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Labour Market Performance of Immigrants: New Evidence from Linked Administrative Data*

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Abstract

Using administrative data from the Annual Survey of Hours and Earnings linked to the 2011 Census of England and Wales, this paper explores the labour market performance of first-generation immigrants and compares it to that of UK-born employees. By focusing on various labour market outcomes and distinguishing immigrants based on their years of residence in the UK, the analysis reveals that more recent immigrants, on average, earn less, work longer hours, and are more likely to be employed in low-skilled occupations or temporary employment compared to observationally equivalent UK-born employees. However, the labour market performance of immigrants with ten or more years of residence in the UK is more comparable to that of their UK-born counterparts. These patterns are similar for males and females, but there is considerable heterogeneity in terms of ethnicity, country of birth, and reason for migration, as well as across the pay distribution.

JEL classification: J24; J31; J61; J71.

Keywords: immigration, linked administrative data, years of residence, labour market outcomes, regression, decomposition.

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1. Introduction

Migration flows and the proportion of the foreign-born population have increased substantially in recent decades in several advanced economies, including the UK. The growing diversity of the population has brought questions surrounding the labour market performance of immigrants to the forefront of political and public debate. Indeed, there has been considerable academic interest in how foreign-born workers fare in the labour market of the host economy, given its importance in determining immigrants' economic well-being (Adamopoulou and Kaya 2020; Tamborini and Villarreal 2021) and their contribution to the wider economy (Algan *et al.* 2010; Kangasniemi and Kauhanen 2013).

The empirical evidence suggests that, in most countries, there are significant disparities in labour market outcomes, with foreign-born workers having lower levels of employment and being more likely to be employed in less stable and lower-paid jobs than host-country born workers (see, for example, Smith 2006 for the US and Dustmann and Frattini 2013 for fifteen Western European countries). While in the UK labour market, foreign-born employees are found to perform better than UK-born workers, with higher levels of employment and earnings on average (Bell 1997; Clark and Lindley 2009); however, this is not universally the case and varies across gender and by the country of origin, and, in the case of pay, across the distribution (Dustmann and Fabbri 2005; Drinkwater *et al*. 2009; Lemos 2013, 2017, 2018).

In this paper, we contribute to this literature by providing the first evidence based on data from the ASHE (hereinafter ASHE) linked to the 2011 Census of England and Wales (hereinafter Census), which includes detailed and accurate information on labour market outcomes, including pay, hours of work, occupation, and type of employment contract from payroll records, as well as a rich set of personal and family characteristics from the Census. Most importantly, the new ASHE-Census 2011 dataset adds information on the country of birth of employees to distinguish between UK-born and non-UK-born individuals.

To investigate the labour market differences, we employ established regression analysis and decomposition methods. In our analysis, we define an immigrant as an individual who was born outside the UK. Unlike many UK studies that do not distinguish between immigrant and British-born minorities, our focus is on the labour performance of first-generation immigrants.[1] We distinguish immigrants based on their years of residence in the UK and examine various labour

[1] Indeed, Dustmann and Fabbri (2005) argue that many important questions are specifically related to first-generation immigrants, who constitute a significant portion of minorities in the UK.

market performance indicators, including hourly pay, weekly hours, employment in low-skill occupations, and temporary employment. Our comparison group is UK-born employees. However, given the significance of ethnicity within the UK context (see, for example, Blackaby *et al.* 1998, 2002; Forth *et al.* 2021; Phan *et al.* 2022), we explore whether our findings vary by ethnicity. Our benchmark models focus on all employees, but we further analyse the heterogeneity of our findings by gender, country of origin and (a proxy for) reason of migration, and, in the case of pay, across the distribution.

We find that more recent immigrants (with less than 10 years of residence in the UK), on average, earn less, work longer, and are more likely to be employed in low-skilled occupations and temporary contracts. Regression-based estimates of these differences, which account for differences in observed personal and work-related characteristics between UK-born and immigrant employees (such as education, region, and tenure), are smaller but significant. In particular, more recent immigrants earn, on average, 5% less, work 4% longer weekly hours, and are 6.7 percentage points more likely to work in low-skilled occupations and 2.9 percentage points more likely to be in temporary employment compared to observationally equivalent UK-born employees.

In contrast, the labour market outcomes for long-term immigrants (with 10 or more years of residence in the UK) are starkly different from those of more recent immigrants. Long-term immigrants earn, on average, 13% more than UK-born employees and are 2.8 percentage points less likely to work in low-skilled occupations. However, after accounting for observed productivity-related characteristics, these differences become statistically insignificant, indicating that the labour market performance of long-term immigrants is more comparable to that of their UK-born counterparts. Our sensitivity analysis confirms the robustness of these patterns to various checks, and in the case of working hours and hourly pay, they are not influenced by overtime or shift work.

Our heterogeneity analyses demonstrate that the identified patterns are similar for males and females but vary by ethnicity, country of birth and reason of migration, and in the case of pay, across the distribution. Notably, significant disparities persist among more recent immigrants and UK-born employees, regardless of ethnicity, while considerable differences are evident among long-term immigrants. In particular, white long-term immigrants earn 3% more and are 2.2 percentage points less likely to hold low-skilled jobs than UK-born employees, while non-white immigrants earn 4% less and are 3.0 percentage points more likely to do so, suggesting the presence of intersectionality of ethnicity and immigration status. The evidence of significant disparities observed among UK-born employees and more recent immigrants, regardless of ethnicity, also reinforces the importance of distinguishing ‘immigrant effects’ from ‘ethnicity effects’ which is particularly significant given

that much of the existing evidence for the UK does not differentiate between country of birth and ethnicity.[2]

We also find considerable heterogeneity among immigrants from different origins, even after accounting for personal and work-related characteristics. For instance, recent immigrants from EU countries on average earn less, work longer hours, and are more inclined to hold low-skilled or temporary positions compared to their UK-born counterparts. In contrast, immigrants from the Old Commonwealth countries earn more and are less likely to work in low-skilled occupations. Disparities are less pronounced among long-term immigrants, albeit with noticeable variations across different country of birth groupings. For example, long-term immigrants from EU countries and Old Commonwealth countries have an hourly pay advantage, while those from New Commonwealth countries earn less than their UK-born counterparts.

Our further analysis suggests likely disparities among recent immigrants by reason for migration, with labour market entrants experiencing a narrower pay gap and being as likely to be employed in low-skilled occupations as UK-born employees. Aligned with existing evidence (see, for example, Ruiz and Vargas-Silva 2018), this suggests that immigrants who arrived in the UK for employment reasons may differ from those who arrived for other reasons, possibly due to a positive selection in terms of their economic performance.

Pay differences between immigrant and UK-born employees also vary across the hourly pay distribution. At the top end of the distribution, long-term immigrants have a pay advantage, while the hourly pay of more recent immigrants is similar to that of comparable UK-born employees. However, regardless of their years of residence in the UK, immigrants at the bottom tail of the distribution earn less than comparable UK-born employees, highlighting the importance of extending attention beyond the mean and focusing particularly on inequality among lower earners.

Our decomposition analysis reveals a significant role for region and education. The higher concentration of non-UK-born employees in high-paid regions such as London and their higher likelihood of having a university degree compared to UK-born individuals narrow the differences for recent immigrants in pay and low-skilled occupations relative to UK-born employees and account for the advantageous labour market outcomes of long-term immigrants. However, regardless of the years of residence in the UK, differences in ethnicity offset these benefits, primarily due to the majority of non-UK-born employees being non-white, reinforcing the concerns regarding ethnic disparities in the UK labour market. Additionally, the shorter average tenure

[2] See Section 2 for a brief overview of this literature.

among recent immigrants also widens the observed differences in all outcomes considered. Nevertheless, the differences observed among more recent immigrants and UK-born employees remain predominantly unexplained.

The remainder of this paper is structured as follows. The next section presents a brief overview of previous UK studies analysing labour market disparities between UK-born and immigrant workers. Section 3 describes the ASHE-Census 2011 dataset and introduces our sample and measures. Section 4 outlines the econometric specification and investigates various labour market performance indicators for immigrants, comparing them with those for UK-born employees. Section 5 focuses on the decomposition of observed differences in labour market performance. Finally, concluding remarks are provided in Section 6.

2. Background

The international literature investigating disparities in labour market outcomes between immigrant and host country-born employees is vast (see, for a recent review, Guzi *et al.* 2021). In the UK context, previous evidence almost exclusively relies on household surveys. For instance, utilising data from the 1972 General Household Survey (hereinafter, GHS), Chiswick (1980) finds that white male immigrants have similar earning patterns to British-born males. However, conditional on observed productivity-related characteristics, earnings of immigrants from ethnic minority groups are around 25% lower, and this difference persists regardless of the time spent in the UK. Using the same data source for the period 1973-1992 and focusing solely on men, Bell (1997) finds comparable results. While white immigrants initially have a pay advantage compared to UK-born workers, immigrants from certain ethnic minority groups experience an earnings disadvantage. Contrary to Chiswick (1980), however, this disadvantage is found to diminish over time spent in the UK.

Using data from the 1979-2004 Labour Force Survey (hereinafter, LFS) and expanding the analysis to include females, Dustmann and Fabbri (2005) find a 40% pay disadvantage for non-white immigrants, although this varies with immigrants' region of origin. More recently, Algan *et al.* (2010) analysing data from the 1993-2007 LFS, find significant pay gaps between first-generation immigrants and UK-born individuals, which are found to be substantially higher than those observed in France or Germany. They also show that relative earnings improve substantially for second-generation immigrants.

To the best of our knowledge, only a small number of studies in the UK context have utilized administrative data sources to explore the labour market performance of immigrants, which offer

the advantages of large sample sizes, high response rates, and accurate and reliable information on labour market indicators. However, similar to much of the UK literature based on household surveys, such evidence primarily focuses on pay and lacks a detailed examination of other labour market outcomes.[3] Among these, Dickens and McKnight (2008) and Lemos (2013, 2017, 2018) use data from the Lifetime Labour Market Database (hereinafter, LLMDB), derived from several administrative datasets linked together by a unique individual identifier (i.e., the national insurance number). Additionally, the study by Phan *et al*. (2022) is the first to utilize data from the linked ASHE-Census.

Due to a lack of information on hours, studies utilising data from the LLMDB focus on weekly rather than hourly pay, and as such, are unable to account for potential differences in working hours between immigrant and UK-born employees. Another limitation of the LLMDB is the absence of other individual characteristics, particularly education, which is found to be important in analysing the labour market performance of immigrants in the UK context (see, for example, Dustmann and Fabbri 2005). Among these studies, the analysis by Dickens and McKnight (2008) for the 1978-2003 period shows a large earnings gap for all immigrant groups, including white European immigrants, contrasting with much of the UK literature. Lemos (2013) explores the earnings gap between UK-born and overseas-born individuals at entry and over time between 1978 and 2006, finding that immigrants from more recent cohorts fare better than earlier ones at entry. The earnings of more recent immigrants are also found to catch up faster with the earnings of UK-born individuals. Exploiting the longitudinal dimension of the same data source, Lemos (2017) shows that while low-paid immigrants, who are found to be disproportionately non-white, face an earnings penalty compared to similar UK-born workers, higher-paid immigrants, who are disproportionately white, do not experience such a penalty. In a follow-up work, Lemos (2018) focuses on both employment and pay, finding that immigrant-native gaps vary across gender, continents of nationality, and lengths of stay.

The analysis of Phan *et al.* (2022), using the data from the ASHE-Census 2011, reveals substantial wage gaps between white and ethnic minority employees, particularly among higher earners, which are unexplained by factors such as employer characteristics or individual attributes. However,

[3] Exceptions in the literature include Elliott and Lindley (2008), who, using data from the 1993-2003 LFS, investigate the occupational attainment of non-white employees. Additionally, Gazioglu and Sloane (1994), utilizing the work histories of 600 migrant residents in London boroughs, explore immigrants' (undesirable) working conditions. More recently, García-Serrano and Hernanz (2023), based on data from the EU LFS and using a multidimensional index, compare the 'job quality' of native and non-native workers across European countries. Their results for the UK show that only workers coming from the new EU Member States (that joined the EU in 2004, 2007, and 2013) exhibit lower 'job quality' than UK-born employees. A more comprehensive descriptive comparison of OECD countries in various labour market indicators, including job contracts, working hours, and job skills, is presented in OECD/EU (2015).

similar to much of the existing literature for the UK, their focus remains on ethnicity wage gaps, without distinguishing between immigrant and UK-born employees.

3. Data

The analysis utilises data from a newly linked administrative dataset, derived from the payroll-based ASHE and the 2011 Census of England and Wales (ONS 2023). The linked ASHE-Census dataset contains detailed and reliable information for employees on pay, hours, and other labour market indicators, such as type of contract and occupation, coming from the ASHE. Additionally, it includes a rich set of personal and family characteristics, including country of birth, education, and ethnicity, collected in the population census.

Unlike much of the literature on labour market differences between UK-born and immigrant employees, which utilises household survey data where labour market outcomes are self-reported and subject to greater measurement error and limited response rates (see, for a similar discussion, Schaefer and Singleton 2023), the ASHE is based on employer records (ONS 2024). These data have been widely used to study labour market inequalities in the UK, particularly in relation to gender (see, among others, Jones and Kaya 2019, and Jewell *et al*. 2020), which is one of the limited personal characteristics of employees ASHE includes.[4] The linked ASHE-Census dataset adds several characteristics of employees that are well-established determinants of labour market outcomes, such as ethnicity, education, marital status, presence of dependent children, and long-term health problems or disability. Most importantly, the linked ASHE-Census dataset adds information on the country of birth of employees to distinguish UK-born and non-UK-born individuals.

In our analysis, we define non-UK-born as a binary indicator that takes a value of one if the country of birth information from the Census is non-UK and zero otherwise. Thus, our focus is on first-generation immigrants. Our benchmark comparison group is UK-born employees. Given the importance of ethnicity in the UK labour market (see, for example, Blackaby *et al.* 1998, 2002; Forth *et al.* 2021; Phan *et al.* 2022), however, in our heterogeneity analysis, we use the information on ethnicity from the Census and compare labour market outcomes within ethnic groups. For non-UK employees, we also use information on the length of residence in the UK, which is a well-established determinant of the labour market performance of immigrants (see, for example, Chiswick 1978; Borjas 1985; Bell 1997; Kahanec and Zimmermann 2011).[5] More specifically, we

[4] Other personal characteristics included in the ASHE dataset are age, home region, and work region.
[5] The length of residence information is only applicable to usual residents who were not born in the UK. It is derived in the Census from the date that a person last arrived to live in the UK, excluding short visits away from the UK.

distinguish between long-term migrants (with 10 or more years of residence in the UK) and more recent immigrants (with less than 10 years of residence in the UK) (see Pendakur and Woodcock 2010, for a similar approach).

The first labour market outcome we consider is the (log) gross hourly pay. The ASHE-Census dataset includes detailed information on the employee earnings and hours during the pay period (the week or the month depending on whether the employee is paid weekly or monthly) that includes the reference date in April coming from the payroll records. Our benchmark hourly pay measure is based on average gross weekly earnings for the reference period divided by the average total paid hours worked during the reference period.[6] However, we explore the sensitivity of our results to the use of alternative measures including gross hourly pay excluding overtime and basic hourly pay. Our second outcome measure is the (log) total weekly paid hours, which equals basic weekly paid hours worked plus weekly paid overtime hours during the reference week. In Section 4, we additionally consider basic paid hours in our sensitivity analysis as an alternative measure. Our third outcome measure is the (probability of) employment in low-skilled occupations. Our definition aligns with that of the ONS (2010) and is based on occupation information measured by the Standard Classification of Occupations (hereinafter, SOC) 2010 (see also Migration Advisory Committee Report 2014).[7] Specifically, we classify an employee as being employed in a low-skilled occupation if the SOC 2010 one-digit title has a skill level below three. Our final labour market outcome measure is the (probability of) temporary employment, which is determined based on the type of contract information. In particular, we classify an individual as being in temporary employment if they hold a temporary employment contract, and as permanent employment if they hold a permanent employment contract.

The sample is restricted to working-age employees (aged 16-64), who are paid an adult rate and whose earnings are not affected by absence. We only consider the main job of an employee observed in ASHE with weekly basic paid hours no less than one and no more than 99 hours.[8] Finally, we restrict our sample to those with non-missing and valid information in all the variables included in the analysis.[9]

[6] We code gross hourly pay outliers, which are ten times above the 99th percentile and below half the first percentile of the gross hourly pay distribution, as missing.

[7] Constructing occupational skill level based on the classification of the employee's occupation also aligns with the classification used by the UK Visas and Immigration to determine eligible occupations and codes for the skilled worker visa (see https://www.gov.uk/government/publications/skilled-worker-visa-eligible-occupations/skilled-worker-visa-eligible-occupations-and-codes [Accessed 21 December 2023]).

[8] The level of observation in ASHE at the individual job level, and as such, individuals holding more than one job may appear multiple times within the dataset throughout the year.

[9] Appendix A provides a detailed discussion of our sample construction and variable description.

Our final sample includes 99,159 observations, of which 10.9% are non-UK-born employees (see Table 1). Among them, 6,364 are long-term immigrants and 4,462 are more recent immigrants. In Table 1, the sample means for our outcome variables are reported by country of origin and by the length of residence in the UK, confirming the relatively higher pay among non-UK-born employees compared to UK-born employees, with the difference averaging about 0.034 log points (or 3.36%).[10] The average weekly hours for non-UK-born employees are also longer, around 0.936 log points (or 154.98%). On the other hand, immigrant employees are more likely to work in low-skilled occupations (by 1.42 percentage points) or with temporary employment contracts (by 3.08 percentage points) than UK-born workers.[11]

Table 1 also reveals noticeable differences by length of residence, with more recent immigrants earning about 0.095 log points (or 9.97%) less than UK-born employees on average, whereas long-term immigrants earn 0.125 log points (or 13.31%) more. Immigrants with less than 10 years of residence in the UK also work longer hours (1.904 log points) and are more likely to work in low-skilled occupations (7.37 percentage points) and with a temporary employment contract (6.77 percentage points) than UK-born employees.[12] However, the differences in hours and temporary employment are less pronounced for immigrants with UK residence of 10 years or more (around 0.258 log points and 0.49 percentage points, respectively). In fact, they are less likely to be employed in low-skilled occupations (by 2.75 percentage points) than UK-born employees.

[Table 1 here]

Appendix Table B2 provides further details and summary statistics for the explanatory variables included in our analysis by country of birth. They highlight several compositional differences between immigrant employees and UK-born employees. Consistent with previous evidence for Britain (see, for example, Dustmann and Fabbri 2005), a lower proportion of immigrants are white compared to UK-born employees. Non-UK-born employees, on average, are more likely to have a degree, be married, and have dependent children than UK-born employees. They are also more likely to work in London, in the healthcare industry, and professional and elementary occupations. While some commonalities are evident across immigrants, there are also some distinct patterns. For

[10] Percentages are calculated as $[exp(log\ difference) - 1] \times 100$.

[11] Evidence suggests that temporary employment in Britain is associated with low pay, lower levels of job satisfaction, and less work-related training compared to permanent employment, although they are often seen as a pathway to securing permanent positions (see Booth *et al*. 2002).

[12] We explore the sample means of our key variables for more disaggregated groups of recent immigrants (with less than 2 years of residence, with 2-4 years of residence, and with 5-9 years of residence) in Appendix Table B1 but observe similar patterns. Therefore, and considering the relatively smaller sample sizes of some of these groups, our analysis considers more recent immigrants as a whole.

instance, while more recent immigrants, on average, are younger, have lower average job tenure, and are less likely to have a long-term health problem or disability, work part-time, and be covered by collective agreements than UK-born employees, immigrants with at least 10 or more years of residence in the UK are more comparable to the UK-born employees in these dimensions.

4. Labour market performance of UK-born and immigrant employees

To explore the differences in labour market outcomes between UK-born and immigrant employees, we estimate a series of regressions with varying controls:

$$y_i = \alpha + \beta I_i + \mathrm{X}_i\delta + \varepsilon_i \quad (1)$$

where the dependent variable y_i is the considered labour market outcome ((log) gross hourly pay, (log) weekly total paid hours, (probability of) employment in a low-skilled occupation, or (probability of) temporary employment) of employee i. In equation (1) each labour market outcome is regressed on a constant term (α), a binary indicator of (non-UK) country of birth (I_i), and ε_{ij} is a random error. The set of control variables X_i with coefficient vector δ varies across specifications, but in the most comprehensive specification, these include personal characteristics including (female) gender, ethnicity, age (and age-squared), highest qualification, long-term health problem or disability, marital status, presence of dependent children; work-related characteristics such as part-time employment, tenure (and tenure squared), (log) employer size, collective agreement, temporary employment contract, occupation, and industry controls.[13,14]

In equation (1), the exclusion and inclusion of personal and work-related characteristics (X_i) provide raw (or unadjusted) and adjusted differences between UK-born and non-UK-born employees in the considered outcome (β), respectively. While in our analysis, we are able to control for a rich set of observable characteristics, unobserved factors remain a potential bias, for example, in terms of selective labour force participation or in- and out-migration. Given the nature of our data, however, we do not observe non-labour market participants or self-employed individuals. As is common in the literature, the population pool from which immigrants are selected in or out is also unobservable. Therefore, following the existing literature (see, for example, Chiswick 1980; Bell 1997; Dustmann and Fabbri 2005; Algan *et al*. 2010), we do not attempt to model this.

[13] See Appendix A for a detailed description of all the variables included in the analysis.
[14] In specifications for temporary employment, control for temporary contract is excluded. Similarly, models concerning the probability of employment in low-skilled occupations exclude occupation among the controls.

Our benchmark estimates are obtained from Ordinary Least Squares (hereinafter, OLS) estimations performed separately for UK-born employees and more recent immigrants (with less than 10 years of residence in the UK), and for UK-born and long-term migrants. As such, we allow the estimate of the difference between UK-born and non-UK-born employees ($\hat{\beta}$) to vary by the length of residence of immigrants. [15,16] Our estimates are unweighted, but we explore the sensitivity of our findings to the application of weights that account for linkage biases. Throughout, we report robust standard errors, but we explore the sensitivity of our findings to the use of employer-level clustered standard errors.

Table 2 presents the estimates of equation (1) for each of the four outcomes considered (Panels A-D). Within each panel, the estimated mean raw (columns (1) and (4)) and adjusted (columns (2)-(3) and (5)-(6)) differences between UK-born and non-UK-born employees are presented, distinguishing more recent (columns (1)-(3)) and long-term (columns (4)-(6)) immigrants. The estimates in columns (2) and (5) are adjusted for personal characteristics, and columns (3) and (6) additionally control for work-related characteristics.[17]

Aligned with the above descriptive statistics, we find a sizable raw hourly pay gap between UK-born employees and more recent immigrants, with non-UK-born employees with less than 10 years of residence in the UK earning 0.095 log points or 9% less than UK-born employees.[18] This gap widens to 12% by the inclusion of personal characteristics but narrows considerably after accounting for work-related characteristics, resulting in a smaller but still significant adjusted pay gap of 5% between UK-born employees and more recent immigrants. Immigrants with less than 10 years of residence also have longer weekly hours than UK-born employees (5%), which diminishes only slightly (to 4%) after accounting for characteristics. Consistent with the descriptive statistics presented in Table 1, the probabilities of employment in low-skilled occupations and temporary employment are larger for more recent immigrants than UK-born employees (by 7.4 percentage points and 6.8 percentage points, respectively). The inclusion of characteristics, however, narrows these differences, particularly for temporary employment, but the differences remain positive and

[15] In our benchmark regression models, we pool UK-born and non-UK-born employees. However, we also explore the impact of allowing returns to characteristics to vary by country of birth in Section 5 using an Oaxaca-Blinder decomposition (Oaxaca 1973; Blinder 1973). As shown by Elder *et al*. (2010), our benchmark regression models provide a proxy for the unexplained gap in an Oaxaca-Blinder decomposition.

[16] In the case of binary outcome variables, the OLS estimate of the coefficient of interest has the Linear Probability Model (hereinafter, LPM) interpretation, and as such, significant estimates of β are interpreted as the change in probabilities.

[17] Table 2 focuses on the coefficient of interest, but we present the full set of coefficient estimates in Appendix Tables B3a and B3b.

[18] Throughout, percentage differences reported are computed as $(e^{\hat{\beta}} - 1) \times 100$, where $\hat{\beta}$ is the OLS coefficient estimate for the non-UK-born dummy.

statistically significant (around 6.7 percentage points for the probability of employment in low-skilled occupations and 2.9 percentage points for the probability of temporary employment).

Table 2 underscores the stark differences between more recent and long-term immigrants. Immigrants with 10 or more years of residence in the UK are paid more compared to UK-born employees (0.125 log points or 13%) and are less likely to work in low-skilled occupations (2.8 percentage points), but these differences narrow considerably after accounting for personal and work-related characteristics, consistent with the influence of compositional differences between UK-born and non-UK-born employees. In fact, the adjusted gap in hourly pay and the difference in the probability of employment in low-skilled occupations are small (less than 1% and 0.3 percentage points) and statistically indifferent from zero. Regarding other labour market outcomes, the raw difference in hours is small and statistically insignificant, but this widens after the inclusion of characteristics and becomes significant. Nevertheless, in the most comprehensive specification where we also control for work-related characteristics, the coefficient estimate indicates that long-term immigrants work longer hours compared to UK-born employees, but the difference remains relatively small (less than 1%) and no longer statistically significant. In terms of the probability of temporary employment, however, there are no significant differences between UK-born employees and long-term immigrants.

[Table 2 here]

4.1. Robustness checks

In Appendix Tables B4a and B4b, we explore the robustness of our benchmark estimates to a series of checks for more recent and long-term immigrants, respectively. These include sensitivity to the application of weights to account for linkage bias (column (1) within each table); exclusion of observations with lower match quality scores (column (2)); clustering of standard errors at the employer level (column (3)); focusing on a more homogenous group of workers by excluding employees working outside England and Wales (column (4)) or part-time employees (column (5)) or restricting the sample to 24-54 years old employees (column (6)). Additionally, we explore the impact of model specification by controlling for an extended set of personal characteristics such as the number of dependent children (instead of a binary indicator of the presence of children), age of the youngest dependent child, religion and (self-assessed) general health status (column (7)), sector

(column (8)), more detailed controls for industry (SIC07 groups instead of regrouped sections) (column (9)), or occupation (SOC10 minor groups instead of major groups) (column (10)).[19,20,21]

In all cases, our results for more recent immigrants remain robust (see Appendix Table B4a), with non-UK-born employees earning less on average, working longer hours, and being more likely to be in low-skilled occupations or temporary employment compared to comparable UK-born workers. For long-term immigrants, we observe similar patterns to our benchmark, with no significant difference in any of the outcomes considered, with a few exceptions (see Appendix Table B4b). The small positive difference between comparable non-UK and UK-born employees becomes significant when part-time employees are excluded from the sample (column (5)) or when detailed occupation controls are included in the model (column (10)). The insignificant hourly pay advantage of long-term immigrants also becomes statistically significant when detailed industry controls are included in the model (column (9)), although the magnitude of this difference remains similar to our benchmark estimate. In all cases, the difference between long-term immigrants and UK-born employees in the probability of employment in low-skilled or temporary jobs remains statistically indifferent from zero, demonstrating the robustness of our core findings.

In the case of binary outcomes (probability of employment in low-skilled or temporary jobs), we further check the sensitivity of our findings by alternatively estimating a probit model. However, our results also remain robust to this choice for both long-term and more recent immigrants (see column (11) within each table).

In Appendix Table B5, we further explore the robustness of our results for hourly pay and weekly hours by using alternative measures. Our findings remain virtually unchanged when employing (log) gross hourly pay excluding overtime payments (column (1)) or (log) basic hourly pay (column (2)). Additionally, our core results remain robust when using weekly basic paid hours, although the differences are now more pronounced, particularly for long-term immigrants. Specifically, the (positive) difference in weekly hours between comparable long-term immigrants and UK-born employees becomes statistically significant, albeit remaining relatively small in magnitude (1%). These additional analyses provide further support to our core findings and suggest that the identified differences in hourly pay and weekly hours between immigrant and UK-born employees are evident

[19] The ASHE-Census dataset includes a match quality score for each record, ensuring reliable linkage between the two data sources. Linked data includes only observations with a match score of at least 0.82 but in our sensitivity analysis, we focus on cases with the highest match score of 1.0.
[20] While population census information is limited to England and Wales, the linked dataset includes a small number of individuals working outside this area (see Appendix Table B2).
[21] See Appendix A for a detailed description of additional control variables used in the sensitivity analysis.

in basic hourly pay and basic hours, and hence, are not driven by other components such as shift work or overtime.

Overall, our results reveal significant differences in the labour market outcomes of immigrants based on their length of residence in the UK. More recent immigrants (with less than 10 years of residence) have lower hourly pay, longer working hours, and a higher likelihood of being in low-skilled or temporary jobs compared to comparable UK-born employees. In contrast, the labour market outcomes of long-term immigrants are more similar to those of observationally equivalent UK-born workers. These findings align with international evidence suggesting that immigrants typically require 10 years or more in the labour market to catch up with host-country-born workers. However, differences between recent and long-term immigrants could also stem from other factors, such as gaining citizenship or naturalization, which may facilitate access to higher-paying or more secure jobs consistent with the removal of employment barriers (see, for example, Bratsberg *et al.* 2002 for the US). [22] Additionally, the preceding commitment of naturalised immigrants to remain in the host country and to acquire skills valued in the labour market could contribute to these differences (Bratsberg *et al.* 2002). Alternatively, selective emigration may play a role. Specifically, if there is negative selective emigration such that return immigration is more likely among immigrants whose labour market performance is lower than those who remain in the host country, then differences in labour market outcomes between long-term immigrants and more recent immigrants could arise. In fact, there is some evidence in the literature suggesting that out-migration might be indeed selective (see Borjas 1989 for the US; Constant and Massey 2003 for Germany; and Dustmann and Weiss 2007 for the UK). A related alternative explanation is compositional differences among immigrant cohorts, with more recent arrivals potentially having lower productivity-enhancing characteristics than earlier arrivals. However, this explanation is less likely in the UK context, given previous evidence suggesting that immigrants from more recent cohorts fare better than earlier ones at entry (see Lemos 2013). While disentangling the impact of each of these factors is challenging, in Section 5 we examine the potential drivers of the observed differences more formally by employing a decomposition approach.

4.2. Heterogeneity analysis

Our benchmark models are estimated by pooling all observations. We now examine whether our results vary by characteristics such as ethnicity, gender, country of origin, and (a proxy for) reasons

[22] Employment barriers may indeed exist, for instance, if there is discrimination by employers, employees, or customers against a particular group of workers (Becker 1971).

for migration, which are found to be important in investigating the labour market performance of immigrant employees compared with UK-born individuals.[23]

Ethnicity

Our benchmark analysis uses UK-born employees as the comparison group. Given the evidence of the importance of ethnicity within the UK labour market context (see, for example, Blackaby *et al.* 1998, 2002; Forth *et al.* 2021; Phan *et al.* 2022), we further explore the differences in labour market outcomes by ethnicity. To do so, we estimate our benchmark model specified in equation (1) separately by ethnicity to distinguish 'immigrant effects' from 'ethnicity effects'.[24] Due to smaller sample sizes in ethnic groups among non-white employees, Table 3 presents these results for white and non-white employees, as do some other studies (see, for example, Forth *et al.* 2022), acknowledging the fact that the latter is a diverse group.[25]

For immigrants with less than 10 years of residence in the UK, the patterns in hourly pay and probability of employment in low-skilled occupations are similar to our benchmark results regardless of ethnicity (columns (1) and (2)). On average, more recent immigrants earn less and are more likely to be employed in low-skilled occupations compared to their UK-born counterparts. However, these differences are more pronounced among non-whites than for whites (10% versus 4% in pay and 8.0 versus 6.6 percentage points in the probability of employment in low-skill occupations). The differences in working hours and probability of temporary employment between more recent immigrants and UK-born employees, however, are only evident among whites.

Turning to the results for long-term immigrants, there are noticeable differences between white and non-white employees in hourly pay and probability of employment in low-skilled occupations (columns (3) and (4)). Among whites, long-term immigrants earn, on average, more (around 3%) and are less likely to be employed in low-skilled occupations (by 2.2 percentage points) than comparable UK-born employees. In contrast, non-white long-term immigrants earn 4% less and are 3.0 percentage points more likely to work in a low-skilled occupation than their UK-born counterparts. In terms of weekly hours and the likelihood of temporary employment, however, there

[23] Given the concentration of non-UK-born employees in certain industries such as healthcare (see Appendix Table B2), we further explored potential heterogeneities by industry. While there are some interesting patterns, overall, these estimates confirm that identified differences between comparable UK-born employees and more recent immigrants are not driven by particular industries (results available upon request).
[24] Ethnicity is excluded among personal controls in the model for white employees.
[25] We exclude a small number of mixed ethnicities (2.93% of the observations) for heterogeneity analysis by ethnicity, as do some other studies (see, for example, Phan *et al.* 2022).

are no significant differences between UK-born and long-term immigrant employees, regardless of their ethnicity.

[Table 3 here]

Overall, these results indicate that the differences in labour market outcomes between immigrants and comparable UK-born employees are more pronounced among non-white employees. Our evidence of diverging patterns for white and non-white long-term employees suggests the intersectionality of ethnicity and immigration status in shaping their labour market outcomes. Furthermore, there remain significant differences among UK-born employees and more recent immigrants, regardless of whether the comparisons are made among white or non-white employees. While the reasons as to why these differences exist remain an area that requires further scrutiny, the presence of such differences reinforces the importance of distinguishing between non-UK-born immigrants and UK-born individuals with diverse ethnicities.[26]

Gender

Next, we consider potential heterogeneities by gender. While a large number of UK studies focus on males (see, for example, Chiswick 1980; Bell, 1997; Clark and Lindley 2009; Hunt 2012; Elliott and Linley 2008), existing evidence that extends the analysis to include females suggests that the overall differences between immigrants and UK-born employees vary by gender, although the patterns identified are mixed. For instance, using survey data from the LFS, Algan *et al*. (2010) find that the difference in hourly pay between UK-born and first-generation immigrants is not as large for females compared to their male counterparts. Using the same data source, Dustmann and Fabbri (2005) find similar patterns for males and females and show that the overall wage differentials between immigrants and British-born individuals are smaller for females. In contrast, based on the analysis of administrative data from the LLMDB, Lemos (2013) shows that the immigrant-native earnings gap is significant and larger for females than for males. The gender difference is also found to be reversed for those who migrated to the UK to seek asylum, with males outperforming females in labour market outcomes, including likelihood of employment, weekly earnings, hourly pay, and number of hours worked (see Ruiz *et al.* 2018).

[26] In the UK context, ethnic background, particularly non-white ethnicity, has also been utilized as a measure of second or subsequent-generation immigrants (see, for example, Algan *et al*. 2010). In this regard, the presence of wider disparities between UK-born and non-UK-born individuals among non-white employees, regardless of the immigrant employees' years of residence in the UK, would be consistent with much improved outcomes for the second or subsequent-generation immigrants.

To explore whether our benchmark results differ for males and females, we estimate a version of equation (1) by gender.[27] Table 4 presents these results. Both male and female immigrants with less than 10 years of residence in the UK (columns (1)-(2)) earn less than their UK-born counterparts, work longer hours, and are more likely to work in low-skilled occupations and temporary employment. While the mean hourly pay gap is around 5%, and the likelihood of employment in low-skilled occupations is about 6 percentage points higher for both male and female immigrants than comparable UK-born employees, the differences in weekly hours and the probability of temporary employment are slightly smaller for males than for females (3% versus 6% in weekly hours and 2.7 percentage points versus 3.1 percentage points in the probability of temporary employment). Turning to long-term immigrants (columns (3)-(4)), the patterns are once again similar, with both males and females with 10 or more years of residence in the UK being comparable to their UK-born counterparts, with no significant differences in any of the outcomes considered.

[Table 4 here]

Country of birth groupings

We now turn to analysing differentials in labour market outcomes based on country of birth. Although ASHE-Census includes detailed information on the country of birth, the sample sizes are too small to conduct separate analyses for each country. Therefore, we categorise immigrant employees' birth countries into five groups, namely European Union (EU) (excluding the UK as of 2011), Old Commonwealth, New Commonwealth, Reminder of Europe and the US, and Other countries, and compare the labour market outcomes of UK-born individuals with those from each country of birth groupings.[28,29] Table 5 presents these estimates.

The most noticeable feature of these results is the apparent heterogeneity by country of birth groupings. Among more recent immigrants, those from the EU (column (1)), New Commonwealth (column (3)), and Other (column (5)) countries have, on average, lower hourly pay than their UK-born counterparts (6%, 8%, and 11%, respectively), while those from Old Commonwealth countries

[27] In these models, gender is excluded among controls.

[28] Country of birth groupings employed in our heterogeneity analysis follow the old country of birth group definitions provided by the ONS (See http//www.ons.gov.uk/ons/rel/migration1/long-term-international-migration/2014/table-3-25.xls [Accessed 26/2/2024]).

[29] A small number of non-UK-born individuals have country of birth information that is not specific enough to be classified into our predefined categories. Therefore, these individuals are excluded from our heterogeneity analysis by country of birth groupings. Specifically, this includes individuals whose country of birth is listed as Europe (Not otherwise specified), Africa (Not otherwise specified), Middle East (Not otherwise specified), Asia (Except Middle East) (Not otherwise specified), North America (Not otherwise specified), Central America (Not otherwise specified), South America (Not otherwise specified), Caribbean (Not otherwise specified), or Antarctica and Oceania (Not otherwise specified).

(column (2)) or the Reminder of Europe or the US (column (4)) earn more (6% and 9%, respectively). The difference in weekly hours also varies. Immigrants from the EU, New Commonwealth, and the Reminder of Europe or the US have longer weekly hours than comparable UK-born employees. However, this difference is statistically indifferent from zero for those from Old Commonwealth and Other countries. In terms of the probability of employment in low-skilled occupations, it is higher for immigrants from the EU, New Commonwealth, and other countries, and lower for those from Old Commonwealth countries than for comparable UK-born employees. However, this difference is not significant between UK-born employees and recent immigrants from the Reminder of Europe or the US. More recent immigrants from the EU and Other countries are also more likely to be in temporary employment than comparable UK-born individuals, while this is not the case for immigrants from Other countries.

Consistent with our benchmark results, the differences are less pronounced for immigrants with 10 or more years of residence in the UK, although the heterogeneous patterns are evident across country of birth groupings. Interestingly, there is now an hourly pay advantage for long-term immigrants from EU countries (column (6)) and Old Commonwealth countries (column (7)) (around 2% and 9%, respectively), while employees from New Commonwealth countries (column (8)) earn (around 2%) less than their UK-born counterparts. We do not observe any other significant differences between long-term immigrants and UK-born employees, except for the likelihood of working in a low-skilled occupation, which is on average lower for immigrants from Old Commonwealth countries than for comparable UK-born employees (5 percentage points).

[Table 5 here]

Overall, these results indicate that immigrants of different origins are far from homogeneous, conditional on observable characteristics. Despite limited comparable previous evidence, some of these estimates are aligned with those from existing UK studies. For instance, our evidence of a pay advantage for immigrants from Old Commonwealth countries is consistent with the findings of Dustmann and Fabbri (2005), who find that individuals from these countries earn, on average, higher wages than comparable British-born individuals. The higher likelihood of being employed in low-skilled occupations for more recent EU immigrants is also consistent with the findings of Drinkwater *et al*. (2009), which show that the majority of post-2004 EU enlargement immigrants in Britain were from new member states (i.e., EU8), who were more likely to be employed in low-paying jobs.

Reason of migration

Previous UK evidence suggests that there are diverse labour market patterns for immigrants who arrived in the UK to enter the labour market and those who arrived for other reasons, such as to complete their education (Clark and Lindley, 2009). Ruiz and Vargas-Silva (2018) also argue that those who migrated for employment reasons are likely to have high success rates in the labour market as they would likely be selected based on their economic performance in the host country.

The ASHE-Census dataset does not include information on reasons for migration for foreign-born employees. However, it includes information on the year of arrival in the UK and employment start date. We use this information to identify a subgroup of labour market entrants (i.e., those who arrived in the UK for employment reasons) whose employment start year coincides with the year of arrival in the UK. For comparative purposes, we also present the estimation results for the remaining non-UK-born employees, who would include immigrants who arrived in the UK for other reasons such as education or accompanying/joining the family, but also some labour market entrants who might have changed their employer throughout their residence in the UK.[30] Our separate estimates for these two groups are presented in Table 6.

The difference in the probability of employment in a low-skilled occupation is now statistically indifferent from zero for this subgroup of labour market entrants, regardless of their years of residence in the UK (columns (1) and (3)). In other words, labour market entrants are neither more nor less likely to be employed in a low-skilled occupation than comparable UK-born employees. However, the differences in hourly pay, weekly hours, and the probability of temporary employment remain significant for more recent labour market entrants (column (1)). In fact, the disparities in weekly hours and the probability of temporary employment are slightly more pronounced for labour market entrants compared to other immigrants (5% versus 4% in weekly hours and 3.5 percentage points versus 2.6 percentage points in the probability of temporary employment). On the other hand, the adjusted hourly pay gap is smaller for recent labour market entrants than for other immigrants (4% versus 6%). Interpreted reasonably cautiously due to the imperfect identification of labour market entrants, these results align with the arguments of Ruiz and Vargas-Silva (2018) and suggest that those who arrived in the UK for employment reasons might differ from immigrants who arrived for other reasons, possibly due to their positive selection in terms of their economic performance.

[30] There could also be a small number of cases where an immigrant arrived in the UK for other reasons but found employment within the same year, or where a labour market entrant who arrived in a year (particularly in the last quarter) did not start their employment until the following year.

[Table 6 here]

4.3. Distributional analysis of hourly pay

To further explore the hourly pay differences across the distribution, we employ the unconditional quantile regression method developed by Firpo *et al.* (2009). In this way, we identify at which points of the hourly pay distribution (for example, whether among low- or high-paid workers), differences between UK-born and non-UK-born individuals are more pronounced. Unconditional quantile regression is similar to standard regression where the dependent variable is replaced by the recentred influence function (hereinafter, RIF). More formally, the RIF for quantile $q(\tau)$ is expressed as:

$$RIF(Y; q(\tau), F_Y) = q(\tau) + \frac{(\tau - \mathbb{I}\{Y \leq q(\tau)\})}{f_Y(q(\tau))} \quad (2)$$

where $\mathbb{I}\{\cdot\}$ is an indicator function for whether the observed value of the dependent variable Y is at or below quantile $q(\tau)$, F_Y is the marginal (unconditional) distribution function, and $f_Y(q(\tau))$ denotes the density function at quantile $q(\tau)$. In its simplest form, unconditional quantile regression can be estimated using OLS (hereinafter, RIF-OLS) (Firpo *et al.* 2009).

We present RIF-OLS estimation results in Table 7 at selected points of the (log) hourly pay distribution for more recent (Panel A) and long-term immigrants (Panel B) separately. Parallel to the analysis at the mean (Table 2), within each panel, we first present raw differences, and then gradually include individual and work-related characteristics among controls.[31]

Focusing first on immigrants with less than 10 years of residence in the UK (Panel A), there is a raw pay gap across the distribution, except at the top end of the distribution (column (5)). Consistent with the analysis at the mean, this gap narrows with the inclusion of work-related characteristics; however, there remains a significant pay gap throughout the hourly pay distribution except at the top end. At the bottom end of the distribution, more recent immigrants earn around 4% less than their UK-born counterparts (column (1)). The gap increases to 8% at the 25th percentile and the median (columns (2) and (3)) and reduces slightly (to 5%) at the 75th percentile (column (4)).

Turning to long-term immigrants, the raw differences suggest that non-UK-born employees earn more than UK-born employees across the earnings distribution, with the difference becoming more pronounced as we move up the earnings distribution (Panel B). For example, at the 90th percentile of the hourly pay distribution, long-term immigrants earn about 23% more than UK-born employees

[31] More complete profiles of the unadjusted and adjusted pay gaps for more recent and long-term immigrants are presented in Appendix Figures B1a and B1b, respectively.

(column (5)), while the raw difference is only 3% at the 10th percentile (column (1)). However, these differences diminish considerably with the inclusion of individual characteristics. In the most comprehensive specification, where we also control for work-related characteristics, the pay advantage of non-UK-born employees remains significant only at the top end of the distribution (column (5)), at about 5%, while those at the bottom end of the distribution earn about 2% less than comparable UK-born employees (columns (1) and (2)).

[Table 7 here]

Consistent with previous evidence for Britain (see, for example, Lemos 2013, 2017), these results show that the pay differences between immigrant and UK-born employees vary across the hourly pay distribution. Regardless of their years of residence in the UK, immigrants at the bottom of the distribution earn less than comparable UK-born employees. At the top end of the distribution, however, long-term immigrants have a pay advantage, while more recent immigrants earn no less or more than comparable UK-born employees. In this respect, our results also align with Hunt (2012) who based on the analysis of LFS data for 1993-2009 shows that foreign-born male workers earn less than British-born individuals at the bottom but more at the top of the earnings distribution. Our estimates further reveal considerable differences by years of residence in the UK. Although it is difficult to identify whether the presence of a pay advantage of long-term immigrants among high-paid employees is due to positive discrimination (in favour of long-term immigrants), an alternative explanation is the presence of a positive selection of immigrants into high-paid positions. Indeed, there is some evidence for Britain consistent with the latter, which suggests that immigrants earn more than UK-born employees due to being endowed with more productivity-enhancing characteristics (Hunt 2012), particularly those employed in high-paying occupations (Elliott and Lindley 2008).

5. Decomposing differences in labour market outcomes

Next, we explore the drivers of the observed differences between UK and non-UK-born employees in labour market outcomes. For this purpose, we apply well-established decomposition methods (Oaxaca 1973; Blinder 1973; Firpo *et al*. 2018) that are widely used in analysing disparities in the economic performance of separate groups of individuals. Our focus here is to identify the portion of the raw gaps explained by differences in observable characteristics between UK-born and immigrant employees, determining the specific factors contributing to the observed differences. The unexplained gaps, representing the portion of the raw gap not accounted for by observable characteristics in the model, provide additional robustness to the estimates of adjusted gaps.

5.1. Decompositions at the mean

To explore the drivers of the observed differences at the mean, we estimate a version of equation (1) separately by country of birth (I):

$$y_i{}^I = \mathrm{X}_i{}^I \delta^I + \varepsilon_i{}^I \tag{3}$$

where the vector X_i includes the above-listed personal and work-related characteristics along with a constant term. In this way, we allow the return to characteristics δ^I to vary by country of birth, i.e., for UK-born ($I = 0$) and non-UK-born ($I = 1$) employees. This approach facilitates an Oaxaca-Blinder (hereinafter, OB) decomposition (Oaxaca 1973; Blinder 1973) of the observed difference between UK-born and immigrant employees in considered labour market outcome as follows:

$$\bar{y}^0 - \bar{y}^1 = (\bar{X}^0 - \bar{X}^1)\hat{\delta}^0 + \bar{X}^1(\hat{\delta}^0 - \hat{\delta}^1) \tag{4}$$

where the bar above a variable denotes the mean value and $\hat{\delta}^I$ is the OLS estimate of the coefficient vector δ^I.[32,33] The first term on the right-hand side of equation (4) comprises the 'explained gap' and measures that part of the observed difference in considered labour market outcome, due to observed characteristics differences between UK-born and non-UK-born employees. The second term, referred to as the 'unexplained gap', reflects differences in returns to unobserved productivity-related characteristics and is often interpreted as the upper bound measure of unequal treatment.

Table 8 presents these results by distinguishing immigrants with less than 10 years of residence in the UK (Panel A) and those with 10 or more years of residence (Panel B).[34] In each column, the observed difference in the considered outcome is separated into its explained and unexplained components. For recent immigrants (Panel A), a portion of the observed differences in all the labour market outcomes considered can be explained by our personal and work-related characteristics. However, the contribution of explained differences to the observed gaps varies considerably. For instance, while around 41% of the 10% observed hourly pay gap is explained by our personal and

[32] In the case of binary outcomes (employment in low-skilled occupations and temporary employment), we employ the standard OB decomposition, using a LPM as in our benchmark regression models (see Section 4). Although the non-linear decomposition may perform better than the OB decomposition based on a LPM, the additional challenges in the computation of detailed decompositions for non-linear models, including the dependence of each variable's contribution to the values of all other covariates, and the path dependence of the alternative decomposition methodologies (see Gomulka and Stern 1990; Yun 2004; Fairlie 2005) are well established.

[33] Equation (4) uses the labour market outcome of an average non-UK-born employee evaluated at the returns for UK-born employees ($\bar{X}^1\hat{\delta}^0$) as the counterfactual, assuming the latter represent the competitive prices. In this regard, the unexplained gap estimated from the OB decomposition provides an additional robustness check for our benchmark regression results, which serve as a proxy for the unexplained gap using the pooled returns (see Section 4).

[34] The full set of coefficient estimates from equation (3) is available upon request.

work-related characteristics, the remaining 6% is unexplained and forms an upper-bound measure of pay inequality between UK-born employees and recent immigrants (column (1)). Similarly, although 60% of the 6.8 percentage points difference in the likelihood of temporary employment can be explained, 2.7 percentage points of this difference remain unexplained (column (4)). In the case of employment in low-skilled occupations, the unexplained portion is as large as 3.9 percentage points, which forms 81% of the observed gap (column (3)). Furthermore, only around 18% of the observed difference in weekly hours can be explained by our personal and work-related characteristics (column (2)).

Turning to the estimates for longer-term immigrants (Panel B), the decomposition results present a different picture. The 12% hourly pay advantage (column (1)) and the 2.8 percentage point advantage in the likelihood of low-skill employment (column (3)) of long-term immigrants can virtually be entirely explained by personal and work-related characteristics. Although the observed differences between UK-born and non-UK-born employees in weekly hours and the likelihood of temporary employment are significantly indifferent from zero, there is a significant unexplained gap for the former (with long-term immigrants working longer than UK-born employees) (column (2)), and a significant explained gap for the latter (with UK-born employees being less likely to work in temporary jobs) (column (4)). These differences, however, remain relatively small in magnitude (1% and 0.7 percentage points, respectively).

[Table 8 here]

Consistent with our benchmark regression results, overall, these estimates suggest that although some of the observed differences in labour market outcomes between more recent immigrants and UK-born employees can be explained by personal and work-related characteristics, a large portion of these differences remains unexplained. However, the advantage of long-term immigrants in hourly pay and the likelihood of employment in low-skilled occupations can entirely be explained.

When we further break down the drivers of the explained gap (see Appendix Tables B6a and B6b), we find that region and education play significant roles. Region explains approximately 66% of the observed hourly pay advantage and 69% of the lower likelihood of low-skilled employment for long-term immigrants (Appendix Table B6b), mainly due to their concentration in high-paid regions such as London (see Appendix Table B2). Similarly, long-term immigrants have a higher proportion of employees with a degree compared to UK-born individuals on average. Consequently, education explains another portion of their advantage in pay and occupational allocation. For more recent immigrants, region and education also contribute to narrowing the observed differences in hourly

pay and the likelihood of low-skilled employment (Appendix Table B6a). Regardless of the years of residence in the UK, however, differences in ethnicity largely offset the influence of education and region, primarily because the majority of non-UK-born employees are non-white (see Appendix Table B2). Additionally, for more recent immigrants, the lower average tenure also plays a significant role. Together with ethnicity, differences in tenure contribute significantly to the observed gap in hourly pay, probability of employment, and likelihood of temporary employment, while differences in industry and part-time employment account for some of the variations in weekly hours. Nevertheless, the observed differences between more recent immigrants and UK-born employees in these outcomes remain largely unexplained.

5.2. Decompositions across the distribution for hourly pay

To further explore the factors driving the observed differences across the hourly pay distribution, we employ the standard OB decomposition using the estimated coefficients of the RIF regression (hereinafter, RIF-OB decomposition), as proposed by Firpo *et al*. (2018). As in the case of mean, our aim here is to assess the contribution of explained and unexplained factors to the observed differences in hourly pay across the distribution.

Figure 1 presents these results by distinguishing more recent (panel a) and long-term immigrants (panel b).[35] For recent immigrants, the observed gap exhibits an inverse-U shape. Consistent with the quantile regression estimates (see Section 4), immigrant workers earn less than UK-born workers across most of the distribution, with the largest difference observed around the median. However, at the top end, there is a pay advantage for immigrant employees, although this is not statistically significant. Characteristics play an important role across the distribution, but their influence remains relatively constant. Consistent with the analysis at the mean, however, observed differences between recent immigrants and UK-born employees across the pay distribution remain largely unexplained except the top end.

For long-term immigrants, the observed hourly pay advantage is evident throughout the distribution, increasing from 3% at the 10th percentile to 18% at the 90th percentile. Consistent with the analysis at the mean, however, this advantage is virtually entirely explained. In fact, in the absence of unexplained influences, the hourly pay difference would have been wider at the lower tail of the distribution. The share of the explained component slightly diminishes across the distribution, but the unexplained gap remains statistically insignificant at and above the median, consistent with the

[35] Appendix Table B7 provides the corresponding estimates at selected points of the distribution.

hourly pay advantage being driven by selection into high-paid positions rather than positive discrimination.

[Figure 1 here]

6. Conclusions

This paper is the first to use linked administrative data from the ASHE-Census to investigate the labour market performance of first-generation immigrants in England and Wales and make comparisons with that of UK-born employees. By providing a comprehensive picture based on this novel dataset, the analysis adds new and policy-relevant evidence to the international and UK literature on the labour market performance of immigrants. Focusing on various labour market outcomes and distinguishing immigrants by years of residence in the UK, we find that more recent immigrants, on average, earn less, work longer hours, and are more likely to be employed in low-skilled occupations or temporary employment than comparable UK-born employees. The labour market performance of long-term immigrants with 10 or more years of residence in the UK, however, is more comparable to their UK-born counterparts, conditional on personal and work-related characteristics. These patterns are robust to a series of sensitivity checks and, in the case of hours and pay, are not driven by overtime or shift work. Our further analyses reveal that the identified patterns are similar for men and women, whereas there are considerable heterogeneities by ethnicity, country of origin, reasons for migration and, in the case of pay, across the distribution.

Our decomposition analysis highlights the important role of work region and education. In particular, immigrant employees' higher concentration in high-paid regions such as London and their greater likelihood of having a degree relative to UK-born individuals contribute to improving their labour market performance. However, consistent with UK evidence and reinforcing concerns relating to ethnic disparities, ethnicity is found to widen disparities in labour market outcomes in favour of UK-born employees, who are disproportionately white. In the case of more recent immigrants, the lower average tenure is also found to be an important factor, although the observed differences among more recent immigrants and UK-born employees remain predominantly unexplained, consistent with labour market inequalities and require further scrutiny.

Our finding of a stark difference between the labour performance of long-term and more recent immigrants also requires further examination. While these differences could be driven by the changing composition of immigrant cohorts, for instance, due to negative selective emigration or changes in selection for in-migration, they can also be due to other factors such as naturalization, which is found to facilitate access to high-paid and/or more secure jobs consistent with the removal

of employment barriers, as well as acquiring or improving host-country specific skills such as language over time. Indeed, our results highlight the need for further analysis to explore the roles of other potential factors of labour market inequalities beyond the personal and work-related characteristics considered here, which we leave for future research.

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Tables

Table 1. Sample means of key variables, by country of birth and length of residence in the UK

	UK-born employees	Non-UK-born employees			All employees
		with less than 10 years of residence	with 10 or more years of residence	All non-UK-born employees	
(log) gross hourly pay	2.498	2.403	2.623	2.532	2.502
	(0.527)	(0.558)	(0.594)	(0.589)	(0.534)
(log) weekly total paid hours	33.605	35.509	33.863	34.541	33.707
	(10.520)	(11.631)	(10.635)	(11.086)	(10.587)
% employed in low-skilled occupations	51.93	59.30	49.18	53.35	52.09
% temporary employment	4.77	11.54	5.26	7.85	5.11
Number of observations	88,333	4,462	6,364	10,826	99,159

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Figures in ( ) are standard deviations. See text for sample restrictions and variable definitions.

Table 2. Differences in labour market outcomes between UK-born and non-UK-born employees by years of residence in the UK

	Non-UK-born employees with less than 10 years of residence			Non-UK-born employees with 10 years or more of residence		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Log gross hourly pay						
Non-UK-born	-0.095***	-0.124***	-0.056***	0.125***	-0.003	0.007
	(0.009)	(0.008)	(0.007)	(0.008)	(0.007)	(0.006)
Personal characteristics	NO	YES	YES	NO	YES	YES
Work-related characteristics	NO	NO	YES	NO	NO	YES
Adjusted R-squared	0.001	0.422	0.600	0.003	0.424	0.600
Panel B. Log weekly total paid hours						
Non-UK-born	0.049***	0.053***	0.040***	0.007	0.015*	0.007
	(0.007)	(0.008)	(0.005)	(0.006)	(0.006)	(0.004)
Personal characteristics	NO	YES	YES	NO	YES	YES
Work-related characteristics	NO	NO	YES	NO	NO	YES
Adjusted R-squared	0.001	0.173	0.605	0.000	0.173	0.604
Panel C. Probability of employment in low-skilled occupations						
Non-UK-born	0.074***	0.082***	0.067***	-0.028***	0.001	-0.003
	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)
Personal characteristics	NO	YES	YES	NO	YES	YES
Work-related characteristics	NO	NO	YES	NO	NO	YES
Adjusted R-squared	0.001	0.255	0.296	0.000	0.258	0.298
Panel D. Probability of temporary employment						
Non-UK-born	0.068***	0.052***	0.029**	0.005	0.002	0.000
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Personal characteristics	NO	YES	YES	NO	YES	YES
Work-related characteristics	NO	NO	YES	NO	NO	YES
Adjusted R-squared	0.004	0.020	0.085	0.000	0.017	0.079
Number of observations	92,795	92,795	92,795	94,697	94,697	94,697

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Presented are the Ordinary Least Squares (OLS) estimates. Dependent variable for each model is indicated within panel titles. Reference category for 'non-UK-born' is UK-born employees. Personal characteristics include age (and its square), gender, ethnicity, education, disability, marital status, presence of dependent children, and work region (eleven NUTS1 categories). Work-related characteristics are tenure (and its square), part-time, temporary employment contract (except in Panel (D)), log firm size, collective agreement, industry (eleven categories for SIC07 regrouped sections), and occupation (except in Panel (C)) (nine categories for SOC10 major groups). All models also include a constant term. Figures in ( ) are robust standard errors. *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively. See text for sample construction and variable definitions.

Table 3. Heterogeneity analysis by ethnicity

	Non-UK-born employees with less than 10 years of residence		Non-UK-born employees with 10 or more years of residence	
	White	Non-white	White	Non-white
	(1)	(2)	(3)	(4)
Panel A. Log gross hourly pay				
Non-UK-born	-0.036***	-0.103***	0.029***	-0.042***
	(0.008)	(0.012)	(0.007)	(0.010)
Adjusted R-squared	0.601	0.601	0.602	0.597
Panel B. Log weekly total paid hours				
Non-UK-born	0.048***	0.004	0.004	-0.001
	(0.006)	(0.011)	(0.005)	(0.009)
Adjusted R-squared	0.605	0.617	0.604	0.607
Panel C. Probability of employment in low-skilled occupations				
Non-UK-born	0.066***	0.080***	-0.022**	0.030*
	(0.009)	(0.014)	(0.008)	(0.013)
Adjusted R-squared	0.299	0.264	0.301	0.283
Panel D. Probability of temporary employment				
Non-UK-born	0.038***	-0.001	0.001	0.002
	(0.007)	(0.010)	(0.004)	(0.008)
Adjusted R-squared	0.082	0.114	0.078	0.093
Number of observations	86,798	5,997	87,542	7,155
% non-UK-born	2.76	34.40	3.59	45.02

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Presented are the Ordinary Least Squares (OLS) estimates. Dependent variable for each model is indicated within panel titles. Reference category for 'non-UK-born' is UK-born employees. All models also control for personal characteristics including age (and its square), gender, ethnicity (except in columns (1) and (3)), education, disability, marital status, presence of dependent children, and work region (eleven NUTS1 categories); work-related characteristics including tenure (and its square), part-time, temporary employment contract (except in Panel (D)), log firm size, collective agreement, industry (eleven categories for SIC07 regrouped sections), occupation (except in Panel (C)) (nine categories for SOC10 major groups) and a constant term. Figures in ( ) are robust standard errors. *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively. See text for sample construction and variable definitions.

Table 4. Heterogeneity analysis by gender

	Non-UK-born employees with less than 10 years of residence		Non-UK-born employees with 10 years or more of residence	
	Males	Females	Males	Females
	(1)	(2)	(3)	(4)
Panel A. Log gross hourly pay				
Non-UK-born	-0.056***	-0.052***	0.009	0.006
	(0.010)	(0.008)	(0.009)	(0.007)
Adjusted R-squared	0.572	0.612	0.569	0.613
Panel B. Log weekly total paid hours				
Non-UK-born	0.031***	0.062***	0.010	0.011
	(0.006)	(0.009)	(0.005)	(0.007)
Adjusted R-squared	0.590	0.561	0.588	0.561
Panel C. Probability of employment in low-skilled occupations				
Non-UK-born	0.066***	0.063***	0.001	-0.006
	(0.011)	(0.010)	(0.009)	(0.008)
Adjusted R-squared	0.262	0.304	0.262	0.306
Panel D. Probability of temporary employment				
Non-UK-born	0.027***	0.031***	-0.005	0.002
	(0.007)	(0.008)	(0.004)	(0.005)
Adjusted R-squared	0.110	0.073	0.103	0.068
Number of observations	44,372	48,423	45,084	49,613
% non-UK-born	4.96	4.67	6.46	6.96

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Presented are the Ordinary Least Squares (OLS) estimates. Dependent variable for each model is indicated within panel titles. Reference category for 'non-UK-born' is UK-born employees. All models also control for personal characteristics including age (and its square), ethnicity, education, disability, marital status, presence of dependent children, and work region (eleven NUTS1 categories); work-related characteristics including tenure (and its square), part-time, temporary employment contract (except in Panel (D)), log firm size, collective agreement, industry (eleven categories for SIC07 regrouped sections), occupation (except in Panel (C)) (nine categories for SOC10 major groups) and a constant term. Figures in ( ) are robust standard errors. *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively. See text for sample construction and variable definitions.

Table 5. Heterogeneity analysis by country of birth groupings

	Non-UK-born employees with less than 10 years of residence					Non-UK-born employees with 10 or more years of residence				
	EU	Old Commonwealth	New Commonwealth	Reminder of Europe and the US	Other	EU	Old Commonwealth	New Commonwealth	Reminder of Europe and the US	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Log gross hourly pay										
Non-UK-born	-0.060***	0.055**	-0.085***	0.085**	-0.111***	0.022*	0.083***	-0.024**	0.001	-0.024
	(0.009)	(0.021)	(0.012)	(0.033)	(0.015)	(0.010)	(0.017)	(0.009)	(0.026)	(0.015)
Adj. R-squared	0.601	0.602	0.601	0.602	0.602	0.601	0.602	0.600	0.602	0.602
Panel B. Log weekly total paid hours										
Non-UK-born	0.061***	-0.014	0.032**	0.033**	0.023	0.012	0.001	0.010	0.009	-0.004
	(0.007)	(0.015)	(0.011)	(0.012)	(0.015)	(0.007)	(0.012)	(0.007)	(0.014)	(0.012)
Adj. R-squared	0.605	0.605	0.605	0.605	0.605	0.605	0.605	0.605	0.605	0.605
Panel C. Probability of employment in low-skilled occupations										
Non-UK-born	0.107***	-0.090***	0.059***	-0.011	0.057**	-0.016	-0.050**	0.018	-0.013	0.023
	(0.011)	(0.022)	(0.015)	(0.031)	(0.018)	(0.010)	(0.018)	(0.010)	(0.023)	(0.016)
Adj. R-squared	0.297	0.297	0.297	0.297	0.297	0.297	0.298	0.298	0.297	0.297
Panel D. Probability of temporary employment										
Non-UK-born	0.043***	0.005	0.004	0.043	0.036**	0.004	-0.000	-0.002	-0.015	0.002
	(0.008)	(0.014)	(0.010)	(0.022)	(0.013)	(0.005)	(0.009)	(0.006)	(0.010)	(0.009)
Adj. R-squared	0.083	0.080	0.081	0.080	0.081	0.080	0.080	0.080	0.080	0.080
Number of obs.	90,140	88,707	89,636	88,530	89,103	90,079	88,868	91,141	88,655	89,239
% non-UK-born	2.00	0.42	1.45	0.22	0.86	1.94	0.60	3.08	0.36	1.02

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Presented are the Ordinary Least Squares (OLS) estimates. Dependent variable for each model is indicated within panel titles. Reference category for 'non-UK-born' is UK-born employees. All models also control for personal characteristics including age (and its square), gender, ethnicity, education, disability, marital status, presence of dependent children, and work region (eleven NUTS1 categories); work-related characteristics including tenure (and its square), part-time, temporary employment contract (except in Panel (D)), log firm size, collective agreement, industry (eleven categories for SIC07 regrouped sections), occupation (except in Panel (C)) (nine categories for SOC10 major groups) and a constant term. Figures in ( ) are robust standard errors. *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively. See text for sample construction and variable definitions.

Table 6. Heterogeneity analysis by proxy for reason for migration

	Non-UK-born employees with less than 10 years of residence		Non-UK-born employees with 10 or more years of residence	
	Subgroup of labour market entrants	Other	Subgroup of labour market entrants	Other
	(1)	(2)	(3)	(4)
Panel A. Log gross hourly pay				
Non-UK-born	-0.038**	-0.062***	0.043	0.005
	(0.014)	(0.007)	(0.040)	(0.006)
Adjusted R-squared	0.601	0.600	0.602	0.600
Panel B. Log weekly total paid hours				
Non-UK-born	0.049***	0.037***	0.013	0.007
	(0.008)	(0.006)	(0.017)	(0.004)
Adjusted R-squared	0.605	0.605	0.605	0.604
Panel C. Probability of employment in low-skilled occupations				
Non-UK-born	0.013	0.079***	-0.038	-0.001
	(0.014)	(0.008)	(0.033)	(0.006)
Adjusted R-squared	0.297	0.296	0.298	0.298
Panel D. Probability of temporary employment				
Non-UK-born	0.035***	0.026***	0.018	-0.000
	(0.010)	(0.006)	(0.013)	(0.003)
Adjusted R-squared	0.081	0.084	0.080	0.079
Number of obs.	89,249	91,879	88,465	94,565
% non-UK-born	1.03	3.86	0.15	6.59

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Presented are the Ordinary Least Squares (OLS) estimates. Dependent variable for each model is indicated within panel titles. Reference category for 'non-UK-born' is UK-born employees. All models also control for personal characteristics including age (and its square), gender, ethnicity, education, disability, marital status, presence of dependent children, and work region (eleven NUTS1 categories); work-related characteristics including tenure (and its square), part-time, temporary employment contract (except in Panel (D)), log firm size, collective agreement, industry (eleven categories for SIC07 regrouped sections), occupation (except in Panel (C)) (nine categories for SOC10 major groups) and a constant term. Figures in ( ) are robust standard errors. *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively. See text for sample construction and variable definitions.

Table 7. Distributional analysis for log gross hourly pay

	(1) 10th percentile	(2) 25th percentile	(3) Median	(4) 75th percentile	(5) 90th percentile
Panel A. Non-UK-born employees with less than 10 years of residence in the UK					
Non-UK-born	-0.083***	-0.153***	-0.140***	-0.088***	-0.015
	(0.008)	(0.010)	(0.011)	(0.012)	(0.016)
Personal characteristics	NO	NO	NO	NO	NO
Work-related characteristic	NO	NO	NO	NO	NO
Adjusted R-squared	0.002	0.003	0.002	0.000	0.000
Non-UK-born	-0.085***	-0.162***	-0.181***	-0.131***	-0.057**
	(0.008)	(0.010)	(0.011)	(0.013)	(0.019)
Personal characteristics	YES	YES	YES	YES	YES
Work-related characteristic	NO	NO	NO	NO	NO
Adjusted R-squared	0.138	0.220	0.307	0.284	0.162
Non-UK-born	-0.042***	-0.084***	-0.083***	-0.053***	-0.008
	(0.008)	(0.009)	(0.009)	(0.012)	(0.018)
Personal characteristics	YES	YES	YES	YES	YES
Work-related characteristic	YES	YES	YES	YES	YES
Adjusted R-squared	0.252	0.389	0.481	0.409	0.230
Number of observations	92,795	92,795	92,795	92,795	92,795
Panel B. Non-UK-born employees with 10 or more years of residence in the UK					
Non-UK-born	0.028***	0.059***	0.127***	0.156***	0.205***
	(0.005)	(0.007)	(0.010)	(0.012)	(0.017)
Personal characteristics	NO	NO	NO	NO	NO
Work-related characteristic	NO	NO	NO	NO	NO
Adjusted R-squared	0.000	0.001	0.002	0.002	0.002
Non-UK-born	-0.034***	-0.035***	-0.020*	-0.007	0.042*
	(0.005)	(0.007)	(0.009)	(0.012)	(0.018)
Personal characteristics	YES	YES	YES	YES	YES
Work-related characteristic	NO	NO	NO	NO	NO
Adjusted R-squared	0.141	0.221	0.310	0.284	0.161
Non-UK-born	-0.022***	-0.019**	-0.006	-0.003	0.045***
	(0.005)	(0.006)	(0.008)	(0.011)	(0.017)
Personal characteristics	YES	YES	YES	YES	YES

Work-related characteristic	YES	YES	YES	YES	YES
Adjusted R-squared	0.261	0.392	0.483	0.407	0.228
Number of observations	94,697	94,697	94,697	94,697	94,697

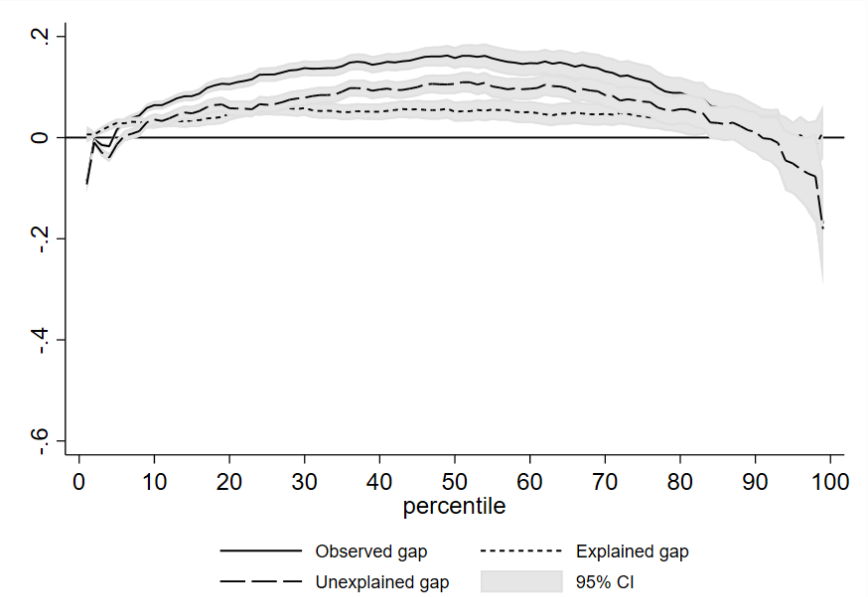
Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Presented are the unconditional quantile regression estimates. Reference category for 'non-UK-born' is UK-born employees. Personal characteristics include age (and its square), gender, ethnicity, education, disability, marital status, presence of dependent children, and work region (eleven NUTS1 categories). Work-related characteristics are tenure (and its square), part-time, temporary employment contract (except in Panel (D)), log firm size, collective agreement, industry (eleven categories for SIC07 regrouped sections), occupation (except in Panel (C)) (nine categories for SOC10 major groups). All models also include a constant term. Figures in ( ) are robust standard errors. *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively. See text for sample construction and variable definitions.

Table 8. Oaxaca-Blinder decomposition results, benchmark model

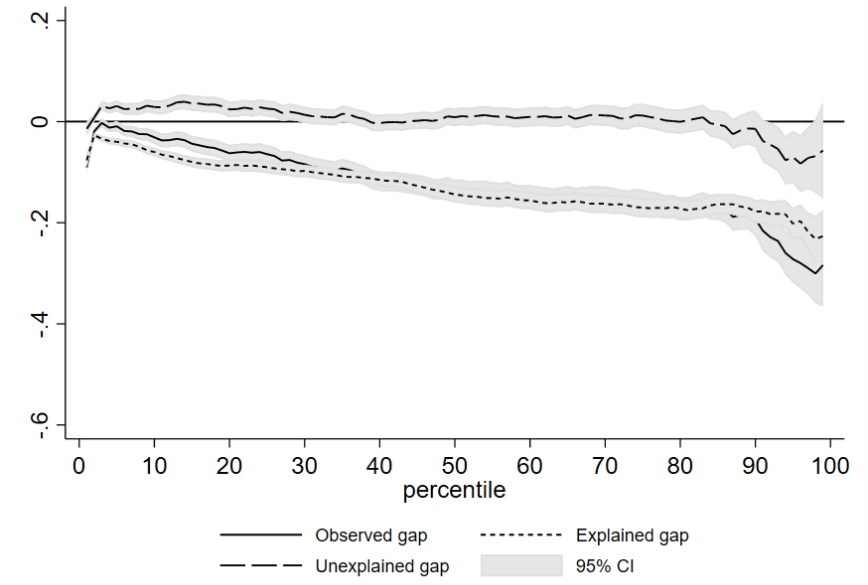
	(1) Log gross hourly pay	(2) Log weekly total paid hours	(3) Probability of employment in low-skilled occupation	(4) Probability of temporary employment
Panel A. Non-UK-born employees with less than 10 years of residence in the UK				
Observed gap	0.095***	-0.049***	-0.074***	-0.068***
	(0.009)	(0.007)	(0.008)	(0.005)
Explained gap	0.039***	-0.009	-0.014*	-0.041***
	(0.008)	(0.006)	(0.007)	(0.003)
	[40.85]	[18.95]	[18.34]	[59.89]
Unexplained gap	0.056***	-0.039***	-0.060***	-0.027***
	(0.007)	(0.006)	(0.008)	(0.006)
	[59.15]	[81.05]	[81.66]	[40.11]
Number of observations	92,795	92,795	92,795	92,795
Panel B. Non-UK-born employees with 10 or more years of residence in the UK				
Observed gap	-0.125***	-0.007	0.028***	-0.005
	(0.008)	(0.006)	(0.007)	(0.003)
Explained gap	-0.131***	0.004	0.035***	-0.007**
	(0.006)	(0.005)	(0.005)	(0.003)
	[104.73]	[-49.89]	[125.48]	[148.19]
Unexplained gap	0.006	-0.011*	-0.007	0.002
	(0.006)	(0.005)	(0.007)	(0.004)
	[-4.73]	[149.89]	[-25.48]	[-48.19]
Number of observations	94,697	94,697	94,697	94,697

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Presented are the Oaxaca-Blinder decomposition results performed using a model which includes personal and work-related characteristics. Dependent variable for each model is indicated within column titles. Decompositions use the relevant male coefficients as the baseline. Figures in ( ) are robust standard errors. Figures in [ ] are proportions of observed gap. *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively. See text for sample construction and variable definitions.

Figures



a. UK-born employees and non-UK-born employees with less than 10 years of residence in the UK



b. UK-born employees and non-UK-born employees with 10 or more years of residence in the UK

Figure 1. Decomposition of the log gross hourly pay difference between UK-born and non-UK-born employees across the distribution

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Presented are the unconditional quantile decomposition results performed using a model which includes personal and work-related characteristics. Dependent variable for each model is log gross hourly pay. Decompositions use the relevant male coefficients as the baseline. Grey shaded area denotes the 95% confidence intervals (CI). See text for sample construction and variable definitions.

Appendices

Appendix A. Further description of the data, sample construction and variables

Further details of sample construction

The analysis uses cross-sectional data for the year 2011 from Drop 2 of the Annual Survey of Hours and Earnings linked to the 2011 Census of England and Wales (hereinafter, ASHE-Census) (ONS 2023). We clean the data (initial sample 182,970 observations), initially restricting the sample to observations with non-missing anonymized enterprise identifiers.

The ASHE-Census dataset includes information on personal characteristics including gender, from both ASHE and Census. A small fraction of employees in the sample has inconsistent values coming from the two data sources. In such cases, we treat inconsistent observations as missing.

The ASHE-Census dataset also includes information on age from both ASHE and the Census. For a small fraction of employees, the difference in age from both sources falls outside the range of [-1,1]. We treat these observations as missing.

To create the tenure variable, we utilize the month and year in which the employee started working for the employer. Following Jewell *et al.* (2020), we recode a tiny number of unrealistic entry dates as missing. These include cases where the start date falls in the future or implies that the employee started working at age fifteen or younger.

In terms of work-related characteristics, a small fraction of employees in the same enterprise (identified using the unique anonymized enterprise identifier) have missing or varying values for the sector. Following Jewell *et al.* (2020), we impute the same value for all employees within an enterprise as the modal value for the employer if a unique non-missing modal value exists. Similarly, a small fraction of employees within the same enterprise have missing or varying values for the industry. Again, we impute the same value for all employees within an enterprise as the modal value for the employer if a unique non-missing modal value exists.

To generate our working sample, we restrict the sample to observations codded with an adult rate marker, with earnings not affected by absence, classified as the main job, aged between 16 and 64 years old, and with weekly basic paid hours no less than one and no more than 99 hours. Next, we code gross hourly pay outliers, which are ten times above the 99 percentile and below half the first percentile of the gross hourly pay distribution as missing. Finally, we further

restrict our sample to include only those observations with non-missing and valid information in all variables included in the analysis.

The final sample includes 99,159 observations, of which 10,826 are non-UK-born employees.

Key variables

Non-UK-born: The ASHE-Census includes information on the country of birth of employees from the Census. To identify non-UK-born individuals, we create a binary indicator variable, which takes a value of one if the country of birth indicator indicates a non-UK birth, and zero if the birth country is the UK. For non-UK employees, we also utilize data on their length of residence in the UK. Length of residence pertains only to usual residents who were not born in the UK and is calculated based on the date of their last arrival to live in the UK, excluding short visits away from the UK.

Gross hourly pay: ASHE-Census provides detailed information on employee earnings and hours during the pay period, which includes the reference date in April, from payroll records. Our primary measure of hourly pay is derived from average gross weekly earnings for the reference period divided by the average total paid hours worked during that period. In our sensitivity analysis, we consider alternative measures of hourly pay, such as gross hourly pay excluding overtime (average gross weekly earnings excluding overtime for the reference period divided by basic paid hours) and basic hourly pay (basic weekly earnings divided by basic paid hours).

Weekly total paid hours: In ASHE-Census, detailed information on employee working hours is available. Our benchmark measure is the average total paid hours worked during the reference period. However, in our sensitivity analysis, we also explore basic paid hours as an alternative measure.

Low-skill occupation: Our definition of low-skill occupation aligns with that of the ONS (2010) and is based on occupation information as measured by the Standard Classification of Occupations (hereinafter, SOC) 2010. According to this classification, SOC 2010 one-digit titles with skill levels 2 and 1 are considered low-skill. These categories include Administrative and secretarial occupations; Caring, leisure, and other service occupations; Sales and customer service occupations; Process, plant, and machine operatives; and Elementary occupations. Therefore, our benchmark measure for low-skilled takes a value of one if the employee's occupation falls within these categories, and zero otherwise.

Temporary employment: We define temporary employment as a binary indicator that takes a value of one if the individual is employed with a temporary employment contract, and zero if the individual is working with a permanent employment contract.

Control variables

Personal characteristics: Age (and age-squared), gender (a binary indicator that takes a value of one if the individual is female and zero if the individual is male), ethnicity (eight categories: white, Indian, Pakistani, Bangladeshi, Chinese, Black Caribbean, Black African, and Other or Mixed), education (five categories: no qualification, GCSEs or apprenticeship, A-level, Degree, and Other/vocational qualification), marital status (a binary indicator of whether the employee is married or registered in a same-sex civil partnership), presence of dependent children (a binary indicator derived from the presence of dependent children in the family and the number of adults in the household, with missing values replaced with zero when there is only one adult in the household), long-term health problem or disability (a binary indicator for whether a long-term health problem or disability limits the employee's day-to-day activities and has lasted at least 12 months), and (work) region (eleven categories defined at NUTS1 level).

Work-related characteristics: Tenure, measured by the total number of years in the present organisation (and tenure-squared), part-time employment (a binary indicator that takes a value of one if the job is part-time and zero for full-time), temporary employment contract (a binary indicator that takes a value of one if the job is temporary or casual and zero otherwise), (log) firm size, measured by the number of employees in the enterprise on the Inter-Departmental Business Register (hereinafter, IDBR), collective bargaining (a binary indicator that takes a value of one if the employee's pay is set with reference to a collective agreement and zero otherwise), industry measured by the Standard Industry Classification (hereinafter, SIC) 2007 (eleven categories for regrouped SIC 2007 sections), and occupation measured by the SOC 2010 (nine categories for SOC 2010 major groups).[36,37]

Extended personal characteristics: Our benchmark analysis excludes other potential determinants of labour market outcomes due to potential correlation between these variables and other explanatory variables. Nevertheless, in our sensitivity analysis we explore the

[36] Temporary employment contract is excluded among controls when the outcome is the probability of temporary employment. Similarly, we exclude occupation controls for specifications where the outcome is the probability of employment in low-skill occupations.
[37] See Appendix Table B2 for the categories of industry and occupation.

robustness of our findings to their inclusion. These variables include number of dependent children (derived from the dependent children in the family and the number of adults in the household where the missing values are replaced with zero when there is only one adult in the household), age of the youngest dependent child (six categories: under 4 years old, 5-7 years old, 8-9 years old, 10-11 years old, 12-15 years old, 16-18 years old, and a value of zero if number of dependent children in the household is zero), religion (nine categories: no religion, Christian, Buddhist, Hindu. Jewish, Muslim, Sikh, Other religion, and Religion not stated), general (self-assessed) health status (a binary indicator that takes value of one if the employee's health was very good, good or fair and zero otherwise).

Sector: We classify the sector of the employee's employer based on the legal status of the employee's employer (enterprise) from the IDBR into three categories: public corporation and nationalised industries, central government, or local authority; private company, sole proprietorship, or partnership; and non-profit body or mutual association. Sector is excluded from our benchmark model due to its potential overlap with industry, but we explore the sensitivity of our results to its inclusion in our robustness checks.

Appendix B. Additional Tables

Table B1. Sample means of key variables for subgroups of immigrants with less than 10 years of residence in the UK

	with less than 2 years of residence	with 2-4 years of residence	with 5-9 years of residence
(log) gross hourly pay	2.349	2.340	2.446
	(0.624)	(0.564)	(0.539)
(log) weekly total paid hours	34.841	35.255	35.752
	(11.959)	(11.572)	(11.609)
% employed in low-skilled occupations	63.33	65.36	55.36
% temporary employment	25.18	12.71	8.78
Number of observations	409	1,432	2,621

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Figures in ( ) are standard deviations. See text for sample restrictions and variable definitions.

Table B2. Descriptive statistics of explanatory variables

	UK-born employees	Non-UK-born employees			All employees
		With less than 10 years of residence	With 10 or more years of residence	All non-UK-born employees	
Length of residence in the UK	-	5.844	28.140	18.951	-
		(2.485)	(12.966)	(14.894)	
Age	41.048	34.759	44.406	40.430	40.981
	(11.426)	(8.179)	(9.900)	(10.379)	(11.318)
Female (%)	52.26	50.72	54.26	52.80	52.32
Ethnicity (%)					
White	95.55	53.77	49.39	51.19	90.70
Indian	1.13	12.77	15.32	14.27	2.57
Pakistani	0.59	2.87	4.29	3.70	0.93
Bangladeshi	0.17	0.63	2.31	1.62	0.33
Chinese	0.12	2.29	3.08	2.75	0.41
Black Caribbean	0.79	1.55	4.64	3.36	1.07
Black African	0.19	9.32	7.28	8.12	1.06
Other or mixed ethnicities	1.46	16.81	13.70	14.98	2.93
Highest level of qualification (%)					
No qualification	7.76	6.05	7.10	6.67	7.64
GCSEs, apprenticeship	37.59	13.90	23.19	19.36	35.60
A-level	16.07	6.36	10.83	8.99	15.30
Degree	36.32	47.38	49.42	48.58	37.66
Other/vocational qualification	2.26	26.31	9.46	16.40	3.80
Work region (%)					
North East	5.05	1.88	1.74	1.80	4.70
North West	13.08	8.23	6.52	7.22	12.44
Yorkshire and The Humber	10.20	5.83	5.22	5.47	9.68
East Midlands	8.28	7.51	6.10	6.68	8.11
West Midlands	10.14	7.80	7.67	7.72	9.88
South West	9.92	7.33	7.04	7.16	9.62
East	10.46	10.56	9.05	9.67	10.37
London	11.44	30.14	38.53	35.07	14.02
South East	15.40	17.53	15.89	16.56	15.52
Wales	5.71	2.67	2.03	2.29	5.33
Scotland	0.32	0.54	0.22	0.35	0.32
Married or registered in a same-sex civil partnership (%)	53.46	64.81	66.28	65.68	54.79
Presence of dependent children (%)	42.88	50.85	50.00	50.35	43.69
Long-term health problem or disability (%)	5.43	2.42	5.64	4.31	5.31
Tenure (years)	8.494	3.368	8.179	6.196	8.243
	(7.856)	(2.550)	(7.151)	(6.192)	(7.725)
Part-time employment (%)	27.45	23.44	26.19	25.06	27.19
Collective agreement (%)	49.88	39.74	50.02	45.78	49.43
Log (Firm size)	7.162	7.082	7.295	7.207	7.167
	(2.996)	(2.768)	(2.887)	(2.840)	(2.979)
Industry (%)					

Agriculture, forestry and fishing; Mining and quarrying	0.60	0.65	0.33	0.46	0.59
Manufacturing	9.90	10.58	7.23	8.61	9.76
Electricity, gas, steam and air conditioning supply; Water supply; sewerage, waste management and remediation activities	1.28	0.52	0.71	0.63	1.21
Construction	3.26	1.61	2.04	1.87	3.11
Wholesale, retail, repair of vehicles	16.66	13.83	13.04	13.37	16.30
Transport and storage; Accommodation and food service; Information and communication	11.75	17.41	14.80	15.88	12.20
Financial and insurance activities; Real estate activities; Professional, scientific and technical activities; Admin and support services	16.27	22.48	18.10	19.91	16.67
Public administration and defence; compulsory social security; Education	24.02	10.29	23.29	17.93	23.35
Human health and social work activities	13.06	20.28	17.71	18.77	13.68
Art, entertainment, and recreation	1.50	1.08	1.13	1.11	1.45
Other activities	1.71	1.28	1.62	1.48	1.68
Occupation (%)					
Managers, directors and senior officials	9.48	6.10	9.37	8.02	9.32
Professional occupations	17.37	21.54	24.78	23.44	18.03
Associate professional and technical occupations	14.71	8.23	12.21	10.57	14.26
Administrative and secretarial occupations	16.50	10.13	14.05	12.43	16.06
Skilled trades occupations	6.50	4.84	4.46	4.62	6.30
Caring, leisure and other service occupations	9.46	11.07	9.63	10.23	9.54
Sales and customer service occupations	10.00	7.40	8.45	8.02	9.78
Process, plant and machine operatives	5.75	8.31	5.22	6.49	5.83
Elementary occupations	10.23	22.39	11.83	16.18	10.88
Number of observations	88,333	4,462	6,364	10,826	99,159

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Figures in ( ) are standard deviations. See text for sample construction and variable definitions.

Table B3a. Full set of coefficient estimates for UK-born and non-UK-born employees with less than 10 years of residence in the UK, benchmark model

	(1) Log gross hourly pay	(2) Log weekly total paid hours	(3) Probability of employment in low-skilled occupations	(4) Probability of temporary employment
Non-UK-born	-0.056***	0.040***	0.067***	0.029***
	(0.007)	(0.005)	(0.008)	(0.005)
Age	0.034***	0.018***	-0.018***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Age-squared	-0.000***	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.134***	-0.051***	0.156***	-0.012***
	(0.003)	(0.002)	(0.003)	(0.002)
Ethnicity				
Indian	-0.067***	-0.012	0.054***	0.005
	(0.009)	(0.008)	(0.011)	(0.007)
Pakistani	-0.072***	-0.014	0.121***	0.006
	(0.013)	(0.014)	(0.017)	(0.011)
Bangladeshi	-0.130***	-0.051	0.075*	0.050*
	(0.022)	(0.030)	(0.033)	(0.025)
Chinese	-0.007	0.002	-0.046	0.037
	(0.025)	(0.014)	(0.031)	(0.021)
Black Caribbean	-0.085***	-0.016	0.052**	0.017
	(0.011)	(0.010)	(0.016)	(0.009)
Black African	-0.155***	-0.046**	0.150***	0.044**
	(0.014)	(0.015)	(0.018)	(0.015)
Other or mixed ethnicities	-0.068***	-0.014	0.062***	0.002
	(0.008)	(0.008)	(0.010)	(0.006)
Education				
GCSE, apprenticeship	0.078***	-0.010*	-0.117***	-0.002
	(0.004)	(0.004)	(0.005)	(0.003)
A-level	0.139***	-0.015**	-0.216***	-0.001
	(0.004)	(0.005)	(0.006)	(0.003)
Degree	0.325***	-0.026***	-0.516***	0.007*
	(0.005)	(0.005)	(0.005)	(0.003)
Other/vocational	0.066***	0.024***	-0.083***	0.008
	(0.007)	(0.007)	(0.009)	(0.005)
Married or registered same-sex civil partnership	0.047***	-0.004	-0.037***	-0.007***
	(0.003)	(0.002)	(0.003)	(0.002)
Long term health problem or disability	-0.051***	-0.028***	0.038***	0.003
	(0.005)	(0.005)	(0.006)	(0.003)
Presence of dependent child	0.031***	-0.039***	-0.018***	0.000
	(0.003)	(0.002)	(0.003)	(0.002)
Tenure (in years)	0.014***	0.003***	-0.008***	-0.014***
	(0.000)	(0.000)	(0.001)	(0.000)

Tenure-squared	-0.000***	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Part-time employment	-0.086***	-0.723***	0.177***	0.051***
	(0.003)	(0.003)	(0.003)	(0.002)
Temporary employment contract	-0.029***	-0.142***	0.042***	-
	(0.005)	(0.008)	(0.006)	
Log firm size	0.013***	0.003***	0.010***	0.004***
	(0.000)	(0.000)	(0.001)	(0.000)
Collective agreement	0.027***	0.003	0.045***	-0.009***
	(0.003)	(0.002)	(0.003)	(0.002)
Work region	YES	YES	YES	YES
Industry	YES	YES	YES	YES
Occupation	YES	YES	YES	YES
Adjusted R-squared	0.600	0.605	0.296	0.085
Number of observations	92,795	92,795	92,795	92,795

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Presented are the Ordinary Least Squares (OLS) estimates. Dependent variable for each model is indicated within panel titles. Reference category for 'non-UK-born' is UK-born employees, for ethnicity white, and for education no qualification. All models also include a constant term. Figures in ( ) are robust standard errors. *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively. See text for sample construction and variable definitions.

Table B3b. Full set of coefficient estimates for UK-born and non-UK-born employees with 10 or more years of residence in the UK, benchmark model

	(1) Log gross hourly pay	(2) Log weekly total paid hours	(3) Probability of employment in low-skilled occupations	(4) Probability of temporary employment
Non-UK-born	0.007	0.007	-0.003	0.000
	(0.006)	(0.004)	(0.006)	(0.003)
Age	0.034***	0.019***	-0.018***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Age-squared	-0.000***	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.136***	-0.052***	0.157***	-0.011***
	(0.003)	(0.002)	(0.003)	(0.002)
Ethnicity				
Indian	-0.059***	-0.002	0.099***	0.008
	(0.009)	(0.007)	(0.010)	(0.005)
Pakistani	-0.086***	-0.019	0.109***	0.013
	(0.012)	(0.013)	(0.016)	(0.009)
Bangladeshi	-0.166***	-0.069**	0.129***	0.041*
	(0.019)	(0.026)	(0.026)	(0.018)
Chinese	-0.049*	-0.006	0.010	0.013
	(0.022)	(0.015)	(0.025)	(0.014)
Black Caribbean	-0.097***	-0.005	0.055***	0.026**
	(0.010)	(0.009)	(0.014)	(0.008)
Black African	-0.199***	0.016	0.148***	0.028*
	(0.013)	(0.011)	(0.018)	(0.011)
Other or mixed ethnicities	-0.069***	-0.008	0.066***	0.007
	(0.008)	(0.007)	(0.010)	(0.005)
Education				
GCSE, apprenticeship	0.081***	-0.008	-0.120***	-0.000
	(0.004)	(0.004)	(0.005)	(0.003)
A-level	0.142***	-0.013**	-0.219***	0.001
	(0.004)	(0.005)	(0.006)	(0.003)
Degree	0.333***	-0.025***	-0.522***	0.009**
	(0.005)	(0.005)	(0.005)	(0.003)
Other/vocational	0.041***	0.021**	-0.063***	0.007
	(0.007)	(0.007)	(0.009)	(0.005)
Married or registered same-sex civil partnership	0.046***	-0.006**	-0.039***	-0.006***
	(0.002)	(0.002)	(0.003)	(0.001)
Long term health problem or disability	-0.052***	-0.027***	0.036***	0.002
	(0.005)	(0.005)	(0.006)	(0.003)
Presence of dependent child	0.033***	-0.038***	-0.017***	-0.000
	(0.003)	(0.002)	(0.003)	(0.002)
Tenure (in years)	0.014***	0.003***	-0.007***	-0.013***
	(0.000)	(0.000)	(0.001)	(0.000)

Tenure-squared	-0.000***	-0.000***	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Part-time employment	-0.086***	-0.720***	0.176***	0.050***
	(0.003)	(0.003)	(0.003)	(0.002)
Temporary employment contract	-0.028***	-0.144***	0.040***	-
	(0.005)	(0.008)	(0.007)	
Log firm size	0.013***	0.004***	0.010***	0.003***
	(0.000)	(0.000)	(0.001)	(0.000)
Collective agreement	0.025***	0.004	0.046***	-0.010***
	(0.003)	(0.002)	(0.003)	(0.002)
Work region	YES	YES	YES	YES
Industry	YES	YES	YES	YES
Occupation	YES	YES	YES	YES
Adjusted R-squared	0.600	0.604	0.298	0.079
Number of observations	94,697	94,697	94,697	94,697

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Presented are the Ordinary Least Squares (OLS) estimates. Dependent variable for each model is indicated within panel titles. Reference category for 'non-UK-born' is UK-born employees, for ethnicity white, and for education no qualification. All models also include a constant term. Figures in ( ) are robust standard errors. *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively. See text for sample construction and variable definitions.

Table B4a. Sensitivity analysis, UK-born employees and non-UK-born employees with less than 10 years of residence in the UK

	(1) Weighted to account for linkage biases	(2) Include linkage match quality score of 1.0	(3) Cluster standard error at employer level	(4) Exclude employees working outside England and Wales	(5) Exclude part-time employees	(6) Include only 25-54 years old employees	(7) Control for extended personal characteristics	(8) Control for sector	(9) Control for detailed industry	(10) Control for detailed occupation	(11) Probit model estimates
Panel A. Log gross hourly pay											
Non-UK-born	-0.051***	-0.052***	-0.056***	-0.056***	-0.054***	-0.063***	-0.056***	-0.054***	-0.040***	-0.051***	-
	(0.007)	(0.009)	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	
Adj. R-squared	0.606	0.597	0.600	0.600	0.558	0.574	0.601	0.600	0.624	0.642	
Panel B. Log weekly total paid hours											
Non-UK-born	0.040***	0.039***	0.040***	0.039***	0.029***	0.032***	0.038***	0.040***	0.038***	0.053***	-
	(0.005)	(0.007)	(0.006)	(0.005)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	
Adj. R-squared	0.608	0.601	0.605	0.606	0.236	0.608	0.606	0.605	0.612	0.173	
Panel C. Probability of employment in low-skilled occupations											
Non-UK-born	0.065***	0.058***	0.067***	0.066***	0.066***	0.080***	0.068***	0.064***	0.052***	-	0.067***
	(0.008)	(0.010)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)		(0.008)
Adj. R-squared	0.314	0.294	0.296	0.296	0.230	0.281	0.297	0.297	0.332		0.245
Panel D. Probability of temporary employment											
Non-UK-born	0.030***	0.028***	0.029***	0.030***	0.030***	0.037***	0.032***	0.030***	0.016***	0.052***	0.019***
	(0.006)	(0.007)	(0.007)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Adj. R-squared	0.091	0.089	0.085	0.085	0.065	0.078	0.086	0.086	0.186	0.020	0.233
Number of obs.	92,151	62,405	92,795	92,489	67,503	72,455	92,795	92,791	92,795	92,795	92,795

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Presented are the Ordinary Least Squares (OLS) estimates (except in column (11) where average marginal effects from a probit model estimate is presented). Unweighted results (except in column (1)). Dependent variable is indicated within panel titles. All models also control for personal characteristics including age (and its square), gender, ethnicity, education, disability, marital status; presence of dependent children (except in column (7) where number of dependent children, age of the youngest dependent child, religion and general health status are controlled for); work-related characteristics including tenure (and its square), part-time (except in column (5)), temporary employment contract (except in Panel D), log firm size, collective agreement, industry (eleven categories for SIC07 regrouped sections (except in column (9) where 265 SIC07 groups are controlled for)), occupation (except in Panel C) (nine categories for SOC10 major groups (except in column (10) where 90 SOC10 minor groups are controlled for)) and a constant term. Figures in ( ) are robust standard errors except in columns (3) and (11) where employer level clustered and delta-method standard errors are reported, respectively. In column (11) reported is the Pseudo R-squared. *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively. See text for sample construction and variable definitions.

Table B4b. Sensitivity analysis, UK-born employees and non-UK-born employees with 10 or more years of residence in the UK

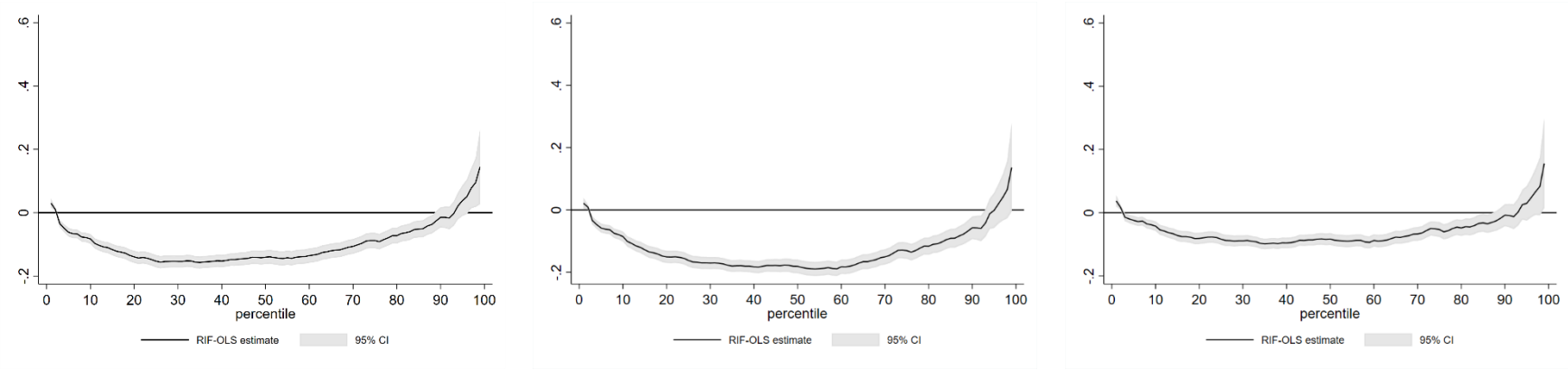
	(1) Weighted to account for linkage biases	(2) Include linkage match quality score of 1.0	(3) Cluster standard error at employer level	(4) Exclude employees working outside England and Wales	(5) Exclude part-time employees	(6) Include only 25-54 years old employees	(7) Control for extended personal characteristics	(8) Control for sector	(9) Control for detailed industry	(10) Control for detailed occupation	(11) Probit model estimates
Panel A. Log gross hourly pay											
Non-UK-born	0.010	0.001	0.007	0.006	0.007	0.006	0.009	0.007	0.012*	0.006	-
	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)	
Adj. R-squared	0.605	0.596	0.600	0.600	0.557	0.574	0.601	0.600	0.624	0.642	
Panel B. Log weekly total paid hours											
Non-UK-born	0.007	0.007	0.007	0.007	0.007***	0.007	0.008	0.007	0.008	0.015*	-
	(0.005)	(0.005)	(0.005)	(0.004)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	
Adj. R-squared	0.607	0.601	0.604	0.604	0.235	0.607	0.605	0.604	0.611	0.173	
Panel C. Probability of employment in low-skilled occupations											
Non-UK-born	-0.002	0.002	-0.003	-0.003	-0.000	-0.003	-0.005	-0.003	-0.004	-	-0.002
	(0.006)	(0.008)	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)		(0.006)
Adj. R-squared	0.315	0.296	0.298	0.298	0.231	0.283	0.299	0.299	0.333		0.246
Panel D. Probability of temporary employment											
Non-UK-born	0.000	-0.002	0.000	0.000	0.001	0.003	0.001	0.000	-0.001	0.002	0.002
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Adj. R-squared	0.085	0.084	0.079	0.079	0.057	0.069	0.080	0.080	0.168	0.017	0.224
Number of obs.	94,038	63,840	94,697	94,401	68,784	73,520	94,697	94,693	94,697	94,697	94,697

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Presented are the Ordinary Least Squares (OLS) estimates (except in column (11) where average marginal effects from a probit model estimate is presented). Unweighted results (except in column (1)). Dependent variable is indicated within panel titles. All models also control for personal characteristics including age (and its square), gender, ethnicity, education, disability, marital status; presence of dependent children (except in column (7) where number of dependent children, age of the youngest dependent child, religion and general health status are controlled for); work-related characteristics including tenure (and its square), part-time (except in column (5)), temporary employment contract (except in Panel D), log firm size, collective agreement, industry (eleven categories for SIC07 regrouped sections (except in column (9) where 265 SIC07 groups are controlled for)), occupation (except in Panel C) (nine categories for SOC10 major groups (except in column (10) where 90 SOC10 minor groups are controlled for)) and a constant term. Figures in ( ) are robust standard errors except in columns (3) and (11) where employer level clustered and delta-method standard errors are reported, respectively. In column (11) reported is the Pseudo R-squared. *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively. See text for sample construction and variable definitions.

Table B5. Sensitivity analysis, alternative measures of hourly pay and weekly hours

	(1) Log gross hourly pay excluding overtime	(2) Log basic hourly pay	(3) Log weekly basic paid hours
Panel A. Non-UK-born employees with less than 10 years of residence in the UK			
Non-UK-born	-0.056***	-0.058***	0.043***
	(0.007)	(0.006)	(0.008)
Adjusted R-squared	0.599	0.614	0.171
Number of observations	92,795	92,795	92,795
Panel B. Non-UK-born employees with less than 10 years of residence in the UK			
Non-UK-born	0.006	0.005	0.014*
	(0.006)	(0.006)	(0.006)
Adjusted R-squared	0.598	0.613	0.171
Number of observations	94,697	94,697	94,697

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Presented are the Ordinary Least Squares (OLS) estimates. Dependent variable for each model is indicated within panel titles. Reference category for 'non-UK-born' is UK-born employees. Personal characteristics include age (and its square), gender, ethnicity, education, disability, marital status, presence of dependent children, and work region (eleven NUTS1 categories). Work-related characteristics are tenure (and its square), part-time, temporary employment contract (except in Panel (D)), log firm size, collective agreement, industry (eleven categories for SIC07 regrouped sections), and occupation (except in Panel (C)) (nine categories for SOC10 major groups). All models also include a constant term. Figures in ( ) are robust standard errors. *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively. See text for sample construction and variable definitions.



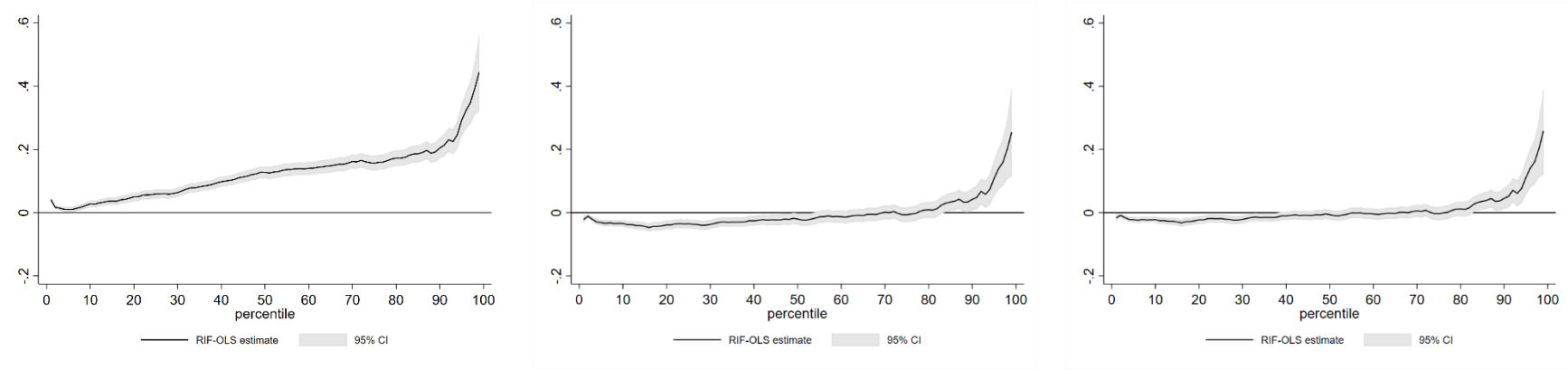
a. Unconditional

b. Conditional on personal characteristics

c. Conditional on personal and work-related characteristics

Figure B1a. Difference in log gross hourly pay between UK-born employees and non-UK employees with less than 10 years of residence in the UK across the distribution

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Presented are the point estimates of the 'non-UK-born' dummy from a series of unconditional quantile regressions across the percentiles of the log gross hourly pay distribution. Reference category for 'non-UK-born' is UK-born employees. Personal characteristics include age (and its square), gender, ethnicity, education, disability, marital status, presence of dependent children, and work region (eleven NUTS1 categories). Work-related characteristics are tenure (and its square), part-time, temporary employment contract (except in Panel (D)), log firm size, collective agreement, industry (eleven categories for SIC07 regrouped sections), occupation (except in Panel (C)) (nine categories for SOC10 major groups). All models include a constant term. Grey shaded area represent the 95% confidence interval (CI). See text for sample construction and variable definitions.



a. Unconditional

b. Conditional on personal characteristics

c. Conditional on personal and work-related characteristics

Figure B1b. Difference in log gross hourly pay between UK-born employees and non-UK employees with 10 or more years of residence in the UK across the distribution

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Presented are the point estimates of the 'non-UK-born' dummy from a series of unconditional quantile regressions across the percentiles of the log gross hourly pay distribution. Reference category for 'non-UK-born' is UK-born employees. Personal characteristics include age (and its square), gender, ethnicity, education, disability, marital status, presence of dependent children, and work region (eleven NUTS1 categories). Work-related characteristics are tenure (and its square), part-time, temporary employment contract (except in Panel (D)), log firm size, collective agreement, industry (eleven categories for SIC07 regrouped sections), occupation (except in Panel (C)) (nine categories for SOC10 major groups). All models include a constant term. Grey shaded area represent the 95% confidence interval (CI). See text for sample construction and variable definitions.

Table B6a. Detailed Oaxaca-Blinder decomposition results, UK-born employees and non-UK-born employees with less than 10 years of residence in the UK

	(1) Log gross hourly pay	(2) Log weekly total paid hours	(3) Probability of employment in low-skilled occupations	(4) Probability of temporary employment
Observed gap	0.095***	-0.049***	-0.074***	-0.068***
	(0.009)	(0.007)	(0.008)	(0.005)
Explained gap	0.039***	-0.009	-0.014*	-0.041***
	(0.008)	(0.006)	(0.007)	(0.003)
	[40.85]	[18.95]	[18.34]	[59.89]
Unexplained gap	0.056***	-0.039***	-0.060***	-0.027***
	(0.007)	(0.006)	(0.008)	(0.006)
	[59.15]	[81.05]	[81.66]	[40.11]
Components of the explained gap				
Female	-0.002*	-0.001*	0.002*	-0.000
	(0.001)	(0.000)	(0.001)	(0.000)
	[-2.18]	[1.65]	[-3.32]	[0.26]
Ethnicity	0.031***	0.006*	-0.032***	-0.008**
	(0.003)	(0.003)	(0.004)	(0.003)
	[32.69]	[-11.79]	[43.78]	[11.97]
Age	0.020***	-0.003***	0.005***	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
	[20.60]	[7.07]	[-6.86]	[0.68]
Education	-0.014***	-0.006***	0.022***	-0.003**
	(0.003)	(0.002)	(0.004)	(0.001)
	[-15.27]	[12.11]	[-30.05]	[5.03]
Work region	-0.059***	0.003***	0.015***	0.002**
	(0.002)	(0.001)	(0.001)	(0.000)
	[-62.60]	[-5.70]	[-19.83]	[-2.32]
Marital status	-0.006***	0.001**	0.004***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
	[-5.93]	[-1.32]	[-6.00]	[-0.93]
Disability	-0.002***	-0.001***	0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
	[-1.60]	[1.61]	[-1.55]	[-0.09]
Presence of dependent children	-0.003***	0.003***	0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
	[-2.82]	[-6.45]	[-1.97]	[0.00]
Tenure	0.044***	0.007***	-0.031***	-0.029***
	(0.001)	(0.001)	(0.001)	(0.001)
	[46.36]	[-15.12]	[42.32]	[43.42]
Part-time employment	-0.003***	-0.029***	0.007***	0.002***
	(0.001)	(0.005)	(0.001)	(0.000)
	[-3.66]	[58.96]	[-9.51]	[-2.91]
Temporary emp. contract	0.002***	0.010***	-0.003***	-
	(0.000)	(0.001)	(0.001)	
	[2.13]	[-20.35]	[4.12]	
Log firm size	0.001	0.000	0.001	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
	[1.06]	[-0.55]	[-1.08]	[-0.40]
Collective agreement	0.003***	0.000	0.005***	-0.001***
	(0.000)	(0.000)	(0.001)	(0.000)

	[2.78]	[-0.82]	[-6.33]	[1.48]
Industry	-0.009***	-0.009***	-0.011***	0.003***
	(0.001)	(0.001)	(0.001)	(0.000)
	[-8.99]	[18.52]	[14.61]	[-4.20]
Occupation	0.036***	0.009***	-	-0.005***
	(0.004)	(0.001)		(0.000)
	[38.28]	[-18.88]		[7.89]
Number of observations	92,795	92,795	92,795	92,795

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Presented are the Oaxaca-Blinder decomposition results performed using a model which includes personal and work-related characteristics. Dependent variable for each model is indicated within column titles. Decompositions use the relevant male coefficients as the baseline. Figures in ( ) are robust standard errors. Figures in [ ] are proportions of observed gap. *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively. See text for sample construction and variable definitions.

Table B6b. Detailed Oaxaca-Blinder decomposition results, UK-born employees and non-UK-born employees with 10 or more years of residence in the UK

	(1) Log gross hourly pay	(2) Log weekly total paid hours	(3) Probability of employment in low-skilled occupations	(4) Probability of temporary employment
Observed gap	-0.125***	-0.007	0.028***	-0.005
	(0.008)	(0.006)	(0.007)	(0.003)
Explained gap	-0.131***	0.004	0.035***	-0.007**
	(0.006)	(0.005)	(0.005)	(0.003)
	[104.73]	[-49.89]	[125.48]	[148.19]
Unexplained gap	0.006	-0.011*	-0.007	0.002
	(0.006)	(0.005)	(0.007)	(0.004)
	[-4.73]	[149.89]	[-25.48]	[-48.19]
Components of the explained gap				
Female	0.003**	0.001**	-0.003**	0.000**
	(0.001)	(0.000)	(0.001)	(0.000)
	[-2.14]	[-14.19]	[-11.57]	[-4.69]
Ethnicity	0.033***	0.007*	-0.034***	-0.009***
	(0.003)	(0.003)	(0.004)	(0.003)
	[-26.59]	[-89.09]	[-123.61]	[182.74]
Age	-0.023***	-0.006***	0.005***	0.002***
	(0.001)	(0.001)	(0.001)	(0.000)
	[18.26]	[79.06]	[17.12]	[-42.83]
Education	-0.028***	-0.000	0.044***	-0.002***
	(0.002)	(0.001)	(0.003)	(0.000)
	[22.21]	[3.00]	[158.88]	[39.48]
Work region	-0.082***	0.004***	0.019***	0.002**
	(0.002)	(0.001)	(0.001)	(0.001)
	[65.86]	[-53.10]	[68.96]	[-41.47]
Marital status	-0.006***	0.001**	0.005***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
	[5.07]	[-9.87]	[18.14]	[-14.49]
Disability	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
	[-0.09]	[-0.76]	[-0.30]	[0.09]
Presence of dependent children	-0.002***	0.003***	0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
	[1.91]	[-38.17]	[4.71]	[0.04]
Tenure	0.001	-0.000	-0.001*	0.001*
	(0.001)	(0.000)	(0.001)	(0.001)
	[-0.57]	[2.55]	[-4.96]	[-22.74]
Part-time employment	-0.001*	-0.009*	0.002*	0.001*
	(0.000)	(0.004)	(0.001)	(0.000)
	[0.87]	[122.36]	[7.98]	[-12.51]
Temporary emp. contract	0.000	0.001	-0.000	-
	(0.000)	(0.000)	(0.000)	
	[-0.12]	[-9.81]	[-0.80]	
Log firm size	-0.002***	-0.000**	-0.001**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
	[1.32]	[6.04]	[-4.76]	[9.00]
Collective agreement	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)

	[0.03]	[0.07]	[-0.23]	[-0.27]
Industry	-0.000	-0.001*	-0.001	-0.001**
	(0.001)	(0.000)	(0.001)	(0.000)
	[0.39]	[15.62]	[-4.09]	[25.00]
Occupation	-0.023***	0.005***	-	-0.002***
	(0.003)	(0.001)		(0.000)
	[18.32]	[-63.60]		[30.84]
Number of observations	94,697	94,697	94,697	94,697

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Presented are the Oaxaca-Blinder decomposition results performed using a model which includes personal and work-related characteristics. Dependent variable for each model is indicated within column titles. Decompositions use the relevant male coefficients as the baseline. Figures in ( ) are robust standard errors. Figures in [ ] are proportions of observed gap. *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively. See text for sample construction and variable definitions.

Table B7. Decomposition of the log gross hourly pay difference between UK-born and non-UK-born employees across the distribution, selected percentiles

	(1) 10th percentile	(2) 25th percentile	(3) 50th percentile	(4) 75th percentile	(5) 90th percentile
Panel A. Non-UK-born employees with less than 10 years of residence in the UK					
Observed gap	0.064***	0.125***	0.157***	0.114***	0.026
	(0.004)	(0.007)	(0.011)	(0.016)	(0.021)
Explained gap	0.028***	0.060***	0.051***	0.042***	0.015***
	(0.006)	(0.008)	(0.010)	(0.012)	(0.013)
	[44.29]	[47.93]	[32.49]	[37.22]	[57.05]
Unexplained gap	0.036***	0.065***	0.106***	0.071***	0.011
	(0.006)	(0.008)	(0.010)	(0.014)	(0.021)
	[55.71]	[52.07]	[67.51]	[62.78]	[42.95]
Number of observations	92,795	92,795	92,795	92,795	92,795
Panel B. Non-UK-born employees with 10 or more years of residence in the UK					
Observed gap	-0.031***	-0.064***	-0.135***	-0.158***	-0.192***
	(0.007)	(0.009)	(0.010)	(0.012)	(0.017)
Explained gap	-0.060***	-0.090***	-0.144***	-0.170***	-0.178***
	(0.004)	(0.006)	(0.008)	(0.010)	(0.012)
	[192.73]	[139.83]	[106.47]	[107.62]	[92.62]
Unexplained gap	0.029***	0.026**	0.009	0.012	-0.014
	(0.007)	(0.008)	(0.009)	(0.012)	(0.019)
	[-92.73]	[-39.83]	[-6.47]	[-7.62]	[7.38]
Number of observations	94,697	94,697	94,697	94,697	94,697

Notes: Author's calculations based on ASHE linked to the 2011 Census - England and Wales. Presented are the unconditional quantile decomposition results performed using a model which includes personal and work-related characteristics. Dependent variable for each model is log gross hourly pay. Decompositions use the relevant male coefficients as the baseline. Figures in ( ) are robust standard errors. Figures in [ ] are proportions of observed gap. *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively. See text for sample construction and variable definitions.