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ORIGINAL ARTICLE

Performance-related pay and the UK gender pay gap

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Abstract

Applying decomposition methods to data from the Annual Survey of Hours and Earnings, we highlight the importance of performance-related pay to the contemporary UK gender pay gap. We find that the lower probability of females being employed in performance-related pay jobs explains a sizeable proportion of the gender pay gap, particularly at the top end of the annual earnings distribution. The latter is driven by its influence within the private sector.

JEL CLASSIFICATION
J31, J33, J45, J71

INTRODUCTION

The extensive international evidence on the gender pay gap (GPG) is predominately based on analysis of usual hourly pay and tends to neglect the role of specific components of pay. Yet, there has been growing emphasis on the role of gender gaps in pay systems where remuneration is in part based on performance, or performance-related pay (PRP).[1] This is both due to evidence of gender differences in the probability of employment in PRP jobs (Manning & Saidi, 2010, for the UK; McGee et al., 2015, for the USA; Xiu & Gunderson, 2013, for China; Zizza, 2013, for Italy) and gender differences in reward to PRP jobs, particularly at the top end of the wage distribution (de la Rica et al., 2015), where there is likely to be greater discretion and/or subjectivity in allocation (Green et al., 2014).[2]

In this study, we quantify the role of PRP to the UK GPG.[3] More specifically, we use high-quality employer-provided information on annual pay and PRP from the UK Annual

[1]Common types of PRP are (i) piecework schemes, (ii) payment by results, (iii) plant or organization incentives, (iv) bonus earnings or pay progression on an assessment or appraisal of an employee's (or team's) performance against previously set objectives, (v) merit pay, (vi) competence-based pay, and (vii) profit related pay (see UNISON, 2017). Unfortunately, our data do not allow us to distinguish the type of PRP. While potentially based on performance, we do not consider promotions as PRP.

[2]The contribution of PRP to gender inequality in the UK has also been recognized by policymakers, with measures of gender gaps in bonuses included in Gender Pay Gap Transparency Legislation.

[3]In terms of UK policy, PRP is considered in a similar way to basic pay, both in relation to equality (the 2010 Equality Act) and taxation legislation. Unlike in some countries (e.g., France (see Nimier-David et al., 2023)), there is no requirement on employers to provide PRP.

Survey of Hours and Earnings (ASHE) and apply a detailed Oaxaca-Blinder (OB) decomposition method at the mean (Blinder, 1973; Oaxaca, 1973) and across the (unconditional) earnings distribution (Firpo et al., 2009, 2018) to quantify the contribution of employment in PRP jobs to the explained and unexplained components of the GPG. Given well-established differences in the prevalence of PRP between the public and private sectors, we also perform a similar within-sector analysis. As such, we provide new evidence on the role of gender differences in employment in PRP jobs, and differential rewards to PRP jobs, to the UK GPG at the mean and across the distribution, and within each sector. In doing so, we contribute contemporary UK evidence to recent international studies on the role of the PRP on the GPG (e.g., Heywood & Parent, 2017, for the USA; Hirsch & Lentge, 2022, for Germany), add to the literature investigating the drivers of the GPG over the earnings distribution (e.g., Arulampalam et al., 2007; Kaya, 2021) and across sectors (e.g., Chatterji et al., 2011; Jones et al., 2018), and contribute to the broader debate as to whether PRP increases wage inequality for groups defined by protected characteristics (Green et al., 2014; Heywood & Parent, 2012).

We find that PRP jobs are an important but overlooked factor in explaining the mean UK GPG. Gender differences in employment in PRP jobs account for 2.6 percentage points or 6% of the observed annual GPG. Indeed, PRP is more important than a range of work-related characteristics typically explored within the literature including tenure, temporary employment, and sector. The role of PRP is robust to controlling for unobserved employer heterogeneity or accounting for the potential selection into, and therefore endogeneity of, PRP jobs. Driven by its influence in the private sector, PRP provides a particularly important contribution at the upper end of the earnings distribution, at the 90th percentile PRP accounts for 5.0 percentage points (13%) of the UK annual GPG or, nearly a third of the explained GPG. While gender differences in the reward to PRP play a more modest role on average, they serve to further widen the GPG, particularly at the bottom of the private-sector pay distribution.

The remainder of this study is structured as follows. Section 2 reviews the existing evidence on the relationship between PRP and the GPG and considers the potential differences by sector. Section 3 introduces the data and measures employed in the analysis. Section 4 sets out the econometric methods and findings exploring the relationship between PRP and the GPG, both at the mean and across the distribution. We examine the robustness of these results in Section 5. Sectoral differences in the relationship between PRP and the GPG are explored in Section 6. Section 7 briefly concludes.

PRP AND THE GPG

The GPG might depend on PRP in two main ways. First, if there are gender differences in the probability of employment in PRP jobs and there is a pay differential between PRP and non-PRP jobs this would give rise to a GPG. Second, the reward to working in a PRP job might differ by gender.

It is well documented that women are less likely than men to receive PRP (see Booth & Frank, 1999, and Manning & Saidi, 2010, for the UK; McGee et al., 2015, for the USA; Xiu & Gunderson, 2013, for China; Zizza, 2013, for Italy), but the reasons for this are difficult to distinguish. Gender differences in risk preferences, particularly evidence that on average women exhibit a lower preference for competition (Niederle & Vesterlund, 2007) and are more risk averse than men (Charness & Gneezy, 2012), will likely reduce female employment in PRP roles where pay is subject to an element of uncertainty. However, discrimination theory offers an additional explanation. For example, employer prejudice might influence the allocation of discretionary bonus payments, resulting in females being less likely to be in PRP roles.

Discrimination theory also provides useful insights into potential gender differences in the reward to PRP. Models of personal prejudice or 'taste-based discrimination' (Becker, 1957) and statistical discrimination (Phelps, 1972) suggest that employers might discriminate against women when there is greater discretion in rewards and where productivity is observed less accurately, respectively. On the one hand, the introduction of remuneration systems based on objective measures of performance may lead to increased transparency in pay and a more direct relationship between pay and productivity, and, as a result, may narrow gender differences in the reward to PRP jobs.[4] On the other hand, when individual performance is more difficult to observe or measure, then the GPG might increase with PRP since payments will be based on more subjective evaluations.[5] Gender differences in the competitive response to PRP (Gneezy et al., 2003) might provide an alternative explanation for gender differences in the reward to PRP jobs. In terms of empirical studies, while there is consistent evidence of a gender gap in the amount of PRP received, there is less consensus as to its relative magnitude compared to the GPG in base pay. For example, while Xiu and Gunderson (2013) show that conditional on receipt of PRP, women receive a lower amount of PRP relative to males in China, they find the unexplained gender gap in PRP is similar to that in base pay. In contrast, de la Rica et al. (2015) find a larger unexplained gender gap in PRP relative to non-PRP components of pay in Spain.

Despite this evidence, PRP is not routinely included as a control in analysis of the GPG (for a review, see Blau & Kahn, 2017).[6] In the UK context, while Booth and Frank (1999) do not explicitly explore the role of PRP on the GPG, they find no significant gender difference in the return to incentive bonuses or profit-related pay using data from the 1991 British Household Panel Survey but show that women are less likely to receive either of these forms of pay when compared to men. In the closest UK study to our own, Manning and Saidi (2010) conclude that PRP, measured at the workplace-occupational level, has only a small impact on the UK hourly GPG at the mean. Using data from the 1998 and 2004 Workplace Employment Relations Survey (WERS), in a similar manner to Booth and Frank (1999), they find the returns to PRP to be similar by gender but suggest there is also only a modest gender gap in the incidence of PRP. A more prominent role for a gender gap in receipt of PRP is, however, identified in the USA by McGee et al. (2015), at least when using data from the 1997 cohort of the National Longitudinal Surveys of Youth (maximum 12% of the hourly GPG).[7]

Green et al. (2014) hypothesize that the influence of PRP on pay inequality will differ across the pay distribution, with PRP at bottom end of the distribution more likely to be based on objective measures of performance, whereas toward the top end of the earnings distribution, PRP will be more likely to depend on subjective evaluations reflecting increasing task complexity. Consistent with this, de la Rica et al. (2015) find a 'glass ceiling' pattern in the unexplained gender gap in the amount of PRP in Spain and, in the context of ethnicity, Heywood and Parent (2012) find that the racial earnings gap is larger in PRP jobs in the USA, especially at the top of the earnings distribution.[8] Also in the US context, Heywood and Parent (2017) find that the GPG is larger in PRP jobs than non-PRP jobs and that this increases at the top of the earnings distribution due to differences among parents. In Germany, Hirsch and

[4]Consistent with this, output-based performance pay, particularly piece rates, has been found to reduce the GPG (Jirjahn & Stephan, 2004). In this case, women might also select into PRP jobs based on objective measures of performance (Geddes & Heywood, 2003; Xiu & Gunderson, 2013).

[5]Discrimination is not necessarily confined to employers. Customer discrimination might similarly affect commission.

[6]Studies on the GPG typically either exclude PRP or do not distinguish PRP from basic pay.

[7]Kangasniemi and Kauhanen (2013) consider the role of separate elements of PRP on the GPG among selected industries in Finland and find that while bonuses have only a small impact after accounting for unobserved individual and firm effects, piece rates and reward rates widen gender earnings inequality.

[8]In contrast, Green et al. (2014) find lower ethnic earnings gap among PRP than non-PRP jobs in the UK.

Lentge (2022) find that lower bonus payments among women explain about 10% of the mean private sector hourly GPG, and this increases higher up the earnings distribution.

In terms of sectoral differences, it is well established that the hourly GPG is typically narrower in the UK public relative to the private sector. Further analysis suggests this is also true after accounting for worker and job-related characteristics (Chatterji et al., 2011; Jones et al., 2018) consistent with greater gender equality, possibly a consequence of the more stringent requirements of existing equality legislation (the 2010 Equality Act), such as the Public Sector Equality Duty.[9] Indeed, studies have highlighted the role of enhanced equality policies and practices (Jones et al., 2018), family-friendly practices (Chatterji et al., 2011), higher rates of union membership (Jones et al., 2018), and greater formalization and transparency of the wage structures (Stewart, 2014) as determinants of greater pay equality within the public sector. PRP has not, however, featured in this debate despite evidence that it widens the earnings distribution in the private sector (see Lemieux et al., 2009, for the USA and Bryson et al., 2018, for the UK), which itself has been associated with an increasing GPG in international comparisons (Blau & Kahn, 1992). Moreover, while recognized as having potential benefits for efficiency and service delivery in the public sector, PRP remains much less prevalent in the UK public sector relative to the private sector (Bryson et al., 2017).[10] Yet, its increasing prevalence (see, e.g., Makinson, 2000, and Winsor, 2011) has generated concerns from unions and Pay Review Bodies about the implications for gender equality.

DATA

The analysis utilizes data from ASHE, the main source of earnings data in the UK, which are based on mandatory reporting by employers to the Office for National Statistics (ONS) and contain detailed and reliable information on pay, including performance-related pay, for a large sample (1% of employee jobs) (ONS, 2022).[11] We provide contemporary evidence, based on April 2019, which pre-dates changes in reward brought by COVID-19 or the subsequent cost-of-living crisis.[12] Pay information from ASHE is recognized as high quality, being based on employer records. ASHE also has several further advantages in this context, particularly that these data are nationally representative, and contain a measure of annual PRP and a comprehensive set of job characteristics, including an accurate measure of sector.[13]

Our sample is restricted to employees who are in their main job, paid an adult (rather than trainee or junior) rate, and whose reference period earnings are not affected by absence.[14,15] Our

[9]A narrower public-sector GPG is not unique to the UK (see Arulampalam et al., 2007, for EU countries).

[10]The challenges of using the PRP schemes in the public sector due to the nature of its activities, where outcomes are complex, difficult to measure and potentially have a wide social impact, have been recognized. It has also been suggested that public-sector employees have 'public service motivation', that is the intrinsic motivation derived from providing the service (see, for a review, Bajorek & Bevan, 2015).

[11]Observations from Northern Ireland are not included in ASHE data in the Secure Data Service.

[12]These data are currently provisional, but the findings are robust to using 2018 (see Section 5).

[13]The main alternative data sources, WERS, Labour Force Survey (LFS), and Understanding Society (USoc) collect self-reported information on pay and PRP. As such, they are subject to more limited response rates and greater measurement error. Additionally, while more detailed categories of PRP are collected in WERS and the LFS, the most recent data for the former are 2011 and pay is reported in bands, whereas in the LFS, PRP is collected for employees whose self-reported last pay contains additions to basic pay and will therefore neglect PRP outside the reference period. The information on PRP is less detailed in USoc but bonuses (whether related to PRP or not) are distinguished from any PRP. Furthermore, none of these surveys contain information on the amount of PRP. The trade-off is that these surveys contain a more comprehensive information on personal characteristics relative to ASHE.

[14]Following Jewell et al. (2020), where relevant, we impute industry for all employees with the same employer as the modal value and drop remaining inconsistent observations.

[15]We exclude those employed in a non-profit body or mutual association given our comparison between the public and private sectors in Section 6, but our results are robust to this choice (see Section 5).

analysis is weighted, so that the estimates of employee jobs are representative of the respective population, but we also report the unweighted number of observations. After excluding those with missing values for any of the variables used in the analysis, our sample contains 141,230 employees.

PRP

There is no universal definition or measure of PRP within the literature. ASHE contains objective information on PRP based on employer payroll records which contrasts to much of the literature that relies on self-reported information from employees. The latter is potentially affected by recall bias and individual differences in understanding and interpretation of elements of PRP. PRP is defined in ASHE to include payments as a result of meeting a performance or productivity objective, such as profit sharing, bonuses, piecework, and commission payments but does not allow separation of these components. It is measured during the reference period (within April each year) and over the last year. Our preferred PRP measure is annual since it enables us to accurately classify PRP jobs where for example, bonus payments might not be paid in the reference period. Indeed, PRP in the reference (pay) period, captures less than 17% of those who received PRP in the preceding year. In the absence of any detail on the specific type of PRP we focus on a binary variable which captures jobs where pay is linked to performance and classify jobs as PRP and non-PRP respectively (see, for a similar approach, Heywood & Parent, 2012).[16]

About 29% of our sample are in PRP jobs (see Table 1), and consistent with the literature, this is higher among males (36.1%) than females (22.3%). PRP accounts for 2.6% of total annual pay or 9.0% among those who have a PRP job. Among the latter, we find a gender gap in the average amount of annual PRP of 46.8% (£7198 for males compared to £3832 for females), which, albeit not adjusted for gender differences in characteristics, including annual hours, is larger than estimates of the observed GPG in annual pay (see below).

Annual pay

For consistency with our measure of PRP, and in order to capture infrequent PRP payments, we follow Green et al. (2014) and use (log) gross annual earnings including incentive pay as our main dependent variable.[17] Since ASHE does not contain information on total annual hours worked, we control for (log) total paid weekly hours during the reference period and a measure of (log) annual weeks worked (derived from gross annual earnings divided by gross weekly earnings following Papps & Greg, 2014).[18] Because the focus of the established GPG literature is typically hourly pay, we explore the sensitivity of our findings by utilizing hourly pay measure derived from annual gross earnings and annualized hours based on reference period weekly hours (Stokes et al., 2017) and hourly pay derived from earnings and hours worked within the reference period (Jewell et al., 2020) (see Section 4). The latter is based on the ONS recommended definition, excluding overtime, but including PRP paid within the reference period.

[16]It should be noted that, although throughout we refer to observations with zero annual PRP as non-PRP jobs, annual PRP may be zero for a given worker for other unobservable reasons including workers' poor performance. Our findings are robust to conditioning our sample on those who were employed in the same job for more than 1 year to enhance the measurement of annual PRP (see Section 5).

[17]This relates to the tax year ending April 5 of the reference year. We remove log annual pay outliers defined as above 10 times the 99th percentile and below half the 1st percentile, but our results are not sensitive to this (see Section 5).

[18]This assumes that weekly working hours during the reference period are an accurate reflection of average working hours per week during the year.

TABLE 1 PRP incidence and amount, and log annual pay by PRP jobs, by gender.

	Male	Female	All
Incidence of PRP (%)	36.11	22.26	29.39
Population size	11,266,833	10,608,538	21,875,370
Number of observations	68,520	72,710	141,230
Amount of PRP (£) (conditional on receipt)			
	7198.26 [3.38] {9.37}	3832.64 [1.85] {8.29}	5961.98 [2.64] {8.97}
Population size	4,068,024	2,361,852	6,429,877
Number of observations	24,320	15,949	40,269
Log annual pay PRP jobs			
	10.504 (0.695)	10.080 (0.806)	10.348 (0.763)
Population size	4,068,024	2,361,852	6,429,877
Number of observations	24,320	15,949	40,269
Log annual pay non-PRP jobs			
	9.926 (0.932)	9.550 (1.010)	9.725(0.992)
Population size	7198,809	8,246,685	15,445,494
Number of observations	44,200	56,761	100,961

Note: Authors' calculation using data from the ASHE 2019. See text for a description of sample construction and variable definitions. Figures in [] and {} represent PRP as a percentage of total annual pay for all employees and conditional on PRP receipt, respectively. Figures in () are standard deviations of the (log) annual pay.

Table 1 presents mean (log) annual gross earnings by gender for PRP and non-PRP jobs. Average annual pay and pay variation (measured by the standard deviation) are both higher in PRP jobs. The average observed pay premium for a PRP job is greater for men than women, which results in the observed annual GPG being wider in PRP jobs at 42.4%, compared to 37.6% for non-PRP jobs.[19] Of course, this could reflect gender differences in selection into PRP jobs, something we return to in Section 5.

Consistent with the literature (see, e.g., Green et al., 2014), the incidence of PRP also varies across the distribution, increasing in earnings for both males and females such that two-thirds of males and more than 45% of females in the top decile are in PRP jobs (see Figure S1). In absolute terms, the gender gap in PRP jobs also widens across the distribution, consistent with prior evidence of particularly large gender differences in the receipt of bonus payments among higher earners.

Explanatory variables

In addition to the controls to capture annualized hours outlined above, ASHE contains detailed information on work-related characteristics such that it is possible to control for a comprehensive range of employee and job characteristics correlated with PRP and known to explain the GPG. Our control variables for work-related characteristics are all well-established determinants of earnings and routinely included in studies of the GPG (see Blau & Kahn, 2017). We include characteristics of the firm such as (log) firm size measured by the number of employees within the organization, as well as the nature of the employment contract including whether the contract is temporary or part-time. To capture gender differences in on-the-job

[19]Throughout percentages are calculated as *exp*(log points) – 1.

human capital accumulation, we control for tenure (years in the present organization) (and tenure-squared). We further control for the coverage of collective agreements to capture the potential influence of unions on pay bargaining. We additionally control for sector, based on the legal status of the enterprise from the Inter-Departmental Business Register, and occupation (2010 Standard Occupational Classification (SOC) unit group) to capture gender differences in job roles.[20,21] While the inclusion of occupation within analysis of the GPG can be debated (see Albrecht et al., 2003) given the relationship between occupation and pay, we retain a measure of broad occupation to capture aggregate skill groups (see Gibbons et al., 2014). A similar argument could be made regarding sector, particularly if the choice to work in the public or private sector is influenced by the availability of PRP, and we explore the sensitivity of our findings to this in Section 5, but include sector in our benchmark specifications and therefore estimate the contribution of PRP to the GPG net of the relationship between sector and pay. In terms of personal characteristics, in addition to gender, ASHE contains information on age (and age-squared), which is used to proxy for work experience, and work region (11 NUTS regions of Great Britain) to capture regional wage differentials. Unfortunately, ASHE does not contain information on marital status or dependent children previously found to be important determinants of the GPG (Heywood & Parent, 2017).

Table S1 contains a full set of summary statistics for the explanatory variables by gender and for PRP and non-PRP jobs.[22] They identify several distinct features of PRP jobs, particularly lower rates of public sector, part-time and temporary employment, larger average firm size, and greater representation in occupations such as Managers, directors and senior officials, and Associate professional and technical occupations. While some established patterns by gender are evident across PRP and non-PRP jobs, for example, females have higher rates of part-time employment, there are also some distinct features. For instance, while females are less likely than men to work in professional occupations in PRP jobs, the reverse is true in non-PRP jobs.

ANALYSIS OF PRP AND THE GPG

We first explore the mean GPG using established decomposition methods (Blinder, 1973; Oaxaca, 1973), widely applied in the international literature.[23] Our focus is isolating the contribution of employment in PRP jobs to the so-called explained and unexplained elements of the GPG. To do this, we estimate the following ordinary least squares (OLS) earnings equation for each gender g (male (m) and female (f)):

$$lnE_i^g = \delta^g PRP_i^g + X_i^g \beta^g + \varepsilon_i^g \tag{1}$$

where the natural logarithm of gross annual earnings of individual i and gender g (lnE_i^g) is regressed on a binary indicator of being employed in a PRP job (PRP_i^g), controls to capture annual hours, and the personal and work-related characteristics outlined above along with a constant term $\left(X_i^g\right)$, and ε_i^g is a random error term. In this way, we allow the return to characteristics (β^g), including employment in PRP jobs (δ^g), to vary by gender.

[20] Sector is excluded in the analysis of the public and private sectors separately. According to this classification jobs in public corporation and nationalized industries, central government or local authority are classified as public; those that are in private company, sole proprietor, or partnership are classified as private.

[21] We do not control for industry due to its overlap with sector, but our findings are robust to its inclusion (see Section 5).

[22] Figures S2a–d further present the incidence of PRP by age group, job tenure bands, firm size bands and broad industry for all employees, and by gender.

[23] Following Green et al. (2014), we also estimate a pooled regression model with an interaction between PRP and gender to explore variation in the GPG between PRP and non-PRP jobs. The adjusted GPG is about 50% larger in PRP jobs, consistent with PRP widening earnings inequality (see Table S2).

This approach facilitates an OB decomposition of the observed GPG into its explained and unexplained components as follows:

$$\overline{lnE}^m - \overline{lnE}^f = \hat{\delta}^m\left(\overline{PRP}^m - \overline{PRP}^f\right) + \left(\overline{X}^m - \overline{X}^f\right)\hat{\beta}^m + \left(\hat{\delta}^m - \hat{\delta}^f\right)\overline{PRP}^f + \overline{X}^f\left(\hat{\beta}^m - \hat{\beta}^f\right) \quad (2)$$

where the bar above a variable denotes the mean value, and $\hat{\delta}^g$ and $\hat{\beta}^g$ are the OLS estimates of coefficient δ^g and coefficient vector β^g, respectively. The first two terms on the right-hand side of Equation (2) comprise the 'explained GPG' and measure that part of the GPG due to gender differences in the observable characteristics, while the third and fourth terms, referred as the 'unexplained GPG', reflect gender differences in the return to those attributes and is often interpreted as an upper bound measure of unequal treatment.[24] As our focus is on the contribution of PRP to the GPG, Equation (2) is formulated to isolate the contribution of PRP to both the explained and unexplained gaps.[25]

To further explore the GPG across the earnings distribution, we utilize a technique developed by Firpo et al. (2009) that is based on a recentered influence function (RIF). In this approach, for quantile $q(\tau)$, the RIF can be expressed as follows:

$$RIF\left(Y; q(\tau), F_Y\right) = q(\tau) + \frac{(\tau - \mathbb{1}\{Y \leq q(\tau)\})}{f_Y(q(\tau))} \quad (3)$$

where $\mathbb{1}\{\cdot\}$ is an indicator function for whether the observed value of the dependent variable Y is at or below quantile $q(\tau)$, F_Y denotes the marginal (unconditional) distribution, and $f_Y(q(\tau))$ is the density at quantile $q(\tau)$. The unconditional quantile regression method proposed by Firpo et al. (2009) is similar to a standard regression, where the dependent variable is replaced by the $RIF\left(Y; q(\tau), F_Y\right)$ (RIF regression). The RIF regression coefficients capture the marginal effect of a change in covariates on the unconditional quantile of the dependent variable and in its simplest form can be estimated using OLS (RIF-OLS) (Firpo et al., 2009). To decompose the GPG across the entire earnings distribution, a standard OB decomposition can be carried out by using the estimated coefficients of the RIF regression (RIF-OB decomposition).

Parallel to our analysis at the mean, in our distributional analysis, we apply the OB decompositions based on separate RIF-OLS regressions for men and women at various quantiles using a specification that mimics Equation (1). In particular, we perform the RIF-OB decomposition as proposed by Firpo et al. (2018), which uses a multistep procedure in combination with a reweighting strategy by DiNardo et al. (1996) by estimating the RIF for each quantile $q(\tau)$ defined in Equation (3) and then fitting the RIF-OLS model conditional on covariates defined in Equation (1) where the estimated RIF is the dependent variable.[26,27] As at the mean, our focus is on the contribution of PRP to the explained and unexplained components of the GPG across the earnings distribution.

We present our decomposition results in Table 2 where estimates at the mean are presented in column (1) and those in columns (2)–(6) relate to selected points of the earnings

[24]Following Blau and Kahn (2017), Equation (2) assumes the male returns represent competitive prices. Our findings are, however, robust to using the female returns (see Section 5).

[25]Given the detailed decomposition of the unexplained gap depends on the choice of omitted category for categorical variables, we compute the decomposition based on normalized effects following Yun (2005).

[26]We do this using the Stata *oaxaca_rif* procedure (Rios-Avila, 2020).

[27]In a similar manner to the mean, we also estimate pooled RIF-OLS models with an interaction between PRP and gender (see Table S10, Panel A). We find evidence that PRP jobs enhance earnings inequality by stretching the earnings distribution, but to a greater extent for males than females. As such, we find that the difference in the GPG between PRP and non-PRP jobs varies across the distribution. Consistent with the arguments of Green et al. (2014), at and above the median, the adjusted GPG is larger in PRP jobs.

TABLE 2 Decomposition of the observed GPG at the mean and selected percentiles of the unconditional log annual pay distribution.

	(1) Mean	(2) 10th	(3) 25th	(4) 50th	(5) 75th	(6) 90th
Observed GPG	0.466***	0.555***	0.590***	0.438***	0.365***	0.384***
	(0.005)	(0.014)	(0.006)	(0.005)	(0.005)	(0.007)
Explained GPG	0.356***	0.759***	0.396***	0.212***	0.129***	0.159***
	(0.005)	(0.015)	(0.006)	(0.004)	(0.003)	(0.005)
	[76]	[137]	[67]	[48]	[35]	[41]
Unexplained GPG	0.110***	−0.205***	0.194***	0.227***	0.236***	0.225***
	(0.003)	(0.015)	(0.006)	(0.004)	(0.004)	(0.006)
	[24]	[−37]	[33]	[52]	[65]	[59]
Explained by PRP	0.026***	0.008***	0.023***	0.025***	0.031***	0.050***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
	[6] {7}	[1] {1}	[4] {6}	[6] {12}	[8] {24}	[13] {31}
Unexplained by PRP	0.006***	0.019***	0.007**	0.001	−0.002	0.014***
	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)
	[1] {5}	[3] {−9}	[1] {4}	[0] {0}	[−1] {−1}	[4] {6}
Population size	21,875,370					
Number of observations	141,230					

Note: (i) OB (column (1)) and RIF-OB (columns (2)–(6)) decompositions are performed using a model which includes personal characteristics (age, age-squared, and eleven regions of GB), work-related characteristics (firm tenure in years, tenure-squared, part-time indicator, temporary contract indicator, (log) firm size, collective agreement indicator, SOC 2010 major groups (nine categories), and a public-sector indicator), (log) total paid weekly hours worked during the reference period, (log) annual weeks worked (generated by dividing the annual pay by weekly pay), and a constant term. (ii) Decompositions are calculated using the relevant male coefficients as the baseline. (iii) Figures in () are standard errors, figures in [] are a percentage of the observed GPG, and those in {} are a percentage of the relevant GPG component (explained or unexplained). (iv) $*p<0.05$, $**p<0.01$, $***p<0.001$.

distribution. Focusing first on the mean, our observed characteristics explain 76%, or 35.6 percentage points of the 59.4% annual GPG, leaving the unexplained gap of 11.6%, consistent with significant potential gender pay inequality.[28] Gender gaps in PRP typically neglected in studies of this nature have a significant role in explaining the observed GPG, accounting for 2.6 percentage points (6%) of the observed annual GPG at the mean. In other words, the lower concentration of females in PRP jobs, whether due to differences in preferences or barriers in access, serves to widen the GPG. In terms of the contribution of other workplace characteristics (see Table S4), the role of PRP is only smaller than part-time employment and occupation and which account for 7.2 percentage points (15%) and 5.3 percentage points (11%) of the GPG, respectively, and have been subject to considerable analysis (see, e.g., Blau & Kahn, 2017).[29] Gender differences in returns to PRP, which contribute to the unexplained GPG, play a more modest role, accounting for 1% of the GPG, but nevertheless widen it further.[30] While the findings are consistent with recent international evidence (see Heywood & Parent, 2017 and Hirsch & Lentge, 2022), they contrast with historical evidence for the UK, for example, Manning and Saidi (2010) who find a

[28]Tables S3a and S3b provide coefficient estimates from the underlying regression models for males and females, respectively.

[29]As might be expected given the focus on annual pay, annual hours (weekly hours (38%) and annual weeks (7%)) play an important role.

[30]Gender differences in returns to PRP jobs might indicate differential treatment but could also reflect gender differences in unobserved productivity. The latter would arise if, for example, males with higher unobserved productivity are more likely to select into PRP jobs or if males exert more effort than females in these roles.

minimal role for PRP on the hourly GPG. Given the differences between this study and our analysis, including in relation to the measurement of PRP and pay, it is, however, not possible to identify whether this reflects a genuine change over time.

Gender differences in PRP jobs play an important role in explaining the GPG across the distribution (Table 2, columns (2)–(6)), but the influence is more pronounced at the higher end of the earnings distribution. For example, at the 90th percentile PRP contributes 5.0 percentage points or 13% of the GPG, nearly one-third of the explained GPG. In this respect, the findings are consistent with Heywood and Parent (2017) for the USA and Hirsch and Lentge (2022) for Germany. While this might suggest employer discretion over receipt of annual bonus payments linked to subjective measures of performance, it could alternatively reflect gender differences in unobserved ability and/or effort across the distribution, and/or selection of women away from certain types of PRP in higher paying roles. As at the mean, we find a less prominent role for gender differences in the returns to PRP. However, PRP has a significant impact on unexplained gap at the top and bottom ends of the earnings distribution. Indeed, at the 10th percentile PRP makes a larger contribution to the unexplained than explained GPG.

SENSITIVITY ANALYSIS

We explore the robustness of our findings in a series of stages. First, in Table 3, we consider the sensitivity of our benchmark decomposition results to the measurement of pay. This has a similar layout to Table 2, but, in Panels A and B, we replace our measure of annual pay with hourly pay based on annual pay and hourly pay based on pay within the reference period, respectively. Using hourly pay derived from annual earnings (Panel A) magnifies the role of PRP in explaining the mean GPG to 4.3 percentage points or 20% of the hourly GPG, where the latter represents more than half of the explained gap. There is also evidence that PRP is particularly important at the top of the hourly pay distribution, but when using this pay measure, the role for PRP at the 10th percentile is even more pronounced. We are, however, cautious in interpreting the latter given the potential for greater measurement error using hourly pay derived from annual earnings at the bottom end of the distribution due to the implicit assumption of continuous employment.[31] The results based on reference period hourly pay (Panel B) are more similar to our benchmark estimates, with an increasing importance of PRP moving up the distribution, albeit the role of PRP relative to the GPG and its explained component is larger in magnitude. While recognizing the important measurement issues involved, our sensitivity analysis provides some reassurance that our benchmark estimates are representative of the role of PRP on the GPG and, if anything, are likely to underestimate its relative contribution.

Our remaining sensitivity analysis focuses on the mean GPG. First, given concerns that PRP might be endogenous, reflecting both employee preferences as well as the potential influence of employer discrimination, we estimate an instrumental variable (IV) specification of the earnings equation using two-stage least squares (2SLS). Following Andelic et al. (2023), we instrument employment in PRP jobs using the prevalence of PRP in the industry (and industry-sector). Reflecting industry norms, we argue the probability of being employed in a PRP job is likely to be positively related to the prevalence of PRP in the industry (2007 Standard Industry Classification (SIC) (nine) aggregated sections – see notes to Figure S2d for full details), or industry-sector; that is, our instrument meets the requirement of relevance. We further argue that it forms a valid exclusion restriction in the

[31]This is because the lower end of the distribution is likely to capture employees who only work part of the year. Consistent with this, the hourly GPG is also much larger than might be anticipated at the 10th percentile.

TABLE 3 Decomposition of the observed GPG at the mean and selected percentiles of the unconditional log annual pay distribution, sensitivity analysis.

	(1) Mean	(2) 10th	(3) 25th	(4) 50th	(5) 75th	(6) 90th
Panel A: (log) hourly pay based on annual pay						
Observed GPG	0.210***	0.189***	0.142***	0.220***	0.213***	0.275***
	(0.004)	(0.013)	(0.003)	(0.004)	(0.005)	(0.007)
Explained GPG	0.080***	0.125***	0.085***	0.069***	0.047***	0.070***
	(0.004)	(0.013)	(0.004)	(0.004)	(0.004)	(0.006)
	[38]	[66]	[60]	[31]	[22]	[25]
Unexplained GPG	0.130***	0.064***	0.057***	0.152***	0.165***	0.204***
	(0.005)	(0.016)	(0.004)	(0.004)	(0.005)	(0.008)
	[62]	[34]	[40]	[69]	[77]	[75]
Explained by PRP	0.043***	0.070***	0.028***	0.029***	0.037***	0.055***
	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
	[20] {54}	[37] {56}	[20] {33}	[13] {42}	[17] {79}	[20] {79}
Unexplained by PRP	0.003	−0.011*	0.006***	0.001	0.009***	0.020***
	(0.002)	(0.006)	(0.002)	(0.002)	(0.002)	(0.004)
	[1] {2}	[−6] {−17}	[4] {11}	[0] {1}	[4] {5}	[7] {10}
	(1) Mean	**(2) 10th**	**(3) 25th**	**(4) 50th**	**(5) 75th**	**(6) 90th**
Panel B: (log) hourly pay based on reference period						
Observed GPG	0.165***	0.042***	0.131***	0.196***	0.174***	0.242***
	(0.003)	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)
Explained GPG	0.069***	0.060***	0.107***	0.075***	0.049***	0.064***
	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)
	[42]	[143]	[82]	[38]	[28]	[26]
Unexplained GPG	0.096***	−0.018***	0.025***	0.121***	0.125***	0.178***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.007)
	[58]	[−43]	[19]	[62]	[72]	[74]
Explained by PRP	0.020***	0.008***	0.015***	0.016***	0.026***	0.036***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
	[12] {29}	[19] {13}	[11] {14}	[8] {21}	[15] {53}	[15] {56}
Unexplained by PRP	0.003**	−0.001	0.005***	−0.002	0.008**	0.013***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
	[2] {3}	[−2] {6}	[4] {20}	[−1] {−2}	[5] {6}	[5] {7}

Note: (i) OB (column (1)) and RIF-OB (columns (2)–(6)) decompositions are performed using a model, which includes personal characteristics (age, age-squared, and eleven regions of GB), work-related characteristics (firm tenure in years, tenure-squared, part-time indicator, temporary contract indicator, (log) firm size, collective agreement indicator, SOC 2010 major groups (nine categories), and a public-sector indicator) and a constant term. (ii) Decompositions are calculated using the relevant male coefficients as the baseline. (iii) Figures in () are standard errors, figures in [] are a percentage of the observed GPG, and those in {} are a percentage of the relevant GPG component (explained or unexplained). (iv) Within each panel, sample and population sizes are 141,230 and 21,875,370, respectively. (v) $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

second-stage earnings equation since, after accounting for other workplace characteristics, the broader use of PRP in the industry/industry-sector will affect individual earnings only through own PRP. Tables S5a and S5b present a full set of estimates from the IV model for each of our alternative proposed instrumental variables, separately by gender. Coefficients from the first-stage linear probability model estimating employment in PRP jobs on the same set of control variables as Equation (1) are presented in Table S5a. These confirm the relevance of our instruments, with the coefficient estimates on the prevalence of PRP in the industry (and industry-sector) sizable and significant at the 1% level for both males and females. Second-stage estimates, where employment in PRP jobs is replaced by the predicted value from the first stage in the earnings equations, are presented in Table S5b. The estimates are similar regardless of the precise choice of instrument but confirm that the relationship between PRP jobs and annual earnings is magnified when accounting for endogeneity, or that OLS estimates (see column (1) in Tables S3a and S3b) are downward biased. There also appears to be a convergence in the relationship between PRP and earnings between gender after accounting for endogeneity, with no significant gender difference in the PRP coefficient estimates in the second-stage IV models. Indeed, utilizing the 2SLS coefficient estimates and predicted values for PRP employment in our OB decompositions removes the role of PRP on the mean annual unexplained GPG. However, it acts to magnify the role of PRP on the explained gap to 5.8 percentage points or 12% of the GPG (see Table S6, columns (2) and (3)).

The remaining columns in Table S6 further demonstrate the robustness of our findings to a wide range of changes in the definition of variables and model specification. These include the inclusion of firm fixed effects to account for unobserved firm heterogeneity, particularly differences in the use of PRP between firms (column (4)) and to firm × occupation fixed effects (column (5)).[32] The results are similar between these specifications but focusing on the within-firm (or within firm-occupation cell) GPG reduces the contribution of PRP to the explained GPG relative to our benchmark, consistent with about a third of the role of PRP reflecting sorting of males to firms (or firm-occupation cells) that are more likely to use PRP. Nevertheless, even within firm-occupation cells, the gap explained by PRP is significant, consistent with a role for gender differences in the probability of employment in PRP jobs on the GPG.

Given concerns about the inclusion of controls for occupation within the earnings equation, we exclude occupation (column (6)) and control for detailed occupation categories, which are often used as a proxy for education in ASHE (see Gibbons et al., 2014), instead of major groups (column (9)). As expected, PRP has a smaller role on the explained gap in the latter than the former and our estimate is situated between these two extremes. Given the potential relationship between sector and PRP, we additionally exclude sector (column (7)) (and sector and occupation (column (8)), but this makes little difference to our findings. Since PRP might in part reflect the role of industry, which is excluded from our specification, we include industry (column (10)), but our results are unaffected. We further check our findings are also similar for full-time employees who are often thought to have more similar commitment to work (column (11)) and to employees working in the same job for more than 1 year (column (12)) to ensure our measure captures annual PRP for all workers. We further explore the definition of annual pay, by excluding incentive pay from annual pay (column (13)) and including (log) annual pay outliers (column (14)). As might be expected, the influence of PRP is smaller in the former, but it remains a significant determinant of the explained GPG, consistent with a role for PRP jobs, over and above their direct influence on incentive pay. We further confirm our findings are not sensitive to the inclusion of non-profit-sector employees within the private sector (column (15)) and to a

[32]We retain singleton observations within the sample, but our estimates are not sensitive to their exclusion (results available upon request). The average number of employee observations within a firm for males (females) in PRP jobs is 102 (129), and the corresponding figure for non-PRP jobs is 68 (81). Within a firm-occupation cell, the corresponding figures are 46 (68) and 25 (35). Given the requirement to have multiple employee observations, the estimates of PRP are inevitably identified from employees within larger firms/firm-occupation cells in the fixed effect specifications.

series of methodological decisions, including changing the OB decomposition to use the relevant female coefficient estimates as baseline (column (16)), to the exclusion of ASHE sampling weights (column (17)), and to the specific choice of ASHE year (column (18)). Our final set of robustness tests explore the role of controls for annualized hours by excluding the controls for part-time employment (column (19)), (log) weeks (column (20)), (log) hours (column (21)), and (log) weeks and (log) hours simultaneously (column (22)). Excluding annual weeks magnifies the role of PRP jobs on the explained GPG, consistent with part of the gender difference in employment in PRP jobs reflecting gender differences in weeks worked per year, but the role of PRP on the unexplained GPG is no longer statistically significant.

VARIATION IN PRP AND THE GPG BY SECTOR

It is well established that both the GPG and use of PRP vary between sectors and, in a corresponding manner to Table 1, Table S7 presents descriptive statistics for our ASHE sample by sector. Sectoral differences in PRP are confirmed with 37.3% of employees in PRP jobs in the private sector, compared to 5.9% in the public sector. While gender differences in sector explain part of the gender gap in PRP jobs, a gender gap is evident within each sector, with males being more likely to receive PRP. Average annual pay by sector shows a mean public sector pay premium in both PRP and non-PRP jobs consistent with the UK literature (see, e.g., Murphy et al., 2020). The GPG in both PRP and non-PRP jobs is lower in the public sector than the private sector, but within each sector the GPG is wider in PRP jobs.[33,34]

To explore sectoral differences in the relationship between PRP and the GPG and their implications for the public and private GPG, we perform OB and RIF-OB decompositions separately by sector. Table 4 presents the corresponding results, where the public (private) sector is in Panel A (Panel B). Gender differences in the incidence of PRP make a significant contribution to the mean GPG within each sector (column (1)) and account for slightly more of the observed GPG in the private (3%) relative to public sector (2%). In this respect, PRP does not have a prominent role in explaining the difference in the explained GPG across sectors. In terms of magnitude, the contribution is smaller than for the entire economy, suggesting sectoral differences in PRP play an important role in driving the overall contribution of PRP to the GPG. Nevertheless, out of the work-related characteristics we consider, only gender differences in occupation and part-time employment are more important than PRP in explaining the within sector mean GPGs (see Table S9). Although the contribution is smaller in magnitude compared to the explained gap, gender differences in rewards to PRP also contribute to the unexplained mean GPG, and more so in the private sector, suggesting significant gender differences in the returns to PRP.

The corresponding RIF-OB decomposition results are presented in columns (2)–(6) of Table 4.[35] With the exception of the lowest decile, gender differences in PRP are an important determinant of the explained GPG across the distribution in both the public and private sectors. In absolute terms, the role of PRP is greater in the private sector compared to the public sector, particularly at the top end of the earnings distribution, aligned to the potential influence of subjective allocation of annual bonuses on the GPG (see Hirsch & Lentge, 2022, for similar evidence in Germany). Figure 1 presents a complete profile of the absolute contribution of PRP in explaining the GPG

[33]After controlling for personal and work-related characteristics in a pooled regression model, the GPG is only significantly wider in PRP jobs in the private sector (see Table S2).

[34]Table S8 confirms that the incidence of PRP rises across the distribution for both genders in each sector.

[35]Corresponding estimates for the pooled RIF-OLS regressions are available in Table S10 (Panels B and C).

TABLE 4 Decomposition of the observed GPG at the mean and selected percentiles of the unconditional log annual pay distribution, by sector.

Panel A: Public sector	**(1) Mean**	**(2) 10th**	**(3) 25th**	**(4) 50th**	**(5) 75th**	**(6) 90th**
Observed GPG	0.418***	0.664***	0.489***	0.369***	0.273***	0.280***
	(0.009)	(0.025)	(0.010)	(0.008)	(0.007)	(0.011)
Explained GPG	0.265***	0.692***	0.282***	0.165***	0.086***	0.071***
	(0.009)	(0.029)	(0.010)	(0.007)	(0.005)	(0.009)
	[63]	[104]	[58]	[45]	[32]	[25]
Unexplained GPG	0.153***	−0.029	0.207***	0.204***	0.187***	0.209***
	(0.007)	(0.031)	(0.011)	(0.008)	(0.007)	(0.011)
	[37]	[−4]	[42]	[55]	[68]	[75]
Explained by PRP	0.008***	0.003	0.009***	0.011***	0.010***	0.014***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
	[2] {3}	[0] {0}	[2] {3}	[3] {7}	[4] {12}	[5] {20}
Unexplained by PRP	0.001*	0.004**	0.005***	0.000	−0.000	0.002
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
	[0] {1}	[1] {−14}	[1] {2}	[0] {0}	[0] {0}	[1] {1}
Population size	5,495,020					
Number of observations	35,241					
Panel B: Private sector	**(1) Mean**	**(2) 10th**	**(3) 25th**	**(4) 50th**	**(5) 75th**	**(6) 90th**
Observed GPG	0.544***	0.677***	0.704***	0.514***	0.448***	0.419***
	(0.006)	(0.017)	(0.008)	(0.006)	(0.006)	(0.009)
Explained GPG	0.432***	0.877***	0.518***	0.274***	0.167***	0.151***
	(0.006)	(0.017)	(0.007)	(0.005)	(0.004)	(0.005)
	[79]	[130]	[74]	[53]	[37]	[36]
Unexplained GPG	0.112***	−0.200***	0.186***	0.240***	0.280***	0.268***
	(0.003)	(0.018)	(0.007)	(0.005)	(0.005)	(0.008)
	[21]	[−30]	[26]	[47]	[63]	[64]
Explained by PRP	0.016***	0.002	0.014***	0.017***	0.021***	0.032***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
	[3] {4}	[0] {0}	[2] {3}	[3] {6}	[5] {13}	[8] {21}
Unexplained by PRP	0.008***	0.039***	0.020***	0.001	−0.013**	−0.005
	(0.002)	(0.006)	(0.003)	(0.003)	(0.004)	(0.006)
	[1] {7}	[6] {−20}	[3] {11}	[0] {0}	[−3] {−5}	[−1] {−2}
Population size	16,380,351					
Number of observations	105,989					

Note: (i) OB (column (1)) and RIF-OB (columns (2)–(6)) decompositions are performed using a model, which includes personal characteristics (age, age-squared, and eleven regions of GB), work-related characteristics (firm tenure in years, tenure-squared, part-time indicator, temporary contract indicator, (log) firm size, collective agreement indicator), SOC 2010 major groups (nine categories)), (log) total paid weekly hours worked during the reference period, (log) annual weeks worked (generated by dividing the annual pay by weekly pay), and a constant term. (ii) Decompositions are calculated using the relevant male coefficients as the baseline. (iii) Figures in () are standard errors, figures in [] are a percentage of the observed GPG, and those in {} are a percentage of the relevant GPG component (explained or unexplained). (iv) *$p<0.05$, **$p<0.01$, ***$p<0.001$.

across sectors based on the estimates at each percentile and illustrates the prominent rise in the contribution of PRP at the top end of the distribution in the private sector, and contrasting relatively stable contribution in the public sector. While there is some evidence that differences in

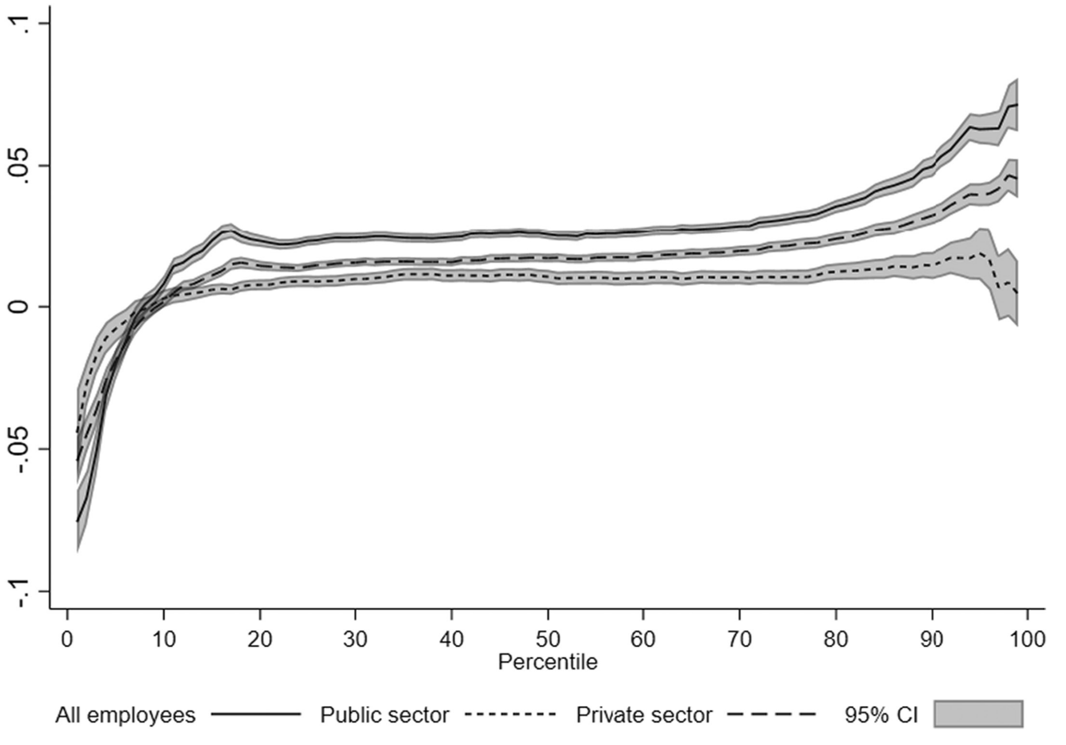

FIGURE 1 GPG explained by PRP across the distribution, all employees, and by sector. *Note*: Figure shows log points of the observed GPG explained by PRP derived from RIF-OB decompositions as described in the text.

reward to PRP also play a significant role via the unexplained GPG, it is only in the lower tail of the distribution (lowest decile in the public sector and lowest quartile in the private sector) where this becomes more important than its contribution to the explained gap.

CONCLUSIONS

In the context of growing concerns relating to the impact of PRP on earnings inequality, we quantify the role of employment in PRP jobs to the UK GPG, both at the mean and across the earnings distribution. Our evidence, based on the application of methods proposed by Heywood and Parent (2012) to employer-provided earnings data from the ASHE, suggests gender differences in employment in PRP jobs represent an important and neglected determinant of the contemporary UK GPG. While aligned to recent evidence for the USA (Heywood & Parent, 2017) and Germany (Hirsch & Lentge, 2022), the importance of PRP contrasts with historical evidence from the UK (see, Manning & Saidi, 2010) and suggests further attention and scrutiny is required.

Gender differences in employment in PRP jobs account for 2.6 percentage points or 6% of the observed annual GPG at the mean. Indeed, PRP is more important than most work-related characteristics typically explored within the literature. It provides a particularly important contribution at the upper end of the distribution, which appears to be driven by its role within the private sector. While gender differences in the rewards to PRP reinforce the impact of gender gaps in PRP incidence on the mean GPG, the influence is far smaller in magnitude.

The importance of gender gaps in the incidence of PRP to the GPG reinforces the need to understand the reasons for gender differences in employment in PRP jobs. Indeed, future research that distinguishes the role of employer exclusion from differences in employee preferences will be critical in informing the extent and nature of an appropriate policy response. Differences in the role of PRP across the private-sector earnings distribution also seem to point to the importance of the nature and implementation of PRP schemes, and future analysis should seek to explore the implications of different types of PRP payments to the GPG using new and alternative forms of data. Such evidence is clearly important in assessing whether specific elements of PRP, including bonus payments, warrant particular attention.

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DATA AVAILABILTY STATEMENT

This work is based on data from the Annual Survey of Hours and Earnings, produced by the Office for National Statistics (ONS) and supplied by the Secure Data Service at the UK Data Archive (http://doi.org/10.5255/UKDA-SN-6689-19). The data are Crown Copyright and has been used by permission.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Appendix S1.

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