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Performance-related Pay and the UK Gender Pay Gap*

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Abstract

This paper explores the role of performance-related pay to the UK gender pay gap at the mean and across the earnings distribution. Applying decomposition methods to data from the Annual Survey of Hours and Earnings, we find that performance-related pay is an important but neglected factor, with the lower probability of females being employed in performance-related pay jobs explaining 12 per cent of the observed mean gender pay gap and making a larger contribution than many work-related characteristics routinely included in studies of this nature. Driven by its influence in the private sector, employment in performance-related pay jobs is more important in explaining the gender pay gap at the top end of the wage distribution, consistent with gender differences in receipt of bonus payments. Gender differences in the reward to performance-related pay jobs have a further, but more modest, role in widening the national and private sector mean gender pay gap.

JEL classification: J31, J33, J45, J71.

Keywords: gender pay gap, performance-related pay, earnings distribution, sector.

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1. Introduction

The extensive international evidence on the gender pay gap (hereinafter, GPG), which is predominately based on analysis of usual hourly pay, tends to neglect the role of specific components of pay. Yet, at the same time, 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 (hereinafter, PRP).¹ This is both due to evidence of gender differences in the probability of employment in PRP jobs (Manning and Saidi, 2010 for the UK; McGee *et al.*, 2015 for the US; Xiu and 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 or subjectivity in allocation (Green *et al.*, 2014). The contribution of PRP to gender inequality in the UK has been recognised, with measures of gender gaps in the receipt and amount of bonuses included in Gender Pay Gap Transparency Legislation.² These data reveal pronounced gender gaps (see GEO, 2018), consistent with bonuses being an inequitable form of pay.

Despite extensive international scrutiny of the GPG and the personal and work-related characteristics explaining this (see, for a review, Blau and Kahn, 2017), including evidence on the importance of job characteristics, the contribution of employment in PRP jobs has received relatively limited attention. This is despite evidence of PRP as a driver of overall wage inequality (for example, Lemieux *et al.*, 2009) and racial wage inequality (for example, Heywood and Parent, 2012), including in the UK (Bryson *et al.*, 2018). Utilising these

¹ Common types of PRP are (i) piecework schemes, (ii) payment by results, (iii) plant or organisation wide incentives, (iv) bonus earnings or pay progression through a pay scale based on an assessment or appraisal of an employee's (or team's) performance against previously set objectives, usually as part of a performance management system, (v) merit pay, (vi) competence based pay, and (vii) profit related pay (see UNISON, 2017). Whilst based on performance, we do not consider promotions as PRP.

² The Equality Act 2010 (Gender Pay Gap Information) Regulations require large employers to calculate and publicly report a range of metrics relating to their organisation GPG annually. See [Gender pay gap reporting: guidance for employers - GOV.UK \(www.gov.uk\)](https://www.gov.uk/guidance/gender-pay-gap-reporting-guidance-for-employers).

frameworks (see, for example, Heywood and Parent, 2012 in the context of ethnicity) this paper provides new evidence by quantifying the role of PRP to the UK GPG. Such evidence is not only important in understanding the drivers of the contemporary GPG but also has implications for employers in terms of the design of payment systems. Consistent with these studies, and prior evidence of a ‘glass ceiling’ pattern in the gender gap in PRP (de la Rica *et al.*, 2015), we consider the role of PRP to the mean GPG, as well as across the wage distribution. Furthermore, we undertake the analysis separately by sector, allowing sectoral variation in the role of PRP on the GPG. While PRP is traditionally associated with employment in the private sector and remains relatively limited in the UK public sector (Bryson *et al.*, 2017), the latter has seen a movement from automatic progression to PRP as an incentive for effort generating concerns from unions and Pay Review Bodies about the implications for gender equality. In considering sectoral differences, we also explore whether PRP contributes to established differences in the GPG, particularly that the observed and unexplained GPG has historically been lower in the public sector (see, for example, Chatterji *et al.*, 2011; Jones *et al.*, 2018).

More specifically, we use high quality employer provided information on hourly pay and annual PRP from the UK Annual Survey of Hours and Earnings (hereinafter, ASHE) and apply detailed Oaxaca-Blinder (hereinafter, OB) decomposition method at the mean (Oaxaca, 1973; Blinder, 1973) and across the (unconditional) wage distribution (Firpo *et al.*, 2009; Firpo *et al.*, 2018) to quantify the contribution of employment in PRP jobs to the explained and unexplained components of the GPG. 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 and sectoral variation in the GPG, both at the mean and across the wage distribution. In doing so, we contribute to the literature investigating the GPG over the earnings distribution (see, for example, Arulampalam *et al.*, 2007; Kaya, 2021) and across

sectors (see, for example, Chatterji *et al.*, 2011; Jones *et al.*, 2018), as well as to the broader debate as to whether PRP increases wage inequality for groups defined by protected characteristics (Heywood and Parent, 2012; Green *et al.*, 2014).

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 2.0 percentage points or 12 per cent of the observed GPG and 29 per cent of the explained component. Indeed, PRP is more important than a range of work-related characteristics typically explored within the literature including tenure, temporary employment and sector. Driven by its influence in the private sector, PRP provides a particularly important contribution at the upper end of the wage distribution, accounting for 3.6 percentage points (15 per cent) of the UK GPG at the 90th percentile and more than half 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 lower end of the pay distribution in the private sector.

The remainder of this paper 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. Sections 4 and 5 set out the econometric methods and findings exploring the relationship between PRP and the GPG among all workers, at the mean and across the distribution, respectively. Sectoral differences in these relationships are explored in Section 6. Section 7 briefly concludes.

2. 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.

In relation to the former, gender differences in risk preferences, particularly evidence that on average women exhibit a lower preference for competition (Gneezy *et al.*, 2003; Niederle and Vesterlund 2007) and are more risk averse than men (Croson and Gneezy, 2009; Charness and Gneezy, 2012) will likely reduce female employment in PRP roles where pay is expected to be subject to an element of uncertainty. Discrimination theory offers an additional explanation, particularly that discrimination against females might restrict access to PRP roles or result in females, on average, being less likely to be in receipt of PRP within a given job. Consistent with either channel, it is well documented that women are less likely than men to receive PRP (see Booth and Frank, 1999 and Manning and Saidi, 2010 for the UK; McGee *et al.*, 2015 for the US; Xiu and Gunderson, 2013 for China; Zizza 2013 for Italy).³

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 will 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, if individual performance is difficult to observe or measure, then PRP may increase the GPG since it will be based on more subjective evaluations.⁵ Consistent with the latter effect dominating, Xiu and Gunderson (2013) show that conditional on receipt of PRP, women receive a lower amount

³ This is particularly true in PRP jobs based on bonuses, where individual performance is often measured subjectively (Geddes and Heywood, 2003).

⁴ Consistent with this, output-based performance pay, particularly piece rates, have been found to reduce earnings differentials by gender (Jirjahn and Stephan, 2004). In this case, women might also select into PRP jobs based on objective measures of performance (Geddes and Heywood, 2003; Jirjahn and Stephan, 2004; Xiu and Gunderson, 2013).

⁵ Discrimination is not necessarily confined to employers. For example, customer discrimination might similarly affect pay in terms of commission.

of PRP relative to males in China. The unexplained gender gap in PRP is, however, similar to that in base pay. In contrast, de la Rica *et al.* (2015) find a larger unexplained gender wage gap in PRP relative to non-PRP in Spain.

Despite this evidence, PRP is not routinely included as a control in analysis of the GPG.⁶ Where it is explored in the UK context, Booth and Frank (1999) find no significant gender difference in the return to incentive bonuses or profit-related pay using data from the 1991 British Household Panel Survey. Manning and Saidi (2010) similarly conclude that PRP, measured at the occupational level, has only a small impact on the mean UK GPG. Using data from the 1998 and 2004 Workplace Employment Relations Survey (hereinafter, WERS), they find similar returns to PRP for males and females and only a modest gender gap in incidence.⁷

Green *et al.* (2014) hypothesise 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 towards the top end of the earnings distribution PRP will depend more 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 the context of ethnicity, Heywood and Parent (2012) find that the racial earnings gap is larger in PRP jobs, especially at the top of the earnings distribution.⁸ In the context of gender, 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 and is driven by differences among parents. In Germany, Hirsch and Lentge

⁶ Studies on the GPG typically either exclude PRP from pay, or include it but do not distinguish PRP from basic pay.

⁷ McGee *et al.* (2015) similarly conclude that PRP explains only a small part of the GPG in the US (maximum 6 per cent). Kangasniemi and Kauhanen (2013) consider the role of separate elements of PRP to 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.

(2022) find that lower bonus payments among women explain about 10 per cent of the mean GPG in the private sector, and a greater amount higher up the earnings distribution.

We contribute to this literature by exploring the role of PRP to the contemporary UK GPG, considering both variation in the incidence and reward to PRP at the mean and across the wage distribution. In doing so, we update earlier UK evidence on the mean GPG, which now dates back over nearly 20 years, extend this to consider differences across the distribution and sector, and thereby provide a useful comparator for existing international evidence.

Sectoral differences

It is well-established that the GPG is, on average, typically narrower in the public relative to the private sector, with further analysis suggesting 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 legislation, such as the Public Sector Equality Duty in the UK.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), as well as greater formalisation and transparency of the wage structures (Stewart, 2014) as determinants of greater pay equality within the public sector.¹⁰ 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 US and Bryson *et al.*, 2018 for the UK), which itself is associated with increasing the GPG in international studies (Blau and Kahn, 1992). Moreover, while recognised as having potential benefits for efficiency and service delivery in the public sector, and increasing in prevalence (see, for example, Makinson

⁹ A narrower public sector GPG (and unexplained GPG) is not unique to the UK (see, for example, Arulampalam *et al.*, 2007 for EU countries).

¹⁰ The main counterargument to this is that, in the absence of market forces, employers may be more able to practice their ‘taste for discrimination’ (Becker, 1957).

Report, 2000 and Winsor Review, 2011), PRP remains much less prevalent in the UK public sector relative to the private sector (Bryson *et al.*, 2017).^{11,12} It is therefore important to understand the implications of changes in the nature of reward (see Biasi and Sarsons, 2022 for recent analysis of the introduction of flexible pay among public sector teachers in the US), including PRP for gender equality, and sectoral differences in the GPG.

3. Data

The analysis utilises data from ASHE, the main source of earnings data in the UK (ONS, 2022), which are based on mandatory reporting by employers to ONS and contain detailed and reliable information on pay, including performance-related pay, for a large sample (one per cent of employee jobs).¹³ 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.¹⁴ Pay information from ASHE is recognised as being high quality, as it is based on employer records. ASHE also has several further advantages in this context, particularly that these data are nationally representative, provide information using the ONS recommended measure of the GPG, contain a measure of annual PRP and a comprehensive set of job-characteristics, including an accurate measure of sector.¹⁵

¹¹ The Work Foundation (2014) present evidence on PRP in public sector, for civil servants, healthcare workers and teachers.

¹² The challenges of using the PRP schemes in 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 recognised. It has also been suggested that public sector employees have ‘public service motivation’, that is the intrinsic motivation derived from providing the service, rather than its financial reward, questioning whether the implementation of PRP schemes in public sector is optimal (see, for a review, Bajorek and Bevan, 2015).

¹³ The analysis does not include Northern Ireland because these observations are not included in ASHE data in the Secure Data Service.

¹⁴ These data are currently provisional, but the findings are robust to using alternative years (see Section 4).

¹⁵ The main alternative sources of data, WERS, Labour Force Survey (hereinafter, LFS) and Understanding Society (hereinafter, USoc) collect self-reported information on pay and PRP. As such, they are subject to a more limited response rates and greater measurement error. Further while detailed categories of PRP are collected in WERS and the LFS, the most recent data for the former is 2011 and pay is reported in bands, whereas in the LFS PRP is only asked from those whose current pay differs from usual pay and will therefore neglect regular PRP. The information on PRP is less detailed in USoc but bonuses are distinguished from any PRP. The trade-off is that these surveys contain a more comprehensive set of personal characteristics relative to ASHE.

Our sample is restricted to employees who are in their main job, paid an adult rate, and whose earnings are not affected by absence.^{16,17} Calibration weights are applied throughout our analysis so the estimates 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 142,739 employees.

PRP

In contrast to most of the literature, ASHE includes objective information on annual PRP pay, that is, where a component of gross annual earnings comes from incentive payments (which includes payments as a result of meeting a performance or productivity objective, such as profit sharing, bonuses, piecework and commission payments), as well as incentive pay paid during the reference period. Since this information is based on employer payroll it is an accurate measure of PRP and independent of employee recall and, understanding and interpretation of elements of PRP. Being based on annual information also enables us to accurately classify PRP jobs where for example, bonus payments might not be paid in the reference period. In the absence of any detail on the nature 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 and Parent, 2012).¹⁸ About 29 per cent of the sample are in PRP jobs (see Table 1), and consistent with the literature this is higher among males (35.8 per cent) than females (22.0 per cent). Moreover, conditional on

¹⁶ 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.

¹⁷ We also exclude those employed in a non-profit body or mutual association given our comparison between the public and private sector in Section 6 but explore the sensitivity of our benchmark results to their inclusion (see Section 4).

¹⁸ 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. In Section 4 we explore the sensitivity of our results to classifying jobs based on PRP in reference (pay) period. However, this measure captures less than 20 per cent of those who received PRP in the preceding year. We further explore the impact of conditioning our sample on those who were employed in the same job for more than one year given annual payments of PRP are more likely to misclassify employees where we do not observe their employment for the full year.

receipt, we find a gender gap in the average amount of annual PRP of 46.6 per cent (£7,184 for males compared to £3,833 for females) which, albeit not adjusted for gender differences in characteristics, including hours of work, is substantially larger than estimates of the GPG in hourly pay (see below), consistent with the widening role of PRP on the GPG (see Table 1).

Hourly pay

In line with the established GPG literature, our main dependent variable is (log) gross hourly pay, which adjusts pay during the reference period for hours worked. This measure is based on the ONS recommended definition, excluding overtime, but including PRP paid within the reference period.^{19,20} Since this measure will not capture all infrequent PRP payments, for example, some annual bonuses, we explore sensitivity of our findings to an hourly pay measure derived from annual gross earnings following Stokes *et al.* (2017). The latter divides gross annual earnings in the preceding year by an annualised measure of hours worked, based on hours in the reference period.²¹ This measure is more closely aligned to our annual PRP measure and, while in principle better reflects total bonus payments made over the year (Stokes *et al.*, 2017), it assumes both continuous employment and that working hours during the reference week are an accurate reflection of average working hours per week during the year.²²

Table 1 presents mean log hourly earnings by gender for PRP and non-PRP jobs. Average hourly pay and pay variation 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 raw GPG being wider in

¹⁹ Gross hourly pay is calculated as gross weekly earnings (basic weekly earnings + incentive pay + additional premium payments for shift, night or weekend work not treated as overtime + pay for other reasons) excluding overtime for the reference period divided by basic weekly paid hours. This also aligns to the hourly pay measure in GPG Transparency Legislation. Our findings are, however, robust to the precise measure of hourly pay (see Section 4).

²⁰ We remove wage outliers defined as above ten times the 99th percentile and below half the 1st percentile.

²¹ In ASHE, there is no information on total annual hours worked.

²² It further does not allow the separation of overtime payments from gross annual pay.

PRP jobs at 23.1 per cent, compared to 11.2 per cent for non-PRP jobs.²³ Of course, this could reflect gender differences in selection into PRP jobs.

[Table 1 here]

Consistent with the literature (see, for example, Green *et al.*, 2014), the incidence of PRP also varies across the distribution, increasing in earnings for both males and females such that nearly 60 per cent of males and more than a third of females in the top decile are in PRP jobs (see Table 2). In both absolute and relative terms, the gender gap in PRP widens across the distribution, consistent with prior evidence of particularly large gender differences in the receipt of bonus payments among higher earners.

[Table 2 here]

Explanatory variables

ASHE also contains detailed information on job characteristics such that it is possible to control for a comprehensive range of employee and work-related characteristics correlated with PRP and known to explain the GPG. Our control variables for work-related characteristics are all well-established determinants of earnings (see Blau and Kahn, 2017) and include (log) firm size measured by the number of employees within the organisation, tenure (years in the present organisation) (and tenure-squared), an indicator for the coverage of collective agreements, a temporary contract indicator and a part-time employment dummy. 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 (hereinafter, SOC) unit group).^{24,25,26} In terms of personal characteristics, in addition to

²³ Throughout percentages are calculated as $\exp(\log \text{ points}) - 1$.

²⁴ Sector is excluded in the analysis of the public and private sector separately. According to this classification jobs in public corporation and nationalised industries, central government or local authority are classified as public; those that are in private company, sole proprietor or partnership are classified as private.

²⁵ We do not control for industry due to its large overlap with sector but explore the sensitivity of our key findings to its inclusion (see Section 4).

gender, ASHE contains information on age (and age-squared), which is used as a proxy for work experience, and work region (11 NUTS level-1 regions of Great Britain).²⁷ Unfortunately ASHE does not contain information on marital status or dependent children previously found to be an important determinant of the GPG (see Heywood and Parent, 2017).

Appendix Table A1 contains a full set of summary statistics for the explanatory variables by gender and for PRP and non-PRP jobs. 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.

4. PRP and the mean GPG

We explore the mean GPG using established OB decomposition methods (Oaxaca, 1973; Blinder, 1973), widely applied in the international literature.²⁸ 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 (hereinafter, OLS) earnings equation for each gender g (male (m) and female (f)):

²⁶ We also explore the robustness of our results to excluding occupation and to including more detailed controls for occupation (4-digit SOC) which is often used as a proxy for education in ASHE (see Gibbons *et al.*, 2014) (see Section 4).

²⁷ The specification is similar to Green *et al.* (2014), albeit we have more (less) information on work-related (personal) characteristics.

²⁸ Following Green *et al.* (2014) we also estimate a pooled regression model with an interaction between PRP and gender, and the personal and work-related characteristics outlined above to explore variation in the adjusted mean GPG between PRP and non-PRP jobs. The adjusted GPG is about 50 per cent larger in PRP jobs, consistent with PRP widening gender wage inequality (see Appendix Table A2).

$$\ln E_i^g = \delta^g PRP_i^g + X_i^g \beta^g + \varepsilon_i^g \quad (1)$$

where the natural logarithm of gross hourly earnings of individual i and gender g ($\ln E_i^g$) is regressed on a binary indicator of being employed in a PRP job (PRP_i^g), and the personal and work-related characteristics outlined above along with a constant term (X_i^g), 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.

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

$$\begin{aligned} \overline{\ln E^m} - \overline{\ln E^f} &= \hat{\delta}^m (\overline{PRP^m} - \overline{PRP^f}) + (\bar{X}^m - \bar{X}^f) \hat{\beta}^m \\ &+ (\hat{\delta}^m - \hat{\delta}^f) \overline{PRP^f} + \bar{X}^f (\hat{\beta}^m - \hat{\beta}^f) \end{aligned} \quad (2)$$

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.²⁹ As our focus is on the contribution of PRP to the GPG, equation (2) is formulated to isolate the contribution of PRP both the explained and unexplained gaps.³⁰

These results are presented in Table 3. Our observed personal and work-related characteristics explain 42 per cent, or 7.0 percentage points of the 17.7 per cent GPG, leaving the unexplained GPG of 10.0 per cent, consistent with significant potential gender wage

²⁹ Following Blau and Kahn (2017), equation (2) uses as the counterfactual the earnings of an average woman at the male returns, assuming the latter represent competitive prices. We nevertheless explore the sensitivity of the findings to applying the female returns (see Section 4).

³⁰ Given the detailed decomposition of the unexplained gap depends on the choice of omitted category for categorical variables we compute the decomposition based on normalised effects following Yun (2005).

inequality.³¹ Gender gaps in PRP, typically neglected in studies of this nature have a significant role in explaining the observed GPG, accounting for 2.0 percentage points (12 per cent) of the observed GPG or 29 per cent of the explained GPG. In other words, the lower concentration of females in PRP jobs, whether due to differences in preferences or restrictions in access, serves to widen the GPG. In terms of the contribution of other characteristics, the role of PRP is second only to occupational segregation which accounts for 4.4 percentage points (26 per cent) of the overall GPG and has been subject to considerable analysis in the literature (see, for example, Blau and Kahn, 2017). Indeed, PRP plays a more important role than part-time employment (9 per cent) a well-established determinant of the GPG (Blau and Kahn, 2017). Gender differences in the return to PRP, which contribute to the unexplained GPG, play a more modest role, accounting for 2 per cent of the GPG but nevertheless widen it further.³²

[Table 3 here]

In Appendix Table A3 we explore the sensitivity of our benchmark OB decomposition results (column (1)) to the inclusion of firm fixed effects to account for unobserved firm heterogeneity, particularly differences in the use of PRP between firms (column (2)), to the inclusion of detailed occupation categories instead of major groups (column (3)) and to the exclusion of occupation (column (4)), to the inclusion of industry (column (5)), to changes in the sample including restricting it to full-time employees (column (6)) and to employees working in the same job for more than one year (column (7)), to the use of a reference period PRP measure (column (8)), to the use of alternative pay measures as dependent variable (columns (9)-(13)) including annual pay as Green *et al.* (2014), to changing the OB method to use the relevant female coefficient estimates as baseline (column (14)), to the exclusion of

³¹ Coefficient estimates from the underlying regression models are available upon request.

³² Gender differences in the return to PRP jobs might indicate differential treatment but could also reflect unobserved productivity effects. The latter would arise if, for example, males with higher unobserved productivity are more likely to select into PRP jobs.

sampling weights (column (15)), to the inclusion of non-profit sector employees within the private sector (column (16)), to the inclusion of (log) hourly pay outliers (column (17)), and to the ASHE year (column (18)).

In most cases the decomposition results are left virtually unchanged. As might be expected given the inclusion of additional elements of PRP, using hourly pay derived from annual earnings (column (9)) magnifies the role of PRP in explaining the GPG to 4.3 percentage points or 21 per cent of the GPG. In contrast, the role of PRP is smaller (but nevertheless significant) when using basic hourly pay (column (11)), consistent with its influence not exclusively being directly through payments for performance. Controlling for firm fixed effects (column (2)) and thereby focusing on the within-firm GPG reduces the contribution of PRP, consistent with some of the role of PRP reflecting sorting of males and females to firms more or less likely to use PRP. Indeed, in this specification the contribution of PRP to the explained and unexplained GPG gap is more equal, consistent with greater gender inequality in rewards to PRP within than between firms. The results are most sensitive to the annual versus reference period measure of PRP (column (8)), with reference period PRP having a smaller, but nevertheless statistically significant, role on the GPG when compared to annual PRP, consistent with reference period PRP being only a partial measure of PRP and neglecting elements, particularly annual bonuses where there might be greater opportunities for discrimination in allocation.

5. PRP and the GPG across the distribution

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

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

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 $RIF(Y; q(\tau), F_Y)$ (hereinafter, 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 (hereinafter, RIF-OLS) (Firpo *et al.* 2009). To decompose the GPG across the entire wage distribution a standard OB decomposition can be carried out by using the estimated coefficients of the RIF regression. This approach, unlike other decomposition methods that rely on conditional quantile regressions (for example, Machado and Mata, 2005) allows a detailed unconditional quantile decomposition (Fortin *et al.*, 2011).³³

Parallel to our analysis at the mean, in our distributional analysis, we first estimate RIF-OLS regressions at various quantiles using a specification that mimics equation (1). Then, we apply the OB decompositions for the unconditional quantiles based on separate RIF-OLS regressions for men and women in combination with a reweighted strategy by DiNardo *et al.* (1996).³⁴ In this way we can compare the unexplained GPG across the wage distribution and identify the presence of ‘sticky floors’ or ‘glass ceilings’, where the unexplained GPG is

³³ In a similar manner to the mean, we also estimate pooled RIF-OLS models with an interaction between PRP and gender. The coefficient estimates are presented in the top panel of Appendix Table A7. 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 wage distribution. Consistent with the arguments of Green *et al.* (2014), at and below the lowest quantile, the adjusted GPG is lower in PRP jobs whereas, at and above the median, the adjusted GPG is larger in PRP jobs.

³⁴ We use the Stata *oaxaca_rif* procedure (Rios-Avila, 2020) to perform the RIF decompositions which implements the multistep procedure described in Firpo *et al.* (2018). This procedure uses a reweighted strategy by DiNardo *et al.* (1996) to construct a counterfactual wage distribution, that is, the distribution of earnings for men if they had the same distribution of observable characteristics as women.

higher at the bottom or top of the wage distribution respectively (see, Arulampalam *et al.*, 2007; Christofides *et al.*, 2013; Kaya, 2021). As at the mean, we focus on the contribution of PRP to the explained and unexplained components of the GPG across the earnings distribution.

Table 4 presents these results. The observed GPG increases across the earnings distribution, from 4.0 per cent at the 10th percentile to 27.0 per cent at the 90th percentile. The unexplained GPG also represents an increasing proportion of the observed GPG across the distribution such that gender wage inequality is far more evident at the top end of the distribution, aligned to the presence of a glass ceiling.³⁵ Indeed, a significant negative unexplained GPG is evident at the 10th percentile, consistent with wage inequality *against* men.³⁶

Gender differences in PRP jobs plays an important role in explaining the GPG across the distribution. PRP plays a more important role at both the upper and lower end of the distribution relative to the median but in absolute terms its role is particularly pronounced at the top of the distribution. Indeed, at the 90th percentile PRP contributes 3.6 percentage points to the GPG and accounts for more than half the explained GPG. In this respect, the findings are consistent with Heywood and Parent (2017) for the US and Hirsch and Lentge (2022) for Germany. While this might reflect employer discretion over receipt of annual bonus payments linked to subjective measures of performance it could alternatively reflect greater unobserved ability of men relative to women at the top of the pay distribution. As at the mean, we find a less prominent role for differences in the returns to PRP, but significant differences in the returns which widen the GPG are evident at the top end of the earnings

³⁵ Following Arulampalam *et al.* (2007) we define a glass ceiling effect as where the unexplained GPG at the 90th percentile exceeds that at other reference points (for example, median) by at least two percentage points.

³⁶ See Appendix Figure A1 for a complete profile across the distribution.

distribution and would be consistent with a similar influence of employer discretion in driving gender inequality in the return to PRP.³⁷

[Table 4 here]

6. Variation in PRP and the GPG by sector

Sections 4 and 5 explore the relationship between PRP and the overall GPG. It is, however, well established that both the GPG and use of PRP vary between sectors. In the past this has motivated attention on the private sector, where there is a higher prevalence of PRP (Bryson *et al.*, 2017). Sectoral differences in PRP are confirmed in our ASHE sample where 36.9 per cent of employees receive PRP in the private sector, compared to 5.8 in the public sector (see Table 5). Males are more likely to receive PRP in each sector, and while the gender gap measured in percentage points is greater in the private relative to the public sector (8.7 compared to 6.0), the relative gender difference is larger in the public sector. The average annual amount of PRP is also higher in the private relative to the public sector consistent with it being a more important component of pay. The absolute and relative gender gap in the annual amount of PRP conditional on receipt is, however, larger in the private sector. The average log of hourly pay by sector for PRP and non-PRB jobs is also presented in Table 5. In the public sector the GPG is similar in PRP and non-PRP jobs at between 18 and 19 per cent. In contrast, the GPG is wider in PRP jobs in the private sector, at 23.9 per cent compared to 19.1 per cent in non-PRP jobs.^{38,39}

³⁷ Consistent with analysis at the mean, the role of PRP is greater when using log hourly pay derived from annual pay as a dependent variable (see Appendix Table A8 top panel). There is also evidence that PRP is particularly important at the top of the distribution, but when using this measure the role for PRP at the 10th percentile is even more pronounced. We are cautious in interpreting the latter given the potential for greater measurement error using the annual pay measure at the bottom end of the distribution given this is likely to capture employees who only work part of the year. Consistent with this, the GPG is also much larger than might be anticipated at the 10th percentile.

³⁸ Both features are also evident when we control for personal and work-related characteristics in a pooled regression model (see Appendix Table A2).

³⁹ Appendix Table A4 also confirms that the incidence of PRP rises across the distribution for both genders in each sector.

[Table 5 here]

To explore sectoral differences in the relationship between PRP and the GPG and their implications the public and private GPG, we perform OB and RIF-OB decompositions separately by sector. Table 6 presents the corresponding results, where the public (private) sector is in the upper (lower) panel. Here, estimates at the mean are presented in column (1) and those in columns (2)-(6) relate to selected points of the earnings distribution. Focusing first on the mean, the observed GPG is larger in the private sector than the public sector. However, in contrast to the earlier literature (Chatterji *et al.*, 2011; Jones *et al.*, 2018), but consistent with recent evidence from Jones and Kaya (2019), a greater proportion of the mean GPG can be explained by observable personal and work-related characteristics in the private sector which results in a larger unexplained GPG in the public sector. In this respect, our evidence is consistent with greater gender pay inequality in the public sector and raises questions as to the effectiveness of the additional legislation in this sector.

Gender differences in the incidence of PRP make a significant contribution to the mean GPG within each sector and account for slightly more of the observed GPG in the private (6 per cent) relative to public sector (4 per cent), although as a proportion of the explained GPG it is more important in the public sector. 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 national contribution of PRP. Nevertheless, only gender differences in occupation and part-time employment are more important than PRP in explaining the within sector mean GPGs (see Appendix Table A5). Gender differences in the reward to PRP also contribute to the unexplained mean GPG in the private sector suggesting gender differences in the returns to PRP, although the contribution is smaller (2 per cent) than

to the explained gap.⁴⁰ Interestingly, there is no evidence of gender differences in the return to PRP within the public sector.

[Table 6 here]

The corresponding RIF-OB decomposition results are presented in columns (2)-(5) of Table 6.⁴¹ While there is evidence that the observed GPG rises across the distribution in both sectors, the increase is more prominent in the private sector. As such, the observed GPG is lower in the private sector relative to the public sector below the median but this trend reverses at and above this point. The percentage of the observed GPG explained within each sector varies dramatically across the distribution. In the public sector the explained component declines and is actually negative at the 90th percentile consistent with higher paying females possessing more productivity enhancing attributes than men. As a result, the unexplained GPG also rises across the distribution in the public sector, indicating greater wage inequality among higher earners and a glass ceiling (see also Jones and Kaya, 2019). At the lower end of the distribution gender inequality remains evident in the public sector but the unexplained GPG is negative in the private sector consistent with possible inequality *against* men.⁴²

Gender differences in PRP are an important determinant of the public sector GPG across the distribution. Relative to the observed GPG, in the private sector PRP plays a more important role at the top and bottom end of the distribution. In absolute terms, the role of PRP dominates at the top end of the distribution in the private sector, aligned to the potential influence of subjective allocation of annual bonuses (see Hirsch and Lentge, 2022 for similar

⁴⁰ Consistent with the previous results, the patterns are the same, but the magnitudes are greater when using hourly pay derived from the annual pay (see Appendix Table A6).

⁴¹ Corresponding estimates for the pooled RIF-OLS regressions are available in Appendix Table A7.

⁴² Indeed, in terms of a comparison across sectors, gender pay inequality is lower in the private sector at and below the median and again at the 90th percentile, but not at the 75th percentile, confirming that sectoral comparisons depend on the point in the wage distribution they are estimated. See Appendix Figure A2 for a complete profile across the distribution.

evidence in Germany). Figure 1 presents a complete profile of the absolute role of PRP in explaining the GPG 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 economy and the private sector, and contrasting relatively stable contribution in the public sector.⁴³ While there is some evidence that differences in reward to PRP also play a significant role via the unexplained GPG, it is only in the lower tail of the private sector distribution (bottom quartile) where this becomes more important than gender differences in PRP incidence. In this respect it seems to contrast with suggestions by Green *et al.* (2014) that more objective measures of performance-related pay at the bottom end of the distribution serve to reduce pay inequality.

7. Conclusions

In the context of growing concerns relating to the impact of PRP on earnings inequality, including on the GPG and within the public sector, we quantify the role of employment in PRP jobs to the UK GPG and sectoral differences in the GPG, both at the mean and across the wage distribution. In contrast to the earlier UK studies (see, for example, Manning and Saidi, 2010), 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.

We find a larger GPG in PRP relative to non-PRP jobs, particularly at the top end of the wage distribution. Gender differences in employment in PRP jobs account for 2.0 percentage points or 12 per cent of the observed mean GPG, and 29 per cent of the explained component.

⁴³ The contribution of PRP across the distribution is also stable in the public sector when using hourly pay derived from the annual pay as a dependent variable. The increasing absolute contribution across the distribution is evident from the 25th percentile in the private sector. As for the economy, PRP displays a prominent role at the 10th percentile in the private sector when using this pay measure (see Appendix Table A8).

Indeed, PRP is more important than most characteristics typically explored within the literature. PRP provides a particularly important contribution at the upper end of the wage distribution, accounting for 3.6 percentage points of the GPG at the 90th percentile and more than half of the explained GPG. While gender differences in employment in PRP roles is an important determinant of the mean GPG in both the public and private sector it does not appear to drive sectoral differences in the GPG. PRP does, however, have a sector specific impact across the distribution, playing a fairly constant role in the public sector but increasing in importance over the wage distribution in the private sector. Interestingly, while gender differences in the rewards to PRP reinforce the impact of gender gaps in PRP incidence on the mean GPG in the private sector there is no evidence of this in the public sector.

Differences in the role of PRP across the earnings distribution and sectors 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. Such evidence is clearly important in assessing whether elements of PRP, including bonus payments, should be subject to policy attention. Our analysis nevertheless suggests that accounting for the nature of compensation schemes can add to our understanding of explanations of the UK GPG at the mean and across the distribution, with important practical insights for the design of employer compensation mechanisms. While our findings seem aligned to recent evidence for the US (Heywood and Parent, 2017) and Germany (Hirsch and Lentge, 2022), given the contrasting results in context of ethnicity between Heywood and Parent (2012) in the US and Green *et al.* (2014) in the UK, it seems important to further assess the generalisability of these findings internationally.

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Table 1. PRP incidence and amount, and log hourly pay by PRP jobs, by gender

Incidence of PRP (%)	Male	Female	All
	35.76	22.02	29.09
Population size	11,377,259	10,724,574	22,101,833
Number of observations	69,235	73,504	142,739
Amount of PRP (£) (conditional on receipt)			
	7,183.95	3,833.10	5,953.23
Population size	4,067,945	2,361,421	6,429,366
Number of observations	24,319	15,945	40,264
Log hourly pay PRP jobs			
	2.924	2.716	2.848
	[0.545]	[0.533]	[0.551]
Population size	4,067,945	2,361,421	6,429,366
Number of observations	24,319	15,945	40,264
Log hourly pay non-PRP jobs			
	2.673	2.567	2.617
	[0.482]	[0.465]	[0.477]
Population size	7,309,314	8,363,153	15,672,467
Number of observations	44,916	57,559	102,475

Notes: Authors' calculation using data from the ASHE 2019. See text for a description of sample construction and variable definitions. Figures in [] are standard deviations of the (log) hourly gross pay.

Table 2. The incidence of PRP across the log hourly gross pay distribution (%)

Pay Decile	Males	Females	All
10	14.69	10.05	12.05
20	25.98	18.37	20.97
30	28.31	21.22	22.68
40	33.46	19.54	25.96
50	36.56	21.96	30.27
60	37.12	24.72	30.96
70	37.98	23.44	31.36
80	39.14	22.77	31.05
90	45.97	22.86	34.92
100	58.36	35.47	50.68

Notes: Authors' calculation using data from the ASHE 2019. See text for a description of sample construction and variable definitions.

Table 3. OB decomposition of the observed GPG at the mean

		Mean	
Observed GPG		0.163***	
		(0.003)	
Explained GPG		0.068***	
		(0.003)	
		[42]	
Unexplained GPG		0.095***	
		(0.003)	
		[58]	
Components of the GPG		Explained	Unexplained
	PRP	0.020***	0.003**
		(0.001)	(0.001)
		[12] {29}	[2] {3}
	Age	0.000	0.298***
		(0.001)	(0.021)
		[0] {0}	[183] {314}
	Work region	0.002***	0.004***
		(0.001)	(0.001)
		[1] {3}	[2] {4}
	Tenure	0.002***	0.006
		(0.000)	(0.003)
		[1] {3}	[4] {6}
	Part-time	0.015***	-0.006*
		(0.002)	(0.003)
		[9] {22}	[-4] {-6}
	Temporary contract	0.000	-0.000
		(0.000)	(0.001)
		[0] {0}	[0] {0}
	Firm size	-0.009***	0.099***
		(0.000)	(0.006)
		[-6] {-13}	[61] {104}
	Collective bargaining	0.000	0.005*
		(0.001)	(0.002)
		[0] {0}	[3] {5}
	Occupation	0.043***	-0.018***
		(0.002)	(0.002)
		[26] {63}	[-11] {-19}
	Public sector	-0.005***	-0.018***
		(0.001)	(0.002)
		[-3] {-7}	[-11] {-19}
Population size		22,101,833	
Number of observations		142,739	

Notes: (i) OB decomposition is 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), a public sector indicator and a constant term. (ii) Decompositions are calculated using the relevant male coefficients as the baseline. The unexplained component includes a constant term. (iii) Figures in () are standard errors and figures in [] ({ }) are a percentage of the observed (explained/unexplained) GPG. (iv) * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 4. RIF-OB decomposition of the observed GPG across the unconditional log hourly pay distribution, selected percentiles

	10 th	25 th	50 th	75 th	90 th
Observed GPG	0.039*** (0.002)	0.126*** (0.003)	0.192*** (0.004)	0.173*** (0.005)	0.239*** (0.006)
Explained GPG	0.058*** (0.002) [149]	0.106*** (0.003) [84]	0.075*** (0.004) [39]	0.048*** (0.004) [28]	0.064*** (0.005) [27]
Unexplained GPG	-0.019*** (0.003) [-49]	0.020*** (0.003) [16]	0.117*** (0.004) [61]	0.125*** (0.005) [72]	0.175*** (0.007) [73]
Explained by PRP	0.008*** (0.000) [21] {14}	0.014*** (0.001) [11] {13}	0.016*** (0.001) [8] {21}	0.026*** (0.001) [15] {54}	0.036*** (0.002) [15] {56}
Unexplained by PRP	-0.001 (0.001) [-3] {5}	0.004*** (0.001) [3] {2}	-0.002 (0.002) [-1] {-2}	0.008** (0.002) [5] {6}	0.013*** (0.003) [5] {7}
Population size	22,101,833				
Number of observations	142,739				

Notes: (i) RIF-OB decomposition is 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), 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 and figures in [] ({ }) are a percentage of the observed GPG (explained/unexplained) at the selected percentile. (iv) * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 5. PRP incidence and amount, and log hourly pay by PRP jobs, by gender and sector

Incidence of PRP (%)		Male	Female	All
Public sector		9.88	3.91	5.82
	Population size	1,768,826	3,756,798	5,525,624
	Number of observations	10,270	25,170	35,440
Private sector		40.52	31.78	36.85
	Population size	9,608,433	6,967,776	16,576,210
	Number of observations	58,965	48,334	107,299
Amount of PRP (£) (conditional on receipt)				
Public sector		2,242.37	1,710.93	1,999.57
	Population size	174,727	146,982	321,709
	Number of observations	1,021	947	1,968
Private sector		7,405.73	3,973.96	6,161.48
	Population size	3,893,218	2,214,439	6,107,657
	Number of observations	23,298	14,998	38,296
Log hourly pay PRP jobs				
Public sector		3.056	2.893	2.982
		[0.413]	[0.428]	[0.428]
	Population size	174,727	146,982	321,709
	Number of observations	1,021	947	1,968
Private sector		2.918	2.704	2.841
		[0.550]	[0.537]	[0.556]
	Population size	1,594,098	3,609,816	5,203,915
	Number of observations	23,298	14,998	38,296
Log hourly pay non-PRP jobs				
Public sector		2.908	2.744	2.794
		[0.435]	[0.428]	[0.438]
	Population size	1,594,098	3,609,816	5,203,915
	Number of observations	9,249	24,223	33,472
Private sector		2.608	2.433	2.529
		[0.476]	[0.444]	[0.472]
	Population size	5,715,216	4,753,337	10,468,552
	Number of observations	35,667	33,336	69,003

Notes: Authors' calculation using data from the ASHE 2019. See text for a description of sample construction and variable definitions. Figures in [] are standard deviations of the (log) hourly gross pay.

Table 6. OB and RIF-OB decomposition of the observed GPG at the mean and selected percentiles of the unconditional log hourly pay distribution, by sector

Public sector	Mean	10 th	25 th	50 th	75 th	90 th
Observed GPG	0.173*** (0.005)	0.124*** (0.005)	0.192*** (0.007)	0.185*** (0.007)	0.142*** (0.008)	0.206*** (0.011)
Explained GPG	0.036*** (0.006) [21]	0.106*** (0.006) [85]	0.114*** (0.007) [59]	0.044*** (0.006) [24]	0.005 (0.007) [4]	-0.036** (0.011) [-17]
Unexplained GPG	0.137*** (0.006) [79]	0.018* (0.008) [15]	0.078*** (0.007) [41]	0.141*** (0.007) [76]	0.137*** (0.008) [96]	0.242*** (0.015) [117]
Explained by PRP	0.007*** (0.001) [4] {19}	0.004*** (0.001) [3] {4}	0.007*** (0.001) [4] {6}	0.007*** (0.001) [4] {16}	0.010*** (0.001) [7] {2}	0.008*** (0.002) [4] {0}
Unexplained by PRP	0.001 (0.001) [1] {1}	0.002*** (0.001) [2] {11}	0.004*** (0.001) [2] {5}	-0.001 (0.001) [-1] {-1}	0.003** (0.001) [2] {2}	0.001 (0.002) [0] {0}
Population size	5,525,624					
Number of observations	35,440					
Private sector	Mean	10 th	25 th	50 th	75 th	90 th
Observed GPG	0.215*** (0.003)	0.017*** (0.002)	0.140*** (0.003)	0.272*** (0.004)	0.287*** (0.006)	0.279*** (0.009)
Explained GPG	0.123*** (0.003) [57]	0.086*** (0.002) [506]	0.163*** (0.003) [116]	0.157*** (0.004) [58]	0.117*** (0.005) [41]	0.090*** (0.006) [32]
Unexplained GPG	0.092*** (0.003) [43]	-0.069*** (0.003) [-406]	-0.023*** (0.004) [-16]	0.115*** (0.004) [42]	0.170*** (0.006) [59]	0.189*** (0.008) [68]
Explained by PRP	0.012*** (0.001) [6] {10}	0.004*** (0.000) [24] {5}	0.008*** (0.000) [6] {5}	0.010*** (0.001) [4] {6}	0.017*** (0.001) [6] {15}	0.024*** (0.001) [9] {27}
Unexplained by PRP	0.004* (0.002) [2] {4}	0.007*** (0.001) [41] {-10}	0.010*** (0.001) [7] {-44}	0.001 (0.002) [0] {1}	0.000 (0.004) [0] {0}	0.004 (0.006) [1] {2}
Population size	16,576,210					
Number of observations	107,299					

Notes: (i) OB and RIF-OB 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 constant term. (ii) Decompositions are calculated using the relevant male coefficients as the baseline. The unexplained component also includes a constant term. (iii) Figures in () are standard errors and figures in [] ({ }) are the percentage of the observed (explained/unexplained) GPG. (iv) * p < 0.05, ** p < 0.01, *** p < 0.001.

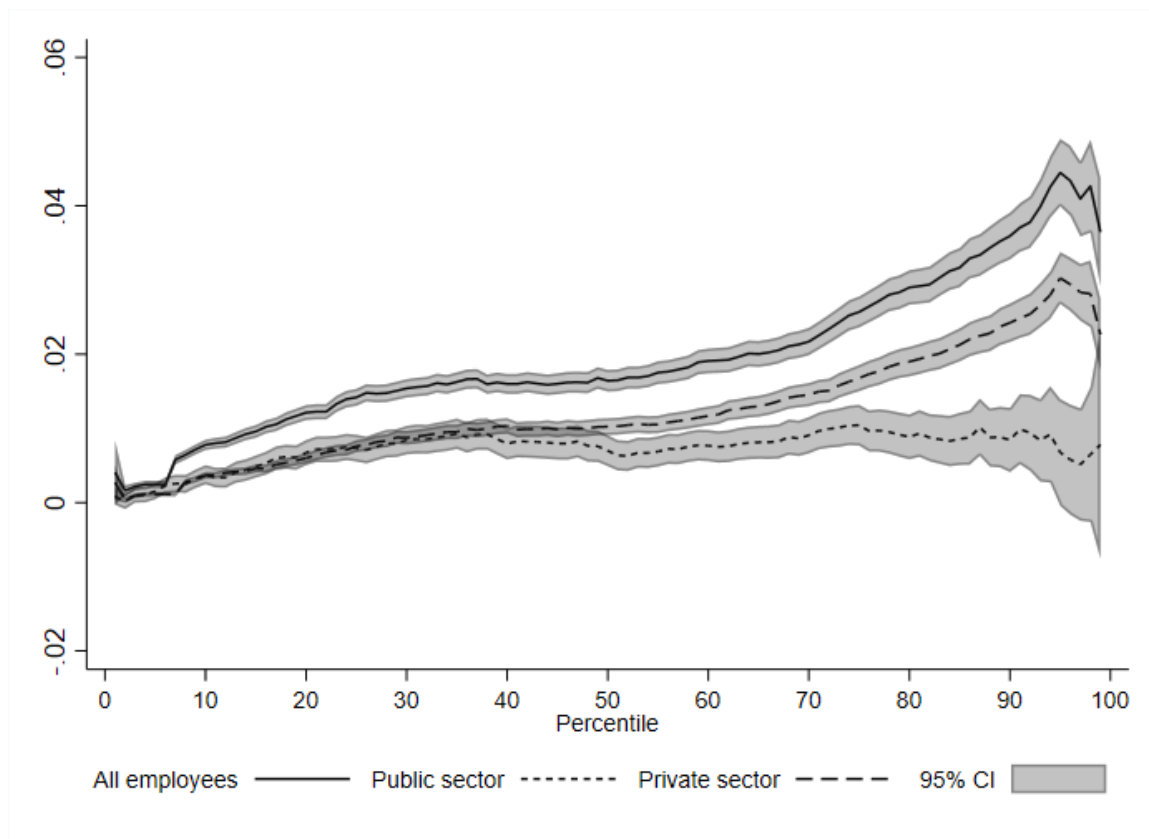


Figure 1. GPG explained by PRP across the distribution, all employees and by sector

Notes: Figure shows log points of the observed GPG explained by PRP derived from RIF-OB decompositions as described in the text.

Appendix: Performance-related Pay and the UK Gender Pay Gap

Table A1. Means of explanatory variables by gender and PRP jobs

	PRP			Non-PRP		
	Male	Female	All	Male	Female	All
Age	41.57	40.42	41.15	40.98	41.67	41.35
Work region (%)						
North East	3.17	3.39	3.25	3.87	4.04	3.96
North West	10.65	10.80	10.70	11.24	11.58	11.42
Yorkshire and The Humber	8.42	7.55	8.10	8.49	8.53	8.51
East Midlands	7.37	7.19	7.30	7.47	6.77	7.10
West Midlands	8.56	7.76	8.27	8.76	8.48	8.61
South West	8.40	8.02	8.26	8.77	8.93	8.86
East	8.97	8.59	8.83	9.47	9.61	9.55
London	18.06	20.01	18.78	14.96	13.86	14.37
South East	15.64	15.60	15.62	13.40	13.41	13.41
Wales	3.77	3.61	3.71	4.61	4.92	4.77
Scotland	7.00	7.47	7.17	8.95	9.86	9.44
Tenure (years)	9.18	8.43	8.90	7.00	6.96	6.98
Contract type (%)						
Part-time	5.16	25.80	12.74	16.77	43.41	30.99
Temporary contract	1.39	1.75	1.52	7.62	9.09	8.40
Firm size	13,043.98	17,373.50	14,634.15	9,542.78	11,313.30	10,487.57
Collective agreement (%)	27.57	26.69	27.25	35.32	49.31	42.78
Occupation (%)						
Managers, directors and senior officials	18.56	13.89	16.85	11.78	6.05	8.72
Professional occupations	19.53	13.76	17.41	21.10	25.22	23.30
Associate professional and technical occupations	20.17	21.61	20.70	14.21	10.85	12.42
Administrative and secretarial occupations	4.81	18.43	9.81	5.65	17.42	11.93
Skilled trades occupations	11.43	1.35	7.73	13.94	1.78	7.45
Caring, leisure and other service occupations	1.12	4.69	2.43	4.37	16.86	11.04
Sales and customer service occupations	6.78	17.76	10.81	5.40	8.44	7.02
Process, plant and machine operatives	9.18	2.11	6.58	10.91	1.48	5.88
Elementary occupations	8.41	6.39	7.67	12.63	11.90	12.24
Public sector (%)	4.30	6.22	5.00	21.81	43.16	33.20

Population size	4,067,945	2,361,421	6,429,366	7,309,314	8,363,153	15,672,467
Number of observations	24,319	15,945	40,264	44,916	57,559	102,475

Notes: Authors' calculation using data from the ASHE 2019. See text for sample construction and variable definitions.

Table A2. Pooled OLS log hourly pay regression coefficients, all employees and by sector

Variable	All employees	Public sector	Private sector
Female	-0.093*** (0.003)	-0.115*** (0.005)	-0.089*** (0.003)
PRP	0.159*** (0.004)	0.120*** (0.012)	0.158*** (0.004)
Female × PRP	-0.046*** (0.005)	-0.029 (0.016)	-0.050*** (0.005)
R^2	0.506	0.500	0.501
Population size	22,101,833	5,525,624	16,576,210
Number of observations	142,739	35,440	107,299

Notes: (i) Specifications include a constant term, 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 constant term. Specifications for 'All employees' also include a public sector indicator. (ii) Standard errors in parentheses. (iii) * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A3. OB decomposition of the observed GPG at the mean, sensitivity analysis

	(1) Benchmark	(2) Control for firm fixed effects	(3) Control for detailed occupation	(4) Exclude occupation among controls	(5) Control for industry	(6) Full-time employees
Observed GPG	0.163*** (0.003)	0.163*** (0.003)	0.163*** (0.003)	0.163*** (0.003)	0.163*** (0.003)	0.111*** (0.003)
Explained GPG	0.068*** (0.003) [42]	0.064*** (0.008) [39]	0.089*** (0.003) [55]	0.040*** (0.003) [25]	0.069*** (0.003) [42]	0.012*** (0.003) [11]
Unexplained GPG	0.095*** (0.003) [58]	0.099*** (0.008) [61]	0.074*** (0.003) [45]	0.123*** (0.003) [75]	0.094*** (0.003) [58]	0.099*** (0.003) [89]
Explained by PRP	0.020*** (0.001) [12] {29}	0.012*** (0.002) [7] {19}	0.016*** (0.001) [10] {18}	0.028*** (0.001) [17] {70}	0.019*** (0.001) [12] {28}	0.016*** (0.001) [14] {133}
Unexplained by PRP	0.003** (0.001) [2] {3}	0.011* (0.005) [7] {11}	0.002* (0.001) [1] {3}	0.005*** (0.001) [3] {4}	0.005*** (0.001) [3] {5}	-0.000 (0.002) [0] {0}
Population size	22,101,833	22,101,833	22,101,833	22,101,833	22,101,833	16,425,853
Number of observations	142,739	142,739	142,739	142,739	142,739	101,218
	(7) Employees worked in the same job for more than one year	(8) PRP indicator based on PRP received in the reference pay period that relates to pay period	(9) Dependent variable: (log) hourly pay based on annual pay	(10) Dependent variable: (log) hourly pay including overtime	(11) Dependent variable: (log) hourly basic pay	(12) Dependent variable: (log) annual pay including the incentive pay

Observed GPG	0.175*** (0.003)	0.163*** (0.003)	0.209*** (0.005)	0.168*** (0.003)	0.152*** (0.003)	0.466*** (0.005)
Explained GPG	0.076*** (0.003) [43]	0.066*** (0.003) [40]	0.081*** (0.005) [39]	0.072*** (0.003) [43]	0.066*** (0.003) [43]	0.357*** (0.005) [77]
Unexplained GPG	0.099*** (0.003) [57]	0.097*** (0.003) [60]	0.128*** (0.005) [61]	0.096*** (0.003) [57]	0.086*** (0.003) [57]	0.109*** (0.003) [23]
Explained by PRP	0.022*** (0.001) [13] {29}	0.003*** (0.000) [2] {5}	0.043*** (0.001) [21] {53}	0.020*** (0.001) [12] {28}	0.014*** (0.001) [9] {21}	0.026*** (0.001) [6] {7}
Unexplained by PRP	0.003* (0.001) [2] {3}	0.000 (0.001) [0] {0}	0.003 (0.002) [1] {2}	0.003* (0.001) [2] {3}	-0.000 (0.001) [0] {0}	0.006*** (0.001) [1] {6}
Population size	17,837,471	22,101,833	22,101,833	22,101,833	22,101,833	22,101,833
Number of observations	115,468	142,739	142,739	142,739	142,739	142,739
	(13) Dependent variable: (log) annual pay excluding the incentive pay	(14) Female coefficients as the baseline	(15) Unweighted	(16) Include non-profit sector as part of private sector	(17) Include (log) hourly pay outliers	(18) ASHE 2018
Observed GPG	0.446*** (0.005)	0.163*** (0.003)	0.139*** (0.003)	0.163*** (0.003)	0.164*** (0.003)	0.170*** (0.003)
Explained GPG	0.338*** (0.005) [76]	0.036*** (0.003) [22]	0.049*** (0.003) [35]	0.070*** (0.003) [43]	0.068*** (0.003) [41]	0.068*** (0.003) [40]
Unexplained GPG	0.108*** (0.003) [24]	0.127*** (0.003) [78]	0.090*** (0.003) [65]	0.093*** (0.003) [57]	0.096*** (0.003) [59]	0.102*** (0.003) [60]

Explained by PRP	0.011*** (0.001) [2] {3}	0.018*** (0.001) [11] {50}	0.018*** (0.001) [13] {37}	0.019*** (0.001) [12] {27}	0.020*** (0.001) [12] {29}	0.020*** (0.001) [12] {29}
Unexplained by PRP	0.002 (0.001) [0] {2}	0.005** (0.002) [3] {4}	0.003** (0.001) [2] {3}	0.004** (0.001) [2] {4}	0.003** (0.001) [2] {3}	0.003* (0.001) [2] {3}
Population size	22,101,833	22,101,833	-	24,292,950	22,109,455	22,119,198
Number of observations	142,739	142,739	142,739	155,916	142,790	145,649

Notes: (i) OB decomposition is 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 (except in column (6)), temporary contract indicator, (log) firm size (except in column (2)), collective agreement indicator, SOC 2010 major groups (nine categories) (except in column (3) where we control for detailed occupation (367 categories)), a public sector indicator (except in column (2)) and a constant term. Specifications in columns (12) and (13) also control for (log) total paid hours worked during the reference period and log annual weeks worked (generated by dividing the annual pay by the weekly pay following Papps and Gregg, 2014). (ii) Decompositions are calculated using the male coefficients as the baseline except in column (14) where female coefficients are used as the baseline. (iii) Figures in () are standard errors and figures in [] ({ }) are the percentage of the observed (explained/unexplained) GPG. (iv) * p < 0.05, ** p < 0.01, *** p < 0.001.

Table A4. The incidence of PRP across the log hourly gross pay distribution (%), by sector

Pay Decile	Public sector			Private sector		
	Males	Females	All	Males	Females	All
10	3.44	1.66	1.82	14.05	10.20	11.29
20	6.24	1.91	3.66	26.64	17.07	21.26
30	7.08	3.37	3.10	29.69	22.96	27.55
40	10.88	3.13	4.96	34.49	28.43	29.96
50	10.74	4.00	6.85	42.35	27.82	35.79
60	9.14	4.92	6.63	42.35	33.88	40.16
70	9.47	4.65	6.15	45.44	39.22	42.40
80	12.92	3.88	5.50	49.01	40.11	45.75
90	14.60	5.21	9.07	54.62	45.62	50.97
100	14.29	6.40	10.51	66.55	55.06	63.34

Notes: Authors' calculation using data from the ASHE 2019. See text for a description of sample construction and variable definitions.

Table A5. OB decomposition of the observed GPG at the mean, by sector

		Public sector		Private sector	
Observed GPG		0.173***		0.215***	
		(0.005)		(0.003)	
Explained GPG		0.036***		0.123***	
		(0.006)		(0.003)	
		[21]		[57]	
Unexplained GPG		0.137***		0.092***	
		(0.006)		(0.003)	
		[79]		[43]	
Components of the GPG		Explained	Unexplained	Explained	Unexplained
PRP		0.007***	0.001	0.012***	0.004*
		(0.001)	(0.001)	(0.001)	(0.002)
		[4] {19}	[1] {1}	[6] {10}	[2] {4}
Age		-0.002	0.429***	0.009***	0.276***
		(0.001)	(0.053)	(0.001)	(0.023)
		[-1] {-6}	[248] {313}	[4] {7}	[128] {300}
Work region		0.005***	0.003	-0.001*	0.003**
		(0.001)	(0.001)	(0.001)	(0.001)
		[3] {14}	[2] {2}	[0] {-1}	[1] {3}
Tenure		0.004***	0.020**	0.005***	0.010**
		(0.001)	(0.008)	(0.000)	(0.004)
		[2] {11}	[12] {15}	[2] {4}	[5] {11}
Part-time		-0.023***	0.040***	0.022***	-0.012***
		(0.004)	(0.006)	(0.002)	(0.003)
		[-13] {-64}	[23] {29}	[10] {18}	[-6] {-13}
Temporary contract		0.000	-0.000	0.000	-0.000
		(0.000)	(0.002)	(0.000)	(0.001)
		[0] {0}	[0] {0}	[0] {0}	[0] {0}
Firm size		-0.000	0.063**	-0.001***	0.082***
		(0.000)	(0.023)	(0.000)	(0.005)
		[0] {0}	[36] {46}	[0] {-1}	[38] {89}
Collective bargaining		-0.000	-0.020	-0.000	0.002*
		(0.000)	(0.014)	(0.000)	(0.001)
		[0] {0}	[-12] {-15}	[0] {0}	[1] {2}
Occupation		0.044***	-0.011	0.076***	-0.016***
		(0.004)	(0.008)	(0.002)	(0.002)
		[25] {122}	[-6] {-8}	[35] {62}	[-7] {-17}
Population size		5,525,624		16,576,210	
Number of observations		35,440		107,299	

Notes: (i) OB decomposition is 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 constant term. (ii) Decompositions are calculated using the relevant male coefficients as the baseline. The unexplained component in each column also includes a constant term. (iii) Figures in () are standard errors and figures in [] ({}) are the percentage of the observed (explained/unexplained) GPG. (iv) * p < 0.05, ** p < 0.01, *** p < 0.001.

Table A6. OB decomposition of the observed GPG at the mean, by sector, sensitivity analysis (Dependent variable: (log) hourly pay based on annual pay)

	Public sector	Private sector
Observed GPG	0.220*** (0.008)	0.271*** (0.006)
Explained GPG	0.034*** (0.008) [15]	0.152*** (0.005) [56]
Unexplained GPG	0.186*** (0.010) [85]	0.119*** (0.006) [44]
Explained by PRP	0.012*** (0.001) [5] {35}	0.027*** (0.001) [10] {18}
Unexplained by PRP	0.001 (0.001) [0] {1}	0.006* (0.003) [2] {5}
Population size	5,525,624	16,576,210
Number of observations	35,440	107,299

Notes: (i) OB decomposition is 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 (except in panel A where we control for firm fixed effects), collective agreement indicator, SOC 2010 major groups (nine categories) and a constant term. (ii) Decompositions are calculated using the male coefficients as the baseline. (iii) Figures in () are standard errors and figures in [] ({}) are percentages of the observed (explained/unexplained) GPG. (iv) * p < 0.05, ** p < 0.01, *** p < 0.001.

Table A7. RIF-OLS log hourly pay regression results, selected percentiles of the unconditional pay distribution, all employees and by sector

All employees	10 th	25 th	50 th	75 th	90 th
Female	-0.022*** (0.002)	-0.057*** (0.002)	-0.086*** (0.003)	-0.128*** (0.006)	-0.173*** (0.008)
PRP	0.031*** (0.001)	0.063*** (0.002)	0.134*** (0.004)	0.195*** (0.007)	0.341*** (0.012)
Female × PRP	0.022*** (0.002)	0.020*** (0.003)	-0.028*** (0.006)	-0.058*** (0.010)	-0.142*** (0.016)
R^2	0.199	0.335	0.435	0.373	0.201
Population size			22,101,833		
Number of observations			142,739		
Public sector	10 th	25 th	50 th	75 th	90 th
Female	-0.036*** (0.003)	-0.044*** (0.004)	-0.096*** (0.007)	-0.123*** (0.007)	-0.211*** (0.013)
PRP	0.001 (0.005)	0.046*** (0.008)	0.176*** (0.016)	0.161*** (0.021)	0.197*** (0.038)
Female × PRP	0.012 (0.008)	-0.014 (0.013)	-0.055* (0.023)	-0.064* (0.028)	-0.063 (0.049)
R^2	0.206	0.360	0.466	0.315	0.156
Population size			5,525,624		
Number of observations			35,440		
Private sector	10 th	25 th	50 th	75 th	90 th
Female	-0.013*** (0.001)	-0.054*** (0.002)	-0.100*** (0.004)	-0.126*** (0.007)	-0.139*** (0.011)
PRP	0.006*** (0.001)	0.033*** (0.002)	0.117*** (0.004)	0.218*** (0.008)	0.406*** (0.014)
Female × PRP	0.017*** (0.002)	0.040*** (0.003)	-0.004 (0.006)	-0.079*** (0.011)	-0.215*** (0.019)
R^2	0.160	0.301	0.416	0.386	0.224
Population size			16,576,210		
Number of observations			107,299		

Notes: (i) Specifications include 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 constant term. Specifications for 'All employees' also include a public sector indicator. (ii) Standard errors in parentheses. (iii)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A8. RIF-OB decomposition of the observed GPG across the distribution, all employees and by sector, sensitivity analysis (Dependent variable: (log) hourly pay based on annual pay)

All employees	10 th	25 th	50 th	75 th	90 th
Observed GPG	0.190*** (0.013)	0.140*** (0.004)	0.220*** (0.004)	0.212*** (0.005)	0.274*** (0.007)
Explained GPG	0.130*** (0.013) [68]	0.085*** (0.004) [61]	0.069*** (0.004) [31]	0.047*** (0.004) [22]	0.070*** (0.006) [26]
Unexplained GPG	0.060*** (0.017) [32]	0.055*** (0.004) [39]	0.151*** (0.004) [69]	0.165*** (0.005) [78]	0.204*** (0.008) [74]
Explained by PRP	0.072*** (0.003) [38] {55}	0.028*** (0.001) [20] {33}	0.029*** (0.001) [13] {42}	0.037*** (0.001) [17] {79}	0.055*** (0.002) [20] {79}
Unexplained by PRP	-0.011 (0.006) [-6] {-18}	0.006*** (0.002) [4] {11}	0.001 (0.002) [0] {1}	0.009*** (0.002) [4] {5}	0.020*** (0.004) [7] {10}
Population size	22,101,833				
Number of observations	142,739				
Public sector	10 th	25 th	50 th	75 th	90 th
Observed GPG	0.202*** (0.011)	0.216*** (0.008)	0.218*** (0.008)	0.160*** (0.008)	0.205*** (0.012)
Explained GPG	0.098*** (0.011) [49]	0.112*** (0.008) [52]	0.043*** (0.007) [20]	-0.000 (0.007) [0]	-0.056*** (0.012) [-27]
Unexplained GPG	0.104*** (0.015) [51]	0.104*** (0.009) [48]	0.175*** (0.008) [80]	0.160*** (0.009) [100]	0.261*** (0.017) [127]
Explained by PRP	0.009*** (0.001) [4] {9}	0.010*** (0.001) [5] {9}	0.011*** (0.001) [5] {26}	0.012*** (0.002) [8] {-}	0.014*** (0.003) [7] {-25}
Unexplained by PRP	-0.000 (0.001) [0] {0}	0.002* (0.001) [1] {2}	-0.001 (0.001) [0] {-1}	0.002 (0.001) [1] {1}	0.002 (0.002) [1] {1}
Population size	5,525,624				
Number of observations	35,440				
Private sector	10 th	25 th	50 th	75 th	90 th
Observed GPG	0.298*** (0.016)	0.157*** (0.004)	0.277*** (0.004)	0.309*** (0.006)	0.314*** (0.009)
Explained GPG	0.276*** (0.016) [93]	0.153*** (0.004) [97]	0.142*** (0.004) [51]	0.106*** (0.005) [34]	0.091*** (0.007) [29]
Unexplained GPG	0.022 (0.021) [7]	0.004 (0.005) [3]	0.135*** (0.005) [49]	0.203*** (0.006) [66]	0.223*** (0.009) [71]
Explained by PRP	0.043*** (0.002) [14] {16}	0.016*** (0.001) [10] {10}	0.019*** (0.001) [7] {13}	0.025*** (0.001) [8] {24}	0.036*** (0.002) [11] {40}
Unexplained by PRP	0.015	0.011***	0.006*	0.000	0.004

	(0.009)	(0.002)	(0.003)	(0.004)	(0.007)
	[5] {68}	[7] {275}	[2] {4}	[0] {0}	[1] {2}
Population size	16,576,210				
Number of observations	107,299				

Notes: (i) RIF-OB decomposition is 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 constant term. Specifications for ‘All employees’ also include a public sector indicator. (ii) Decompositions are calculated using the relevant male coefficients as the baseline. (iii) Figures in () are standard errors and figures in [] ({ }) are percentages of the observed (explained/unexplained) GPG. (iv) * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

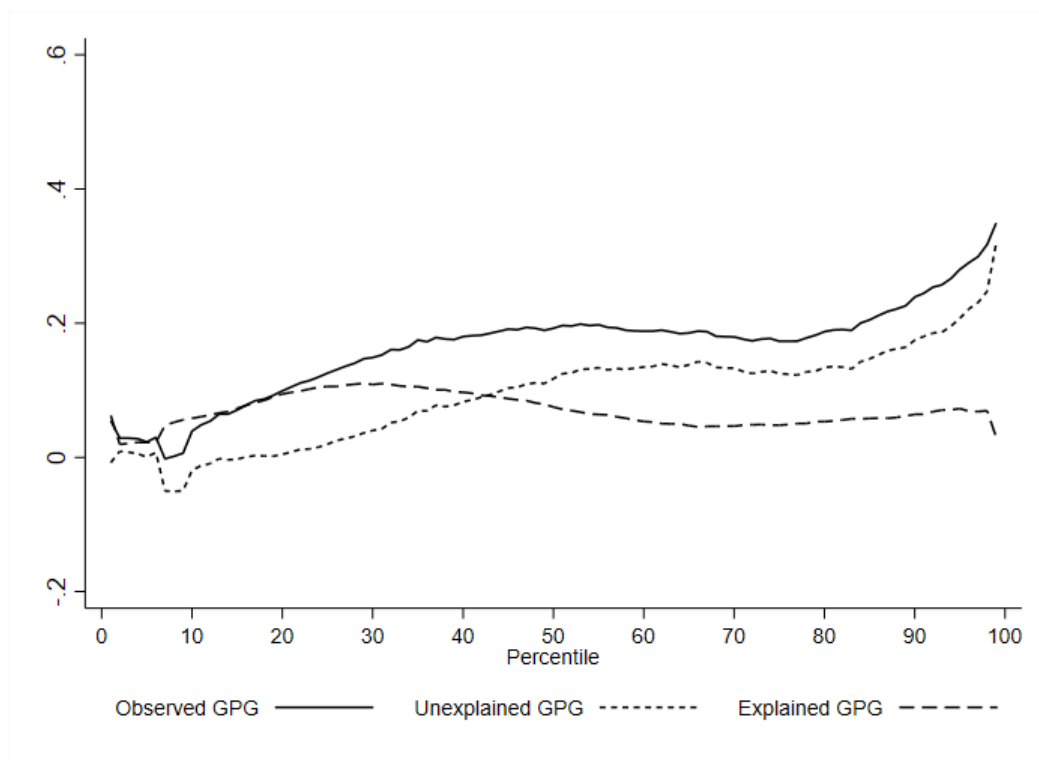
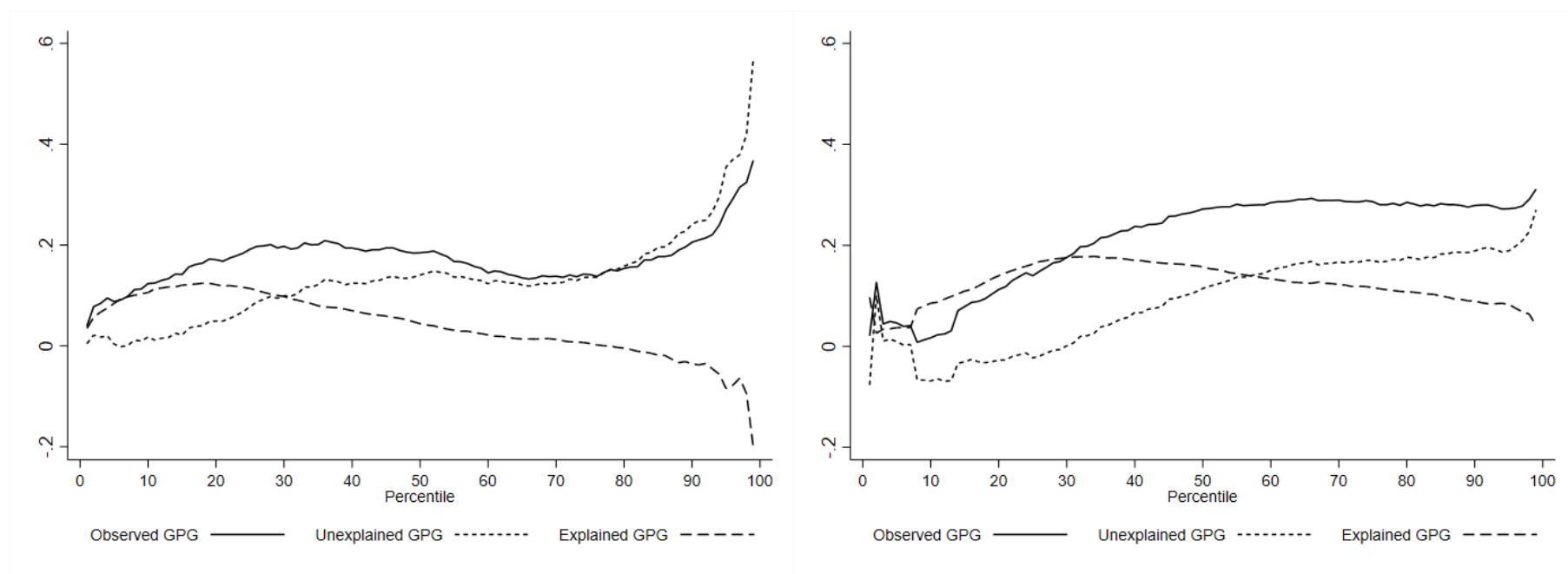


Figure A1. Decomposition of the observed GPG across the distribution

Notes: Figure shows the observed GPG and its explained and unexplained components (all in log points) derived from RIF-OB decompositions as described in the text.



(a) Public sector

(b) Private sector

Figure A2. Decomposition of the observed GPG across the distribution, by sector

Notes: Figure shows the observed GPG and its explained and unexplained components (all in log points), by sector, derived from RIF-OB decompositions as described in the text.