***	[100%]	-0.106***	[100%]	-0.171***	[100%]	-0.022	[100%]	-0.261***	[100%]
	Explained	-0.049***	[31.8%]	-0.009	[8.5%]	-0.074***	[43.6%]	0.086*	[-395.4%]	-0.112**	[42.8%]
	Unexplained	-0.105***	[68.2%]	-0.097***	[91.5%]	-0.096***	[56.4%]	-0.108*	[495.4%]	-0.149***	[57.2%]
	N	*103,150*		*4,910*		*14,749*		*312*		*528*	
(7) Hourly pay including working overtime	Raw GPG	-0.144***	[100%]	-0.102***	[100%]	-0.158***	[100%]	0.001	[100%]	-0.260***	[100%]
	Explained	-0.034***	[23.9%]	0.005	[-4.9%]	-0.068***	[43.1%]	0.124**	[12925.3%]	-0.097**	[37.1%]
	Unexplained	-0.109***	[76.1%]	-0.107***	[104.9%]	-0.090***	[56.9%]	-0.123**	[-12825.3%]	-0.164***	[62.9%]
	N	*124,963*		*6,011*		*17,173*		*370*		*641*	
(8) Industry controls	Raw GPG	-0.140***	[100%]	-0.097***	[100%]	-0.156***	[100%]	0.004	[100%]	-0.254***	[100%]
	Explained	-0.047***	[33.4%]	-0.001	[1.5%]	-0.082***	[52.3%]	0.102*	[2344.6%]	-0.125***	[49.0%]
	Unexplained	-0.093***	[66.6%]	-0.096***	[98.5%]	-0.074***	[47.7%]	-0.098*	[2244.6%]	-0.130***	[51.0%]
	N	*124,963*		*6,011*		*17,173*		*370*		*641*	
(9) Excluding occupations and sector	Raw GPG	-0.140***	[100%]	-0.097***	[100%]	-0.156***	[100%]	0.004	[100%]	-0.254***	[100%]
	Explained	-0.047***	[33.5%]	-0.021***	[21.6%]	-0.055***	[35.2%]	0.025	[579.9%]	-0.141***	[55.6%]
	Unexplained	-0.093***	[66.5%]	-0.076***	[78.4%]	-0.101***	[64.8%]	-0.021	[-479.9%]	-0.113**	[44.4%]

	N	*124,963*	*6,011*	*17,173*	*370*	*641*
(10) Median GPG	Raw GPG	-0.161*** [100%]	-0.124*** [100%]	-0.137*** [100%]	0.090 [100%]	-0.360*** [100%]
	Explained	-0.065*** [40.5%]	-0.044 [35.3%]	-0.084*** [61.1%]	0.085 [94.1%]	-0.260*** [72.2%]
	Unexplained	-0.095*** [59.5%]	-0.080*** [64.7%]	-0.053*** [38.9%]	0.005 [5.9%]	-0.100*** [27.8%]
	N	*124,963*	*6,011*	*17,173*	*370*	*641*
(11) Area by Residences	Raw GPG		-0.102*** [100%]	-0.124*** [100%]	-0.055 [100%]	-0.237*** [100%]
	Explained		0.002 [-1.9%]	-0.048*** [38.9%]	0.004 [-7.3%]	-0.031 [13.0%]
	Unexplained		-0.104*** [101.9%]	-0.076*** [61.1%]	-0.059 [107.3%]	-0.206*** [87.0%]
	N		*6,242*	*14,307*	*501*	*422*
(12)Exclude individuals who commute across regions	Raw GPG	-0.125*** [100%]	-0.086*** [100%]	-0.130*** [100%]	0.046 [100%]	-0.263*** [100%]
	Explained	-0.023*** [18.4%]	0.012 [-13.3%]	-0.051*** [39.7%]	0.122** [266.5%]	-0.116* [44.0%]
	Unexplained	-0.102*** [81.6%]	-0.098*** [113.3%]	-0.078*** [60.3%]	-0.076 [-166.5%]	-0.147** [56.0%]
	N	*109,492*	*5,587*	*12,587*	*287*	*528*
(13) Exclude individuals who commute across localities	Raw GPG	-0.113*** [100%]	-0.090*** [100%]	-0.110*** [100%]	0.099 [100%]	-0.177* [100%]
	Explained	-0.013*** [11.9%]	0.005 [-6.0%]	-0.022 [20.5%]	0.187** [188.9%]	0.066 [-37.2%]
	Unexplained	-0.100*** [88.1%]	-0.095*** [106.0%]	-0.087*** [79.5%]	-0.088 [-88.9%]	-0.243** [137.2%]
	N	*72,980*	*4,171*	*4,300*	*188*	*150*
(14) Exclude those who worked in another region region before 2019	Raw GPG	-0.153*** [100%]	-0.071* [100%]	-0.215*** [100%]		
	Explained	-0.015** [9.8%]	0.065* [-91.5%]	-0.097*** [45.1%]		
	Unexplained	-0.138*** [90.2%]	-0.136*** [191.5%]	-0.118*** [54.9%]		
	N	*35,838*	*738*	*5,284*		

Notes: *Notes*: (i) Oaxaca-Blinder and Machado and Mata (2005) methods are used to decompose the GPG at the mean and median respectively, using male coefficients as the baselines (unless otherwise stated). (ii) Figures in [] are proportion of the raw GPG. (iii) $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. (iv) Standard errors for the Machado and Mata (2005) decomposition are bootstrapped 500 replications. (v) Specification includes individual characteristics, workplace characteristics, occupations and sector (unless otherwise stated). (vi) Sample is all-employees (unless otherwise stated). (vii) Industry controls are defined using 1-digit SIC 2007 codes. (viii) There are 15,471 individuals who commute across regions and 51,983 who commute across localities. (iv). Individuals who worked in another region in 2018, compared to 2019 are excluded. This results in an unusable sample size for localities.

Source: Author calculations based on weighted ASHE 2022 data (unless otherwise specified).

Table B.15: Definitions of Area Characteristics

Area Characteristic	**Data source**	**Definition**	**Restrictions**
Area Deprivation	English Index of Multiple Deprivation	Two measures derived from the IMD and its seven domains: • Average rank: Population-weighted average of the combined ranks for the LSOAs within a local area. • Proportion of LSOAs in most deprived decile: Share of LSOAs in England's most deprived decile. These measures account for both overall deprivation and concentrated disadvantage.	Excludes local authorities without a NUTS 3 equivalent (140 areas retained).
Wage inequality	ASHE 2022	90/10 log hourly wage inequality ratio	
Industrial composition	ASHE 2022	Proportion of employees in broad industry groups (SIC 2007), following (Jones and Kaya, 2022b)	Excludes areas with fewer than 10 employees in an industry.
Unemployment rate	APS 2022	12-month average unemployment rate for individuals aged 16–64.	Excludes local area estimates based on zero or disclosive samples (0-2).
Rurality	2011 Rural Urban Classification	Proportion of rural population in a local area, based on classification from 'Urban with City and Town' to 'Largely Rural'.	
Union membership	ASHE 2022	Proportion of employees who are union members.	
Public sector employment	ASHE 2022	Percentage of employees working in the public sector.	

Table B.16: Correlation Coefficients between Gender Pay Gaps and Area Characteristics

	Area Characteristic	**Raw GPG**	**Explained Gap**	**Unexplained Gap**
Area deprivation	IMD rank	0.312***	0.344***	0.013
	IMD proportion	-0.154*	-0.274***	0.099
	Income deprivation rank	0.343***	0.336***	0.065
	Income deprivation proportion	-0.197*	-0.262***	0.031
	Employment deprivation rank	0.292***	0.423***	-0.100
	Employment deprivation proportion	-0.179*	-0.296***	0.081
	Education, Skills Training deprivation rank	0.138	0.414***	-0.296***
	Education, Skills Training deprivation proportion	-0.052	-0.285**	0.229**
	Health and Disability deprivation rank	0.199*	0.340***	-0.127
	Health and Disability deprivation proportion	-0.152	-0.251***	0.076
	Crime deprivation rank	0.166*	0.141*	0.031
	Crime deprivation proportion	-0.102	-0.127	0.043
	Housing and Services deprivation rank	0.058	-0.163*	0.284***
	Housing and Services deprivation proportion	-0.101	0.043	-0.167*
	Living Environment deprivation rank	0.250***	0.081	0.230***
	Living Environment deprivation proportion	-0.135	-0.096	-0.058
	90/10 log wage inequality ratio	0.335***	0.475***	-0.026
Industrial Composition	Non-manufacturing (A, B, D, E) (91 local areas)	-0.244*	-0.275***	-0.071
	Manufacturing (C) (152 local areas)	0.150	-0.052	0.270***
	Construction industry (F) (143 local areas)	0.170*	-0.065	0.308**
	Distribution, Hotels and restaurant (G, I) (160 local areas)	-0.084	-0.102	-0.011
	Transport and communication(H, J) (156 local areas)	0.197**	0.316***	-0.059
	Business and Services and Finance (K, L, M, N) (160 local areas)	0.306***	0.485***	-0.078
	Public administration, education and social work (O, P, Q) (160 local areas)	-0.412***	-0.375***	-0.189**
	Other services (R, S, T, U) (160 local areas)	-0.028	0.131	-0.179*
Local Labour Market Characteristics	Unemployment Rate (155 local areas)	-0.253**	-0.182*	-0.166*
	Male unemployment rate (140 local areas)	-0.174*	-0.155	-0.086
	Female unemployment rate (134 local areas)	-0.228**	-0.159	-0.154*
	Rurality	0.124	-0.020	0.198*
	Union representation	-0.241**	-0.344***	0.021
	Public sector employment	-0.344***	-0.370***	-0.098

Notes: (i) IMD inequality estimates exclude local authorities without a single NUTS 3 equivalent, leaving 140 English local areas. (ii) Industry estimates follow SIC 2007 broad industry codes, following Jones and Kaya (2022a) and Jones and Kaya (2022b). ‘A - Agriculture, forestry and fishing’ is combined with ‘B, D, E - Energy and water’ due to small sample sizes. Local areas with fewer than 10 employees in a sector are excluded. The number of valid local areas varies by sector and are detailed in the table. (iii) Unemployment rates are from the APS (12 months to December) for those aged 16-64 years. Local areas with zero or disclosive samples (0-2) are excluded.(iv) Rurality is from the 2011 Rural Urban Classification for English local areas. (v) $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Source: Author calculations based on weighted ASHE 2022 data.

Table B.17: Decomposition of the raw Gender Pay Gap across Areas by Industry, Sensitivity Analysis

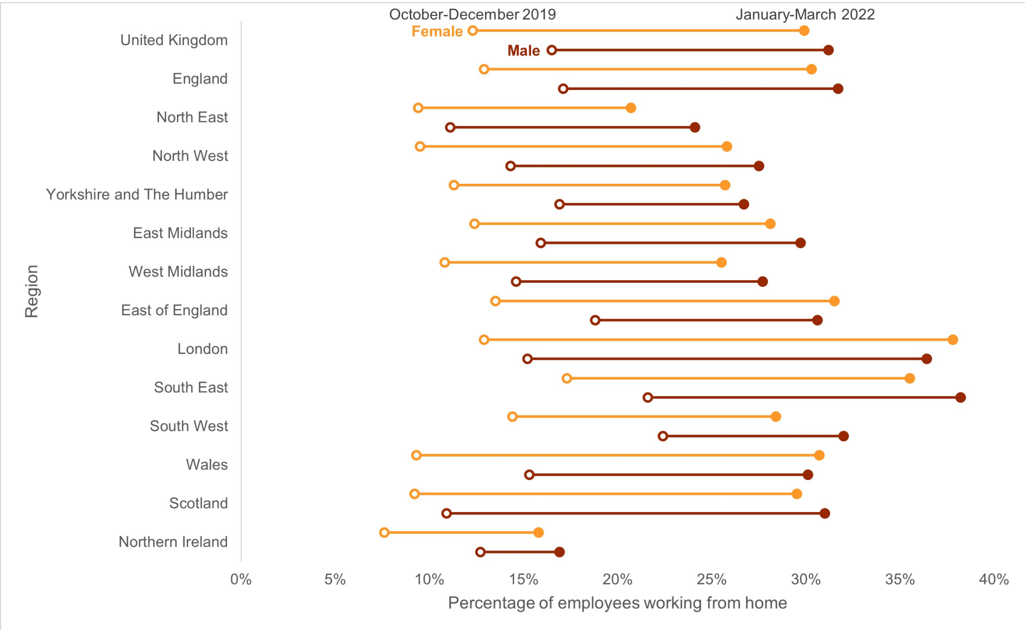
		Manufacturing and Construction		**Public admin, Education and Social work**				**Manufacturing and Construction**		**Public admin, Education and Social work**	
National	Raw GPG	-0.142***	[100%]	-0.171***	[100%]	East of England	Raw GPG	-0.117***	[100%]	-0.170***	[100%]
	Explained	-0.013	[9.2%]	-0.069***	[40.7%]		Explained	-0.038	[32.5%]	-0.056***	[33.2%]
	Unexplained	-0.129***	[90.8%]	-0.101***	[59.3%]		Unexplained	-0.079**	[67.5%]	-0.114***	[66.8%]
	N	*14,995*		*43,870*			*N*	*1,593*		*3,428*	
North East	Raw GPG	-0.046	[100%]	-0.165***	[100%]	London	Raw GPG	-0.195***	[100%]	-0.124***	[100%]
	Explained	-0.022	[48.5%]	-0.079***	[48.1%]		Explained	-0.104**	[53.1%]	-0.055***	[44.3%]
	Unexplained	-0.024	[51.5%]	-0.086***	[51.9%]		Unexplained	-0.091*	[46.9%]	-0.069***	[55.7%]
	N	*595*		*2,102*			*N*	*893*		*5,375*	
North West	Raw GPG	-0.108***	[100%]	-0.190***	[100%]	South East	Raw GPG	-0.174***	[100%]	-0.164***	[100%]
	Explained	0.026	[-24.4%]	-0.088***	[46.1%]		Explained	-0.031	[17.5%]	-0.054***	[32.6%]
	Unexplained	-0.134***	[124.4%]	-0.103***	[53.9%]		Unexplained	-0.143***	[82.5%]	-0.111***	[67.4%]
	N	*1,790*		*5,077*			*N*	*1,830*		*5,580*	
Yorkshire and the Humberside	Raw GPG	-0.143***	[100%]	-0.204***	[100%]	South West	Raw GPG	-0.176***	[100%]	-0.161***	[100%]
	Explained	0.037	[-25.7%]	-0.078***	[38.4%]		Explained	-0.032	[18.1%]	-0.083***	[51.8%]
	Unexplained	-0.180***	[125.7%]	-0.125***	[61.6%]		Unexplained	-0.144***	[81.7%]	-0.077***	[48.2%]
	N	*1,624*		*3,653*			*N*	*1,418*		*3,663*	
East Midlands	Raw GPG	-0.153***	[100%]	-0.184***	[100%]	Wales	Raw GPG	-0.148***	[100%]	-0.150***	[100%]
	Explained	-0.018	[11.8%]	-0.113***	[61.4%]		Explained	-0.029	[19.5%]	-0.057**	[37.7%]
	Unexplained	-0.135***	[88.2%]	-0.071***	[38.6%]		Unexplained	-0.119***	[80.5%]	-0.093***	[62.3%]
	N	*1,486*		*2,754*			*N*	*821*		*2,747*	
West Midlands	Raw GPG	-0.147***	[100%]	-0.161***	[100%]	Scotland	Raw GPG	-0.156***	[100%]	-0.139***	[100%]
	Explained	-0.034	[23.3%]	-0.049***	[30.7%]		Explained	-0.016	[10.5%]	-0.059**	[42.2%]
	Unexplained	-0.113***	[76.7%]	-0.112***	[69.3%]		Unexplained	-0.140***	[89.5%]	-0.080***	[57.8%]
	N	*1,830*		*3,847*			*N*	*1,115*		*5,644*	

Notes: (i) Estimates are based on OB decompositions of mean GPGs, using relevant male wage coefficients as the reference. (ii) Specifications includes individual characteristics, work-related characteristics (including occupation and sector), as defined in Table B.3, Appendix B. (iii) Figures in [] are proportions of the unadjusted GPG. (iv) $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Source: Author calculations based on weighted ASHE 2022 data.

Appendix C

Figure C.1: Change in Homeworking from Q3 2019 to Q1 2022, by Gender and Region



Notes: (i) Data not seasonally adjusted.

Source: QLFS, ONS (2022e).

Table C.1: Summary of Data Sources of Measures of Commuting in the UK

Data Source	**Commuting Measure**	**Summary**
QLFS	Direct self-reported measure of usual one-way home to work travel time in minutes.	Travel to work questions are asked annually in the fourth quarter and every quarter every three years to all respondents in employment, except those on government schemes or those working from home or using their home as a working base. These self-reported measures are easy to administer, but are subject to self-reporting biases that may correlate with socio-demographic factors.
Understanding Society	Direct self-reported measure of usual time taken for respondents to get to work each day, door to door in minutes.	Captured in each wave, with additional information on the mode of travel. Self-reported data allows for the analysis of subjective commuting experiences but is prone to biases, such as rounding or over/under-estimation, which may vary across demographic groups.
ASHE	Indirect measures of commutes, based on home and workplace postcodes.	Commutes are estimated using trip planner apps, eliminating the need for self-reported data. This approach provides objective measures but assumes standardised travel routes and modes, which may not reflect individual variations in actual commuting behaviour.
2021 Census	Direct self-reported measure of usual travel-to-work mode and indirect measure of commuting distance based on the geometric distance between home and workplace postcodes.	Includes data for individuals aged 16 and over who identified a physical workplace or depot as their main place of work. However, commuting patterns during the 2021 Census were influenced by COVID-19-related disruptions, including government guidance and lockdown restrictions, limiting generalisability to typical commuting behaviour.
Opinions and Lifestyle Survey	Direct self-reported measures of commuting frequency, mode of transport, and time spent commuting.	Flexible survey capturing shifts in commuting patterns, including during the COVID-19 pandemic. It provides valuable insights into changes in travel behaviour and remote working trends but is limited by a smaller sample size, restricting the scope for granular demographic analysis.

Table C.2: Variable Definitions

Variables	LFS Variable	Definition	Wage Equation	Commuting Equation
Dependent Variables				
(Log) Hourly wages	*HOURPAY*	Log of gross hourly pay	✓	
Commute time	*TRVTME*	Self-reported usual home to work travel time (minutes) (one way)	✓	✓
Individual Characteristics				
Female	*SEX*	Dummy variable, equals 1 if female, 0 if male	✓	✓
Age (and Age^2)	*AGE*	Age in years	✓	✓
Disabled	DISEA	Dummy variable, equals 1 if current disability, 0 if no current disability	✓	✓
Ethnicity	Derived from *ETHUKEUL*	Dummy variable, equals 1 if white ethnicity, 0 if ethnicity is Mixed/Multiple ethnic groups, Indian, Pakistani, Bangladeshi, Chinese, Any other Asian background, Black/African/ Caribbean/Black British or Other ethnic group	✓	✓
Highest qualification	Derived from			
Degree or equivalent	*HIQUL15D*	Dummy variable, equals 1 if highest qualification is university degree or equivalent, 0 if highest qualification is not university degree or equivalent	✓	✓
Higher education		Dummy variable, equals 1 if highest qualification is higher education, 0 if highest qualification is not higher education	✓	✓
A level or equivalent		Dummy variable, equals 1 if highest qualification is A-level or equivalent, 0 if highest qualification is not A-level or equivalent	✓	✓
GCSEs A-C or equivalent		Dummy variable, equals 1 if highest qualification is GCSEs A*-C or equivalent, 0 if highest qualification is not GCSEs A*-C or equivalent	✓	✓
Other qualifications		Dummy variable, equals 1 if highest qualification is Other qualifications, 0 if highest qualification is not Other qualifications	✓	✓
No qualification		Dummy variable, equals 1 if highest qualification is no qualifications, 0 if highest qualification is not no qualifications	✓	✓
Household Composition				
Marital Status	Derived from			
Single, never married	*MARSTA*	Dummy variable, equals 1 if single, never married, 0 if not single, never married	✓	✓
Married		Dummy variable, equals 1 if married or civil partnership, 0 if not married or civil partnership	✓	✓
Separated, widowed or divorced		Dummy variable, equals 1 if separated, widowed or divorce, 0 if not separated, widowed or divorced	✓	✓
Number of dependent children in family under five	*FDPCH2*, *FDPCH4*	Number of dependent children in family under 5 years, equals zero if no children	✓	✓

Number of dependent children in family aged between 5-16 years	FDPCH16, *FDPCH2*, *FDPCH4*	Number of dependent children in family aged 5-16 years in the family, equals zero if no children	✓	✓
Job Characteristics				
Full-time	*FTPT*	Dummy variable, equals 1 if employed full-time, 0 if employed part-time	✓	✓
Public sector	*PUBLICR*	Dummy variable, equals 1 if public sector, 0 if private sector	✓	✓
Temporary contract	*JOBTYP*	Dummy variable, equals 1 if non-permanent, 0 if permanent	✓	✓
Tenure (and tenure^2)	*EMPMON*	Months continuously employed with current employer	✓	✓
Trade union member	*UNION*	Dummy variable, equals 1 if trade union member, 0 if not trade union member	✓	✓
Workplace size (employees)	Derived from			
$\leq$25	*MPNR02*	Dummy variable, equals 1 if workplace has 24 or less employees, 0 if place of work has 25 employees or more	✓	✓
25-49		Dummy variable, equals 1 if workplace has 25-49 employees, 0 if place of work has 24 or less or 50 or more employees	✓	✓
50-249		Dummy variable, equals 1 if workplace has 50-249 employees, 0 if workplace has 49 or less or 250 or more employees	✓	✓
250 - 499		Dummy variable, equals 1 if workplace has 250-499 employees, 0 if place of work has 249 or less or 500 or more employees	✓	✓
$\geq$ 500		Dummy variable, equals 1 if workplace has 500 or more employees, 0 if place of work has 499 or less employees.	✓	✓
Occupation (SOC2020)	Derived from			
Managers & senior officials	*SC20MMJ*	Dummy variable, equals 1 if occupation is managers and senior officials, 0 if occupation is not managers and senior officials	✓	✓
Professional		Dummy variable, equals 1 if occupation is professional, 0 if occupation is not professional	✓	✓
Associate professional		Dummy variable, equals 1 if occupation is associate professional, 0 if occupation is not associate professional	✓	✓
Administrative		Dummy variable, equals 1 if occupation is administrative and secretarial, 0 if occupation is not administrative and secretarial	✓	✓
Skilled trades		Dummy variable, equals 1 if occupation is skilled trades, 0 if occupation is not skilled trades	✓	✓
Caring, leisure and other service		Dummy variable, equals 1 if occupation is caring, leisure and other service, 0 if occupation is not caring, leisure and other service	✓	✓
Sales & customer service		Dummy variable, equals 1 if occupation is sales and customer service, 0 if occupation is not sales and customer service	✓	✓

Process, plant & machine operatives		Dummy variable, equals 1 if occupation is process, plant and machine operatives, 0 if occupation is not process, plant and machine operatives	✓	✓
Elementary occupations		Dummy variable, equals 1 if occupation is elementary occupations, 0 if occupation is not elementary occupations	✓	✓
Region of workplace				
Tyne and Wear	*REGWKR*	Dummy variable, equals 1 if region of place of work is Tyne & Wear, 0 if region of place of work is not Tyne & Wear	✓	✓
Rest of Northern region		Dummy variable, equals 1 if region of place of work is Rest of Northern region, 0 if region of place of work is not Rest of Northern Region	✓	✓
South Yorkshire		Dummy variable, equals 1 if region of place of work is South Yorkshire, 0 if region of place of work is not South Yorkshire	✓	✓
West Yorkshire		Dummy variable, equals 1 if region of place of work is West Yorkshire, 0 if region of place of work is not West Yorkshire	✓	✓
Rest of Yorkshire & Humberside		Dummy variable, equals 1 if region of place of work is Rest of Yorkshire & Humberside, 0 if region of place of work is not Rest of Yorkshire & Humberside	✓	✓
East Midlands		Dummy variable, equals 1 if region of place of work is East Midlands, 0 if region of place of work is not East Midlands	✓	✓
East Anglia		Dummy variable, equals 1 if region of place of work is East Anglia, 0 if region of place of work is not East Anglia	✓	✓
Central London		Dummy variable, equals 1 if region of place of work is Central London, 0 if region of place of work is not Central London	✓	✓
Inner London (not central)		Dummy variable, equals 1 if region of place of work is Inner London (not central), 0 if region of place of work is not Inner London (not central)	✓	✓
Outer London		Dummy variable, equals 1 if region of place of work is Outer London, 0 if region of place of work is not Outer London	✓	✓
Rest of South East		Dummy variable, equals 1 if region of place of work is Rest of South East, 0 if region of place of work is not Rest of South East	✓	✓
South West		Dummy variable, equals 1 if region of place of work is South West, 0 if region of place of work is not South West	✓	✓
West Midlands Metropolitan		Dummy variable, equals 1 if region of place of work is West Midlands Metropolitan, 0 if region of place of work is not West Midlands Metropolitan	✓	✓
Rest of West Midlands		Dummy variable, equals 1 if region of place of work is Rest of West Midlands, 0 if region of place of work is not Rest of West Midlands	✓	✓

Greater Manchester and Merseyside		Dummy variable, equals 1 if region of place of work is Greater Manchester and Merseyside, 0 if region of place of work is not Greater Manchester and Merseyside	✓	✓
Rest of North West		Dummy variable, equals 1 if region of place of work is Rest of North West, 0 if region of place of work is not Rest of North West	✓	✓
Wales		Dummy variable, equals 1 if region of place of work is Wales, 0 if region of place of work is not Wales	✓	✓
Strathclyde		Dummy variable, equals 1 if region of place of work is Strathclyde, 0 if region of place of work is not Strathclyde	✓	✓
Rest of Scotland		Dummy variable, equals 1 if region of place of work is Rest of Scotland, 0 if region of place of work is not Rest of Scotland	✓	✓
Northern Ireland		Dummy variable, equals 1 if region of place of work is Northern Ireland, 0 if region of place of work is not Northern Ireland	✓	✓
Other				
2023		Dummy variable equals 1 if observed in 2023, 0 if observed in 2022	✓	✓
Proxy respondent	*PRXREL*	Dummy variable equals 1 if proxy respondent, 0 if not proxy respondent	✓	✓
Instrumental Variable				
Average industry commute time		Average commute time within an industry sector (one-digit SIC), excluding individual i		✓

Table C.3: Summary Statistics for all Explanatory Variables, by Gender and Commuter Status

	Commuters			Non-Commuters			%
	All	Male	Female	All	Male	Female	Commuters
All (%)	71.05	69.54	72.35	28.95	30.46	27.65	-
N	*7,161*	*3,246*	*3,915*	*2,918*	*1,422*	*1,496*	
Individual Characteristics							
Age (years)	42.99	43.06	42.93	44.11	44.29	43.93	-
N	*7,161*	*3,246*	*3,915*	*2,918*	*1,422*	*1,496*	
Disabled (%)	17.61	14.20	20.43	16.35	12.59	19.92	72.55
N	*1,261*	*461*	*800*	*477*	*179*	*298*	*1,261*
White ethnicity (%)	89.21	89.13	89.27	89.51	88.96	90.04	70.98
N	*6,388*	*2,893*	*3,495*	*2,612*	*1,265*	*1,347*	*6,388*
Highest qualification (%)							
Degree or equivalent	38.40	34.17	41.92	59.66	61.18	58.22	61.23
N	*2,750*	*1,109*	*1,641*	*1,741*	*870*	*871*	*2,750*
Higher education	7.95	7.52	8.30	7.68	8.30	7.09	71.75
N	*569*	*244*	*325*	*224*	*118*	*106*	*569*
A-level or equivalent	22.68	24.89	20.84	19.23	19.41	19.05	74.32
N	*1,624*	*808*	*816*	*561*	*276*	*285*	*1,624*
GCSEs A*-C or equivalent	20.08	20.55	19.69	10.97	8.93	12.90	81.80
N	*1,438*	*667*	*771*	*320*	*127*	*193*	*1,438*
Other/No qualifications	10.89	12.88	9.24	2.46	2.18	2.74	91.55
N	*780*	*418*	*362*	*72*	*31*	*41*	*780*
Household Composition							
Marital status (%)							
Single, never married	36.20	37.62	35.02	32.01	30.24	33.69	73.51
N	*2,592*	*1,221*	*1,371*	*934*	*430*	*504*	*2,592*
Married	52.03	53.76	50.60	56.92	62.87	51.27	69.17
N	*3,726*	*1,745*	*1,981*	*1,661*	*894*	*767*	*3,726*
Separated, widowed or divorced	11.77	8.63	14.38	11.07	6.89	15.04	72.30
N	*843*	*280*	*563*	*323*	*98*	*225*	*843*
Number of children under five years old	0.16	0.15	0.16	0.18	0.20	0.17	-
old *N*	*7,161*	*3,246*	*3,915*	*2,918*	*1,422*	*1,496*	
Number of children aged between	0.45	0.42	0.48	0.40	0.39	0.41	-
5-16 years *N*	*7,161*	*3,246*	*3,915*	*2,918*	*1,422*	*1,496*	
Job Characteristics							
Full-time (%)	72.15	88.51	58.60	83.89	94.44	73.86	67.85
N	*5,167*	*2,873*	*2,294*	*2,448*	*1,343*	*1,105*	*5,167*
Pubic sector (%)	32.36	21.97	40.97	25.67	16.81	34.09	75.57
N	*2,317*	*713*	*1,604*	*749*	*239*	*510*	*2,317*
Temporary contract (%)	3.95	3.97	3.93	3.43	3.16	3.68	73.89
N	*283*	*129*	*154*	*100*	*45*	*55*	*283*
Tenure (months)	108.34	111.61	105.62	105.78	108.93	102.79	-
N	*7,161*	*3,246*	*3,915*	*2,918*	*1,422*	*1,496*	
Trade union member(%)	28.81	25.23	31.78	16.59	13.36	19.65	81.00
N	*2,063*	*819*	*1,244*	*484*	*190*	*294*	*2,063*
Workplace size (employees) (%)							
≤25	33.40	30.62	35.71	33.34	33.97	32.75	71.08
N	*2,392*	*994*	*1,398*	*973*	*483*	*490*	*2,392*
25-49	14.02	13.62	14.36	7.16	7.31	7.02	82.77
N	*1,004*	*442*	*562*	*209*	*104*	*105*	*1,004*
50-249	26.38	27.66	25.31	18.06	18.71	17.45	78.19
N	*1,889*	*898*	*991*	*527*	*266*	*261*	*1,889*
250-499	5.85	6.78	5.08	8.60	8.79	8.42	62.54
N	*419*	*220*	*199*	*251*	*125*	*126*	*419*
500+	20.35	21.32	19.54	32.98	31.22	34.36	60.33
N	*1,457*	*692*	*765*	*958*	*444*	*514*	*1,457*
Occupation (%)							
Managers & senior officials	8.90	12.75	5.70	14.84	17.16	12.63	59.53
N	*637*	*414*	*223*	*433*	*244*	*189*	*637*
Professional	25.46	21.75	28.53	41.06	46.62	35.76	60.34
N	*1,823*	*706*	*1,117*	*1,198*	*663*	*535*	*1,823*
Associate professional	12.07	12.38	11.80	22.86	21.59	24.06	56.43
N	*864*	*402*	*462*	*667*	*307*	*360*	*864*
Administrative	10.21	5.27	14.30	13.78	6.89	20.32	64.52
N	*731*	*171*	*560*	*402*	*98*	*304*	*731*
Skilled trades	7.68	14.79	1.79	2.30	3.94	0.74	89.14
N	*550*	*480*	*70*	*67*	*56*	*11*	*550*

Caring, leisure and other service	10.47	4.13	15.73	1.64	0.77	2.47	93.98
N	*750*	*134*	*616*	*48*	*11*	*37*	*750*
Low-skilled	25.22	28.93	22.15	3.53	3.02	4.01	94.60
N	*1,806*	*939*	*867*	*103*	*43*	*60*	*1,806*
Region of workplace							
Tyne and Wear (%)	1.91	1.94	1.89	1.13	-	-	80.59
N	*137*	*63*	*74*	*33*			*137*
Rest of Northern region (%)	4.36	3.97	4.67	2.16	-	-	83.20
N	*312*	*129*	*183*	*63*			*312*
South Yorkshire (%)	2.30	2.13	2.45	1.64	-	-	77.46
N	*165*	*69*	*96*	*48*			*165*
West Yorkshire (%)	3.52	3.76	3.32	4.59	-	-	65.28
N	*252*	*122*	*130*	*134*			*252*
Rest of Yorkshire and Humber (%)	2.78	2.80	2.76	2.60	-	-	72.36
N	*199*	*91*	*108*	*76*			*199*
East Midlands (%)	8.41	8.19	8.58	8.22	-	-	71.50
N	*602*	*266*	*336*	*240*			*602*
East Anglia (%)	3.38	3.57	3.22	3.84	-	-	68.36
N	*242*	*116*	*126*	*112*			*242*
Central London (%)	4.26	4.99	3.65	-	-	-	100.00
N	*305*	*162*	*143*				*305*
Inner London (not central) (%)	2.42	2.53	2.32	3.84	-	-	60.70
N	*173*	*82*	*91*	*112*			*173*
Outer London (%)	3.30	3.23	3.35	4.90	-	-	62.27
N	*236*	*105*	*131*	*143*			*236*
Rest of South East (%)	15.96	15.71	16.17	25.33	-	-	60.73
N	*1,143*	*510*	*633*	*739*			*1,143*
South West (%)	8.87	8.56	9.12	10.45	-	-	67.55
N	*635*	*278*	*357*	*305*			*635*
West Midlands Metropolitan (%)	3.21	3.11	3.30	3.05	-	-	72.10
N	*230*	*101*	*129*	*89*			*230*
Rest of West Midlands (%)	3.92	3.42	4.34	4.46	-	-	68.37
N	*281*	*111*	*170*	*130*			*281*
Greater Manchester and Merseyside (%)	4.47	4.68	4.29	4.83	-	-	69.41
N	*320*	*152*	*168*	*141*			*320*
Rest of North West (%)	3.73	4.00	3.50	3.12	-	-	74.58
N	*267*	*130*	*137*	*91*			*267*
Wales (%)	4.27	4.50	4.09	3.74	-	-	73.73
N	*306*	*146*	*160*	*109*			*306*
Strathclyde (%)	2.21	2.22	2.20	2.09	-	-	72.15
N	*158*	*72*	*86*	*61*			*158*
Rest of Scotland (%)	4.85	4.87	4.83	4.59	-	-	72.14
N	*347*	*158*	*189*	*134*			*347*
Northern Ireland (%)	11.88	11.80	11.95	5.41	-	-	84.34
N	*851*	*383*	*468*	*158*			*851*
Commuting method							
Private Transport	73.28	74.69	72.12	-	-	-	-
N	*5,242*	*2,420*	*2,822*				
Public Transport	11.93	11.73	12.09	-	-	-	-
N	*853*	*380*	*473*	-	-	-	-
Pedestrian Methods	14.79	13.58/	15.79	-	-	-	-
N	*1,058*	*440*	*618*	-	-	-	-

Notes: (i) Variable means are constructed on the basis of the estimation sample and are rounded to two decimal places. (ii) 'Other qualifications' and 'no qualifications' are merged to ensure no statistical disclosure for non-commuters. Similarly, low-skilled occupations (Sales & customer service, Process, plant & machine operatives, and Elementary occupations) are combined to ensure no statistical disclosure. The breakdown by gender and work region is also omitted for non-commuters to ensure no statistical disclosure. (iii) Commuting method is derived from the *TRVMTH* variable in the QLFS. Private transport refers to those who usually commute via car, van, minibus, works van, motorbike, moped, scooter, or taxi. Public transport refers to those who usually commute via bus, coach, private bus, railway train or light railway, tram. Pedestrian methods refer to those who usually commute via bicycle or walking. Eight individuals are not included in the analysis as they report usually commuting via another method.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters.

Table C.4: Descriptive Characteristics of Long and Short Commuters

	Long	Short		Long	Short
Commute time (minutes)	57.37	10.33	**Hourly pay** (£)	20.81	14.13
N	*1,484*	*2,841*	*N*	*1,484*	*2,841*
Female (%)	48.25	59.87			
N	*716*	*1,701*			
Individual Characteristics			**Household Composition**		
Age (years)	42.33	44.39	Marital Status (%)		
N	*1,484*	*2,841*	Single, never married	37.06	35.02
Disabled (%)	17.18	19.15	*N*	*550*	*995*
N	*255*	*544*	Married	52.96	52.27
White ethnicity (%)	86.39	91.94	*N*	*786*	*1,485*
N	*1,282*	*2612*	Separated, widowed or divorced	9.97	12.71
Highest qualification (%)			*N*	*148*	*361*
Degree or equivalent	55.66	29.57	Number of children under	0.18	0.13
N	*826*	*840*	five years old *N*	*1,484*	*2,841*
Higher education	6.87	7.92	Number of children aged between	0.48	0.46
N	*102*	*225*	5-16 years *N*	*1,484*	*2,841*
A-level or equivalent	17.59	25.45			
N	*261*	*723*			
GCSEs A*-C or equivalent	12.74	23.48			
N	*189*	*667*			
Other/No qualifications	7.14	13.59			
N	*106*	*386*			
Job Characteristics			**Region of workplace**		
Full-time (%)	84.23	65.15	Tyne and Wear (%)	2.29	1.20
N	*1,250*	*1,851*	*N*	*34*	*34*
Pubic sector (%)	35.92	30.90	Rest of Northern region (%)	3.10	5.77
N	*533*	*878*	*N*	*46*	*164*
Temporary contract (%)	3.57	4.22	South Yorkshire (%)	1.62	2.32
N	*53*	*120*	*N*	*24*	*66*
Tenure (months)	105.22	111.15	West Yorkshire (%)	3.23	2.92
N	*1,484*	*2,841*	*N*	*48*	*83*
Trade union member(%)	30.19	27.28	Rest of Yorkshire and Humber (%)	1.89	3.06
N	*448*	*775*	*N*	*28*	*87*
Workplace size (employees) (%)			East Midlands (%)	5.05	9.40
$\leq$25	24.53	39.04	*N*	*75*	*267*
N	*364*	*1,109*	East Anglia (%)	2.56	3.66
25-49	10.98	15.84	*N*	*38*	*104*
N	*163*	*450*	Central London (%)	14.82	0.60
50-249	25.20	26.54	*N*	*220*	*17*
N	*374*	*754*	Inner London (not central) (%)	7.21	0.92
250-499	7.41	4.29	*N*	*107*	*26*
N	*110*	*122*	Outer London (%)	5.26	2.50
500+	31.87	14.29	*N*	*78*	*71*
N	*473*	*406*	Rest of South East (%)	14.29	17.49
Occupation (%)			*N*	*212*	*497*
Managers & senior officials	12.13	6.90	South West (%)	6.00	9.86
N	*180*	*196*	*N*	*89*	*280*
Professional	37.47	19.18	West Midlands Metropolitan (%)	3.44	2.46
N	*556*	*545*	*N*	*51*	*70*
Associate professional	14.42	10.59	Rest of West Midlands (%)	2.16	5.56
N	*214*	*301*	*N*	*32*	*158*
Administrative	8.69	10.63	Greater Manchester and	4.58	3.27
N	*129*	*302*	Merseyside (%) *N*	*68*	*93*
Skilled trades	6.67	7.29	Rest of North West (%)	3.10	3.98
N	*99*	*207*	*N*	*46*	*113*
Caring, leisure and other service	5.46	14.08	Wales (%)	2.29	5.49
N	*81*	*400*	*N*	*34*	*156*
Sales and customer service	4.72	8.62	Strathclyde (%)	2.83	1.97
N	*70*	*245*	*N*	*42*	*56*
Process, plant and machine operatives	3.91	6.79	Rest of Scotland (%)	3.98	4.93
N	*58*	*193*	*N*	*59*	*140*
Elementary occupations	6.54	15.91	Northern Ireland (%)	10.31	12.64
N	*97*	*452*	*N*	*153*	*359*

Notes: (i) Variable means are constructed on the basis of the estimation sample and are rounded to two decimal places. (ii) 'Other qualifications' and 'no qualifications' are merged to ensure no statistical disclosure for non-commuters. (iii) Long commuters are defined as those whose commuting time is at least 10 minutes longer than the average within their sector, while short commuters are defined as those whose commuting time is at least 10 minutes shorter than the sector average.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters.

Table C.5: Test Statistics to Evaluate the Suitability of the Instrumental Variable

Test	**Hypotheses**	**Test statistic**	**Decision rule**
Endogeneity between commute time and wages	**Null hypothesis** (H_0): The variable is exogenous (i.e., uncorrelated with the error term). **Alternative hypothesis** (H_1): The variable is endogenous (i.e., correlated with the error term).	Durbin-Wu-Hausman Test: Chi-square statistic (for one regressor) or Wald F-statistic (for multiple regressors).	A low p-value (< 0.05) leads to rejection of the null hypothesis, indicating that the variable is endogenous.
Relevance of the instrument	**Null hypothesis** (H_0): The instrument is weakly correlated with the endogenous regressor. **Alternative hypothesis** (H_1): The instrument is strongly correlated with the endogenous regressor.	First-stage F-statistic: Compare the F-statistic to Stock-Yogo critical values.	If $F \geq 10$, the instrument is generally considered strong. If $F < 10$, the instrument may be weak, leading to biased IV estimates.

Table C.6: Full Set of Coefficient Estimates for the Commuting Regression

	Pooled - Employees						Male	Female	Pooled - Self-employed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	-3.714***	-3.177***	-3.936***	-3.972***	-2.331***	-2.253***	-	-	-6.605**
	(0.493)	(0.488)	(0.480)	(0.482)	(0.543)	(0.520)			(2.350)
Instrumental variable									
Average industry commute time		0.930***	0.793***	0.793***	0.652***	0.471***	0.522***	0.433***	0.571**
		(0.065)	(0.064)	(0.064)	(0.066)	(0.064)	(0.092)	(0.090)	(0.181)
Individual Characteristics									
Age			0.424***	0.465***	0.167	0.207	0.451*	0.092	-0.576
			(0.128)	(0.140)	(0.145)	(0.139)	(0.221)	(0.179)	(0.664)
Age^2			-0.006***	-0.006***	-0.002	-0.002	-0.006*	-0.001	0.007
			(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.007)
Disabled			-0.339	-0.357	0.154	0.221	-1.707	1.126	3.167
			(0.627)	(0.630)	(0.623)	(0.598)	(1.047)	(0.702)	(2.269)
Ethnicity			-2.710***	-2.768***	-2.629***	0.908	2.254	-0.454	7.779*
			(0.771)	(0.776)	(0.772)	(0.763)	(1.251)	(0.946)	(3.074)
Highest Qualification									
Higher education			-4.928***	-4.905***	-3.353***	-2.155*	-0.071	-3.382**	0.386
			(0.928)	(0.929)	(0.933)	(0.897)	(1.486)	(1.095)	(3.597)
A-level or equivalent			-7.922***	-7.917***	-5.074***	-3.857***	-2.480*	-4.843***	4.534
			(0.637)	(0.638)	(0.702)	(0.676)	(1.079)	(0.854)	(2.683)
GCSEs A*-C or equivalent			-7.426***	-7.410***	-4.013***	-2.555***	-0.907	-3.755***	3.067
			(0.673)	(0.676)	(0.754)	(0.727)	(1.155)	(0.920)	(2.946)
Other qualification			-9.071***	-9.075***	-5.105***	-4.364***	-1.173	-6.642***	-0.299
			(1.040)	(1.042)	(1.105)	(1.062)	(1.601)	(1.421)	(3.579)
No qualifications			-11.124***	-11.122***	-6.130***	-4.968***	-3.210	-6.478***	-2.123
			(1.159)	(1.164)	(1.231)	(1.184)	(1.790)	(1.570)	(3.974)
Household Variables									
Marital status									
Married				0.118	-0.147	0.311	2.049*	-1.010	-4.554
				(0.652)	(0.644)	(0.618)	(1.002)	(0.770)	(2.633)
Separated, widowed or divorced				1.222	1.086	1.681*	1.353	1.226	-6.360
				(0.906)	(0.893)	(0.856)	(1.518)	(1.010)	(3.573)
Number of children under 5 years old				0.212	0.319	0.127	0.433	-0.536	-0.290
in the household				(0.594)	(0.589)	(0.564)	(0.911)	(0.710)	(2.189)
Number of children aged between 5-16 years				-0.412	-0.095	-0.095	0.483	-0.740	-0.282

	(0.329)	(0.327)	(0.315)	(0.519)	(0.393)	(1.144)
Job Characteristics						
Full-time		3.055***	2.667***	2.343	2.211***	-0.564
		(0.604)	(0.580)	(1.291)	(0.634)	(2.299)
Public Sector		-1.473*	-0.962	0.911	-2.158**	-
		(0.602)	(0.578)	(0.995)	(0.694)	
Temporary contract		-0.719	-0.230	-1.714	0.045	-
		(1.237)	(1.185)	(1.955)	(1.468)	
Tenure		-0.012	-0.013*	-0.015	-0.010	0.045*
		(0.007)	(0.006)	(0.010)	(0.008)	(0.022)
Tenure^2		0.000	0.000	0.000	0.000	-0.000*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trade union member		-1.031	-0.455	-1.966*	0.618	5.935
		(0.586)	(0.567)	(0.901)	(0.726)	(4.125)
Workplace size						
25-49 employees		0.471	0.464	1.743	-0.617	-
		(0.743)	(0.713)	(1.178)	(0.870)	
50-249 employees		1.670**	1.333*	2.072*	0.853	-
		(0.625)	(0.600)	(0.968)	(0.748)	
250-499 employees		5.327***	4.326***	3.642*	5.318***	-
		(1.056)	(1.013)	(1.551)	(1.331)	
500+ employees		6.548***	5.265	3.957***	6.357***	-
		(0.714)	(0.689)	(1.110)	(0.861)	
Occupation						
Professional		-1.650	-0.802	-1.948	1.708	9.629**
		(0.978)	(0.938)	(1.353)	(1.352)	(3.469)
Associate Professional		-2.831**	-2.018*	-2.505	-0.164	10.574**
		(1.052)	(1.008)	(1.472)	(1.438)	(3.910)
Administrative		-5.111***	-3.361**	-2.070	-1.404	10.181
		(1.110)	(1.067)	(1.894)	(1.421)	(8.152)
Skilled trades		-5.051***	-3.176**	-3.482*	-4.111	2.145
		(1.183)	(1.137)	(1.434)	(2.435)	(3.169)
Caring, leisure and other service		-7.393***	-5.398***	-7.705***	-2.263	3.350
		(1.131)	(1.088)	(2.103)	(1.430)	(3.850)
Sales & customer service		-5.834***	-4.891***	-6.177**	-2.028	2.324
		(1.245)	(1.197)	(1.990)	(1.590)	(5.285)
Process, plant & machine operatives		-9.561***	-7.353***	-9.379***	-0.351	1.055
		(1.272)	(1.224)	(1.539)	(2.538)	(3.680)

Elementary occupations	-8.025***	-6.144***	-8.030***	-2.573	4.123
	(1.126)	(1.084)	(1.544)	(1.579)	(4.055)
Region of workplace					
Tyne and Wear		-20.017***	-20.966***	-19.284***	-36.599***
		(1.958)	(3.070)	(2.506)	(7.441)
Rest of Northern region		-25.215***	-20.528***	-28.750***	-54.532***
		(1.553)	(2.448)	(2.001)	(6.906)
South Yorkshire		-23.844***	-21.256***	-26.312***	-40.500***
		(1.851)	(2.977)	(2.327)	(6.906)
West Yorkshire		-22.068***	-22.916***	-22.037***	-38.073***
		(1.632)	(2.485)	(2.144)	(6.867)
Rest of Yorkshire and Humber		-25.661***	-25.375***	-26.038***	-49.881***
		(1.754)	(2.712)	(2.269)	(6.636)
East Midlands		-25.106***	-21.830***	-28.205***	-43.232***
		(1.362)	(2.084)	(1.788)	(4.919)
East Anglia		-22.653***	-18.801***	-25.657***	-44.543***
		(1.647)	(2.526)	(2.156)	(5.777)
Inner London (not central)		-3.712*	3.483	-10.198***	-24.199***
		(1.794)	(2.768)	(2.337)	(6.355)
Outer London		-14.758***	-14.964***	-15.003***	-36.538***
		(1.643)	(2.567)	(2.113)	(5.926)
Rest of South East		-23.176***	-19.765***	-26.031***	-39.230***
		(1.248)	(1.892)	(1.658)	(4.299)
South West		-24.448***	-20.985***	-27.364***	-44.677***
		(1.348)	(2.064)	(1.773)	(4.715)
West Midlands Metropolitan		-19.342***	-19.603***	-19.530***	-32.695***
		(1.659)	(2.615)	(2.119)	(5.904)
Rest of West Midlands		-27.312***	-24.604***	-30.030***	-48.761***
		(1.590)	(2.564)	(2.015)	(5.485)
Greater Manchester and Merseyside		-20.812***	-19.420***	-22.168***	-27.530***
		(1.537)	(2.341)	(2.020)	(5.587)
Rest of North West		-25.845***	-26.630***	-24.547***	*-53.964***
		(1.607)	(2.433)	(2.127)	(7.729)
Wales		-27.414***	-28.562***	-26.386***	-47.680***
		(1.565)	(2.379)	(2.060)	(5.730)
Strathclyde		-20.222***	-18.239***	-22.499***	-42.018***
		(1.875)	(2.929)	(2.402)	(8.437)
Rest of Scotland		-23.556***	-19.193***	-27.178***	48.211***

						(1.511)	(2.333)	(1.971)	(6.063)
Northern Ireland						-24.265***	-22.345***	-26.386***	-37.347***
						(1.308)	(1.974)	(1.740)	(4.520)
2023	-0.027	-0.032	0.056	0.049	-0.011	-0.083	-0.013	-0.147	-0.741
	(0.497)	(0.490)	(0.479)	(0.479)	(0.471)	(0.451)	(0.723)	(0.558)	(1.710)
Proxy respondent	-0.837	-0.398	0.017	0.159	0.017	0.302	0.955	-0.721	3.417
	(0.509)	(0.503)	(0.508)	(0.521)	(0.514)	(0.493)	(0.777)	(0.639)	(1.827)
Adjusted R^2	0.076	0.0349	0.0791	0.0791	0.1121	0.1872	0.1693	0.2180	0.1838
N	*7,161*	*7,161*	*7,161*	*7,161*	*7,161*	*7,161*	*3,246*	*3,915*	*942*
F-statistic	-	*203.86*	*151.61*	*151.45*	*97.36*	*54.50*	*31.94*	*23.03*	-
p-value	-	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	

Notes: (i) Estimates are based on a pooled OLS commuting equation. (ii) Males, Degree or equivalent, Single, never married, <25 employees, Managers and senior officials, Central London, 2022 and non-proxy respondents are the reference categories. All models include a constant and year term. (iii) Standard errors in parenthesis. (iv) *p<0.05, **p<0.01, ***p<0.001. (v) Estimates in specification (6) form the first stage of the 2SLS model that addresses potential endogeneity between commute time and wages. Figures reported in the final two rows are the test statistics relating to the explanatory power of the instrument within each specification (not reported for the self-employed, as there is limited data on pay for this group).

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters.

Table C.7: Detailed Decomposition of the Gender Gap in Commuting

Raw CGG	-3.635***		[100%]	
	(0.500)			
Explained CGG	-1.067*		[29.35%]	
	(0.483)			
Unexplained CGG	-2.568***		[70.65%]	
	(0.628)			
	Explained		**Unexplained**	
Individual characteristics				
Age	0.012	[-0.32%]	-7.002	[192.63%]
	(0.017)	{-1.11%}	(5.769)	{272.66%}
Disabled	0.070	[-1.93%]	0.402*	[-11.06%]
	(0.045)	{-6.58%}	(0.180)	{-15.65%}
Ethnicity	-0.001	[0.02%]	-2.413	[66.38%]
	(0.004)	{0.06%}	(1.398)	{93.96%}
Highest qualification	0.440***	[-12.10%]	-0.350*	[9.63%]
	(0.088)	{-41.24%}	(0.138)	{13.63%}
Household Variables				
Marital status	0.102	[-2.81%]	-0.006	[0.16%]
	(0.053)	{-9.56%}	(0.058)	{0.22%}
Children	-0.047	[1.29%]	-0.656	[18.05%]
	(0.028)	{4.39%}	(0.336)	{25.55%}
Job Characteristics				
Average industry commute time	-0.230***	[6.34%]	-2.333	[64.17%]
	(0.062)	{21.59%}	(3.373)	{90.82%}
Full-time	-0.661***	[18.18%]	-0.117	[3.22%]
	(0.191)	{61.95%}	(1.273)	{4.56%}
Public sector	-0.410**	[11.28%]	-0.674*	[18.54%]
	(0.134)	{38.43%}	(0.267)	{26.25%}
Temporary contract	-0.000	[0.00%]	0.070	[-1.92%]
	(0.001)	{0.00%}	(0.097)	{-2.72%}
Tenure	0.009	[-0.25%]	0.601	[-16.53%]
	(0.024)	{-0.84%}	(0.763)	{-23.40%}
Trade union member	0.040	[-1.11%]	0.652	[-17.94%]
	(0.048)	{-3.80%}	(0.293)	{-25.39%}
Firm size	-0.228**	[6.27%]	-0.144*	[3.96%]
	(0.074)	{21.37%}	(0.059)	{5.61%}
Occupation	0.240	[-6.60%]	0.138	[-3.80%]
	(0.386)	{-22.49%}	(0.337)	{-5.37%}
Region of workplace	-0.471**	[12.96%]	0.230*	[-6.33%]
	(0.155)	{44.14%}	(0.092)	{-8.96%}
2023	-0.000	[0.01%]	-0.055	[1.51%]
	(0.002)	{0.03%}	(0.374)	{2.14%}
Proxy respondent	0.068	[-1.86%]	0.972	[-26.74%]
	(0.060)	{-6.33%}	(0.374)	{-37.85%}

Notes: (i) The OB method is used to decompose the mean CGG using male coefficients as the baseline. (ii) Specification includes individual characteristics (age, age^2, disability, white ethnicity and highest qualification indicators), household variables (marital status, number of children under the age of 4 and 5-16), job characteristics (full-time, public sector, temporary contract, trade union and firm size indicators, tenure and tenure^2, and SOC 2020 major groups (nine categories)), region of workplace (20 regions), year and proxy indicators and a constant. (iii) Detailed decomposition of the unexplained gap is based on normalised effects following Yun (2005). The unexplained component includes a constant. (iv) Figures in () are standard errors and figures in [] ({}) are a percentage of the observed (explained/unexplained) CGG. (v) *p<0.05, **p<0.01, ***p<0.001.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters.

Table C.8: Decomposition of the mean Gender Gap in Commuting, by age

	≥ 40		> 40	
Raw CGG	-3.001***	[100%]	-4.107***	[100%]
	(0.749)		(0.678)	
Explained CGG	0.516	[-17.19%]	-1.968**	[47.92%]
	(0.834)		(0.643)	
Unexplained CGG	-3.517***	[117.19%]	-2.139**	[52.08%]
	(1.029)		(0.834)	
Explained CGG	0.516	[-17.19%]	-1.968**	[47.92%]
Individual characteristics	0.405*	[-13.50%]	0.584***	[-14.22%]
	(0.175)	{78.55%}	(0.145)	{-29.68%}
Marital status	0.005	[-0.16%]	0.231**	[-5.63%]
	(0.077)	{0.92%}	(0.087)	{-11.75%}
Number of children aged under the age of 5	-0.112	[3.72%]	-0.008	[0.20%]
	(0.067)	{-21.63%}	(0.082)	{0.41%}
Number of children aged between 5-16	-0.258*	[8.60%]	0.053	[-1.29%]
	(0.122)	{-50.03%}	(0.039)	{-2.70%}
Job characteristics	0.694	[-23.13%]	-2.377***	[57.89%]
	(0.766)	{134.57%}	(0.563)	{120.81%}
Region of workplace	-0.406	[13.53%]	-0.433*	[10.55%]
	(0.242)	{-78.71%}	(0.215)	{22.02%}

Notes: (i) The OB method is used to decompose the mean CGG using male coefficients as the baseline. (ii) Specification includes individual characteristics, household variables, job characteristics and region of workplace (20 regions), year and proxy indicators and a constant.(iii) Detailed decomposition of the unexplained gap is based on normalised effects following Yun (2005). The unexplained component includes a constant. (iv) Figures in () are standard errors and figures in [] ({}) are a percentage of the observed (explained/unexplained) CGG. (v) *p<0.05, **p<0.01, ***p<0.001.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters.

Table C.9: Full Set of Coefficient Estimates for the Wage Regression (OLS model)

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.149***	-0.124***	-0.155***	-0.153***	-0.093***	-0.093***
	(0.013)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
(Self-reported) Commute time		0.007***	0.005***	0.005***	0.003***	0.002***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Individual Characteristics						
Age			0.055***	0.046***	0.028***	0.028***
			(0.003)	(0.003)	(0.003)	(0.003)
Age^2			-0.001***	-0.000***	-0.000***	-0.000***
			(0.000)	(0.000)	(0.000)	(0.000)
Disabled			-0.084***	-0.071***	-0.040**	-0.038**
			(0.014)	(0.014)	(0.013)	(0.013)
Ethnicity			0.075***	0.089***	0.057***	0.086***
			(0.018)	(0.018)	(0.016)	(0.016)
Highest Qualification						
Higher education			-0.231***	-0.231***	-0.142***	-0.131***
			(0.021)	(0.021)	(0.019)	(0.019)
A-level or equivalent			-0.297***	-0.291***	-0.103***	-0.096***
			(0.015)	(0.015)	(0.015)	(0.015)
GCSEs A*-C or equivalent			-0.409***	-0.398***	-0.188***	-0.177***
			(0.015)	(0.015)	(0.016)	(0.016)
Other qualification			-0.481***	-0.469***	-0.227***	-0.228***
			(0.024)	(0.024)	(0.023)	(0.023)
No qualifications			-0.580***	-0.562***	-0.279***	-0.267***
			(0.027)	(0.027)	(0.026)	(0.025)
Household Composition						
Marital Status						
Married				0.088***	0.054***	0.056***
				(0.015)	(0.013)	(0.013)
Separated, widowed or divorced				-0.023	-0.015	-0.008
				(0.021)	(0.018)	(0.018)
Number of children aged under the age of 5				0.049***	0.035**	0.033**
				(0.013)	(0.012)	(0.012)
Number of children aged between 5-16				0.007	0.012	0.012
				(0.007)	(0.007)	(0.007)
Job Characteristics						
Full-time					0.053***	0.051***

		(0.013)	(0.012)
Public sector		-0.087***	-0.083***
		(0.012)	(0.012)
Temporary contract		0.014	0.018
		(0.026)	(0.025)
Tenure		0.001***	0.001***
		(0.000)	(0.000)
Tenure^2		-0.000**	-0.000**
		(0.000)	(0.000)
Trade union member		0.008	0.014
		(0.012)	(0.012)
Workplace size (%)			
25-49 employees		-0.002	-0.000
		(0.015)	(0.015)
50-249 employees		0.082***	0.078***
		(0.013)	(0.013)
250-499 employees		0.132***	0.132***
		(0.022)	(0.022)
500+ employees		0.184***	0.176***
		(0.015)	(0.015)
Occupation			
Professional		-0.033	-0.025
		(0.020)	(0.020)
Associate Professional		-0.250***	-0.245***
		(0.022)	(0.022)
Administrative		-0.358***	-0.347***
		(0.023)	(0.023)
Skilled trades		-0.409***	-0.392***
		(0.025)	(0.024)
Caring, leisure and other service		-0.501***	-0.490***
		(0.023)	(0.023)
Sales & customer service		-0.528***	-0.521***
		(0.026)	(0.025)
Process, plant & machine operatives		-0.445***	-0.427***
		(0.026)	(0.026)
Elementary occupations		-0.504***	-0.490***
		(0.023)	(0.023)
Region of residence			
Tyne and Wear			-0.273***

						(0.042)
Rest of Northern region						-0.215***
						(0.034)
South Yorkshire						-0.267***
						(0.040)
West Yorkshire						-0.197***
						(0.035)
Rest of Yorkshire and Humberside						-0.223***
						(0.038)
East Midlands						-0.248***
						(0.030)
East Anglia						-0.287***
						(0.036)
Inner London (not central						-0.101**
						(0.039)
Outer London						-0.098**
						(0.035)
Rest of South East						-0.167***
						(0.027)
South West						-0.201***
						(0.030)
West Midlands Metropolitan						-0.221***
						(0.036)
Rest of West Midlands						-0.269***
						(0.035)
Greater Manchester and Merseyside						-0.188***
						(0.033)
Rest of North West						-0.226***
						(0.035)
Wales						-0.254***
						(0.034)
Strathclyde						-0.186***
						(0.401)
Rest of Scotland						-0.253***
						(0.033)
Northern Ireland						-0.220***
						(0.029)
2023	-0.009	-0.009	0.001	-0.000	-0.000	-0.001
	(0.013)	(0.012)	(0.011)	(0.011)	(0.010)	(0.010)

Proxy	-0.069***	-0.063***	0.017	-0.003	-0.010	-0.007
	(0.013)	(0.013)	(0.012)	(0.012)	(0.011)	(0.011)
Adjusted R^2	0.0211	0.0901	0.2788	0.2877	0.4283	0.4379
N	*7,161*	*7,161*	*7,161*	*7,161*	*7,161*	*7,161*

Notes: (i) Estimates are based on a pooled OLS earnings equation. (ii) Males, Degree or equivalent, Single, never married, <25 employees, Managers and senior officials, Central London and non-proxy respondents are the reference categories. (iii) All models include a constant and a year term. (iv) Standard errors in parenthesis. (v) *p<0.05, **p<0.01, ***p<0.001.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters.

Table C.10: Full Set of Coefficient Estimates for the Wage Regression (2SLS model)

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.149***	-0.026	-0.057	-0.056*	-0.048**	-0.040*
	(0.013)	(0.020)	(0.019)	(0.019)	(0.016)	(0.019)
Predicted commute time		0.033***	0.027***	0.026***	0.020***	0.024***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Individual Characteristics						
Age			0.044***	0.034***	0.024***	0.023***
			(0.004)	(0.005)	(0.004)	(0.004)
Age^2			-0.000***	-0.000***	-0.000***	-0.000***
			(0.000)	(0.000)	(0.000)	(0.000)
Disabled			-0.071***	-0.058**	-0.040*	-0.041*
			(0.020)	(0.020)	(0.017)	(0.018)
Ethnicity			0.130***	0.144***	0.098***	0.059*
			(0.025)	(0.025)	(0.022)	(0.024)
Highest Qualification						
Higher education			-0.109***	-0.112***	-0.080**	-0.080**
			(0.033)	(0.032)	(0.027)	(0.029)
A-level or equivalent			-0.111***	-0.110***	-0.014	-0.011
			(0.030)	(0.029)	(0.024)	(0.026)
GCSEs A*-C or equivalent			-0.227***	-0.220****	-0.114***	-0.118***
			(0.030)	(0.030)	(0.023)	(0.025)
Other qualification			-0.259***	-0.253***	-0.134***	-0.128***
			(0.042)	(0.042)	(0.033)	(0.038)
No qualifications			-0.311***	-0.298***	-0.169***	-0.155***

	(0.049)	(0.048)	(0.037)	(0.042)
Household Composition				
Marital Status				
Married		0.085***	0.056***	0.049**
		(0.021)	(0.017)	(0.019)
Separated, widowed or divorced		-0.045	-0.031	-0.042
		(0.029)	(0.024)	(0.027)
Number of children under the age of 5		0.041*	0.026	0.028
		(0.019)	(0.016)	(0.017)
Number of children aged between 5-16 years		0.017	0.014	0.015
		(0.010)	(0.009)	(0.010)
Job Characteristics				
Full-time			-0.006	-0.014
			(0.019)	(0.022)
Public sector			-0.053**	-0.054**
			(0.017)	(0.018)
Temporary contract			0.024	0.020
			(0.033)	(0.036)
Tenure			0.001***	0.001***
			(0.000)	(0.000)
Tenure^2			-0.000**	-0.000**
			(0.000)	(0.000)
Trade union member			0.027	0.024
			(0.016)	(0.017)
Workplace size (%)				
25-49 employees			-0.007	-0.007
			(0.020)	(0.022)
50-249 employees			0.051**	0.047*
			(0.018)	(0.019)
250-499 employees			0.036	0.034
			(0.032)	(0.036)
500+ employees			0.066*	0.056
			(0.027)	(0.031)
Occupation				
Professional			-0.013	-0.015
			(0.027)	(0.029)
Associate Professional			-0.211***	-0.211***
			(0.029)	(0.032)
Administrative			-0.276***	-0.281***

	(0.033)	(0.035)
Skilled trades	-0.310***	-0.312***
	(0.036)	(0.038)
Caring, leisure and other service	-0.379***	-0.377***
	(0.036)	(0.040)
Sales & customer service	-0.395***	-0.384***
	(0.039)	(0.045)
Process, plant & machine operatives	-0.279***	-0.264***
	(0.043)	(0.049)
Elementary occupations	-0.360***	-0.350***
	(0.038)	(0.042)
Region of residence		
Tyne and Wear		0.191
		(0.106)
Rest of Northern region		0.359**
		(0.118)
South Yorkshire		0.281*
		(0.118)
West Yorkshire		0.307**
		(0.108)
Rest of Yorkshire and Humberside		0.368**
		(0.124)
East Midlands		0.320**
		(0.115)
East Anglia		0.229*
		(0.229)
Inner London (not central)		-0.010
		(0.058)
Outer London		0.239**
		(0.081)
Rest of South East		0.363***
		(0.107)
South West		0.359**
		(0.114)
West Midlands Metropolitan		0.225*
		(0.098)
Rest of West Midlands		0.350**
		(0.127)
Greater Manchester and Merseyside		0.291**

						(0.102)
Rest of North West						0.366**
						(0.122)
Wales						0.370**
						(0.127)
Strathclyde						0.279**
						(0.105)
Rest of Scotland						0.286*
						(0.112)
Northern Ireland						0.331**
						(0.112)
2023	-0.009	-0.008	-0.001	-0.002	-0.000	0.001
	(0.013)	(0.018)	(0.015)	(0.015)	(0.013)	(0.014)
Proxy	-0.069***	-0.041*	0.022	-0.001	-0.007	-0.011
	(0.013)	(0.019)	(0.016)	(0.016)	(0.014)	(0.015)
Durbin (score) chi2(1)	-	*234.846*	*146.075*	*141.858*	*68.403*	*58.025*
p-value	-	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
N	*7,161*	*7,161*	*7,161*	*7,161*	*7,161*	*7,161*

Notes: (i) Estimates are from the second stage of the IV (two-stage least squares (2SLS)) model. that pools across genders and years. (ii) 2022, Males, Degree or equivalent, Single, never married, <25 employees, Managers and senior officials, Central London and non-proxy respondents are the reference categories. (iii) All models include a constant and year term. (iv) Standard errors in parenthesis. (v) *p<0.05, **p<0.01, ***p<0.001. (vi) Figures reported in the final two rows are the Durbin (score) chi2(1) statistic for endogeneity between commute time and wages within each column.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters.

Table C.11: Full set of Coefficient Estimates for the Wage Regression (OLS and 2SLS models), by Gender

	OLS		2SLS	
	Male	Female	Male	Female
Commute time	0.002***	0.002***		
	(0.000)	(0.000)		
Predicted commute time			0.019***	0.031***
			(0.005)	(0.007)
Individual Characteristics				
Age	0.031***	0.028***	0.024***	0.025***
	(0.005)	(0.004)	(0.006)	(0.006)
Age^2	-0.000***	0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Disabled	-0.044*	-0.035*	-0.013	-0.065*
	(0.021)	(0.016)	(0.029)	(0.026)
Ethnicity	0.179***	0.020	0.134***	0.027
	(0.026)	(0.021)	(0.036)	(0.034)
Highest Qualification				
Higher education	-0.221***	-0.058*	-0.214***	0.040
	(0.030)	(0.025)	(0.040)	(0.047)
A-level or equivalent	-0.135***	-0.067***	-0.091**	0.069
	(0.022)	(0.019)	(0.031)	(0.048)
GCSEs A*-C or equivalent	-0.235***	-0.124***	-0.216***	-0.015
	(0.024)	(0.021)	(0.031)	(0.044)
Other qualification	-0.309***	-0.135***	-0.284***	0.056
	(0.033)	(0.032)	(0.043)	(0.072)
No qualifications	-0.346***	-0.192***	-0.284***	-0.011
	(0.037)	(0.036)	(0.051)	(0.074)
Household Composition Characteristics				
Martial status				
Married	0.066***	0.054**	0.033	0.079**
	(0.021)	(0.017)	(0.028)	(0.028)
Separated, widowed or divorced	0.019	-0.004	-0.000	-0.039
	(0.031)	(0.023)	(0.041)	(0.037)
Number of children under 5 years	0.052**	0.013	0.042	0.026
	(0.019)	(0.016)	(0.025)	(0.026)
Number of children aged between 5-16 years	0.013	0.010	0.004	0.032*
	(0.011)	(0.009)	(0.014)	(0.015)
Job Characteristics				
Full-time	0.051	0.038**	-0.007	-0.026
	(0.026)	(0.014)	(0.038)	(0.028)
Public sector	-0.071***	-0.080***	-0.079**	-0.012
	(0.020)	(0.016)	(0.027)	(0.031)
Temporary contract	-0.030	-0.074*	0.007	0.071
	(0.040)	(0.033)	(0.053)	(0.053)
Tenure	0.000	0.001***	0.001*	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure^2	-0.000	-0.000***	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Trade union member	-0.000	0.022	0.034	0.006
	(0.018)	(0.016)	(0.026)	(0.026)
Workplace size				
25-49 employees	0.019	-0.019	-0.008	0.001
	(0.024)	(0.020)	(0.032)	(0.032)
50-249 employees	0.119***	0.048**	0.079**	0.023
	(0.020)	(0.017)	(0.028)	(0.028)
250-499 employees	0.160***	0.114***	0.093*	-0.038
	(0.032)	(0.030)	(0.045)	(0.063)
500+ employees	0.240***	0.118***	0.169***	-0.067
	(0.023)	(0.020)	(0.035)	(0.058)
Occupation				
Professional	-0.070*	0.021	-0.044	-0.032
	(0.028)	(0.031)	(0.037)	(0.051)
Associate Professional	-0.242***	-0.229***	-0.203***	-0.238***
	(0.030)	(0.032)	(0.041)	(0.052)
Administrative	-0.379***	-0.317***	-0.343***	-0.284***
	(0.039)	(0.032)	(0.052)	(0.052)
Skilled trades	-0.368***	-0.469***	-0.299***	-0.324***

	(0.029)	(0.055)	(0.043)	(0.095)
Caring, leisure and other service	-0.508***	-0.480***	-0.380***	-0.420***
	(0.043)	(0.032)	(0.066)	(0.054)
Sales & customer service	-0.523***	-0.504***	-0.390***	-0.410***
	(0.041)	(0.035)	(0.064)	(0.062)
Process, plant & machine operatives	-0.434***	-0.339***	-0.270***	-0.315***
	(0.032)	(0.057)	(0.061)	(0.091)
Elementary occupations	-0.474***	-0.500***	-0.334***	-0.414***
	(0.032)	(0.036)	(0.056)	(0.061)
Region of workplace				
Tyne and Wear	-0.315***	-0.233***	0.079	0.330
	(0.063)	(0.057)	(0.134)	(0.175)
Rest of Northern region	-0.209***	-0.223***	0.174	0.601**
	(0.051)	(0.046)	(0.122)	(0.231)
South Yorkshire	-0.243***	-0.277***	0.158	0.483*
	(0.061)	(0.053)	(0.134)	(0.219)
West Yorkshire	-0.186***	-0.194***	0.232	0.447*
	(0.052)	(0.049)	(0.131)	(0.187)
Rest of Yorkshire and Humberside	-0.186***	-0.248***	0.286	0.509*
	(0.056)	(0.053)	(0.147)	(0.217)
East Midlands	-0.218***	-0.270***	0.181	0.539*
	(0.043)	(0.042)	(0.121)	(0.225)
East Anglia	-0.207***	-0.355***	0.140	0.384
	(0.052)	(0.050)	(0.116)	(0.211)
Inner London (not central)	-0.098	-0.094	-0.162*	0.212
	(0.057)	(0.053)	(0.076)	(0.117)
Outer London	-0.054	-0.137**	0.221*	0.299*
	(0.053)	(0.048)	(0.101)	(0.138)
Rest of South East	-0.155***	-0.178***	0.215	0.571**
	(0.039)	(0.039)	(0.112)	(0.208)
South West	-0.167***	-0.229***	0.225	0.562*
	(0.043)	(0.041)	(0.119)	(0.220)
West Midlands Metropolitan	-0.208***	-0.222***	0.163	0.342*
	(0.054)	(0.048)	(0.122)	(0.168)
Rest of West Midlands	-0.331***	-0.239***	0.122	0.623**
	(0.053)	(0.047)	(0.140)	(0.240)
Greater Manchester and Merseyside	-0.171***	-0.194***	0.193	0.449*
	(0.048)	(0.046)	(0.117)	(0.186)
Rest of North West	-0.257***	-0.200***	0.236	0.521*
	(0.051)	(0.049)	(0.148)	(0.206)
Wales	-0.232***	-0.285***	0.288	0.480*
	(0.050)	(0.047)	(0.154)	(0.217)
Strathclyde	-0.196***	-0.186***	0.150	0.458*
	(0.060)	(0.055)	(0.122)	(0.192)
Rest of Scotland	-0.277***	-0.237***	0.082	0.547*
	(0.048)	(0.046)	(0.115)	(0.220)
Northern Ireland	-0.205***	-0.229***	0.203	0.531*
	(0.041)	(0.040)	(0.122)	(0.212)
2023	0.001	-0.004	0.001	-0.000
	(0.015)	(0.013)	(0.019)	(0.020)
Proxy	-0.028	0.008	-0.042*	0.032
	(0.016)	(0.014)	(0.021)	(0.024)
Adjusted R^2	0.4371	0.4326		
N	*3,246*	*3,915*	*3,246*	*3,915*
Durbin (score) chi2(1)	-	-	*24.085*	*36.254*
p-value	-	-	*0.0000*	*0.0000*

Notes: (i) Estimates are based on a pooled OLS earnings equation or from the second stage of the IV (two-stage least squares (2SLS)) model. (ii) Males, Degree or equivalent, Single, never married, <25 employees, Managers and senior officials, Central London, 2022 and non-proxy respondents are the reference categories. (iii) All models include a constant and year term. (iv) Standard errors in parenthesis. (v) *p<0.05, **p<0.01, ***p<0.001. (vi) Figures reported in the final two rows are the Durbin (score) chi2(1) statistic for endogeneity between commute time and wages within each column.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters.

Table C.12: Detailed Decomposition of the Gender Pay Gap without Commute Time

Raw GPG	-0.143***		[100%]	
	(0.013)			
Explained GPG	-0.034**		[23.43%]	
	(0.013)			
Unexplained GPG	-0.109***		[76.22%]	
	(0.014)			
	Explained		**Unexplained**	
Individual characteristics				
Age	0.002	[-1.35%]	-0.159	[111.19%]
	(0.001)	{-5.76%}	(0.124)	{145.87%}
Disabled	-0.002*	[1.43%]	0.002	[-1.40%]
	(0.001)	{6.09%}	(0.004)	{-1.83%}
Ethnicity	0.000	[-0.02%]	-0.146***	[102.10%]
	(0.000)	{-0.09%}	(0.030)	{133.94%}
Highest qualification	0.010***	[-7.13%]	0.011***	[-7.97%]
	(0.002)	{-30.45%}	(0.003)	{-10.46%}
Household Composition Variables				
Marital status	-0.002	[1.20%]	0.001	[-0.42%]
	(0.001)	{5.10%}	(0.001)	{-0.56%}
Children	0.001	[-0.38%]	-0.009	[6.06%]
	(0.001)	{-1.60%}	(0.007)	{7.95%}
Job Characteristics				
Full-time	-0.013**	[9.16%]	-0.012	[8.39%]
	(0.004)	{39.10%}	(0.027)	{11.01%}
Public sector	-0.016***	[11.40%]	-0.004	[2.50%]
	(0.003)	{48.66%}	(0.006)	{3.28%}
Temporary contract	-0.000	[0.02%]	0.004*	[-2.99%]
	(0.000)	{0.09%}	(0.002)	{-3.92%}
Tenure	-0.002	[1.50%]	0.046**	[-32.10%]
	(0.001)	{6.39%}	(0.016)	{-42.11%}
Trade union member	0.002	[-1.08%]	0.007	[-4.76%]
	(0.001)	{-4.60%}	(0.006)	{-6.25%}
Firm size	-0.006***	[4.11%]	-0.000	[0.33%]
	(0.002)	{17.55%}	(0.001)	{0.43%}
Occupation	-0.002	[1.18%]	-0.016*	[11.26%]
	(0.010)	{5.04%}	(0.007)	{14.77%}
Region of workplace	-0.004*	[2.99%]	0.001	[-0.99%]
	(0.002)	{12.78%}	(0.002)	{-1.30%}
2023	-0.000	[0.01%]	-0.002	[1.41%]
	(0.000)	{0.03%}	(0.008)	{1.85%}
Proxy respondent	-0.001	[0.36%]	-0.018	[12.80%]
	(0.001)	{1.55%}	(0.013)	{16.79%}

Notes: (i) The OB method is used to decompose the mean GPG using male coefficients as the baseline. (ii) Specification includes individual characteristics (age, age^2, disability, white ethnicity and highest qualification indicators), household variables (marital status, number of children under the age of 4 and 5-16), job characteristics (full-time, public sector, temporary contract, trade union and firm size indicators, tenure and tenure^2, and SOC 2020 major groups (nine categories), region of workplace (20 regions), year and proxy indicators and a constant. (iii) Detailed decompositions of the unexplained gap is based on normalised effects following Yun (2005). The unexplained component includes a constant. (iv) Figures in () are standard errors and figures in [] ({}) are a percentage of the observed (explained/unexplained) GPG. (v) *p<0.05, **p<0.01, ***p<0.001.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters.

Table C.13: Detailed Decomposition of the Gender Pay Gap with Commute Time (OLS and 2SLS models)

	OLS				2SLS			
Raw GPG	-0.143***		[100%]		-0.143***		[100%]	
	(0.013)				(0.013)			
Explained GPG	-0.041*		[28.39%]		-0.045***		[31.26%]	
	(0.013)				(0.013)			
Unexplained GPG	-0.102***		[71.33%]		-0.098***		[68.81%]	
	(0.014)				(0.014)			
	Explained		**Unexplained**		**Explained**		**Unexplained**	
Commute time	-0.009***	[6.22%]	0.018	[-12.52%]	-0.015***	[10.14%]	0.073	[-50.91%]
	(0.002)	{21.92%}	(0.014)	{-17.55%}	(0.003)	{32.44%}	(0.058)	{-73.98%}
Individual characteristics								
Age	0.002	[-1.33%]	-0.149	[104.20%]	0.002	[-1.26%]	-0.164	[114.69%]
	(0.001)	{-4.68%}	(0.004)	{146.08%}	(0.001)	{-4.03%}	(0.124)	{166.67%}
Disabled	-0.002*	[1.54%]	0.001*	[-0.83%]	-0.002	[1.36%]	0.001	[-0.94%]
	(0.001)	{5.42%}	(0.004)	{-1.17%}	(0.001)	{4.34%}	(0.004)	{-1.36%}
Ethnicity	0.000	[-0.02%]	-0.142***	[99.30%]	0.000	[-0.01%]	-0.143***	[100.00%]
	(0.000)	{-0.07%}	(0.030)	{139.22%}	(0.000)	{-0.05%}	(0.030)	{145.33%}
Highest qualification	0.009***	[-6.34%]	0.073	[-51.19%]	0.008***	[-5.93%]	0.013	[-8.81%]
	(0.002)	{-22.34%}	(0.017)	{-71.76%}	(0.002)	{-18.97%}	(0.003)	{-12.80%}
Household Variables								
Marital status	-0.002	[1.36%]	-0.008	[5.87%]	-0.002	[1.08%]	0.001	[-0.43%]
	(0.001)	{4.80%}	(0.016)	{8.24%}	(0.001)	{3.47%}	(0.001)	{-0.63%}
Children	0.001	[-0.46%]	-0.007	[5.01%]	0.001	[-0.38%]	-0.007	[5.21%]
	(0.001)	{-1.62%}	(0.007)	{7.03%}	(0.001)	{-1.22%}	(0.007)	{7.57%}
Job Characteristics								
Full-time	-0.011**	[7.97%]	-0.012	[8.11%]	-0.012**	[8.25%]	-0.011	[7.90%]
	(0.004)	{28.08%}	(0.026)	{11.37%}	(0.004)	{26.40%}	(0.026)	{11.48%}
Public sector	-0.015***	[10.63%]	-0.002	[1.44%]	-0.014***	[9.93%]	-0.002	[1.22%]
	(0.003)	{37.44%}	(0.006)	{2.02%}	(0.003)	{31.77%}	(0.006)	{1.77%}
Temporary contract	-0.000	[0.02%]	0.004	[-2.91%]	-0.000	[0.02%]	0.004*	[-2.90%]
	(0.000)	{0.07%}	(0.002)	{-4.08%}	(0.000)	{0.07%}	(0.002)	{-4.21%}
Tenure	-0.002	[1.51%]	0.045**	[-31.47%]	-0.002	[1.35%]	0.043**	[-29.93%]
	(0.002)	{5.32%}	(0.016)	{-44.12%}	(0.001)	{4.32%}	(0.016)	{-43.50%}
Trade union member	0.001	[-1.01%]	0.006	[-3.90%]	0.001	[-0.90%]	0.005	[-3.78%]
	(0.001)	{-3.55%}	(0.006)	{-5.47%}	(0.001)	{-2.86%}	(0.006)	{-5.50%}
Firm size	-0.005***	[3.71%]	-0.054***	[37.76%]	-0.005***	[3.52%]	-0.000	[0.07%]
	(0.002)	{13.08%}	(0.015)	{52.94%}	(0.001)	{11.25%}	(0.001)	{0.10%}
Occupation	-0.003	[1.90%]	0.019	[-13.57%]	-0.001	[0.89%]	-0.015*	[10.77%]
	(0.010)	{6.70%}	(0.033)	{-19.02%}	(0.010)	{2.84%}	(0.007)	{15.65%}
Region of workplace	-0.003	[2.17%]	-0.022	[15.31%]	-0.004*	[2.57%]	0.000	[-0.63%]
	(0.002)	{7.66%}	(0.048)	{21.47%}	(0.002)	{8.23%}	(0.002)	{-0.92%}

2023	-0.000	[0.01%]	-0.002	[1.34%]	0.000	[0.01%]	-0.002	[1.34%]
	(0.000)	{0.02%}	(0.008)	{1.87%}	(0.000)	{0.02%}	(0.008)	{1.95%}
Proxy respondent	-0.001	[0.50%]	-0.020	[14.27%]	-0.001	[0.57%]	-0.021	[14.41%]
	(0.001)	{1.77%}	(0.012)	{20.00%}	(0.001)	{1.84%}	(0.012)	{20.93%}

Notes: (i) The OB method is used to decompose the mean GPG using male coefficients as the baseline. (ii) Specification includes individual characteristics (age, age^2, disability, white ethnicity and highest qualification indicators), household variables (marital status, number of children under the age of 4 and 5-16), job characteristics (full-time, public sector, temporary contract, trade union and firm size indicators, tenure and tenure^2, and SOC 2020 major groups (nine categories), region of workplace (20 regions), year and proxy indicators and a constant. (iii) Detailed decomposition of the unexplained gap is based on normalised effects following Yun (2005). The unexplained component includes a constant. (iv) Figures in () are standard errors and figures in [] ({}) are a percentage of the observed (explained/unexplained) GPG. (v) *p<0.05, **p<0.01, ***p<0.001.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters.

Table C.14: OB decomposition of the observed mean CGG, sensitivity analysis

	(1) Benchmark	(2) Log commute time	(3) 90-minute limit on commute time	(4) Primarily commuting industries	(5) Excluding proxy responses
Raw CGG	-3.635***	-0.143***	-3.140***	-3.386***	-3.262***
	(0.500)	(0.019)	(0.432)	(0.893)	(0.669)
Explained CGG	-1.067*	-0.044*	-0.908*	-0.951	-2.301***
	(0.483)	(0.020)	(0.428)	(1.091)	(0.602)
	[29.35%]	[30.98%]	[28.91%]	[28.01%]	[70.56%]
Unexplained CGG	-2.568***	-0.098***	-2.232***	-2.435*	-0.960
	(0.628)	(0.025)	(0.542)	(1.283)	(0.804)
	[70.65%]	[69.02%]	[71.09%]	[71.92%]	[29.44%]
Explained CGG					
Individual characteristics	0.522***	0.022***	0.488***	0.077	0.448**
	(0.100)	(0.004)	(0.092)	(0.328)	(0.151)
	[-14.35%] {-48.90%}	[-15.73%] {50.77%}	[-15.55%] {-53.79%}	[-2.27%] {-8.07%}	[-13.72%] {-19.45%}
Household variables	0.056	0.002	0.067	0.207	0.116
	(0.060)	(0.003)	(0.054)	(0.020)	(0.116)
	[-1.53%] {-5.21%}	[-1.37%] {-4.43%}	[-2.13%] {-7.37%}	[-6.13%] {-21.82%}	[-3.55%] {-5.03%}
Job characteristics	-1.240**	-0.051**	-1.008**	-1.840	-1.997***
	(0.439)	(0.018)	(0.386)	(0.986)	(0.517)
	[34.11%] {116.22%}	[35.98%] {116.11%}	[32.10%] {111.04%}	[54.33%] {193.52%}	[61.24%] {86.79%}
Region of workplace	-0.471**	-0.015**	-0.445**	0.467	-0.866***
	(0.155)	(0.005)	(0.141)	(0.276)	(0.240)
	[12.97%] {44.19%}	[10.56%] {34.08%}	[14.19%] {49.07%}	[-13.78%] {-49.10%}	[26.56%] {37.65%}
N	*7,161*	*7,161*	*7,097*	*2,087*	*4,521*

	(6) Employees worked in the same job for > 12 months	(7) Private sector	(8) Full-time employees	(9) QLFS 2018 + 2019	(10) Waves 1-5 2022
Raw CGG	-3.841***	-3.540***	-1.767**	-5.309***	-4.618***
	(0.547)	(0.612)	(0.611)	(0.419)	(0.400)
Explained CGG	-1.414**	-0.969	1.085	-2.004***	-0.850*
	(0.545)	(0.624)	(0.633)	(0.385)	(0.375)
	[36.81%]	[27.36%]	[-61.40%]	[37.74%]	[18.41%]
Unexplained CGG	-2.427***	-2.572***	-2.852***	-3.306***	-3.768***
	(0.701)	(0.779)	(0.788)	(0.516)	(0.501)
	[63.19%]	[72.64%]	[161.40%]	[62.26%]	[81.59%]
Explained CGG					
Individual characteristics	0.619***	0.260*	0.947***	0.250***	0.356***
	(0.113)	(0.106)	(0.195)	(0.066)	(0.076)
	[-16.11%] {-43.76%}	[-7.35%] {-26.87%}	[-53.61%] {87.31%}	[-4.71%] {-12.47%}	[-7.71%] {-44.88%}
Household variables	0.132*	0.075	0.059	-0.022	-0.033
	(0.060)	(0.089)	(0.095)	(0.042)	90.044)

	[-3.45%] {-9.37%}	[-2.11%] {-7.72%}	[-3.36%] {5.47%}	[0.41%] {1.09%}	[0.71%] {3.88%}
Job characteristics	-1.647***	-1.152*	-0.093	-1.725***	-0.648
	(0.496)	(0.556)	(0.570)	(0.349)	(0.342)
	[42.89%] {116.51%}	[32.55%] {118.97%}	[5.29%] {-8.61%}	[32.50%] {86.10%}	[14.03%] {76.24%}
Region of workplace	-0.555**	-0.186	0.101	-0.516***	-0.535***
	(0.176)	(0.210)	(0.214)	(0.125)	(0.123)
	[14.45%] {39.25%}	[5.25%] {19.19%}	[-5.70%] {9.29%}	[9.72%] {25.75%}	[11.59%] {62.94%}
N	*5,940*	*4,844*	*5,167*	*13,620*	*12,304*
	(11) Female coefficients as the baselines	(12) Pooled coefficients as the baseline			
Raw CGG	-3.635***	-3.635***			
	(0.500)	(0.497)			
Explained CGG	-1.281**	-1.383***			
	(0.535)	(0.327)			
	[35.25%]	[38.03%]			
Unexplained CGG	-2.354	-2.253			
	(0.669)	(0.520)			
	[64.76%]	[61.97%]			
Explained CGG					
Individual characteristics	0.117	0.365***			
	(0.115)	(0.078)			
	[-3.22%] {-9.14%}	[-10.04%] {-26.39%}			
Household variables	0.045	0.083			
	(0.088)	(0.047)			
	[-1.22%] {-3.47%}	[-2.27%] {-5.98%}			
Job characteristics	-1.056*	-1.412***			
	(0.495)	(0.270)			
	[29.06%] {82.45%}	[38.83%] {102.11%}			
Region of workplace	-0.297	-0.390**			
	(-0.297)	(0.148)			
	[8.17%] {23.17%}	[10.72%] {28.20%}			
N	*7,161*	*7,161*			

Notes: (i) The OB method is used to decompose the mean CGG using male coefficients are the baseline (unless otherwise specified). (ii) Specification includes individual characteristics, household variables, job characteristics and region of workplace (20 regions), year and proxy indicators and a constant. (iii) Primary commuting industries are accommodation and food service activities, other service activities, transportation and storage, construction and manufacturing industries Decompositions are calculated using the relevant male coefficients as the baseline. (iv) Figures in () are standard errors and figures in [] ({}) are a percentage of the observed (explained/unexplained) CGG. (v) *p<0.05, **p<0.01, ***p<0.001.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters, unless otherwise specified.

Table C.15: OB decomposition of the observed mean GPG, sensitivity analysis

	(1) Benchmark	(2) IV: average commute time within industry (2-digit SIC)	(3) Log commute time	(4) Excluding anyone paid overtime	(5) Excluding proxy responses
Observed GPG	-0.143***	-0.144***	-0.143***	-0.143***	-0.189***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.016)
Explained GPG	-0.045***	-0.047***	-0.044***	-0.042***	-0.082***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.015)
	[31.26%]	[32.71%]	[31.01%]	[29.03%]	[43.24%]
Unexplained GPG	-0.098***	-0.097***	-0.099***	-0.102***	-0.107***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.017)
	[68.81%]	[67.29%]	[68.99%]	[70.97%]	[56.76%]
Explained by commute time	-0.015***	-0.017***	-0.015***	-0.014***	-0.015***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
	[10.14%] {32.44%}	[11.73%] {35.86%}	[10.23%] {33.01%}	[9.73%] {33.50%}	[7.95%] {18.39%}
Unexplained by commute time	0.073	0.082	0.053	0.076	0.042
	(0.058)	(0.067)	(0.061)	(0.059)	(0.068)
	[-50.91%] {-73.98%}	[-57.23%] {-85.05%}	[-36.82%] {-53.36%}	[-53.23%] {-75.00%}	[-30.35%] {-40.85%}
N	*7,161*	*7,141*	*7,161*	*6,555*	*5,940*
F-statistic	*54.50*	*94.31*	*60.19*	*46.62*	*45.93*
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*

	(6) Employees worked in the same job for > 12 months	(7) Private sector	(8) Full-time employees	(9) Without workplace region	(10) With region of residence
Observed GPG	-0.151***	-0.178***	-0.093***	-0.143***	-0.143***
	(0.014)	(0.015)	(0.014)	(0.013)	(0.013)
Explained GPG	-0.039**	-0.082***	0.007	-0.051***	-0.050***
	(0.014)	(0.015)	(0.015)	(0.013)	(0.013)
	[25.71%]	[46.35%]	[-7.65%]	[35.35%]	[34.65%]
Unexplained GPG	-0.113***	-0.095***	-0.100***	-0.092***	-0.093***
	(0.016)	(0.017)	(0.016)	(0.014)	(0.014)
	[74.29%]	[53.65%]	[107.65%]	[64.65%]	[65.35%]
Explained by commute time	-0.015***	-0.018***	-0.014***	-0.023***	-0.022***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
	[9.66%] {37.57%}	[9.92%] {21.40%}	[16.32%] {46.17%}	[16.78%] {60.00%}	[15.27%] {44.07%}
Unexplained by commute time	0.046	0.077	-0.161	0.106	0.098
	(0.061)	(0.065)	(0.0885)	(0.067)	(0.064)
	[-30.35%] {-40.85%}	[-43.48%] {-81.04%}	[-173.33%] {-161.02%}	[-73.86%] {-114.26%}	[-68.42%] {-104.70%}
N	*5,940*	*4,844*	*5,167*	*7,161*	*7,161*
F-statistic	*45.93*	*47.80*	*52.95*	*97.36*	*78.59*
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0 .000*

	(11) QLFS 2018 + 2019	(12) Female coefficients as the baseline	(13) Pooled coefficients as the baseline
Observed GPG	-0.171***	-0.143***	-0.143***
	(0.009)	(0.013)	(0.013)
Explained GPG	-0.037***	-0.056***	-0.053***
	(0.009)	(0.013)	(0.010)
	[21.30%]	[39.15%]	[37.25%]
Unexplained GPG	-0.135***	-0.087***	-0.090***
	(0.009)	(0.014)	(0.011)
	[78.70%]	[60.85%]	[62.75%]
Explained by commute time	-0.011***	-0.011***	-0.013***
	(0.001)	(0.002)	(0.002)
	[6.37%] {29.89%}	[7.48%] {19.10%}	[8.84%] {23.74%}
Unexplained by commute time	0.056*	0.069	0.071
	(0.023)	(0.055)	(0.054)
	[-32.63%] {41.46%}	[-48.26%] {-79.31%}	[-49.62%] {-79.08%}
N	*13,620*	*7,161*	*7,161*
F-statistic	*59.13*	*54.50*	*54.50*
p-value	*0.000*	*0.000*	*0.000*

Notes: (i) OB decomposition is performed using a model which includes individual characteristics (age, age^2, disability, white ethnicity and highest qualification indicators), household variables (marital status, number of children under the age of 4 and 5-16), job characteristics (full-time, public sector, temporary contract, tenure and tenure^2, and SOC 2020/2010 (major groups), region of workplace (20 regions), year and proxy indicators and a constant, unless otherwise specified. Each decomposition use the predicted values of commute time instrumented by the average commute time of individuals in the same one digit industry, except in column (2) which uses two-digit industry averages for industries with more than 10 individuals. (ii) Decompositions are calculated using the relevant male coefficients as the baseline, except in column (12) and (13) where female and pooled coefficients are used, respectively. The unexplained component includes a constant. (iii) The decomposition of the unexplained gap are based on normalised effects following Yun (2005). (iv) Figures in () are standard errors and figures in [] ({}) are a percentage of the observed (explained/unexplained) GPG. (iv) *p<0.05, **p<0.01, ***p<0.001.

Source: Author calculations based on pooled QLFS 2022 and 2023 data from the fourth quarters, unless otherwise specified.

Appendix D

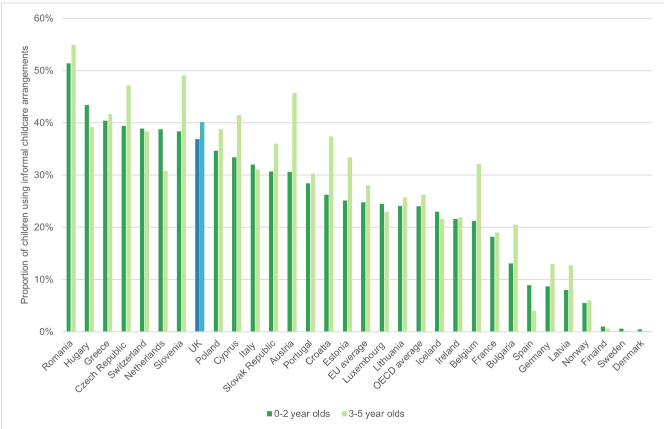


Figure D.1: Proportion of Children using Informal Childcare during a Typical Week, by Age

Notes: (i) Data refer to 2019, apart from for Iceland and the UK, which refer to 2018. (ii) Informal childcare refers to unpaid care, usually provided by a grandparent or by other relatives, friends or neighbours. It excludes any care that is paid-for, regardless of who is providing the paid-for care.

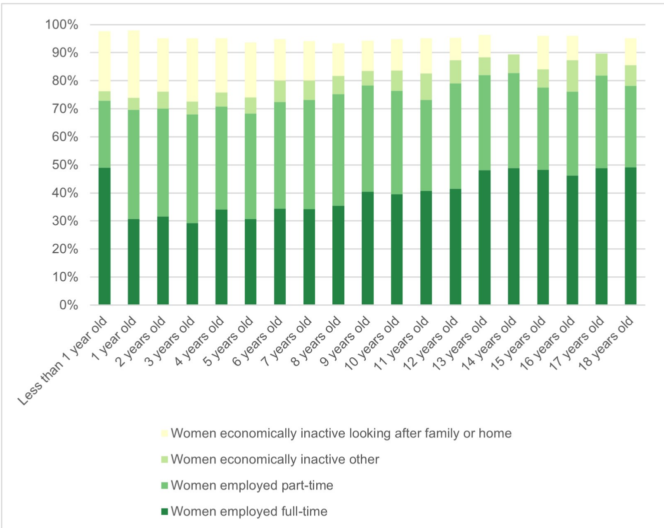


Figure D.2: Proportion of Mothers Working Full-time by Age of Youngest Dependent Child

Notes: (i) Totals may not sum to 100% due to rounding and suppression. Categorises with small sample sizes (e.g. those unemployed and economically inactive looking after family or home for single age groups 14 and 17 years) are not included. (ii) The LFS categorises women on maternity leave and on a career break as in employment.

Source: QLFS April-June 2021, ONS (2022b)

Table D.1: Summary of key childcare policy and legislation implemented by the Welsh Government and UK Government, 1997-2024

Policy	**Where Applied**	**Summary**
National Childcare Strategy (1998)	Specific to England, although many aspects were also important for the other UK nations.	Aimed to ensure universal access to quality and affordable childcare for children aged 0-14 in every neighbourhood, with the explicit aim of promoting mother's employment and children's future educational achievements, as a means of addressing child poverty. It introduced 12.5 hours free education for all four year olds for 33 weeks per year, later extended to three year olds and 15 hours a week in 2004, increased to 38 weeks per year in 2005.
Sure Start (1998)	England, although similar policies introduced elsewhere in the UK.	An early intervention program for under fours, delivered initially through local programs, directed by a range of stakeholders within the most deprived areas. It provided a range of integrated services, including childcare, early education, healthcare and family support. It was introduced to local areas in waves, so that by 2005, there was a Sure Start Children's Centre in every community.
Childcare Tax Credit (2003)	Applied throughout the UK.	Introduced as part of the wider tax credit system, this policy provided financial assistance to working families to help cover the costs of childcare, determined by income and the number of children in need of childcare. These have been replaced by Universal Credit.
Flying Start (2006)	Wales, very similar to the Sure Start programme in England.	A targeted early intervention program that offered access to additional support services to families with children under four who lived in disadvantaged areas, including intensive health visiting service, parenting support and support for speech, language and communication development. Since September 2022, it has been extended to all areas in Wales.
Childcare Act (2006)	Throughout the UK, although now devolved.	Set in legislation some of the key commitments of the UK Government's 10-year childcare strategy, aiming to transform childcare and early years services. It required local authorities to ensure sufficient childcare, introduced an education and care framework, and Ofsted registers.
Early Years Foundation Stage (2008)	England only, but equivalents in Wales and Scotland.	Established a framework for early education and care for children from birth to five years old. It outlined learning and development standards and emphasised the importance of quality and consistent provision.
Foundation Phase (2010)	Wales.	A distinctive curriculum for children aged three to seven in Wales, promoting holistic learning and development through play-based activities, through emphasising experimental learning, personal and social development and language acquisition.
Universal Credit (2013)	Rolled out across the entire UK from 2013-2024 (in Wales from April 2017 - December 2018).	Replaced Childcare Tax Credit to provide working parents up to 85% of childcare costs up to a limit, no matter how many hours worked (although the support can be reduced if thought that the childcare costs are excessive for the number of hours in paid work).

Tax-Free Childcare (2017)	England.	Introduced a government scheme to support working parents of children aged under 4 with childcare costs. Eligible families can open a Tax-Free Childcare account, receiving a government top-up of £2 for every £8 that they contribute to their account.
30 Hours Free Childcare (2017)	England.	Building upon the extended entitlement, this policy provided eligible working parents in England with 30 hours of free childcare per week for three and four year olds during term time. It's aim was to support parent's employment and reduce childcare costs, in conjunction with the Tax-Free Childcare (2017) policy.
Early Years National Funding Formula (2017)	England.	Sitting alongside the Tax-Free Childcare and 30 Hours Free Childcare policies, this aimed to provide fair and transparent funding for early years education and childcare providers, seeking to allocate funding based on factors such as child age, local cost factors and the needs of disadvantaged children.
Childcare Offer for Wales (2019)	Wales, the equivalent of the 30 Hours Free Childcare policy in England.	Provides eligible working parents of children aged three or four with 30 hours of funded childcare per week for up to 48 weeks a year. It aims to support parental employment and reduce childcare costs, while also promoting early education development.
Childcare Taster Sessions (2019)	Wales.	This initiative allows parents and children to participate in free childcare taster sessions before accessing the Offer. It aims to familiarise families with childcare settings and enable children to transition smoothly into formal childcare.
Childcare Sufficiency Assessments	All local authorities in Wales.	As a statutory duty of the Childcare Act 2006, Childcare Sufficiency Assessments are required to be conducted regularly to better understand parents/carers' use of childcare, the overall supply of childcare and any additional factors that may impact on the demand of childcare over the next five years. These assessments help ensure sufficient childcare provision and inform future policy decisions.

Table D.2: Rollout of the Childcare Offer for Wales by Local Authority and Ward

Local Authority	Rollout data	Initial rollout
Blaenau Gwent Council	Full rollout across all wards	September 2017
Bridgend County Borough Council	Full rollout across all wards	April 2019
City of Cardiff Council	Butetown, Ely, Grangetown, Splott, Caerau, Riverside, Cathays, Adamsdown, Plasnewydd, Llanrumney	September 2018
	Lisvane, Creigiau/St Fagans, Pentyrch, Whitchurch and Tongwynlaid, Rumney, Trowbridge, Pontprennau/Old St Mellons, Fairwater, Llandaff, Radyr, Canton, Llandaff North, Gabalfa, Penylan, Heath, Cyncoed, Pentwyn, Rhiwbina, Llanishen	January 2019
Carmarthenshire County Council	Full rollout across all wards	January 2019
Caerphilly Council	Full rollout across all wards	September 2018
Ceredigion Council	Full rollout across all wards	September 2018
Conwy Council	Betws yn Rhos, Uwchaled, Llangernyw, Betws-y-Coed, Trefriw, Caerhun, Eglwysbach, Uwch Conwy, Llansannan, Gogarth, Crwst, Mostyn, Gele, Kinmel Bay, Tudno, Llanddulais, Pentre Mawr, Abergele Pensarn, Towyn, Gower	September 2018
	Bryn, Pandy, Pant-yr-Afon/Penmaenan, Conwy,Penrhyn, Llansanffraid, Mochdre, Rhiw, Capelulo, Deganwy, Pensarn, Marl, Craig-y-Don, Eirias, Llysfaen, Llandrillo yn Rhos, Glyn, Colwyn	January 2019
Denbighshire Council	Full rollout across all wards	January 2019
Flintshire Council	Full rollout across all wards	April 2018
Gwynedd Council	Full rollout across all wards	April 2018
Isle of Anglesey Council	Full rollout across all wwards	April 2018
Merthyr Tydfil Council	Full rollout across all wards	January 2019
Monmouthshire Council	Full rollout across all wards	January 2019
Neath Port Talbot Council	Baglan, Pontardawe, Glyncorrwg, Resolven, Onllwyn, Lower Brynamman, Aberavon, Tai-bach, Gwaun-Cae-Gurwen, Gwynfi, Blaengwrach, Bryn-Coch South	September 2018
	Cadoxton, Cymmer, Crynant, Neath East, Trebanos, Allt-Wen, Ystalyfera, Tonna, Sandfields West, Sandfields East, Cimla	December 2018
	Margam, Bryn and Cwmavon, Rhos, Pelenna, Seven Sisters, Glynneath, Coedffranc West, Briton Ferry West, Port Talbot, Neath North, Dyffryn, Bryn-Coch North, Cwmllynfell, Aberdulais, Coedffranc Central, Neath South, Briton Ferry East, Neath South, Coedffranc North, Godre'r Graig	January 2019
Newport Council	Liswerry, Rogerstone, Shaftesbury, St Julians, Gaer, Stow Hill, Malpas	September 2018
	Langstone, Llanwern, Graig, Marshfield, Bettws, Caerleon, Pillgwenlly, Allt-yr-Yn, Alway, Ringland, Tredegar Park, Victoria, Beechwood	November 2018
Pembrokeshire Council	Full rollout across all wards	April 2019
Powys Council	Full rollout across all wards	April 2019

Rhondda Cynon Taf Council	Thigos, Pont-y-Clun, Llantrisant Town, Aberdare West/Llwydcoed, Mountain Ash East, Aberaman South, Llantwit Fardre, Ton-Teg, Ynyshir, Aberaman North, Hirwaun, Tylorstown, Abercynon, Aberdare East, Beddau, Tyn-y-Nant, Church Village, Ferndale, Peny-y-Waun, Penrhiwceiber, Mountain Ash West	January 2018
	Brynna, Llanharry, Llanharan, Taffs Well, Treforest, Rhydfelen Central/Llan, Hawthorn, Talbot Green, Graig, Trallwng	April 2018
	Maerdy, Treherbert, Ynysybwl, Tonyrefail West, Gilfach Goch, Pen-y-Graig, Cwm Clydach, Ystrad, Llwyn-y-Pia, Tonyrefail East, Cymmer, Rhondda, Treorchy, Pentre, Cwmbach, Tonypandy, Trealaw, Pontypridd Town, Porth, Glyncoch, Cilfynydd	September 2018
Swansea Council	West Cross, Morriston, Pontardulais, Oystermouth, Newton, Penclawdd, Llangyfelach, Mawr, Dunvant, Gorseinon	July 2017
	Llansamlet, Cockett, Lower Loughor, Upper Loughor, Penderry, Gowerton, Kingsbridge, Penllergaer, Penyrheol	January 2018
	Mynyddbach, Bishopston, Fairwood, Clydach, Gower, Pennard, Killay South, Killay North, Mayals, Uplands, Castle, Townhill, Cwmbwrla, Landore, Sketty, St Thomas, Bonymaen,	January 2019
Torfaen Council	Full rollout across all wards	September 2018
Vale of Glamorgan Council	Full rollout across all wards	April 2019
Wrexham Council	Overton, Bronington, Holt, Rossett, Ponciau, Llay, Coedpoeth, New Broughton, Brymbo, Gwersyllt West, Gwersyllt East and South, Gwersylt North, Gresford East and West, Marford and Hoseley	September 2018
	Dyffryn Ceiriog/Ceiriog Valley, Penycae and Ruabon South, Marchweil, Chirk South, Minera, Ruabon Llangollen Rural, Cefn, Chirk North, Pencae, Johnstown, Esclusham, Brynyffynnon, Bryn Cefn, Pant, Erddig, Hermitage, Offa, Smithfield, Whitegate, Queensway, Gwenfro, Grosvenor, Maesydre, Stansty, Acton, Garden Village, Little Acton, Wynnstay, Cartrefle, Rhosnesni, Borras Park, Plas Madoc	January 2019

Notes: (i) Data obtained from Freedom of Information requests to Welsh Government and individual Local Authorities.

Table D.3: Variable Definitions

Variables	APS Variable	Definition
Dependent Variables		
Employment Status	Derived from *ILODEFR*	Dummy variable equals 1 if parent reports their basic economic activity as in employment, 0 if parent reports their basic economic activity as ILO unemployed or inactive.
Parental Characteristics		
Mother	*SEX*	Dummy variable, equals 1 if parent is a mother, 0 if parent is a father.
Age (and age^2)	*AGE*	Age (in years) of parent
Low education (< A-levels)	Derived from *HIQUL15D*	Dummy variable, equals 1 if parent reports that their highest qualification are GCSE grades A*-C or equivalent, Other qualification, or no qualification, 0 if parent reports that their highest qualification is A-levels, Higher education or degree or equivalent.
Cohabitation	derived from *MARCHUK* and *LIV12W*	Dummy variable, equals 1 if parent reports that spouse is a household member or whether living together as a couple, 0 if parent reports that spouse is not a household member nor living together as a couple.
Number of dependent children in family aged under 16	*FDPCH16*	Number of dependent children in family aged under 16.

Table D.4: Sample Means for Explanatory Variables in the RDD analysis, by Gender and Eligibility Status

	Not yet eligible			Eligible		
	All	**Mothers**	**Fathers**	**All**	**Mothers**	**Fathers**
Dependent Variable						
Employment Rate (%)	75.00	62.71	94.59	74.56	67.69	83.67
N	*72*	*37*	*35*	*85*	*44*	*41*
Parental Characteristics						
Age (years)	33.21	32.47	34.38	36.78	34.85	39.35
N	*96*	*59*	*37*	*114*	*65*	*49*
Low Education (< A-Levels) (%)	38.54	38.98	37.84	35.96	36.92	34.69
N	*37*	*23*	*14*	*41*	*24*	*17*
Cohabitation (%)	79.17	66.10	100.00	85.96	76.92	97.96
N	*76*	*39*	*37*	*98*	*50*	*48*
Number of dependent children in family	1.90	1.78	2.08	1.78	1.80	1.76
aged under 16 years old *N*	*96*	*59*	*37*	*114*	*65*	*49*

Notes: (i) Variable means are constructed on the basis of the estimation sample and rounded to two decimal places. (ii) Positive case sample sizes are provided in italics after each estimation.

Source: Author calculations based on pooled April 2019 - March 2020 APS.

Table D.5: Impact of Eligibility on Observable Characteristics

	(1) Age	(2) Low education (< A-levels)	(3) Cohabitation	(4)Number of dependent children
Offer	4.794	-0.096	0.259	0.462
	(0.3825)	(0.236)	(0.180)	(0.481)
Days	0.044	0.004	0.008	-0.018
	(0.136)	(0.008)	(0.006)	(0.017)
Days^2	0.001	0.000	0.000	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Offer x Days	-0.120	0.003	-0.013	0.010
	(0.177)	(0.011)	(0.008)	(0.022)
Offer x Days^2	-0.000	-0.000	-0.000	0.000
	(0.002)	(0.000)	(0.000)	(0.000)
September cohort	-0.140	0.101	0.287***	-0.333
	(2.113)	(0.130)	(0.099)	(0.266)
September cohort x Offer	2.696	-0.180	-0.298**	-0.159
	(2.778)	(0.171)	(0.131)	(0.349)
January cohort	-0.689	0.236*	0.215**	0.441
	(2.113)	(0.130)	(0.099)	(0.266)
January cohort x Offer	0.214	-0.323*	-0.362***	0.129
	(2.870)	(0.177)	(0.135)	(0.361)
Calendar month fixed effects	No	No	No	No
Local authority fixed effects	No	No	No	No
R^2	0.0794	0.0301	0.737	0.0742
N	*210*	*210*	*210*	*210*

Notes: (i) This table reports ITT estimates based on April 2019 - March 2020 from RDD regressions using 90-days either side of the relevant cut-off as the bandwidth and parental characteristics as the outcome variables. (ii) The regressions control for a second order polynomial in the difference between the age of the child and the relevant cut-off, and an interaction between this polynomial and the cutoff. (iii) Figures in () are standard errors. (iv) *< 0.10, **< 0.05, ***p<0.01.

Source: Author calculations based on pooled April 2019 - March 2020 APS.

Table D.6: Full RDD Estimates of the Heterogeneous Impact by Parental Subgroup, and for Hours Worked

	(1) Mothers	(2) Youngest child	(3) Non-trial areas	(4) Usual Hours Worked
Offer	0.226	0.309	0.275	-1.213
	(0.209)	(0.235)	(0.197)	(9.996)
Days	-0.001	0.001	-0.000	0.161

	(0.008)	(0.008)	(0.008)	(0.325)
Days^2	0.000	0.000	0.000	0.003
	(0.000)	(0.000)	(0.000)	(0.003)
Offer x Days	-0.005	-0.008	-0.005	-0.124
	(0.009)	(0.010)	(0.009)	(0.402)
Offer x Days^2	0.000	0.000	0.000	-0.003
	(0.000)	(0.000)	(0.000)	(0.004)
September cohort	0.098	0.117	0.100	7.560
	(0.132)	(0.134)	(0.132)	(6.518)
September cohort x Offer				-2.991
				(6.507)
January cohort	0.099	0.114	0.102	0.387
	(0.132)	(0.132)	(0.132)	(6.980)
January cohort x Offer				5.992
				(7.330)
Mother	-0.193***	-0.149***	-0.152***	-14.930***
	(0.082)	(0.057)	(0.057)	(2.400)
Mother x Offer	0.075			
	(0.107)			
Youngest		-0.045		
		(0.116)		
Youngest x Offer		-0.076		
		(0.153)		
Non-trial area			0.013	
			(0.160)	
Non-trial area x Offer			-0.077	
			(0.155)	
Age	0.074***	0.074***	0.075***	3.390***
	(0.022)	(0.022)	(0.022)	(0.903)
Age^2	-0.001***	-0.001***	-0.001***	-0.044***
	(0.000)	(0.000)	(0.000)	(0.012)
Low education	-0.204***	-0.199***	-0.198***	-6.496**
	(0.058)	(0.058)	(0.059)	(2.527)
Cohabitation	0.320***	0.314***	0.322***	10.240***
	(0.087)	(0.088)	(0.087)	(3.841)
Number of dependent children	-0.070**	-0.073**	-0.070**	-1.974
	(0.030)	(0.031)	(0.030)	(1.313)
Calendar month fixed effects	Yes	Yes	Yes	Yes
Local authority fixed effects	Yes	Yes	Yes	Yes
R^2	0.4308	0.4347	0.4299	0.4893
N	*210*	*210*	*210*	*197*

Notes: (i) This table reports ITT estimates from RDD regressions using a 90-day bandwidth either side of the cutoffs and a flexible function in the age of the child (in days). (ii) The first month of the term, the Cardiff local authority and the April term cohort are the reference categories. (iv) Figures in () are standard errors. (v) *p<0.10, **p<0.05, ***p<0.01.

Source: Author calculations based on pooled April 2019 - March 2020 APS.

Table D.7: Full RDD Estimates of the Heterogeneous Impact, Pooled Data, Impact Varies by Term

	(1) Mothers	(2) Youngest child	(3) Non-trial areas	(4) Proxy
Offer	0.297	0.354	0.352	0.409*
	(0.248)	(0.261)	(0.236)	(0.239)
Days	-0.001	0.001	-0.001	-0.004
	(0.008)	(0.008)	(0.008)	(0.008)
Days^2	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Offer x Days	-0.005	-0.007	-0.004	-0.002
	(0.010)	(0.010)	(0.010)	(0.009)
Offer x Days^2	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
September cohort	0.157	0.164	0.167	0.145
	(0.159)	(0.161)	(0.159)	(0.157)
September cohort x Offer	-0.117	-0.097	-0.134	-0.123

	(0.157)	(0.159)	(0.157)	(0.154)
January cohort	0.108	0.116	0.113	0.123
	(0.167)	(0.167)	(0.167)	(0.165)
January cohort x Offer	-0.016	-0.008	-0.022	-0.043
	(0.170)	(0.172)	(0.170)	(0.168)
Mother	-0.188**	-0.149***	-0.150***	-0.121***
	(0.083)	(0.057)	(0.057)	(0.058)
Mother x Offer	0.068			
	(0.107)			
Youngest		-0.045		
		(0.117)		
Youngest x Offer		-0.064		
		(0.156)		
Non-trial area			0.042	
			(0.164)	
Non-trial area x Offer			-0.097	
			(0.157)	
Proxy				0.171*
				(0.088)
Proxy x Offer				-0.035
				(0.112)
Age	0.074***	0.074***	0.075***	0.066***
	(0.022)	(0.022)	(0.022)	(0.022)
Age^2	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Low education	-0.205***	-0.199***	-0.197***	-0.238***
	(0.060)	(0.060)	(0.060)	(0.060)
Cohabitation	0.314***	0.311***	0.312***	0.270***
	(0.092)	(0.092)	(0.092)	(0.093)
Number of dependent children	-0.072**	-0.074**	-0.072**	-0.066**
	(0.030)	(0.031)	(0.030)	(0.030)
Calendar month fixed effects	Yes	Yes	Yes	Yes
Local authority fixed effects	Yes	Yes	Yes	Yes
R^2	0.4336	0.4368	0.4335	0.4534
N	*210*	*210*	*210*	*210*

Notes: (i) This table reports ITT estimates from RDD regressions using a 90-day bandwidth either side of the cutoffs and a flexible function in the age of the child (in days). (ii) The first month of the term, the Cardiff local authority and the April term cohort are the reference categories. (iv) Figures in () are standard errors. (v) *p<0.10, **p<0.05, ***p<0.01.

Source: Author calculations based on pooled April 2019 - March 2020 APS.

Table D.8: Sensitivity of the RDD Estimates to the Choice of Bandwidth and Age Function Specification

	(1)	(2)	(3)	(4)
Bandwidth	60-day		90-day	
Function of age	Linear	Quadratic	Linear	Quadratic
Offer	0.676**	0.786**	0.284	0.345
	(0.317)	(0.394)	(0.175)	(0.235)
Days	-0.003	-0.020	-0.003*	-0.001
	(0.004)	(0.016)	(0.002)	(0.008)
$Days^2$		-0.000		0.000
		(0.000)		(0.000)
Offer x Days	-0.002	0.023	0.002	-0.005
	(0.005)	(0.020)	(0.002)	(0.010)
Offer x $Days^2$		0.000		0.000
		(0.000)		(0.000)
September cohort	0.300	0.276	0.167	0.163
	(0.197)	(0.199)	(0.157)	(0.158)
September cohort x Offer	-0.415	-0.441*	-0.113	-0.123
	(0.256)	(0.257)	(0.155)	(0.156)
January cohort	0.300	0.339	0.103	0.111
	(0.227)	(0.237)	(0.164)	(0.166)
January cohort x Offer	-0.315	-0.361	-0.002	-0.018
	(0.251)	(0.258)	(0.169)	(0.170)

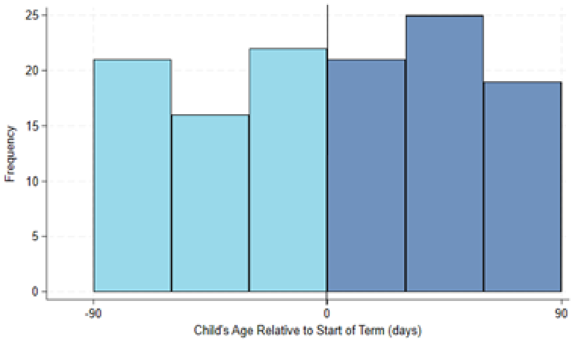
Mother	-0.160**	-0.158**	-0.147**	-0.150***
	(0.071)	(0.071)	(0.057)	(0.057)
Age	0.070**	0.069**	0.073***	0.074***
	(0.027)	(0.027)	(0.021)	(0.022)
Age^2	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Low education	-0.287***	-0.294***	-0.203***	-0.204***
	(0.078)	(0.078)	(0.059)	(0.059)
Cohabiting	0.235**	0.243**	0.326***	0.318***
	(0.117)	(0.117)	(0.090)	(0.092)
Number of Dependent children	-0.052	-0.060	-0.070**	-0.071**
	(0.055)	(0.055)	(0.030)	(0.030)
Calendar month fixed effects	Yes	Yes	Yes	Yes
Local authority fixed effects	Yes	Yes	Yes	Yes
R^2	0.4766	0.4855	0.4293	0.4322
N	*146*	*146*	*210*	*210*

Notes: (i) This table reports ITT estimates based on the April 2019-March 2020 from RDD regressions when bandwidth size and the degree of the polynomial function used to control for the child's age (in days) varies. (ii) The first month of each term, the Cardiff local authority and the April term cohort are the reference categories. (iii) Figures in () are standard errors. (iv) *p<0.10, **p<0.05, ***p<0.01.

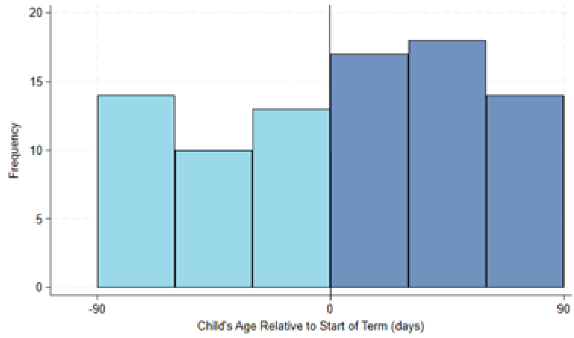
Source: Author calculations based on pooled April 2019 - March 2020 APS.

Figure D.3: Distribution of Parents around the Pooled Cutoff based on Parental Characteristics

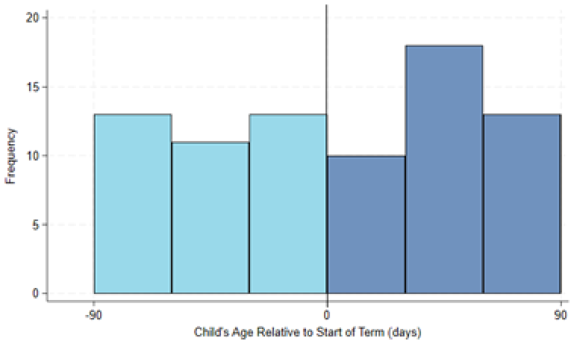
(a) Mothers



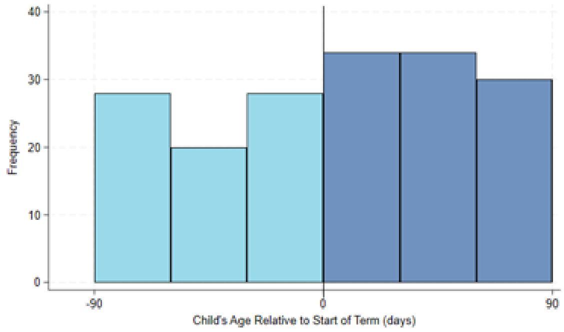
(b) Fathers



(c) Low education (< A-Levels)



(d) Cohabitation

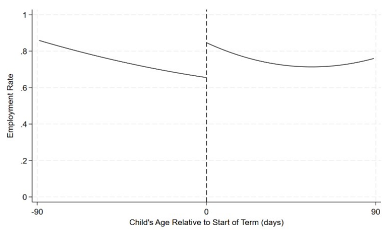


Notes: (i) Underlying N for a=124, b=86, c=78 and d=174. (ii) Width of bars is 30 days.

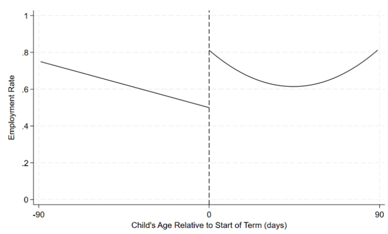
Source: Author calculations based on pooled April 2019 - March 2020 APS.

Figure D.4: Parental Employment Rates around the Pooled Cutoff

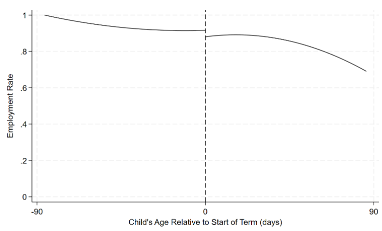
(a) All parents



(b) Mothers



(c) Fathers



Notes: (i) Underlying N for a=210, b=124, c=86. (ii) The lines are estimates of quadratic regressions of the employment rate (on the y-axis) on the age of the relevant child (in days) relative to the pooled cutoff.

Source: Author calculations based on pooled April 2019 - March 2020 APS.

Table D.9: Sample Means for Explanatory Variables in the Static, Dynamic ((a) and (b)) and Staggered (c) DiD Approaches by Treatment Group and Respective Control Group

(a) April 2018 Treatment Group

	Treatment Group		**Control Group**	
	Pre-Offer	Post-Offer	Pre-Offer	Post-Offer
Dependent variables				
Employment rate (%)	77.92	75.56	73.21	75.38
N	*60*	*34*	*123*	*49*
Parental Characteristics				
Mothers (%)	53.25	57.78	55.95	60.00
N	*41*	*26*	*94*	*39*
Age (years)	33.94	35.49	35.67	34.18
N	*77*	*45*	*168*	*65*
Low Education (<A-Levels)	41.56	40.00	39.88	40.00
N	*32*	*18*	*67*	*26*
Cohabitation	-	-	86.90	83.08
N	-	-	*146*	*54*
Number of dependent children	1.88	2.07	2.21	2.26
in family under 16 *N*	*77*	*45*	*168*	*65*
N	*77*	*45*	*168*	*65*

(b) September 2018 Treatment Group

	Treatment Group		**Control Group**	
	Pre-Offer	Post-Offer	Pre-Offer	Post-Offer
Dependent variables				
Employment rate (%)	74.14	77.78	73.89	73.33
N	*265*	*211*	*54*	*167*
Parental Characteristics				
Mothers (%)	55.75	60.00	56.65	60.00
N	*97*	*27*	*115*	*18*
Age (years)	34.10	35.07	35.64	32.63
N	*174*	*45*	*203*	*30*
Low Education (<A-Levels)	43.68	44.44	39.41	43.33
N	*76*	*20*	*80*	*13*
Cohabitation	88.51	-	86.70	-
N	*154*	-	*176*	-
Number of dependent children	2.12	1.98	2.20	2.37
in family under 16 *N*	*174*	*45*	*203*	*30*
N	*174*	*45*	*203*	*30*

(c) Staggered DiD approach

	Treatment Group			**Control Group**
	All	Pre-Offer	Post-Offer	All
Dependent variables				
Employment rate (%)	74.65	75.36	72.00	74.22
N	*129*	*35*	*150*	*22*
Parental Characteristics				
Mothers (%)	56.06	55.36	58.67	56.44
N	*199*	*155*	*44*	*127*
Age (years)	34.34	34.12	35.15	35.44
N	*355*	*280*	*75*	*225*
Low Education (<A-Levels)	41.13	41.07	41.33	38.67
N	*146*	*115*	*31*	*87*
Cohabitation	86.76	89.29	77.33	87.11
N	*308*	*250*	*58*	*196*
Number of dependent children	2.07	2.03	2.23	2.23
in family under 16 *N*	*355*	*280*	*75*	*225*
N	*355*	*280*	*75*	*225*

Notes: (i) The pre-Offer period is defined relative to the rollout of the Offer for each treatment group, which in turn defines respective control group in (a) and (b). (ii) The control group in (c) is formed of parents residing in wards that received the Offer in April 2019. The treatment group is pooled from parents residing in wards that received the Offer in September 2017, January 2018, April 2018 and September 2018. (iii) Variable means are constructed on the basis of the estimation sample and rounded to two decimal places. (iv) Positive case sample sizes are provided in italics after each estimation; some are suppressed to ensure no statistical disclosure. (v) The N below the threshold for the control group's dependent variable is critical for evaluating the Offer's impact on employment rates and does not compromise the statistical robustness of the DiD approach, as parents are pooled across groups and time periods. Further, it should not be considered as disclosive, as the control group is made from parents in 194 wards in Bridgend, Pembrokeshire, Powys and the Vale of Glamorgan across a variety of time periods in the APS, making it hard to identify individuals.

Source: Author calculations based on pooled January 2016 - March 2019 (December 2018) APS (for (c)).

Table D.10: Summary of Selected Staggered DiD Approaches

Methodology	**Summary and Assumptions**	**Advantages**	**Relevance for Evaluating the Offer**
Callaway and Sant'Anna (2021)	Non-parametric method accommodating treatment effect heterogeneity and staggered adoption. Relaxes the common trends assumption.	Flexibility in handling heterogeneity and staggered rollout; estimates dynamic impacts.	Ideal for estimating phased rollout impacts, capturing treatment effects as wards receive the Offer.
Sun and Abraham (2021)	Event-study approach addressing biases in static and dynamic DiD models with staggered timing. Assumes common trends and accurate treatment timing.	Identifies dynamic effects and mitigates biases when extending static and dynamic DiD models with staggered timing.	Useful for analysing how the Offer's impact changes over time, though sensitive to event period specification.
Borusyak et al. (2024)	Constructs synthetic controls for each treatment group, pooling controls to estimate effects. Assumes common trends and no anticipation, requires large control pool	Reduces biases in staggered adoption settings.	Compares treated wards with matched controls, effective with sufficient control units.
Chaisemartin and D'Haultfœuille (2020)	Accounts for treatment effect heterogeneity and group-specific effects. Assumes heterogeneity is captured within groups.	Unbiased estimates with heterogeneous effects with group-specific insights.	Provides insights into how the Offer's impact varies across different treatment groups and wards.

Table D.11: Static DiD Estimates of the Impact of Offer Eligibility by Mother and Youngest Child Eligibility

	April 2018 Treatment Group		September 2018 Treatment	
	Mothers	Youngest child	Mothers	Youngest child
Treatment group (yes=1, no=0)	-0.156	-0.038	-0.217**	-0.212*
	(0.166)	(0.186)	(0.045)	(0.112)
Post-Offer (Post-Apr/Sept 2018=1,	-0.068	0.019	0.002	0.264*
Pre-Apr/Sept 2018=0)	(0.091)	(0.097)	(0.127)	(0.137)
Treatment group*Post-Offer	0.082	-0.017	0.016	-0.210
	(0.144)	(0.203)	(0.162)	(0.192)
Mother	-0.324***	-0.257***	-0.292***	-0.233***
	(0.062)	(0.044)	(0.056)	(0.039)
Mother*Treatment group	0.085		0.118	
	(0.107)		(0.080)	
Mother*Post-Offer	0.165		0.052	
	(0.116)		(0.155)	
Mother*Treatment group*Post-Offer	-0.109		-0.048	
	(0.187)		(0.203)	
Youngest		-0.047		0.022
		(0.072)		(0.062)
Youngest*Treatment group		-0.073		0.083
		(0.119)		(0.089)
Youngest*Post-Offer		0.010		-0.355**
		(0.131)		(0.164)
Youngest*Treatment group*Post-Offer		0.074		0.298
		(0.237)		(0.228)
Age	0.051***	0.054***	0.056***	0.053***
	(0.018)	(0.018)	(0.015)	(0.039)
Age^2	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Low education	-0.120***	-0.120***	-0.207***	-0.213***
	(0.046)	(0.047)	(0.040)	(0.000)
Cohabitation	0.170**	0.158**	0.087	0.079
	(0.071)	(0.072)	(0.060)	(0.060)
Number of dependent children in family	-0.085***	-0.089***	-0.059**	-0.051**
aged under 16 years old	(0.025)	(0.026)	(0.023)	(0.023)
Parental characteristics	Yes	Yes	Yes	Yes
Calendar month fixed effects	Yes	Yes	Yes	Yes
Local authority fixed effects	Yes	Yes	Yes	Yes
R^2	0.2760	0.2744	0.2876	0.2954
N	*355*	*355*	*452*	*452*

Notes: (i) This table reports static DiD estimates based on pooled January 2016 - March 2019 APS. (ii) The regressions control for the age and age squared of the parent, dummies for low education and cohabitation status and the number of dependent children in the household.(iii) January, 2016 and the Cardiff local authority are the reference categories. (iv) Figures in () are standard errors. (v) *p<0.10, **p<0.05, ***p<0.01.

Source: Author calculations based on pooled April 2019 - March 2020 APS.

Table D.12: Static DiD Estimates of the Impact of Offer Eligibility on Hours Worked

(a) April 2018 Treatment Group

	Hours Worked				
	(1)	(2)	(3)	(4)	(5)
Treatment group (yes=1, no=0)	-2.397	-2.565	1.816	-2.212	1.435
	(2.184)	(1.823)	(5.112)	(1.933)	(5.288)
Post-Offer (Post-Apr/Sept 2018=1,	-3.700	-2.232	-2.512	-2.723	-3.128
Pre-Apr/Sept 2018=0)	(2.363)	(1.922)	(1.953)	(2.052)	(2.108)
Treatment group*Post-Offer	6.127	4.318	5.075	4.223	5.157
	(3.782)	(3.086)	(3.122)	(3.266)	(3.325)
Mother		-15.300***	-15.427***	-15.313***	-15.402***
		(1.471)	(2.472)	(1.503)	(1.506)
Age		1.918***	1.675**	1.860***	1.586**
		(0.636)	(0.653)	(0.659)	(0.696)
Age^2		-0.022***	-0.020**	-0.022***	-0.019**
		(0.008)	(0.008)	(0.008)	(0.008)
Low education		0.699	0.319	0.548	0.188
		(1.499)	(1.522)	(1.553)	(0.576)
Cohabiting		-0.486	-1.043	-0.584	-1.113
		(2.709)	(2.751)	(2.779)	(2.828)
Number of dependent children in		-0.222	-0.217	-0.464	-0.428
family		(0.823)	(0.860)	(0.871)	(0.928)
Parental characteristics	No	Yes	Yes	Yes	Yes
Local authority fixed effects	No	No	Yes	No	Yes
Calendar month fixed effects	No	No	No	Yes	Yes
R^2	0.0124	0.3725	0.3927	0.3837	0.4041
N	*259*	*259*	*259*	*259*	*259*

(b) September 2018 Treatment Group

	Hours Worked				
	(1)	(2)	(3)	(4)	(5)
Treatment group (yes=1, no=0)	0.011	0.073	-4.812	0.26	-4.934
	(1.682)	(1.438)	(3.736)	(1.499)	(3.795)
Post-Offer (Post-Apr/Sept 2018=1,	-3.163	-2.972	-3.810	-3.159	-4.142
Pre-Apr/Sept 2018=0)	(3.224)	(2.738)	(2.830)	(2.992)	(3.072)
Treatment group*Post-Offer	3.861	4.124	4.368	4.183	4.255
	(4.185)	(3.559)	(3.630)	(3.723)	(3.792)
Mother		-14.533***	-14.867***	-14.523***	-14.851***
		(1.391)	(3.630)	(1.405)	(1.397)
Age		1.660***	1.547***	1.679***	1.575***
		(0.558)	(0.569)	(0.584)	(0.595)
Age^2		-0.020***	-0.019***	-0.020***	-0.019***
		(0.007)	(0.007)	(0.007)	(0.007)
Low education		-0.175	-0.586	-0.131	-0.441
		(1.433)	(1.455)	(1.466)	(1.491)
Cohabiting		-0.208	-1.164	-0.719	-1.645
		(2.370)	(2.381)	(2.442)	(2.458)
Number of dependent children in		-0.190	-0.473	-0.159	-0.494
family		(0.797)	(0.826)	(0.826)	(0.859)
Parental characteristics	No	Yes	Yes	Yes	Yes
Local authority fixed effects	No	No	Yes	No	Yes
Calendar month fixed effects	No	No	No	Yes	Yes
R^2	0.0036	0.3095	0.3506	0.3240	0.3652
N	*326*	*326*	*326*	*326*	*326*

Notes: (i) This table reports static DiD estimates based on pooled January 2016 - March 2019 APS. Non-employed parents are assigned a value of zero. (ii) The pre-Offer period is defined relative to the rollout of the Offer for each treatment group, which in turn defines each April 2019 control group. (iii) January, 2016 and the Cardiff local authority are the reference categories. (iv) Figures in () are standard errors. (v) *p<0.10, **p<0.05, ***p<0.01.

Source: Author calculations based on pooled January 2016 - March 2019 APS.

Table D.13: Dynamic DiD Estimates of the Impact of Offer Eligibility on Parental Employment Rates for the April 2018 Treatment Group

	(1)	(2)	(3)	(4)	(5)
Treatment group (yes=1, no=0)	-0.095	-0.113	-0.038	-0.117	-0.051
	(0.172)	(0.154)	(0.221)	(0.154)	(0.223)
January 2016	0.024	0.083	0.118	0.080	0.119
	(0.149)	(0.134)	(0.134)	(0.134)	(0.134)
April 2016	0.007	0.039	0.045	0.062	0.073
	(0.126)	(0.113)	(0.113)	(0.132)	(0.132)
September 2016	-0.137	-0.143	-0.104	-0.022	0.008
	(0.129)	(0.115)	(0.118)	(0.146)	(0.148)
January 2017	0.088	0.005	0.023	0.003	0.022
	(0.135)	(0.120)	(0.121)	(0.121)	(0.122)
April 2017	-0.095	-0.070	-0.071	-0.036	-0.035
	(0.118)	(0.105)	(0.108)	(0.135)	(0.139)
September 2017	-0.021	0.016	0.016	0.124	0.119
	(0.125)	(0.112)	(0.113)	(0.138)	(0.139)
January 2018	-	-	-	-	-
April 2018	0.010	0.038	0.056	0.053	0.064
	(0.119)	(0.106)	(0.106)	(0.131)	(0.132)
September 2018	0.011	0.010	0.020	0.099	0.108
	(0.131)	(0.117)	(0.121)	(0.150)	(0.155)
January 2019	-0.137	0.027	0.039	0.031	0.042
	(0.179)	(0.162)	(0.163)	(0.162)	(0.163)
January 2016*Treatment Group	0.310	0.327	0.283	0.334	0.284
	(0.263)	(0.235)	(0.235)	(0.235)	(0.236)
April 2016*Treatment Group	0.183	0.150	0.137	0.136	0.131
	(0.213)	(0.189)	(0.192)	(0.190)	(0.193)
September 2016*Treatment Group	0.220	0.173	0.120	0.259	0.233
	(0.289)	(0.257)	(0.266)	(0.266)	(0.276)
January 2017*Treatment Group	-0.005	-0.052	-0.070	-0.046	-0.053
	(0.232)	(0.207)	(0.209)	(0.209)	(0.211)
April 2017*Treatment Group	0.366	0.259	0.256	0.242	0.261
	(0.215)	(0.191)	(0.199)	(0.194)	(0.202)
September 2017*Treatment Group	-0.396	-0.427	-0.430	-0.506**	-0.514**
	(0.244)	(0.217)	(0.220)	(0.224)	(0.227)
January 2018*Treatment Group	-	-	-	-	-
April 2018*Treatment Group	0.157	0.103	0.083	0.124	0.118
	(0.212)	(0.191)	(0.192)	(0.192)	(0.193)
September 2018*Treatment Group	-0.011	0.049	0.037	0.058	0.041
	(0.224)	(0.199)	(0.201)	(0.205)	(0.207)
January 2019*Treatment Group	0.220	0.038	0.018	0.032	0.019
	(0.261)	(0.234)	(0.236)	(0.235)	(0.237)
Mothers		-0.254***	-0.255***	-0.254***	-0.256***
		(0.044)	(0.043)	(0.044)	(0.044)
Age		0.065***	0.056***	0.064***	0.055***
		(0.017)	(0.018)	(0.017)	(0.018)
Age^2		-0.001***	-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)
Low Education (<A-Levels)		-0.116***	-0.128***	-0.117***	-0.129***
		(0.045)	(0.046)	(0.046)	(0.046)
Cohabitation		0.153**	0.141**	0.173**	0.164**
		(0.069)	(0.069)	(0.070)	(0..070)
Number of dependent children in family under 16		-0.078***	-0.075***	-0.084***	-0.081***
		(0.024)	(0.025)	(0.024)	(0.025)
Parental characteristics	No	Yes	Yes	Yes	Yes
Local authority fixed effects	No	No	Yes	No	Yes
Calendar month fixed effects	No	No	No	Yes	Yes
R^2	0.0681	0.2818	0.3012	0.2994	0.3201
N	*355*	*355*	*355*	*355*	*355*

Notes: (i) This table reports dynamic DiD estimates for each term based on pooled January 2016-March 2019 APS. (ii) The interaction terms between the term and the treatment group indicate the impact of Offer eligibility in each term. Coefficients and their confidence intervals for specification (1) and (5) are presented in Figure 5.5a and 5.5b, respectively. (iii) January, the Cardiff local authority and the term before the Offer introduction for each treatment group are the reference categories. (iv) Figures () are standard errors. (v) *p<0.10, **p<0.05, ***p<0.01.

Source: Author calculations based on pooled January 2016 - March 2019 APS.

Table D.14: Dynamic DiD Estimates of the Impact of Offer Eligibility on Parental Employment Rates for the September 2018 Treatment Group

	(1)	(2)	(3)	(4)	(5)
Treatment group (yes=1, no=0)	-0.082	-0.027	-0.155	-0.010	-0.115
	(0.110)	(0.099)	(0.129)	(0.100)	(0.131)
January 2016	0.014	0.067	0.096	0.009	0.060
	(0.139)	(0.124)	(0.124)	(0.141)	(0.142)
April 2016	-0.002	0.000	-0.007	0.001	0.014
	(0.114)	(0.101)	(0.101)	(0.103)	(0.103)
September 2016	-0.146	-0.179	0.158	-0.357	-0.302
	(0.117)	(0.104)	(0.104)	(0.140)	(0.141)
January 2017	0.079	-0.044	-0.037	-0.093	-0.067
	(0.123)	(0.110)	(0.110)	(0.132)	(0.133)
April 2017	-0.105	-0.109	-0.138	-0.081	-0.113
	(0.104)	(0.093)	(0.094)	(0.094)	(0.095)
September 2017	-0.031	-0.006	-0.024	-0.074	-0.160
	(0.113)	(0.100)	(0.100)	(0.132)	(0.134)
January 2018	-0.010	-0.032	-0.051	-0.092	-0.090
	(0.121)	(0.108)	(0.108)	(0.127)	(0.128)
April 2018	-	-	-	-	-
September 2018	0.001	-0.037	-0.046	-0.233	-0.021
	(0.120)	(0.106)	(0.108)	(0.144)	(0.148)
January 2019	-0.146	-0.005	-0.003	-0.071	-0.039
	(0.172)	(0.155)	(0.155)	(0.168)	(0.170)
January 2016*Treatment Group	-0.057	-0.257	-0.262	-0.255	-0.266
	(0.193)	(0.173)	(0.174)	(0.175)	(0.177)
April 2016*Treatment Group	0.048	0.003	0.021	-0.043	-0.060
	(0.159)	(0.142)	(0.142)	(0.148)	(0.148)
September 2016*Treatment Group	0.123	0.100	0.052	0.078	0.008
	(0.191)	(0.171)	(0.172)	(0.172)	(0.174)
January 2017*Treatment Group	-0.157	-0.101	-0.085	-0.115	-0.109
	(0.181)	(0.160)	(0.162)	(0.161)	(0.163)
April 2017*Treatment Group	0.308	0.218	0.254	0.168	0.197
	(0.156)	(0.140)	(0.141)	(0.144)	(0.145)
September 2017*Treatment Group	0.091	-0.031	-0.055	-0.051	-0.085
	(0.188)	(0.168)	(0.168)	(0.174)	(0.174)
January 2018*Treatment Group	0.153	0.065	0.095	0.058	0.081
	(0.172)	(0.153)	(0.154)	(0.155)	(0.155)
April 2018*Treatment Group	-	-	-	-	-
September 2018*Treatment Group	0.023	-0.024	-0.026	-0.027	-0.033
	(0.174)	(0.155)	(0.158)	(0.160)	(0.163)
January 2019*Treatment Group	0.290	0.056	0.017	0.052	-0.004
	(0.211)	(0.189)	(0.190)	(0.190)	(0.191)
Mothers		-0.237***	-0.233***	-0.236***	-0.233***
		(0.040)	(0.039)	(0.040)	(0.039)
Age		0.064***	0.058***	0.062***	0.055***
		(0.014)	(0.015)	(0.015)	(0.015)
Age^2		-0.001***	-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)	(0.000)
Low Education (<A-Levels)		-0.217***	-0.222***	-0.220***	-0.226***
		(0.040)	(0.041)	(0.041)	(0.041)
Cohabitation		0.095	0.076	0.085	0.072
		(0.060)	(0.060)	(0.061)	(0.061)
Number of dependent children in family under 16		0.065	-0.055**	-0.061***	-0.052**
		(0.022)	(0.023)	(0.023)	(0.024)
Parental characteristics	No	Yes	Yes	Yes	Yes
Local authority fixed effects	No	No	Yes	No	Yes
Calendar month fixed effects	No	No	No	Yes	Yes
R^2	0.0307	0.2496	0.2879	0.2637	0.3027
N	452	452	452	452	452

Notes: (i) This table reports dynamic DiD estimates for each term based on pooled January 2016-March 2019 APS. (ii) The interaction terms between the term and the treatment group indicate the impact of Offer eligibility in each term. Coefficients and their confidence intervals for specification (1) and (5) are presented in Figure 5.5c and 5.5d, respectively. (iii) January, the Cardiff local authority and the term before the Offer introduction for each treatment group are the reference categories. (iv) Figures () are standard errors. (v) *p<0.10, **p<0.05, ***p<0.01.

Source: Author calculations based on pooled January 2016 - March 2019 APS.

Table D.15: Staggered DiD Estimates of the Impact of Offer Eligibility by Mother and Youngest Child Eligibility

		Mothers only (1)	Youngest child eligible (1)
Overall ITT effect on Treated		0.174	0.175
		(0.155)	(0.169)
Dynamic effects (event study estimates)	Pre-Offer average	0.291	0.166
		(0.139)	(0.113)
	Post-Offer average	0.153	0.130
		(0.163)	(0.201)
	8 terms pre-Offer	0.285	0.087
		(0.280)	(0.242)
	7 terms pre-Offer	0.285	0.289**
		(0.193)	(0.144)
	6 terms pre-Offer	0.232	0.442***
		(0.202)	(0.132)
	5 terms pre-Offer	0.169	-0.141
		(0.190)	(0.187)
	4 terms pre-Offer	0.424	0.156
		(0.173)	(0.145)
	3 terms pre-Offer	0.410**	0.182
		(0.188)	(0.178)
	2 terms pre-Offer	0.230	0.147
		(0.177)	(0.143)
	1 term pre-Offer	-	-
	Term of Offer introduction	0.208	0.216
		(0.159)	(0.151)
	$\geq$ 1 term post-Offer	0.099	0.043
		(0.219)	(0.286)
	Leads / Lags	-8 / $\geq$ 1	-8 / $\geq$ 1
	N	*326*	*385*
Pre-trend test	Chi-squared	321.939	36.282
	p-value	0.000	0.001
Parental characteristics		No	No
Local authority fixed effects		No	No
Calendar month fixed effects		No	No

Notes: This table reports the overall ITT effects of Offer eligibility on employment rates for particular parental subgroups, estimated using the Callaway and Sant'Anna (2021) staggered DiD approach, with the April 2019 treatment group as the control group. The overall ITT effect captures the average effect for all eligible parents across treatment groups and terms, regardless of whether the Offer was actually accessed. (ii) Dynamic effects reflect time-varying impacts, using the term before Offer introduction as the reference term (event time -1), using the 'long2' option, so that pre-Offer estimates are constructed symmetrically to post-Offer estimates and are comparable to traditional dynamic DiD estimators (Roth, 2024). (iii) The underlying *N* for the mothers only graph is 326, for the control group is 127 and for the September 2017, January 2018, April 2018 and September 2018 treatment groups is 10, 19, 60 and 110, respectively across all terms. Underlying *N* for the youngest child only graph is 385, for the control group is 139 and for the September 2017, January 2018, April 2018 and September 2018 treatment groups is 14, 21, 79 and 132, respectively across all terms. (iv) Parental characteristics include age and age squared of the parent, dummies for low education and cohabitation status and the number of dependent children in the household. (v) Figures in () are standard errors. (vi) *p<0.10, **p<0.05, ***p<0.01. (vii) The chi-squared statistics tests whether all pre-Offer estimates are equal to zero.

Source: Author calculations based on pooled January 2016 - December 2018 APS.

Table D.16: Staggered DiD Estimates of the Impact of Offer Eligibility on Hours Worked

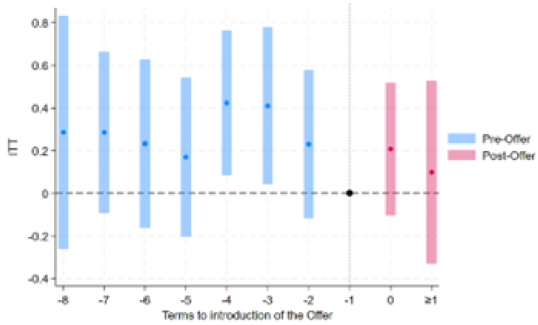
		(1)	(2)
Overall ITT effect on Treated		5.574	3.839
		(4.776)	(5.003)
Dynamic effects (event study estimates)	Pre-Offer average	1.598	1.789
		(4.152)	(3.964)
	Post-Offer average	6.399	4.771
		(5.092)	(5.470)
	8 terms pre-Offer	-3.641	-4.886
		(8.958)	(10.329)
	7 terms pre-Offer	-0.661	0.825
		(5.749)	(5.272)
	6 terms pre-Offer	2.704	1.719
		(5.711)	(6.089)
	5 terms pre-Offer	-0.006	0.820
		(5.945)	(7.285)
	4 terms pre-Offer	3.868	6.816
		(5.106)	(4.979)
	3 terms pre-Offer	4.522	2.013
		(5.164)	(4.701)
	2 terms pre-Offer	4.399	5.214
		(5.532)	(5.515)
	1 term pre-Offer	-	-
	Term of Offer introduction	4.234	2.325
		(4.844)	(5.047)
	$\geq$ 1 term post-Offer	8.563	7.218
		(6.873)	(7.864)
	Leads / Lags	-8 / $\geq$ 1	-8 / $\geq$ 1
	N	*569*	*569*
Pre-trend test	Chi-squared	96.374	117.060
	p-value	0.000	0.000
Parental characteristics		No	Yes
Local authority fixed effects		No	No
Calendar month fixed effects		No	No

Notes: This table reports the overall ITT effects of Offer eligibility on hours worked, estimated using the Callaway and Sant'Anna (2021) staggered DiD approach, with the April 2019 treatment group as the control group. The overall ITT effect captures the average effect for all eligible parents across treatment groups and terms, regardless of whether the Offer was actually accessed. (ii) Dynamic effects reflect time-varying impacts, using the term before Offer introduction as the reference term (event time -1), using the 'long2' option, so that pre-Offer estimates are constructed symmetrically to post-Offer estimates and are comparable to traditional dynamic DiD estimators (Roth, 2024). (iii) Non-employed parents are coded as working zero hours, with the sample size (N) for the control group is 221 across all terms, and for the September 2017, January 2018, April 2018 and September 2018 treatment groups, it is 16, 32, 109 and 191, respectively across all terms. (iv) Parental characteristics include age and age squared of the parent, dummies for low education and cohabitation status and the number of dependent children in the household. (v) Figures in () are standard errors. (vi) *p<0.10, **p<0.05, ***p<0.01. (vii) The chi-squared statistics tests whether all pre-Offer estimates are equal to zero.

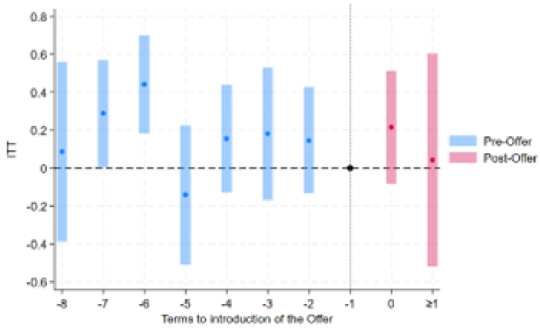
Source: Author calculations based on pooled January 2016 - December 2018 APS.

Figure D.5: Staggered DiD Event Study Graphs of the Impact of Offer Eligibility on Parental Employment Rates by Mother and Youngest Child Eligibility and on Hours Worked

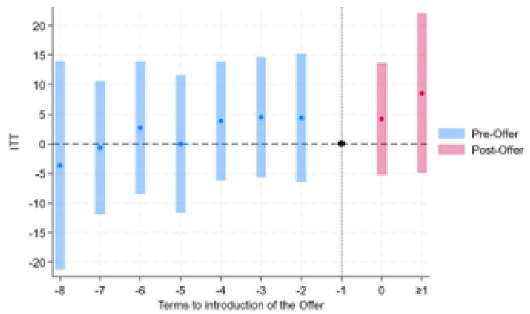
(a) Mothers, No controls



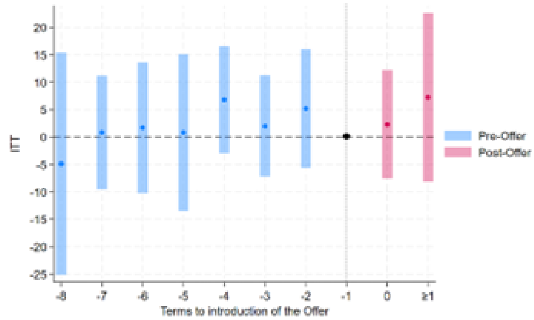
(b) Youngest child eligibility, No controls



(c) Unemployed Coded as Zero, No controls



(d) Unemployed Coded as Zero, Parental controls



Notes: (i) These graphs plot the estimates of the ITT effect of Offer eligibility on employment rates for particular parental subgroups and on hours worked by event period (defined as terms to the introduction of the Offer) and their 95% confidence intervals, derived using the Callaway and Sant'Anna (2021) DiD estimator with an event-study specification. (ii) ITT estimates represent the average effect of the Offer for eligible parents for each event period relative to the term the Offer was introduced, regardless of whether the Offer was actually accessed. (iii) The dynamic effects show the time-varying impact of Offer eligibility based on event periods, with dynamic effects for the pre-Offer and post-Offer terms in reference to the term before Offer introduction. Term 0 indicates the term the Offer was introduced. (iv) The plotted points represent ITT estimates, and the error bars represent 95% confidence intervals. (v) Underlying N for the mother only graph is 326, for the control group is 127 and for the September 2017, January 2018, April 2018 and September 2018 treatment groups is 10, 19, 60 and 110, respectively across all terms (Figure (a)). Underlying N for the youngest child only graph is 385, for the control group is 139 and for the September 2017, January 2018, April 2018 and September 2018 treatment groups is 14, 21, 79 and 132, respectively across all terms (Figure (b)). Underlying N for Figure (c) and (d), where non-employed parents are coded as working zero hour, is 569, for the control group is 221 and for the September 2017, January 2018, April 2018 and September 2018 treatment groups is 16, 32, 109 and 191, respectively across all terms. (vi) Figure (d) include controls for the age and age squared of the parent, dummies for low education and cohabitation status, and the number of dependent children in the household. (vii) Corresponding estimates for the heterogeneity analysis can be found in Table D.15, Appendix D and for the hours worked in Table D.16, Appendix D.

Source: Author calculations based on pooled January 2016 - December 2018 APS.

Table D.17: ITT Summary, derived from Callaway and Sant'Anna (2021) DiD estimator, Sensitivity Analysis

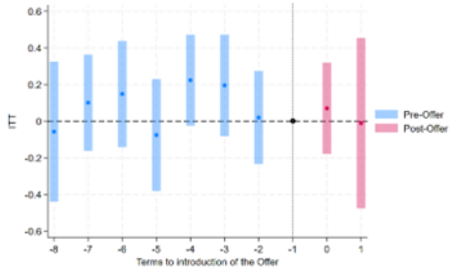
		A: Excluding Proxy responses	**B**: Apr-18 & Sep-18 Treatment Group only		**C**: Different Control Group				**D**: Extra Parental Controls	
					Not yet treated		Jan-19 & Apr-19			
		(1)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Overall ITT on Treated		0.024	0.051	0.068	0.175	0.209*	0.153	0.154	0.146	0.172
		(0.151)	(0.137)	(0.139)	(0.117)	(0.121)	(0.105)	(0.106)	(0.111)	(0.237)
Dynamic effects	Pre-Offer average	0.186	0.079	0.088	0.130	0.114	0.082	0.099	0.128	0.153
(event study		(0.123)	(0.104)	(0.108)	(0.096)	(0.101)	(0.086)	(0.087)	(0.099)	(0.187)
estimates)	Post-Offer average	0.005	0.030	0.056	0.188	0.234*	0.168	0.164	0.156	0.197
		(0.170)	(0.163)	(0.162)	(0.125)	(0.130)	(0.115)	(0.114)	(0.120)	(0.218)
	8 terms pre-Offer	0.057	-0.057	-0.067	-0.057	-0.067	-0.136	-0.117	-0.046	-0.063
		(0.237)	(0.194)	(0.184)	(0.195)	(0.184)	(0.162)	(0.162)	(0.196)	(0.488)
	7 terms pre-Offer	0.195	0.101	0.103	0.124	0.121	0.100	0.124	0.092	0.119
		(0.167)	(0.134)	(0.139)	(0.133)	(0.137)	(0.113)	(0.116)	(0.135)	(0.207)
	6 terms pre-Offer	0.249	0.149	0.170	0.220	0.169	0.144	0.113	0.200	0.207
		(0.176)	(0.148)	(0.163)	(0.135)	(0.151)	(0.126)	(0.132)	(0.140)	(0.288)
	5 terms pre-Offer	-0.002	-0.075	0.005	0.047	0.104	0.025	0.075	0.051	0.086
		(0.177)	(0.156)	(0.211)	(0.135)	(0.179)	(0.125)	(0.133)	(0.136)	(0.288)
	4 terms pre-Offer	0.302*	0.224*	0.295**	0.254**	0.253**	0.162	0.211**	0.231*	0.280
		(0.159)	(0.127)	(0.130)	(0.117)	(0.123)	(0.102)	(0.104)	(0.121)	(0.218)
	3 terms pre-Offer	0.273	0.195	0.122	0.245*	0.170	0.200*	0.185*	0.272**	0.301
		(0.172)	(0.142)	(0.135)	(0.126)	(0.122)	(0.116)	(0.113)	(0.128)	(0.192)
	2 terms pre-Offer	0.227	0.020	-0.011	0.078	0.048	0.079	0.102	0.096	0.143
		(0.153)	(0.130)	(0.148)	(0.130)	(0.149)	(0.111)	(0.124)	(0.123)	(0.211)
	1 term pre-Offer	-	-	-	-	-	-	-	-	-
	Term of Offer introduction	0.052	0.070	0.079	0.154	0.170	0.127	0.138	0.130	0.131
		(0.145)	(0.127)	(0.135)	(0.119)	(0.125)	(0.105)	(0.109)	(0.111)	(0.280)
	$\geq$ 1 term post-Offer	-0.042	-0.011	0.033	0.221	0.298*	0.210	0.190	0.183	0.263
		(0.246)	(0.237)	(0.235)	(0.173)	(0.181)	(0.161)	(0.163)	(0.166)	(0.204)
	Leads / Lags	-8 / 1	-8 / 1	-8 / 1	-8 / $\geq$ 1	-8 / $\geq$ 1	-8 / $\geq$ 1	-8 / $\geq$ 1	-8 / $\geq$ 1	-8 / $\geq$ 1
	N	*377*	*530*	*530*	*580*	*580*	*875*	*875*	*575*	*575*
Pre-trend test	Chi-squared	109.59	30.459	24.159	446.999	220.581	713.839	248.602	511.852	200.343
	p-value	0.000	0.004	0.030	0.000	0.000	0.000	0.000	0.000	0.000
Parental characteristics		No	No	Yes	No	Yes	No	Yes	No	Yes
Local authority fixed effects		No	No	No	No	No	No	No	No	No
Calendar month fixed effects		No	No	No	No	No	No	No	No	No

Notes: (i) This table reports the overall ITT effects of Offer eligibility on parental employment rates, estimated using the Callaway and Sant'Anna (2021) staggered DiD approach, with the April 2019 treatment group as the control group. The overall ITT captures the average effect for all eligible parents across treatment groups and terms, regardless of whether the Offer was actually accessed. (ii) Dynamic effects reflect time-varying impacts, using the term before Offer introduction as the reference term, so that pre-Offer estimates are constructed symmetrically to post-Offer estimates and are comparable to traditional dynamic DiD estimators (Roth, 2024). (iii) In panel A, the sample size (N) for the control group is 145 across all terms, and for the September 2017, January 2018, April 2018 and September 2018 treatment groups is 11, 24, 74 and 134, respectively. In panel B, N for the control group is 225 across all terms, and for the April 2018 and September 2018 treatment groups is 110 and 195, respectively. In panel C, when using the not yet treated as the control group, the N are 17, 33, 110, 195, and 225 for the treatment groups, respectively. When using the January 2019 and April 2019 groups as controls, N are 17, 33, 220, 195, 295, and 225, respectively. In panel D, the control group has an N of 221, with 17, 33, 110, and 194 for the treatment groups. (iv) Parental characteristics include age and age squared of the parent, dummies for low education and cohabitation status and the number of dependent children in the household. In panel D, additional controls include dummies for ethnicity and disability. (v) Figures in () are standard errors. (vi) *p<0.10, **p<0.05, ***p<0.01. (viii) The chi-squared statistics tests whether all pre-Offer estimates are equal to zero.

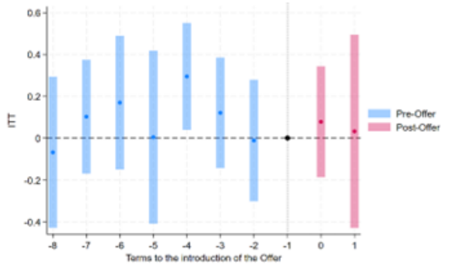
Source: Author calculations based on pooled April 2019 - March 2020 APS.

Figure D.6: Staggered DiD Event Study Graphs of the Impact of Offer Eligibility on Parental Employment Rates, Sensitivity Analysis

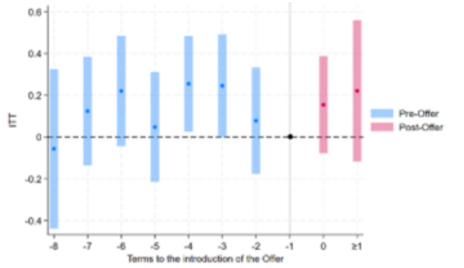
(a) April 2018 and September 2018 Treatment Groups only, no controls



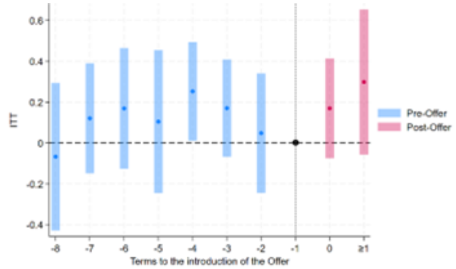
(b) April 2018 and September 2018 Treatment Groups only, parental controls



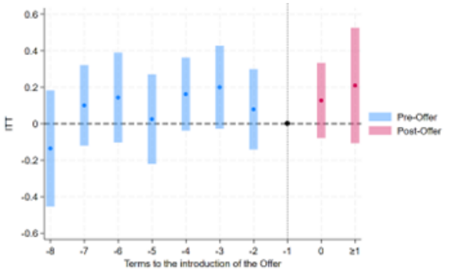
(c) Not yet treated control group, no controls



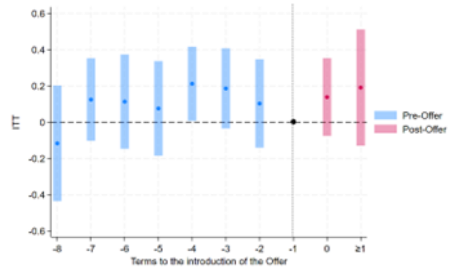
(d) Not yet treated control group, parental controls



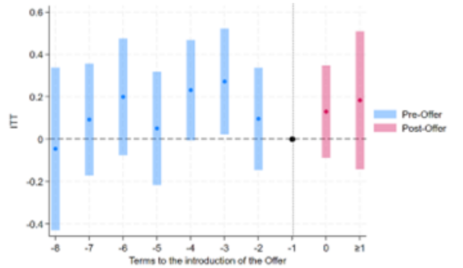
(e) January and April 2019 control group, no controls



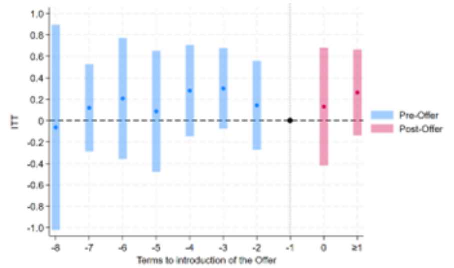
(f) January and April 2019 control group, parental controls



(g) Extra parental controls, no controls



(h) Extra parental controls, parental controls



Notes: (i) These graphs plot ITT estimates of Offer eligibility on parental employment rates by event period (defined as terms to the introduction of the Offer) and their 95% confidence intervals, using the Callaway and Sant'Anna (2021) staggered DiD approach. (ii) ITT estimates represent the average effect of the Offer for each event period relative to the term of Offer introduction, regardless of whether the Offer was actually accessed. (iii) Dynamic effects show the time-varying impact across pre- and post-Offer periods, with the term before Offer introduction as the reference (term 0 indicates the term of Offer introduction). (iv) The plotted points represent ITT estimates, and the error bars represent 95% confidence intervals. (v) In Figures (a) and (b), the underlying N is 530 with 225 for the control group and 110 and 195 for the April 2018 and September 2018 treatment groups, respectively. In Figures (c) and (d), N is 580, formed of 17, 33, 110, 195 and 225 for the September 2017, January 2018, April 2018, September 2018 and April 2019 treatment groups, respectively. In Figure (e) and (f), N is 875, formed of 17, 33, 110, 195, 295 and 225 for the September 2017, January 2018, April 2018, September 2018, January 2019 and April 2019 treatment groups, respectively. In Figures (g) and (h), N is 575 with 221 for the control group and 17, 33, 110 and 194 for the September 2017, January 2018, April 2018 and September 2018 treatment groups, respectively. (vi) Figures (b), (d), (f) and (h) control for the age and age squared of the parent, dummies for low education and cohabitation status, and the number of dependent children in the household, with additional controls for ethnicity and disability in Figure (h). (vii) Estimates correspond to Table D.17, Appendix D.

Source: Author calculations based on pooled January 2016 - December 2018 APS.

Table D.18: Staggered DiD Estimates of the Impact of Offer Eligibility on Parental Employment Rates, January 2014-March 2019, Sensitivity Analysis

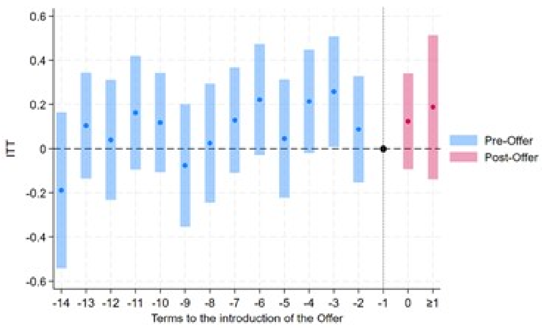
		(1)	(2)
Overall ITT on Treated		0.143	0.166
		(0.111)	(0.117)
Dynamic effects (event study estimates)	Pre-Offer average	0.088	0.113
		(0.091)	(0.097)
	Post-Offer average	0.156	0.193
		(0.120)	(0.123)
	14 terms pre-Offer	-0.189	-0.233
		(0.180)	(0.193)
	13 terms pre-Offer	0.104	0.094
		(0.122)	(0.122)
	12 terms pre-Offer	0.039	0.112
		(0.138)	(0.179)
	11 terms pre-Offer	0.162	0.199
		(0.131)	(0.150)
	10 terms pre-Offer	0.118	0.132
		(0.115)	(0.123)
	9 terms pre-Offer	-0.077	-0.019
		(0.141)	(0.152)
	8 terms pre-Offer	0.025	0.071
		(0.137)	(0.135)
	7 terms pre-Offer	0.129	0.159
		(0.122)	(0.127)
	6 terms pre-Offer	0.222*	0.240*
		(0.129)	(0.139)
	5 terms pre-Offer	0.045	0.126
		(0.136)	(0.181)
	4 terms pre-Offer	0.214*	0.297**
		(0.119)	(0.126)
	3 terms pre-Offer	0.258**	0.203
		(0.127)	(0.124)
	2 terms pre-Offer	0.087	0.082
		(0.122)	(0.142)
	1 term pre-Offer	-	-
	Term of Offer introduction	0.124	0.122
		(0.111)	(0.123)
	$\geq$ 1 term post-Offer	0.188	0.264
		(0.166)	(0.170)
	Leads / Lags	-14 / $\geq$ 1	-14 / $\geq$ 1
	N	*1,040*	*1,040*
Pre-trend test	Chi-squared	705.604	294.767
	p-value	0.000	0.000
Parental characteristics		No	Yes
Local authority fixed effects		No	No
Calendar month fixed effects		No	No

Notes: (i) This table reports the overall ITT effects of Offer eligibility on parental employment rates, estimated using the Callaway and Sant'Anna (2021) staggered DiD approach, with the April 2019 treatment group as the control group. The overall ITT effect captures the average effect for all eligible parents across treatment groups and terms, regardless of whether the Offer was actually accessed. (ii) Dynamic effects reflect time-varying impacts, using the term before Offer introduction as the reference term (event time -1), using the 'long2' option, so that pre-Offer estimates are constructed symmetrically to post-Offer estimates and are comparable to traditional dynamic DiD estimators (Roth, 2024). (iii) The underlying N for the control group is 417 across all terms and for the September 2017, January 2018, April 2018 and September 2018 treatment groups is 53, 51, 194 and 325, respectively across all terms. (iv) Parental characteristics include age and age squared of the parent, dummies for low education and cohabitation status and the number of dependent children in the household. (v) Figures in () are standard errors. (vi) *p<0.10, **p<0.05, ***p<0.01. (vii) The chi-squared statistics tests whether all pre-Offer estimates are equal to zero.

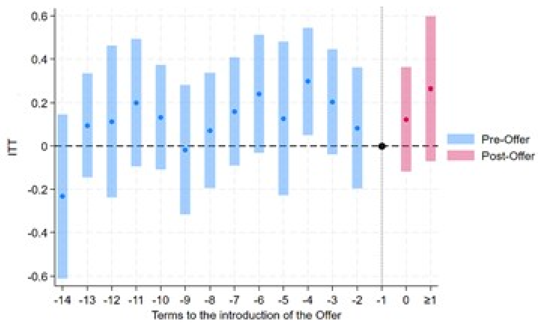
Source: Author calculations based on pooled April 2019 - March 2020 APS.

Figure D.7: Staggered DiD Estimates of the Impact of Offer Eligibility on Parental Employment Rates, January 2014-March 2019, Sensitivity Analysis

(a) No controls



(b) Parental controls



Notes: (i) These graphs plot ITT estimates of Offer eligibility on parental employment rates by event period (defined as terms to the introduction of the Offer) and their 95% confidence intervals, using the Callaway and Sant'Anna (2021) staggered DiD approach. (ii) ITT estimates represent the average effect of the Offer for each event period relative to the term of Offer introduction, regardless of whether the Offer was actually accessed. (iii) Dynamic effects show the time-varying impact across pre- and post-Offer periods, with the term before Offer introduction as the reference (term 0 indicates the term of Offer introduction). (iv) The plotted points represent ITT estimates, and the error bars represent 95% confidence intervals. (v) The underlying N for the control group is 417 across all terms and for the September 2017, January 2018, April 2018 (vi) Figure (b), control for the age and age squared of the parent, dummies for low education and cohabitation status, and the number of dependent children in the household, with additional controls for ethnicity and disability in Figure (h). (vii) Estimates correspond to Table D.18, Appendix D.

Source: Author calculations based on pooled January 2016 - December 2018 APS.