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Abstract

Most studies of ethnic wage gaps rely on household survey data. As such, they are unable to examine the degree to which wage gaps arise within or between firms. We contribute to the literature using high quality employer-employee payroll data on jobs, hours, and earnings, linked with the personal and family characteristics of workers from the population census for England and Wales. We reveal substantial unexplained wage gaps disadvantaging ethnic minority groups among both women and men. These disparities occur predominantly within firms rather than between them and are especially pronounced among higher earners. The patterns vary significantly by gender and by ethnic minority group compared to white workers. Since most of the wage disadvantage for ethnic minorities is within-firm, our results suggest that the UK's recent legislative reforms on firm-level gender pay gap reporting should be expanded to encompass ethnicity pay gap

Keywords: Employer-Employee Data, Unconditional Quantile Regression, Decomposition Methods, UK Labour Market
JEL Codes: J31; J7; J71

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This work was produced using statistical data from the UK's Office for National Statistics (ONS). The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.
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1. Introduction

A vast literature already describes substantial ethnic wage gaps in the United Kingdom across the earnings distribution (e.g., Algan et al., 2010; Blackaby et al., 1994; Blackaby, et al., 1998; Blackaby et al., 2002; Longhi et al., 2013; Stewart, 1983). These gaps vary across ethnic minority groups and by gender (Longhi & Brynin, 2017). In contrast to the gender wage gap, there is no clear evidence of convergence in these gaps over time (Clark & Nolan, 2021; Li & Heath, 2020). Most existing studies rely on household survey data and, therefore, cannot assess the role of firms in shaping ethnic wage disparities. Yet, there is growing recognition that firms influence wage determination, contrary to the standard assumption in labour economics that most employers are wage takers. Moreover, it is also now well-established that a large proportion of the growth in wage inequality over the past few decades, in the UK and other countries, is due to the differences in wages *between* rather than *within* firm (e.g., Barth et al., 2016; Song et al., 2019 for the US; Card et al., 2013 for Germany; Schaefer & Singleton, 2020 for the UK); besides human capital, firms are important contributors to wage variation.

Ethnic wage gaps in Britain may be affected by differences across employers if, for example, there is some degree of segregation by ethnicity across firms, which may arise from discriminatory hiring practices (Heath & Di Stasio, 2019), or from workers sorting into firms based on their expectations about employer tolerance for diversity (e.g., Avery et al., 2013). However, evidence from the United States almost three decades ago suggested that the difference between the average earnings of Black and White workers "is primarily a within-firm phenomenon" (Carrington & Troske, 1998: 231), as opposed to a between-firm phenomenon. Carrington and Troske (1998) also found that within-plant ethnic wage gaps were largely accounted for by traditional observed characteristics, such as education or experience, even if a significant but smaller residual component remained.

To date, only one study has examined ethnic wage differences within British workplaces using linked employer-employee data. Using data from 1998 to 2011, Forth et al. (2023a) found substantial ethnic segregation of employees across workplaces but also concluded that average ethnic wage gaps in Britain predominantly occur *within* workplaces, rather than between them, echoing the results of Carrington and Troske (1998) for the United States. Forth et al. (2023a) infer that the sorting of workers by ethnicity across employers plays little role in accounting for ethnic wage gaps in Britain. This might occur if, for example, employers have unbiased hiring practices but discriminate based on ethnicity in new hire pay or subsequent promotions, whether statistically or based on taste. Although such discrimination within firms would be illegal under UK equalities legislation, the same law applies to hiring discrimination, for which there is persistent and recent evidence from correspondence (CV) studies (Heath & Di Stasio, 2019). There is also survey evidence for the UK indicating significant ethnic differences in the reporting of unfair treatment in the workplace (Wheatley & Gifford, 2019), and in unfair treatment in promotions (Heath & Cheung, 2006). For the United States, there is also evidence of ethnic discrimination in relation to dismissals (Giuliano et al., 2011). Another possible reason for within-employer wage gaps, hinted at by Forth et al. (2023a), is poorer quality matches between jobs and skills among ethnic minority workers, leading to skills underutilisation.

In this paper, we use a newly created employer-employee dataset for England and Wales to study the distribution of ethnic wage gaps, addressing the influence of firm-specific pay effects (i.e., the different amounts of pay that employees earn just because they happen to work for one employer rather than another). Although Forth et al. (2023a) conducted similar analysis, their sample sizes were relatively small, so they focused on the gap between white and all non-white employees, offering only limited analysis hinting at the heterogeneity in gaps between different ethnic groups, and studying only wage gaps at the mean. Our sample sizes allow us to overcome these limitations, such that we can examine wage gaps between white employees and six non-white ethnic groups, for men and women separately, and across the wage distribution. Furthermore, in contrast to Forth et al.'s (2023a) reliance on banded, self-reported wage data, we exploit precise records of earnings and hours of work returned by employers from their payrolls, due to a statutory request from the UK's national statistical authority.

Our dataset links the payroll-based Annual Survey of Hours and Earnings (ASHE) to the 2011 Census of England and Wales. Thus, we add a rich set of personal and family characteristics for employees from the Census to the accurate components of pay and employer identification coming from the ASHE. We call this new dataset ASHE-Census. It contains approximately 0.5 percent of the population of employees in England and Wales in 2011. This allows us to estimate for the first time how much the distribution of wage gaps for different ethnic groups in England and Wales are influenced by firm-specific wages.[2] First, we estimate covariate-adjusted gender-ethnicity wage gaps, both at the mean and selected percentiles of the overall unconditional employee wage distribution. We distinguish whether these unexplained wage gaps occur within firms (between coworkers) or because of the different distributions by gender-ethnicity across employers. We also decompose the distributions of ethnic wage gaps, by applying an extension of the Oaxaca-Blinder (O-B) wage

[2] Our approach is nevertheless limited because of the small samples of ethnic minority workers typically observed within firms in the UK and our dataset, such that we are unable to estimate separate within and across-firm component contributions to pay gaps (e.g., for gender, see Card et al., 2016). We also do not use longitudinal data, so the "firm-specific wage effect" throughout this study is the unobserved firm-specific component of the error in a one period wage model, such that the returns to observable characteristics are estimated using variation between colleagues in that period.

decomposition method to unconditional quantile regression (Firpo et al., 2009, Firpo et al., 2018; Rios-Avila, 2020.[3]

We find substantial variation in ethnic wage gaps across the wage distribution and by gender, depending on which ethnic group is compared with white employees. This heterogeneity would otherwise be obscured by either pooling non-white employees or only focusing on the central tendency of these gaps (as in the case of Forth et al., 2023a). We also show that, where substantial gaps exist between the wages of white and ethnic minority employees, these cannot typically be accounted for by who people work for – echoing the findings of Carrington and Troske (1998) for the United States.

Among men, accounting for firm-specific wages and other worker characteristics, the explained parts of ethnic wage gaps generally favour ethnic minority employees (e.g., in the case of high-earning Indian male employees). However, we find significant unexplained (or residual) gaps, predominantly within firms. These unexplained gaps between some ethnic minority and white wage distributions, particularly among men, are at least as large as the observed gaps (e.g., for high earning Black Caribbean employees).[4] These findings are consistent with the notion of 'glass ceilings', potentially linked to discriminatory pay and promotion practices, making it difficult for ethnic minorities to reach the higher echelons within firms unless they possess substantially higher wage-relevant attributes than their white colleagues.

Our findings have potentially important implications for policy, since they highlight the likely substantial role played by firms in the treatment of ethnic minority workers. As well as in accounting for the size and persistence of ethnic wage gaps in Britain, both positive and negative, the results show that the gaps vary across the distribution, not only on average but to a greater extent among higher earning workers. Our results suggest that policy makers may want to consider the substantial influence that some employers are having, either directly or indirectly, on the likelihood of ethnic minorities working for them, as also evidenced by the discriminatory hiring practices that have been consistently implicated by field experiments. At the same time, since ethnic wage disparities are predominantly a within rather than a between firm phenomenon, there is arguably scope and

[3] For other recent applications of these decomposition methods that analyse the distributions of pay gaps, see Clark and Nolan (2021), who study ethnicity wage gaps in the UK over time using household survey data, and Kaya (2021), who studies the gender wage gap in Turkey using employer-employee linked data.

[4] To the best of our knowledge, this is the first evidence highlighting the likely scale of this issue for Black Caribbean men within the British labour market. However, our findings align with recent evidence on the lack of black board members in the UK's FTSE 100 London City firms, in banking and finance (see "Impenetrable glass ceiling for Black workers in financial firms"; https://www.ftadviser.com/your-industry/2020/10/21/impenetrable-glass-ceiling-for-black-workers-in-financial-firms/, accessed 12 February 2024. The general lack of ethnic diversity on UK corporate boards was also documented in the initial and monitoring reports of the independent Parker Review (Parker, 2017).

justification, based on our findings, to extend current UK legislation on firm-level gender pay gap reporting and transparency, by encompassing ethnicity and even its interaction with gender.[5]

The remainder of the paper proceeds as follows: Section 2 describes the ASHE-Census dataset; Section 3 describes our estimation methods and presents the main results on covariate-adjusted gender-ethnic wage gaps, on average and at selected unconditional quantiles of the overall wage distribution, for England and Wales in 2011; Section 4 focuses on the influence of observable characteristics on the differences between white and ethnic minority wage distributions; and Section 5 concludes. The Online Appendix contains further details about the ASHE-Census dataset and more detailed estimates concerning the distributions of gender-ethnicity wage gaps in England and Wales.

2. Data

We use a recently released employer-employee dataset for England and Wales to study the distribution of gender-ethnic wage gaps, analysing whether these are accounted for within firms, between co-workers, or across firms. The dataset comes from linking the payroll-based Annual Survey of Hours and Earnings (ASHE) of 2011 (Office for National Statistics, 2021) to the 2011 Census of England and Wales (Office for National Statistics, 2020). This linkage combines a rich set of personal and family characteristics for employees (e.g., education, ethnicity, dependent children, etc.), collected in the national population census, with the accurate components of pay and employer identification coming from the ASHE. We call this dataset the ASHE-Census (Forth et al., 2023b; Office for National Statistics, 2023a). It contains wage observations for around 0.5 percent of the population of employees in England and Wales. The ASHE has recently been used in cross-section and longitudinally over employers and employees to study the influence of firm-specific wage effects for various patterns of pay in the UK (e.g., Bell et al., 2022; Jewell et al., 2020; Pham et al., 2024; Schaefer & Singleton, 2020; Singleton, 2019; Stokes et al., 2017). The ASHE-Census dataset adds several well-known covariates of wages that were missing from those studies. By identifying the ethnicity of employees in ASHE, we can estimate the distributions of ethnic wage gaps in England and Wales for men and women separately and, for the first time, we are able to establish whether they are accounted for by unexplained differences in pay between co-workers within firms, or by the distribution (segregation) of workers across firms that tend to pay relatively high or low wages, after accounting also for a traditional set of explanatory characteristics, such as education and labour

[5] For evidence on the impacts of gender pay reporting: in the UK (introduced in 2017), see Duchini et al. (2024) and Jones et al. (2022); in Denmark (introduced in 2007), see Bennedsen et al. (2022); in Austria (introduced in 2011, but internal reporting within firms only), see Gulyas et al. (2023).

market experience.[6] Online Appendix A gives extended details about the ASHE-Census dataset, sample selection and their effects on the estimation sample sizes, and descriptions for all the variables used throughout our analysis, including their categories and the transformations used in our regression models. A more recent Census of England and Wales was conducted in 2021, but those data have not yet been linked to ASHE; the ASHE-Census data we use here are thus the latest available.

We focus on basic hourly wages (henceforth just the "wage"), derived by dividing an employee's basic weekly earnings by their corresponding record of basic weekly paid hours, all excluding overtime. Basic wages allow us to abstract from any different tendency of employees across ethnicity and gender to self-select or choose overtime and shift premium work. For this reason, basic wages are the natural choice for an analysis of firm-specific wages and the amount of wage variation by gender and ethnicity within firms. Even so, the Online Appendix contains comparable versions of our main results which include overtime and other components of pay in the derivation of gross hourly wages.[7]

We restrict our estimation sample to employees aged 25 to 64 years, who did not incur any loss of pay in the reference period, and who were not paid at an apprenticeship rate. We only consider the main job of an employee observed in ASHE, which has a record of basic hours worked in the reference period, in April 2011, of at least one and no more than ninety-nine hours per week. Along with white employees, we consider six broad ethnic minority groups for England and Wales in this study, corresponding to the largest minority groups recorded by the Census: Indian, Pakistani, Bangladeshi, Chinese, Black African, and Black Caribbean. Due to small sample sizes, we do not include employees who reported mixed or other ethnicities on the Census. Throughout, white refers to employees who reported on the Census as having a British, English, Irish, Gypsy or another white ethnic background. Before any analysis, we trim the top and the bottom 0.5 percentiles of the overall basic hourly wage distribution over all employees remaining in ASHE-Census, after the aforementioned sample selection criteria.

The employers (or firms) that we study in the ASHE are observed at the enterprise level, which is a specific administrative definition of employers that can be considered equivalent to the firm. An enterprise can contain several local units (or plants). We believe this is the appropriate level to study

[6] Since the first version of this current paper was published (Phan et al., 2022), a few other studies have used the ASHE-Census to explore UK pay patterns: Forth and Jones (2025) use the dataset to decompose disability pay gaps within and between firms; Kaya (2024) does similarly for the migrant wage gap; and Hall et al. (2024) use the longitudinal aspect of ASHE linked with Census 2011 to analyse ethnic minority and migrant pay gaps over the life-cycle, notwithstanding the possible sample attrition issues for ASHE when following the 2011 cross-section over time.

[7] We also provide some basic descriptive information on ethnicity wage gaps using gross hourly earnings, calculated as the ratio of gross weekly pay to usual weekly hours including overtime (see Table 1). This second wage measure is somewhat like the gross hourly pay reported by the household respondents in the UK Labour Force Survey, which is used in Clark and Nolan (2021) in their analysis of ethnicity wage distributions. In our descriptive analysis of the Annual Population Survey in the Online Appendix, of which the Labour Force Survey is the main part, we use some of the same wage records and measure of wages as in Clark and Nolan (2021).

firm-specific wages, because pay determination systems and practices in multi-plant organisations tend to be determined at the enterprise level.[8] In multivariate analyses we control for general wage differences between regional labour markets, using data on the employee's workplace location recorded in ASHE, because some firms have employees who are dispersed throughout England and Wales.

2.1 A first look at the differences in wages and employment by ethnicity in ASHE-Census

Table 1 shows the raw mean ethnic wage gaps among employees in England and Wales in 2011 from the ASHE-Census data. Among ethnic groups, Chinese employees had the highest mean hourly wages, followed by Indian and white employees. The rankings of mean wages by ethnic group are the same whether we consider gross hourly earnings or basic hourly wages from the payroll-based ASHE. Table 1 also shows the mean wages of employees by ethnicity from the UK's Annual Population Survey (APS) (Office for National Statistics, 2022). The APS is a boosted and combined version of the household-based Quarterly Labour Force Survey that is used for most UK national labour market statistics besides pay. Average hourly wages in the APS for 2011 show a similar pattern across ethnic groups to what we observe in the ASHE-Census, with the same rankings across ethnic minority groups and white employees. Further descriptive estimates of ethnic wage gaps in our ASHE-Census sample, including by gender and looking beyond the mean, are illustrated in Figure 1 and Online Appendix A. The latter also includes further comparisons to equivalent statistics and distributions obtained from the APS, which use some of the same wage records and measures as in Clark & Nolan (2021). Figure 1 expands on Table 1, by showing raw ethnic wage gaps from ASHE-Census for men and women separately.[9] It emphasises the importance of comparing ethnic wage gaps within gender because the patterns in those gaps vary markedly across men and women. That said, the hourly earnings rankings by ethnicity are generally the same within men or women, with Chinese employees earning the most, followed by Indian employees. Among men and women, the most poorly paid are Bangladeshis.

[8] Brown et al. (2003) found that pay-setting in large UK companies mostly takes place at the enterprise level: in half of these companies, corporate management was determining pay directly, while in one-third corporate management was establishing the limits within which local managers had to negotiate.

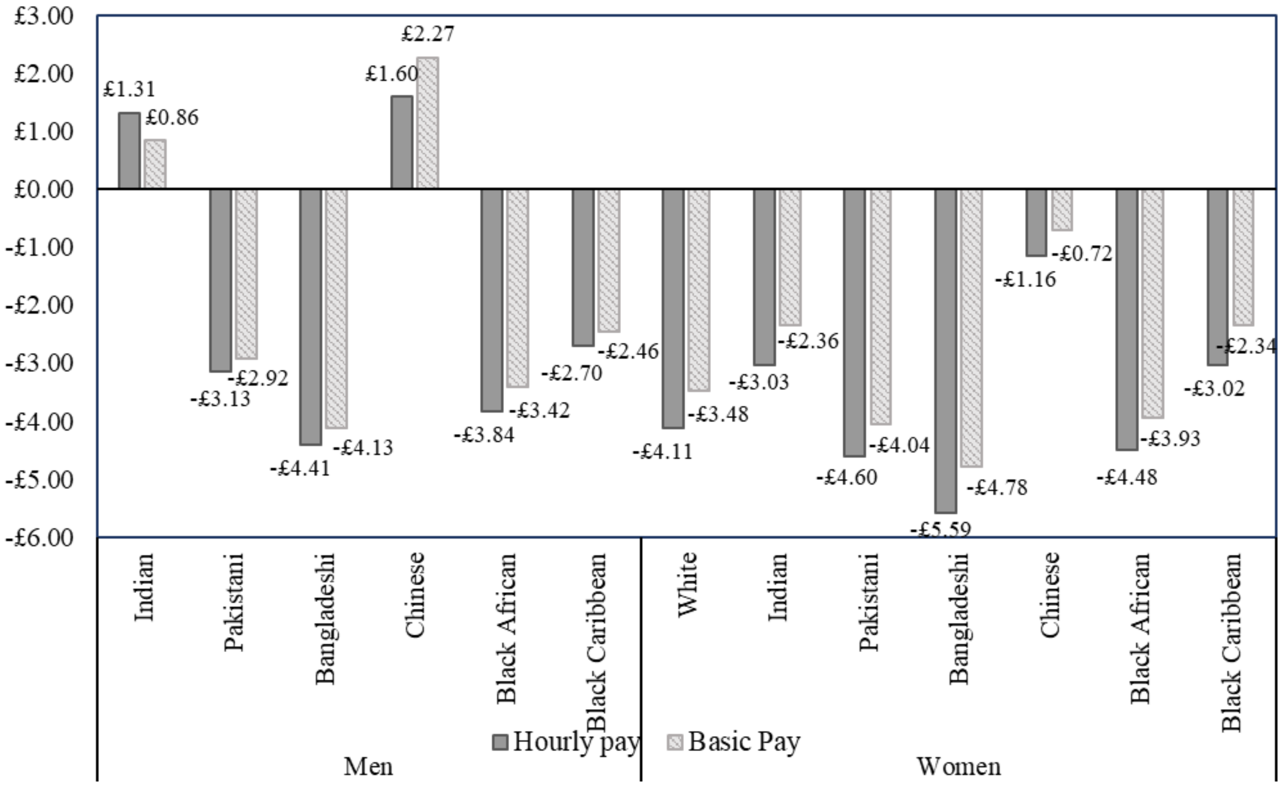
[9] Online Appendix Figures A1-A3 show kernel density estimates of employee hourly wages, by ethnicity and gender, comparing the ASHE-Census and APS datasets. Overall, we are reassured by these statistics and comparisons that the ASHE-Census can provide reasonably representative descriptions of employee wages for England and Wales.

TABLE 1: Absolute average ethnic wage levels and gaps among employees aged 25-64 in England and Wales, 2011

Ethnicity	ASHE-Census 2011						APS 2011		
	Gross hourly earnings			Basic hourly wage			Hourly wage		
	N	Mean	Premium (+)/ Penalty (-)	*N*	Mean	Premium (+)/ Penalty (-)	*N*	Mean	Premium (+)/ Penalty (-)
Chinese	463	£17.04	£2.18	460	£16.53	£2.38	177	£14.51	£1.46
Indian	2703	£16.13	£1.27	2690	£15.20	£1.06	1,283	£13.99	£0.94
white	**91,830**	**£14.86**	**-**	**91447**	**£14.14**	**-**	**46,128**	**£13.05**	**-**
Black Car.	1,116	£14.10	-£0.76	1110	£13.57	-£0.57	419	£12.35	-£0.71
Pakistani	940	£13.30	-£1.55	933	£12.61	-£1.53	473	£11.96	-£1.09
Black Afr.	1,168	£12.82	-£2.04	1163	£12.26	-£1.88	659	£11.71	-£1.34
Bangladeshi	311	£12.15	-£2.70	310	£11.59	-£2.55	174	£10.30	-£2.76

Notes: author calculations using the ASHE-Census 2011 and Annual Population Survey 2011 datasets. These are unweighted sample statistics. See Online Appendix A & the following section for discussion of some population sample weights for ASHE-Census and estimates that use them.

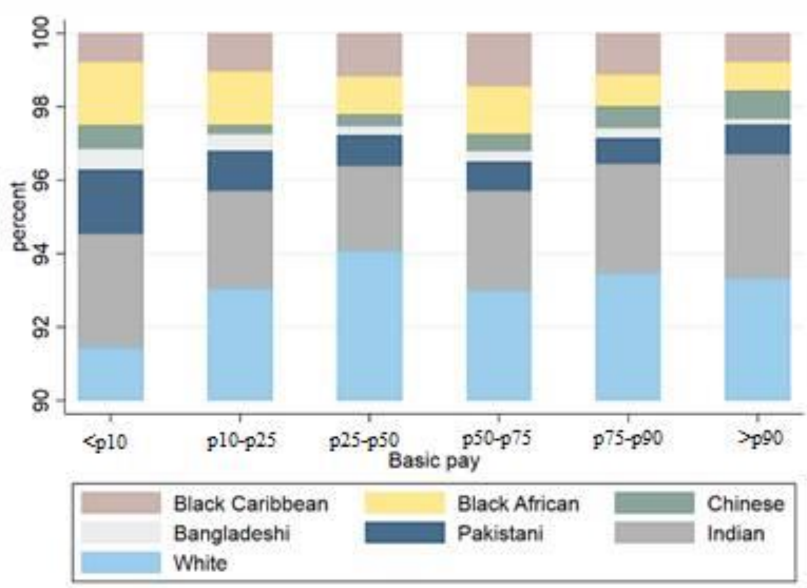
FIGURE 1: Absolute mean gender-ethnic hourly wage gaps, relative to white men, among employees in England and Wales, ASHE-Census 2011



Notes: author calculations using ASHE-Census 2011 dataset. 'Hourly pay' refers to total gross weekly earnings, including overtime, divided by weekly hours worked. 'Basic Pay' refers only to basic weekly earnings divided by basic weekly hours, as discussed in the main text. The wage gaps are calculated as the mean wage of gender-ethnicity group X minus the mean wage of white men. These figures are unweighted. For hourly pay, *N* white (F=47,938 and M=43,892), *N* Indian (F=1,360 and M=1,343), *N* Pakistani (F=362 and M=578), *N* Bangladeshi (F=115 and M=196), *N* Chinese (F=262 and M=201), *N* Black African (F=625 and M=543), and *N* Black Caribbean (F=687 and M=429). For the basic pay, *N* White (F=47,685 and M=43,762), *N* Indian (F=1,349 and M=1,341), *N* Pakistani (F=356 and M=577, *N* Bangladeshi (F=114 and M=196), *N* Chinese (F=262 and M=198), *N* Black African (F=621 and M=542), and *N* Black Caribbean (F=682 and M=428).

Figure 2 gives a general overview of the ethnic distribution of employees at different parts of the overall basic hourly wage distribution for our analysis sample in 2011. White workers make up more than 90 percent of the employees in every part of the overall wage distribution, but their presence varies across the quantile ranges shown. White workers are relatively underrepresented at the bottom and most overrepresented in the second quartile of the wage distribution. Pakistani, Bangladeshi, and Black African employees are more represented at the bottom of the wage distribution and generally constitute a diminishing proportion of all workers moving up the percentiles. By contrast, Chinese and Indian employees are relatively overrepresented at the top of the overall wage distribution. Black Caribbean employees are generally under-represented towards both the bottom and the top of the basic hourly wage distribution.

FIGURE 2: Stacked percentages of employees by ethnicity at different parts of the basic hourly wage distribution in England and Wales, analysis sample, ASHE-Census 2011



Notes: author calculations using ASHE-Census 2011 dataset, ages 25-64 only. "p10-p25" refers to employees earning from the 10th percentile of basic hourly wages up to the 25th, etc. See Table 1 for sample sizes of employees by ethnicity. Interpretation: the first bar shows that around 91% of employees earning in the bottom ten percentiles of the overall employee wage distribution, in our ASHE-Census analysis sample, are white, just over 2.5% are Indian, just less than 2% are Pakistani, and so on.

3. Estimates of unexplained (adjusted) gender-ethnicity wage gaps

In this section, we investigate whether firm-specific wage effects alter some basic estimates of the unexplained (or residual) gender-ethnic wage gaps. In doing so we can establish whether these total unexplained wage gaps are accounted for by the unexplained differences in wages between co-workers within the same firm, or by the unexplained differences in the wages that firms pay their employees regardless of their ethnicity.

3.1 Estimation

Mean log wage gaps

For the mean adjusted (log) gaps, we begin by estimating wage equations of the following form using Ordinary Least Squares (OLS):

$$y_i = \alpha + \theta_{Z(i)} + \mathbf{x}_i\boldsymbol{\beta} + \sigma_{M(i)} + \varphi_{J(i)} + \varepsilon_i \qquad (1)$$

The dependent variable, $y_i = \ln \omega_i$, is the log wage of employee i. $\theta_{Z(i)}$ indicates a series of specific wage effects for the gender-ethnicity of an employee, where $z = Z(i)$ is an indicator function that person i is in gender-ethnic-minority group z, and where $z = 0$ (the excluded category) indicates white men. Estimates of these parameters can then be used to trace out adjusted wage gaps, by gender within ethnic minority groups, and between ethnic minority groups by gender. $\mathbf{x}_i$ is a row vector of relevant controls for wage determination, containing the following variables which are described fully in Online Appendix A: quadratics in individual age and tenure at the current firm; highest qualification level; general health status; whether working part-time; whether married; number of children; age of the youngest child – variables we would expect to correlate with and partly account for unobserved accumulated human capital, including through general work experience, especially among women (e.g., see for the UK, Costa Dias et al., 2020); Nomenclature of Territorial Units for Statistics Level 1 (NUTS1; e.g., London, Wales) region of work; and whether non-UK born. $\boldsymbol{\beta}$ is a column vector containing the parameters for each of these control variables. $\sigma_{M(i)}$ gives occupation-specific wage effects (SOC10 3-digit), where $m = M(i)$ is an indicator function that person i is in occupation m. $\varphi_{J(i)}$ are firm-specific wage effects (fixed over all employees observed in the same firm in 2011), where $j = J(i)$ is an indicator function that person i is an employee at firm j. The remaining wage heterogeneity is captured by the error term, ε_i.

When we omit the firm-specific wage effects from Equation (1), $\theta_{Z(i)}$ can be interpreted as giving the average wage gaps between gender-ethnic groups that are not explained by the observed characteristics in $\mathbf{x}_i$. This is comparable to traditional estimates of gender-ethnic wage gaps that have been obtained from UK household surveys (e.g., Longhi et al., 2013). When the firm-specific wage effects are included in Equation (1), $\theta_{Z(i)}$ instead only give the portions of the overall average unexplained wage gaps that occur because of differences in pay between the co-workers within firms that have on average the same observable characteristics in $\mathbf{x}_i$. To recover the remainder of the total unexplained wage gaps from this model, we then gather up the estimates $\varphi_{J(i)}$ from Equation (1), for each employee, and regress them again on indicators of gender-ethnicity and some observed firm-specific characteristics:[10]

$$\hat{\varphi}_{J(i)} = a + \pi_{Z(i)} + \mathbf{k}_i \boldsymbol{b} + e_i \tag{2}$$

$\mathbf{k}_i$ is a row vector of firm-specific variables that come from the UK government's administrative register of employers: an indicator for private sector status, as well as linear and squared terms for the number of employees in the firm. $\boldsymbol{b}$ is the column vector containing the parameters for these variables and e_i is the residual. $\pi_{Z(i)}$ gives the association between an employee's gender and ethnicity and the unobserved firm-specific effects estimated from Equation (1). We interpret these as the amount of the overall average gender-ethnic wage gap that is unexplained between firms, which arises from the different distribution of workers over firms that pay residually different average wages. For this two-step regression model, we henceforth refer to estimates of θ_z from Equation (1) as providing the 'Unexplained Within Firm' wage gaps and estimates of π_Z from Equation (2) as providing the 'Unexplained Between Firm' wage gaps. The sum of these gives the 'Total Unexplained' wage gaps, which are comparable (though not identical due to covariances) to what is obtained directly from the estimation of Equation (1) when omitting the firm-specific wage effects.

It is important to note here that $\pi_{Z(i)}$ are, in effect, gender-ethnic group averages of firm-specific wage residuals. They do not identify the tendency of different groups in the population to receive different firm-specific wage premia, that is, the extent to which different groups are more or less likely to sort into high-wage than low-wage firms. Doing so would require panel data and the estimation of an AKM-style wages model (e.g., Card et al., 2018), where more economically meaningful firm-fixed wage effects can be identified by exploiting the mobility of workers across firms within the largest connected set of workers and firms (for an example using the longitudinal ASHE and studying the gender wage gap in Great Britain, see Jewell et al., 2020).

[10] Note that Equation (2) could also be estimated at the level of the firm with weights given by the sample number of employees in each firm that were used to estimate Equation (1), with the same results for the parameters. We prefer the employee-level approach though as we can then keep our standard errors consistently estimated as being robust to firm-level clustering.

Unconditional quantiles of the wage distribution

Moving beyond a study of the average white and ethnic minority employees, to estimate the influence of ethnicity and gender throughout the log wage distribution, we also use Unconditional Quantile Regression (UQR) (Firpo et al., 2009). This is equivalent to estimating the Recentred Influence Function (RIF) of log wages for a particular quantile τ of log wages, $\hat{Q}_\tau$, and then estimating Equation (1) for each considered quantile with $\widehat{RIF}(y_i, \hat{Q}_\tau)$ as the dependent variable, using OLS:

$$\widehat{RIF}(y_i, \hat{Q}_\tau) = \hat{Q}_\tau + \frac{\tau - \mathbb{1}\{y_i \leq \hat{Q}_\tau\}}{f_y(\hat{Q}_\tau)} = \alpha_\tau + \theta_{Z(i),\tau} + \mathbf{x}_i\boldsymbol{\beta}_\tau + \sigma_{M(i),\tau} + \varphi_{J(i),\tau} + \varepsilon_i \qquad (3)$$

where $f_y(\cdot)$ is the density of the marginal distribution of log wages, estimated using a Gaussian kernel and Silverman plugin bandwidth.

The UQR method allows us to study whether the unexplained relationship between ethnicity and wages varies for relatively low, middling, or high earners. Rios-Avila and Maroto (2022) give a review on how to interpret and compare linear regression, conditional quantile regression (CQR), and UQR models, particularly in the presence of fixed effects, using studies of the motherhood penalty in earnings as a salient example. CQR models would allow us to look at how a person being Indian rather than white tends to affect the conditional distribution of wages, conditional on the other covariates, including the firm-specific wage effects. As Rios-Avila and Maroto (2022) explain and demonstrate, because results from CQR models depend on the conditioning characteristics, researchers typically then report results for the average person (at mean characteristics) or report average conditional quantile effects across the whole estimation sample. However, CQR would not allow us to ask the perhaps more policy-relevant question of how much ethnicity matters for the unconditional distribution of earnings. UQR does allow this, and instead of an average effect in the linear regression case, $\theta_{Z(i),\tau}$ traces out what differences there would be between quantiles of the overall wage distribution by moving between imaginary worlds where every person's gender-ethnicity (within a firm) can change form one type to another. In other words, the estimates of $\theta_{Z(i),\tau}$ can tell us what differences there would be in the τth quantile of the wage distribution when comparing extreme cases case where every person in the population was a white woman with another where everybody was a Black Caribbean man. Rather than such an extreme thought experiment, it can be easier to see that rescaled estimates of $\theta_{Z(i),\tau}$ can also tell us how quantiles of the unconditional wage distribution are sensitive to very small or marginal changes in the incidence of different gender-ethnicity groups in the sample, e.g., a 0.1 percentage point increase in the share of the population who are Bangladeshi men, offset by a 0.1 percentage point decrease in the share of the population who are white men – if being a Bangladeshi man is associated with no wage penalty compared with a white man at some quantile, then the overall wage distribution would not move at that point when changing the ethnic composition of the population. This is analogous to the linear regression case in terms of considering whether being Bangladeshi matters for the average person's wages.

We also estimate UQR model equivalents of Equation (2), the second step of the regression model, which allows us to distinguish between the Unexplained Within and Unexplained Between firm portions of the Total Unexplained wage gaps, between observed unconditional quantiles of different gender-ethnicity group wage distributions. These can also be interpreted in terms of whether the overall employee wage distribution is sensitive to small changes in the incidence of gender-ethnicity within firms or between firms.

For all models, we estimate standard errors that are robust to clustering at the firm level, reflecting the sampling nature of the ASHE survey (approximately 1% of employees per firm appear in the survey so long as the firm responds and their data is processed by ONS). To estimate Equations (1) & (3) fully, with the firm-specific wage effects, and the second-step regressions using those estimated effects (i.e., Equation (2) and its UQR equivalents), we must restrict the estimation samples to only employees for whom at least one other co-worker is observed in the ASHE-Census dataset (with no missing values for control variables, and after the other sample selection described in Appendix A).

3.2 Results for mean log wage gaps

Before considering the more selected sample for the two-step regression models described above, which will inevitably be somewhat biased toward larger firms compared with the whole of ASHE-Census, Table 2 show estimates of Equation (1) using all the ASHE-Census 2011 employee observations described in Section 2 and Online Appendix A, with basic hourly wages as the dependent variable. Columns (I-II) show the estimates for the raw average gender-ethnicity log wage gaps, with all the other variables in Equation (1) omitted; columns (III-IV) show estimates of the total unexplained or adjusted gender-ethnicity log wage gaps when the personal, family and job characteristics in $\mathbf{x}_i$ are added to the model; and columns (V-VI) show these estimates after 3-digit occupation categories are also controlled for. Firm-specific wage effects are not added to these specifications. In each case, the first column shows unweighted estimates, and the second column applies the ASHE-Census sampling weights described in Online Appendix A. Overall, the weights appear to make little difference.

TABLE 2: Estimates of gender-ethnic log basic hourly wage gaps at the mean, employees in England and Wales, 2011

	(I)	(II)	(III)	(IV)	(V)	(VI)
1. Male	0.199***	0.214***	0.125***	0.138***	0.108***	0.109***
	(0.009)	(0.008)	(0.005)	(0.005)	(0.004)	(0.004)
Ethnicity (excl. cat., white):						
2. Indian	0.055***	0.066***	-0.084***	-0.079***	-0.053***	-0.052***
	(0.017)	(0.018)	(0.014)	(0.014)	(0.010)	(0.010)
3. Pakistani	-0.035	-0.043	-0.068***	-0.070***	-0.019	-0.023
	(0.026)	(0.028)	(0.022)	(0.022)	(0.015)	(0.016)
4. Bangladeshi	-0.062	-0.058	-0.063*	-0.057*	-0.023	-0.024
	(0.040)	(0.042)	(0.032)	(0.033)	(0.023)	(0.024)
5. Chinese	0.162***	0.166***	-0.005	-0.002	0.009	0.005
	(0.038)	(0.039)	(0.027)	(0.028)	(0.021)	(0.023)
6. Black African	-0.008	-0.022	-0.204***	-0.203***	-0.102***	-0.098***
	(0.021)	(0.022)	(0.015)	(0.016)	(0.011)	(0.012)
7. Black Caribbean	0.107***	0.111***	-0.088***	-0.089***	-0.038***	-0.040***
	(0.021)	(0.022)	(0.016)	(0.016)	(0.012)	(0.013)
Interaction terms:						
8. Indian × Male	-0.044*	-0.019	-0.003	0.015	-0.009	-0.000
	(0.024)	(0.025)	(0.019)	(0.020)	(0.014)	(0.015)
9. Pakistani × Male	-0.151***	-0.121***	-0.093***	-0.076**	-0.089***	-0.082***
	(0.037)	(0.039)	(0.029)	(0.030)	(0.022)	(0.023)
10. Bangladeshi × Male	-0.157***	-0.156***	-0.188***	-0.184***	-0.164***	-0.169***
	(0.051)	(0.057)	(0.044)	(0.048)	(0.035)	(0.039)
11. Chinese × Male	-0.060	-0.063	-0.003	-0.001	-0.036	-0.028
	(0.061)	(0.064)	(0.045)	(0.045)	(0.036)	(0.037)
12. Black African × Male	-0.174***	-0.154***	-0.123***	-0.126***	-0.064***	-0.069***
	(0.033)	(0.035)	(0.025)	(0.026)	(0.019)	(0.020)
13. Black Caribbean × Male	-0.217***	-0.213***	-0.095***	-0.098***	-0.082***	-0.084***
	(0.029)	(0.031)	(0.024)	(0.024)	(0.019)	(0.020)
Individual characteristics	N	N	Y	Y	Y	Y
Family characteristics	N	N	Y	Y	Y	Y
Occupation (3-digit) effects	N	N	N	N	Y	Y
ASHE-Census weighted	N	Y	N	Y	N	Y
N of employees	90,120	89,523	90,120	89,523	90,120	89,523
R^2	0.040	0.044	0.441	0.451	0.638	0.640

Notes: author calculations using ASHE-Census 2011 dataset. This table reports wage equation estimates for employees in England and Wales, 2011. Column (I) reports the results controlling for gender-ethnic intersectionality only, while column (III) controls for further individual and family characteristics. Column (V) extends the estimates by additionally controlling for the SOC10 3-digit occupation effects. Columns (II), (IV) and (VI) report results using the ASHE-Census weights that are comparable to the unweighted estimates in Columns (I), (III) and (V), respectively. Individual characteristics: age, age squared, education, marital status, tenure, tenure squared, part-time, non-UK born, health status, and workplace region. Family characteristics: number of children, age of the youngest child. ***, **, * indicate significant differences from zero, two-sided tests, at the 1%, 5%, and 10% level, respectively, with standard errors robust to firm-level clustering in parentheses.

The results show that white men, in general, earn significantly higher wages than white women (row 1). Among women, three minority groups – Chinese, Black Caribbean and Indian – earn significantly higher hourly wages, on average, relative to white women (rows 3, 5 &7, column I). However, these positive gaps disappear with the addition of controls, including occupations, and, in the case of Indian and Black Caribbean women, become significant wage penalties of around 5 and 4 per cent, respectively (column V). With the addition of the control variables Black African women also earn significantly less than white women on average, by 10 log points or 11 per cent (row 6, column V).

Among men, the hourly wage gap estimates by ethnicity in Table 2 are more stable across the model specifications. Taking column V, for example, as an illustration, combining the coefficients of "Indian" and "Indian × Male" (rows 2 & 8) illustrates that Indian men earn significantly less than white men, on average, after controlling for individual, family and occupation characteristics, with a wage penalty of approximately 6 log points. All other ethnicity groups except Chinese – Pakistani, Bangladeshi, Black African and Black Caribbean men – also experience significant average wage penalties relative to white men, after including the traditional set of control variables and the occupation fixed effects. Similar results are also found when we study gross hourly earnings instead of basic hourly wages instead (see Online Appendix B1).

Introducing the possibility that employer characteristics could be important in explaining gender-ethnic wage gaps, columns (I-II) of Table 3 go a step further than the final columns of Table 2, by adding the variables in $\mathbf{k}_i$ (private sector status and firm size) as regressors in Equation (1). The inclusion of these employer controls leads to marginally greater estimated wage penalties for ethnic minority groups, and the overall patterns of gender-ethnicity wage gaps remain largely unchanged as compared to the results of column (V) in Table 2, though notably the wage penalties for Pakistani and Bangladeshi women become statistically significant (see Online Appendix B2 for results when using gross hourly earnings).

Henceforth, we restrict our focus to the sub-sample of ASHE-Census where employees can be observed with at least one co-worker in the dataset. Column (III) of Table 3 replaces the observed firm characteristics in $\mathbf{k}_i$ with the firm-specific wage effects $\varphi_{J(i)}$, thereby showing the unweighted estimates of the Unexplained Within firm (that is, between co-worker) gender-ethnic wage gaps, from the full Equation (1) at the mean. Column (V) of Table 3 shows the equivalent estimates applying the ASHE-Census sample weights. Columns (IV) and (VI) show the estimates of Equation (2), for the Unexplained Between firm part of the observed gender-ethnicity wage gaps, where these estimates can be summed with those in Columns (III) and (V), respectively, to recover the Total Unexplained gaps, which can be interpreted similar to the estimates obtained in the final two columns of Table (2) by omitting the firm-specific wage effects from Equation (1).

TABLE 3: Estimated gender-ethnic log basic hourly wage gaps at the mean, employees in England and Wales, 2011: Unexplained Gaps Within vs Between Firms

	Adjusted: employer characteristics		Adjusted: within firms	Adjusted: between firm	Adjusted: within firms	Adjusted: between firms
	(I)	(II)	(III)	(IV)	(V)	(VI)
1. Male	0.112***	0.112***	0.098***	0.044***	0.098***	0.044***
	(0.004)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)
Ethnicity (excl. cat., white):						
2. Indian	-0.071***	-0.071***	-0.063***	0.021***	-0.063***	0.024***
	(0.010)	(0.010)	(0.008)	(0.008)	(0.008)	(0.008)
3. Pakistani	-0.034**	-0.037**	-0.023	-0.006	-0.026*	-0.006
	(0.015)	(0.016)	(0.015)	(0.010)	(0.015)	(0.010)
4. Bangladeshi	-0.054**	-0.055**	-0.049**	0.012	-0.045*	0.011
	(0.023)	(0.023)	(0.025)	(0.016)	(0.025)	(0.017)
5. Chinese	-0.010	-0.014	-0.012	0.067***	-0.010	0.069***
	(0.022)	(0.023)	(0.020)	(0.017)	(0.020)	(0.019)
6. Black African	-0.109***	-0.106***	-0.091***	0.001	-0.090***	0.000
	(0.011)	(0.012)	(0.012)	(0.009)	(0.012)	(0.009)
7. Black Caribbean	-0.037***	-0.038***	-0.021**	0.020**	-0.023**	0.021**
	(0.012)	(0.013)	(0.011)	(0.008)	(0.011)	(0.008)
Interaction terms:						
8. Indian × Male	-0.008	0.001	-0.015	0.000	-0.014	0.009
	(0.014)	(0.015)	(0.011)	(0.010)	(0.011)	(0.011)
9. Pakistani × Male	-0.090***	-0.083***	-0.079***	-0.009	-0.079***	-0.000
	(0.022)	(0.023)	(0.020)	(0.014)	(0.020)	(0.016)
10. Bangladeshi × Male	-0.160***	-0.164***	-0.111***	0.015	-0.113***	0.032
	(0.034)	(0.038)	(0.033)	(0.024)	(0.034)	(0.027)
11. Chinese × Male	-0.041	-0.033	-0.043	0.017	-0.042	0.014
	(0.036)	(0.038)	(0.031)	(0.031)	(0.032)	(0.033)
12. Black African × Male	-0.064***	-0.068***	-0.054***	-0.033**	-0.055***	-0.033**
	(0.019)	(0.020)	(0.017)	(0.013)	(0.017)	(0.014)
13. Black Caribbean × Male	-0.080***	-0.082***	-0.085***	-0.013	-0.086***	-0.012
	(0.019)	(0.020)	(0.017)	(0.012)	(0.017)	(0.013)
Individual characteristics	Y	Y	Y	Y	Y	Y
Family characteristics	Y	Y	Y	Y	Y	Y
Occupation (3-digit) effects	Y	Y	Y	Y	Y	Y
Employer characteristics	Y	Y	Y	Y	Y	Y
ASHE-Census weighted	N	Y	N	N	Y	Y
N of employees	90,120	89,523	67,932	67,932	67,467	67,467
R^2	0.638	0.640	0.764	0.044	0.763	0.035

Notes: author calculations using ASHE-Census 2011 dataset. This table extends the wage equation estimates in Table 2 for employees in England and Wales, 2011. Column (I) reports results controlling additionally for employer characteristics, while column (II) applies the ASHE-Census sampling weights. Columns (III) and (IV) show adjusted wage estimates distributed between a within-firm effect and a between-firm effect, respectively, without sampling weights. Columns (V) and (VI) show the equivalent results with the ASHE-Census weight applied. Employer characteristics: private sector firm status, employer size, employer size squared. We also check the Durbin-Wu-Hausman test statistic, χ^2 =1,550.6 (*p*-value=0.000), which suggests that a model with employer fixed effects is at least as consistent as a random effects variant and thus preferred.
***, **, * indicate significant differences from zero, two-sided tests, at the 1%, 5%, and 10% levels, respectively, with standard errors robust to firm-level clustering in parentheses.

The total unexplained gender wage gap at the mean for white employees is around 14 log points, of which a majority of 10 log points is within firms while a significant 4 log points is attributed the distribution of employees between firms (row 1, columns III & IV of Table 3). This pattern suggests that most of the gender wage gap persists within the same workplace whilst a small but non-negligible portion of is due to the different firms where white men and women work. This finding is consistent with other UK evidence that firm-level segregation, or sorting, contributes significantly to overall gender wage disparities (e.g., Jewell et al., 2020; Pham et al., 2024).

Among women, the total average unexplained negative wage gaps of Indian, Bangladeshi, and Black African employees are accounted for by significant unexplained pay differences within firms (rows 2, 4, & 6, columns III & V of Table 3). The within-firm unexplained wage gaps for Pakistani women compared with white women are around 2-3 long points but not significant at the 5% level (row 3, columns III & V). For Black Caribbean women, a significant unexplained average within firm wage penalty of 2 log points is cancelled out by an unexplained between firm wage premium compared to white women, leaving a total unexplained wage gap of approximately zero (row 7, columns III & IV). Chinese women have a total unexplained wage premium over white women of 5.5 log points (row 5, columns III & IV), which is accounted for by them on average working at firms that pay higher average residual wages than where white women work.

The patterns of unexplained wage gaps for Indian and Chinese men relative to white men, within and between firms, are similar as those among women (rows 8 & 11, columns III & IV of Table 3). However, men from the other ethnic groups – Pakistani, Bangladeshi, Black African, and Black Caribbean – all face significantly and substantially greater within firm average wage penalties, compared to white men, than women from those ethnic groups do compared to white women (rows 9, 10, 12 & 13, columns III & IV). These average unexplained within firm wage penalties for the men of these ethnic minority groups are approx. 5-10 per cent or more compared to white men. Black African men also face a greater between firm unexplained wage penalty than do women from the same ethnic group (row 12). The results from columns (III) and (IV) of Table 3 are approximately unchanged in columns (V) and (VI) when the ASHE-Census sampling weights are applied to the estimates. These results are also robust to using gross hourly earnings as the wage measure in Online Appendix Table B2. Henceforth, when moving beyond the mean, we focus on regression model estimates that do not apply the ASHE-Census sampling weights.

3.3 Results for unconditional quantiles

Table 4 shows the estimates of Equation (3) for selected percentiles of the overall basic hourly wage distribution. The results in row 1 indicate that the total unexplained gender wage gap among white employees increases in magnitude at higher percentiles of the wage distribution, driven predominantly by unexplained wage differences between coworkers within firms. For instance, there is a total unexplained negative wage gap of approximately 23 log points between the 90th percentiles of white men and women's wages, of which 21 log points are unexplained within firms and 2 log points are accounted for by the unexplained differences in the firms men and women work for.

Among women, we generally see that the patterns of unexplained ethnic wage gaps at the mean, in total and within or between firms, as described above in Table 3 and repeated in columns (I) and (VII) of Table 4, are driven by larger wage gaps among higher earners. These gaps for most ethnic groups are also mostly accounted for by unexplained wage differences within firms. For instance, the 90th percentile of Indian women earners face an unexplained within firm wage gap of around 17 log points to the 90th percentile of white women earners (row 2, column VI). The comparable significant negative wage gaps faced by high-earning Bangladeshi, Black African, and Black Caribbean women are 15, 27, and 12 log points, respectively (rows 4, 6 & 7, column VI). The results also show that relatively high-earning Pakistani, Bangladeshi, and Black Caribbean men experience significantly larger within firm unexplained wage penalties, compared with white men, than women from the same ethnic minority groups do when compared with white women (rows 9, 10 & 13, columns V & VI). For instance, the 90th percentile of Black Caribbean male employee earners face an unexplained wage penalty of 30 log points within firms compared to their white male coworkers, from a total unexplained penalty of 32 log points (see Online Appendix Table B3 for comparable estimates using gross hourly earnings as the dependent variable in the wage regression models).

In general, the results so far show that the unexplained wage gaps of ethnic minority employees are: 1) large and statistically significant, both among men and among women; 2) larger among higher earners, especially among men; and 3) mostly accounted for by unexplained wage gaps within rather than between firms. Further, the gaps between ethnic minority men and white men are generally significantly larger than among women, and the largest unexplained gaps are for Black African and Black Caribbean men. In the next section, we further decompose and illustrate these ethnic differences in wages across the earnings distribution for the four largest ethnic minority groups in our sample: Indian, Pakistani, Black African, and Black Caribbean.

TABLE 4: Estimated gender-ethnic log basic hourly wage gaps at the mean and unconditional quantiles, England and Wales, 2011

	Unexplained Within Firms						Unexplained Between Firms					
	Mean	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)
1. Male	0.098***	0.023***	0.049***	0.085***	0.141***	0.211***	0.044***	0.045***	0.076***	0.057***	0.026***	0.020***
	[0.004]	[0.004]	[0.006]	[0.007]	[0.009]	[0.013]	[0.004]	[0.008]	[0.012]	[0.006]	[0.007]	[0.007]
2. Indian	-0.063***	0.017	-0.029*	-0.039***	-0.099***	-0.165***	0.021***	-0.008	0.009	0.016*	0.026**	0.067***
	[0.009]	[0.011]	[0.017]	[0.015]	[0.020]	[0.029]	[0.008]	[0.009]	[0.009]	[0.009]	[0.011]	[0.016]
3. Pakistani	-0.023	-0.034	0.014	-0.017	-0.021	-0.074	-0.006	-0.025*	-0.014	-0.002	0.005	0.032
	[0.015]	[0.026]	[0.025]	[0.028]	[0.033]	[0.055]	[0.010]	[0.014]	[0.016]	[0.012]	[0.016]	[0.024]
4. Bangladeshi	-0.049**	0.034	-0.022	-0.086*	-0.076	-0.154**	0.012	-0.020	-0.002	0.039*	0.026	0.015
	[0.024]	[0.039]	[0.041]	[0.047]	[0.060]	[0.070]	[0.016]	[0.018]	[0.021]	[0.023]	[0.039]	[0.040]
5. Chinese	-0.012	0.007	0.031	-0.055	-0.001	-0.017	0.067***	0.011	0.068***	0.070***	0.091***	0.095*
	[0.026]	[0.020]	[0.025]	[0.050]	[0.064]	[0.089]	[0.017]	[0.014]	[0.016]	[0.018]	[0.030]	[0.053]
6. Black Afr.	-0.091***	0.043***	0.023	-0.063***	-0.218***	-0.270***	0.001	-0.030***	-0.002	-0.018	0.030*	0.030
	[0.013]	[0.016]	[0.019]	[0.022]	[0.032]	[0.037]	[0.009]	[0.011]	[0.013]	[0.011]	[0.016]	[0.020]
7. Black Carib.	-0.021*	0.005	0.028	0.017	-0.038	-0.119***	0.020**	-0.004	0.026***	0.028***	0.021	0.040**
	[0.012]	[0.013]	[0.018]	[0.024]	[0.029]	[0.036]	[0.008]	[0.009]	[0.010]	[0.011]	[0.014]	[0.020]
8. Indian × Male	-0.015	-0.014	0.008	-0.056**	0.008	0.010	0.000	0.007	-0.017	-0.010	0.008	0.009
	[0.013]	[0.012]	[0.023]	[0.023]	[0.028]	[0.045]	[0.010]	[0.010]	[0.011]	[0.013]	[0.015]	[0.024]
9. Pakistani× Male	-0.079***	0.013	-0.092***	-0.072*	-0.132***	-0.093	-0.009	0.002	-0.032	-0.031*	-0.006	-0.004
	[0.021]	[0.032]	[0.036]	[0.039]	[0.045]	[0.071]	[0.014]	[0.017]	[0.020]	[0.019]	[0.022]	[0.033]
10. Bangladeshi× Male	-0.111***	-0.027	-0.070	-0.019	-0.213**	-0.216*	0.015	-0.022	-0.031	-0.022	0.076*	0.076
	[0.037]	[0.046]	[0.051]	[0.064]	[0.087]	[0.117]	[0.024]	[0.022]	[0.025]	[0.030]	[0.040]	[0.060]
11. Chinese× Male	-0.043	-0.027	-0.080**	0.025	-0.093	-0.096	0.017	0.008	-0.031	0.010	0.023	0.081
	[0.040]	[0.029]	[0.034]	[0.061]	[0.093]	[0.171]	[0.031]	[0.019]	[0.024]	[0.028]	[0.050]	[0.098]
12. Black Afr. × Male	-0.054***	-0.076***	-0.099***	-0.069*	-0.028	-0.032	-0.033**	-0.023	-0.042**	-0.021	-0.044*	-0.052*
	[0.019]	[0.025]	[0.031]	[0.036]	[0.043]	[0.054]	[0.013]	[0.016]	[0.019]	[0.019]	[0.023]	[0.027]
13. Black Carib. × Male	-0.085***	0.012	-0.050*	-0.065	-0.172***	-0.183***	-0.013	-0.018	-0.010	0.004	-0.012	-0.053**
	[0.020]	[0.019]	[0.028]	[0.044]	[0.041]	[0.053]	[0.012]	[0.012]	[0.016]	[0.025]	[0.020]	[0.026]

Notes: author calculations using ASHE-Census 2011 dataset. *N*=67,932 for all models. Columns (I)-(VI) show the within-firm contributions to the overall unexplained gender-ethnicity wage gaps, estimated using OLS at the mean or UQR for selected quantiles. *N* of distinct firm-specific wage effects estimated within these models is 7,477. Columns (VII)-(XII) show the additional between-firm contributions. The estimates are unweighted, and the same control variables are included in the regression models as in columns (III) & (IV) of Table 3.
***, **, * indicate significant differences from zero, two-sided tests, at the 1%, 5%, and 10% levels, respectively, with standard errors robust to firm-level clustering in parentheses.

4. Decomposing gender-ethnic wage gaps

Going a step further than the previous section, we revisit the cumulative roles that the differences in observable worker and job characteristics have in the observed wage gaps between ethnic minority and white employees within each gender. We do so using the regression model estimates from the previous section, applying two-way Oaxaca-Blinder-style decompositions (Blinder, 1973; Oaxaca, 1973) between different groups of employees, both for the gaps between the sample mean log wages of groups of employees as well as at selected quantiles of the respective estimated wage distributions (10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles).

4.1 Methodology

Mean log wage gaps

We can use our pooled model parameter estimates from Equations (1) and (2), estimated over all employees regardless of their gender or ethnicity, to decompose the differences in the mean log wages between any two gender-ethnic groups of workers within the sample, A and B (e.g., Indian men and white men) into five parts:

$$
\begin{aligned}
E[y_i \mid i \in A] - E[y_i \mid i \in B] = \{(E[\mathbf{x}_i\widehat{\boldsymbol{\beta}} \mid i \in A] - E[\mathbf{x}_i\widehat{\boldsymbol{\beta}} \mid i \in B]\} \\
+\{(E[\hat{\sigma}_{M(i)} \mid i \in A] - E[\hat{\sigma}_{M(i)} \mid i \in B]\} \\
+\{(E[\mathbf{k}_i\widehat{\boldsymbol{b}} \mid i \in A] - E[\mathbf{k}_i\widehat{\boldsymbol{b}} \mid i \in B]\} \\
+\{(E[\hat{\theta}_{Z(i)} \mid i \in A] - E[\hat{\theta}_{Z(i)} \mid i \in B]\} \\
+\{(E[\hat{\pi}_{Z(i)} \mid i \in A] - E[\hat{\pi}_{Z(i)} \mid i \in B]\} \qquad (4)
\end{aligned}
$$

The first three parts on the right-hand-side give the amount of the average log wage gap between the employees in groups A and B that are accounted for by differences in: first, the set of traditionally observed wage-relevant personal and job characteristics in $\mathbf{x}_i$; second, the 3-digit occupation-specific wage effects given by $\hat{\sigma}_m$; and third, the observed firm characteristics in $\mathbf{k}_i$. Together, these first three parts of (4) are often referred to in the literature as the 'Explained' amount from an Oaxaca-Blinder-style decomposition. They can also be interpreted as a counterfactual, conditional on the other factors included in the wage models, for how different a mean log wage gap would be, from what is observed, if the two groups of employees had similar distributions over the observed characteristics, assuming they would receive the same wage returns or effects associated with those characteristics as the average employee in the whole population.[11]

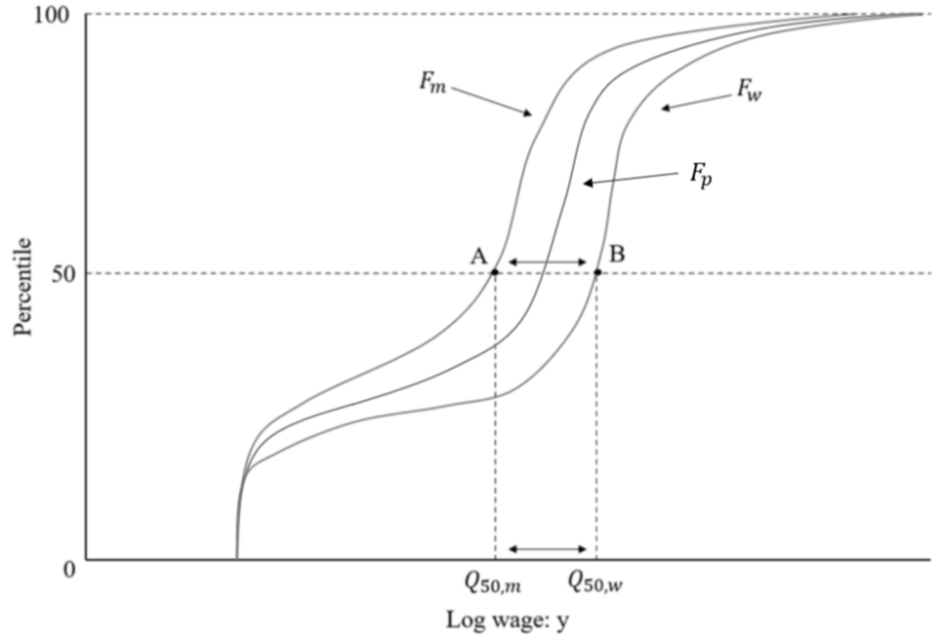
The final two parts of Equation (4) are the Unexplained Within Firm and Unexplained Between Firm portions of the overall observed mean wage gap, together giving the Total Unexplained gap. These parts will match exactly the estimates and results discussed in the previous section and presented in Tables 3 & 4. Due to the especially small sample sizes of Bangladeshi and Chinese employees, we do not describe any specific decomposition results for these groups but still include them when comparing the white and pooled ethnic minority wage distributions, as well as when comparing all men and all women.

Gaps between the quantiles of wage distributions

To decompose the estimated gaps between the quantiles of any two different gender-ethnicity groups of employees, we use the UQR model results from the previous section and apply the equivalent Oaxaca-Blinder-style methods to these as we describe above for the mean (see Firpo et al., 2018; Rios-Avila, 2020). Figure 3 illustrates the hypothetical gap between the median wages of two groups of employees within our estimation sample, with the population or pooled wage distribution (cumulative density function), F_p, represented as lying between those for the two groups. Using the parameters from the UQR regression models described in the previous section, estimated over all the employees pooled together, we can then estimate how much of the observed gaps between the quantiles of the wage distributions of two groups of employees (i.e., the horizontal gaps between F_m and F_w in Figure 3) can be 'Explained' by the different distributions over observable characteristics, equivalent to the first three parts of Equation (4), and how much is 'Unexplained', either within or between firms. The estimates for the unexplained parts of the decompositions in this section can vary marginally from those presented in Table 4. This is because the decompositions, using RIF-regression, require the additional step of estimating the marginal distribution of log wages for each sub-group of workers (see Figure 3). The analysis in the previous section, from which we derive the 'Explained' parts in the decomposition here, only required us to estimate the marginal distribution of log wages across all gender-ethnic groups. As such, since the latter uses a much larger sample size, our preferred estimates for the Unexplained Within Firm and Unexplained Between Firm wage gaps, at the selected percentiles, are those shown in Table 4.

[11] For evidence on how the influence of firm-specific wages in wage inequality patterns, especially changes over time, depend on whether occupation wage effects and segregation across firms are also accounted for see for the US, Handwerker (2023), and for Great Britain, Schaefer and Singleton (2020).

FIGURE 3: Illustration of the unconditional gap between quantiles of gender-ethnic minority and white wage distributions



Notes: as drawn, the cumulative density function (CDF) of ethnic minority group m, F_m, is everywhere equal to or to the left of the white CDF, F_w, indicating that white workers have higher wages at every quantile of the respective unconditional wage distributions. The gap between A and B at the medians of the two wage distributions, $\Delta_{50,m} = Q_{50,m} - Q_{50,w}$, is what we decompose using Unconditional Quantile Regression and Oaxaca-Blinder methods, for this and other selected quantiles. The parameters for this decomposition come from our model estimates in the previous section, from the population or pooled wage distribution of all employees, illustrated in the Figure as F_p.

4.1 Results

Table 5 summarises the results of decomposing the log basic hourly ethnic wage gaps among women in England and Wales in 2011, using the methods outlined above. Online Appendix B4 gives the equivalent results considering gross hourly earnings. Further, Figure 4 shows the decomposition results graphically: panel (a) shows total raw wage gaps, at the sample mean and between selected percentiles, for each of the four groups of ethnic minority women compared with white women; panel (b) shows the cumulative amounts of the raw wage gaps that is 'Explained' by individual, family, occupation, or employer characteristics; panel (c) shows the amount that is residually unexplained within firms, between coworkers; and panel (d) shows the amount that is residually unexplained by what firms people work for. The comparable amounts (bars) in panels (b)-(d) sum to the total raw wage gaps shown in panel (a).

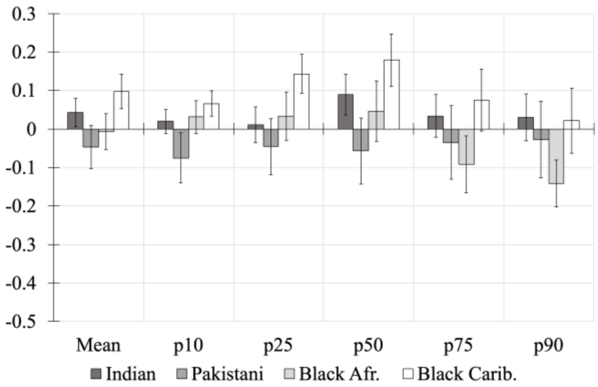
Except for Pakistani women, the individual and family characteristics in our regression models contribute positively and significantly to ethnic wage gaps, not only at the mean but across the earnings distribution. This implies that factors such as age, education, occupation, and region of work would generally contribute towards higher observed wages among ethnic minority than white female employees, were they remunerated at the average rates as estimated in the population. The observable employer characteristics of private sector status and size do not generally account for observed ethnic wage gaps among women. However, occupations and their associated wage effects tend to account for some of the observed negative wage gaps among ethnic minority women, notably so, for example, for the 90th percentile of Black African women earners: 10 log points of a total 14 log point observed wage gap is accounted for by Black African women generally working in lower paying occupations than white women.

Overall, the decomposition results in Figure 4 and Table 5 underline the substantial unexplained within-firm wage penalties faced by ethnic minority women, compared to their white women coworkers, especially among higher earners. These wage penalties are generally larger than what is actually observed in raw wages because ethnic minority women have individual and family characteristics that would otherwise suggest significantly higher wages than for their white women coworkers.

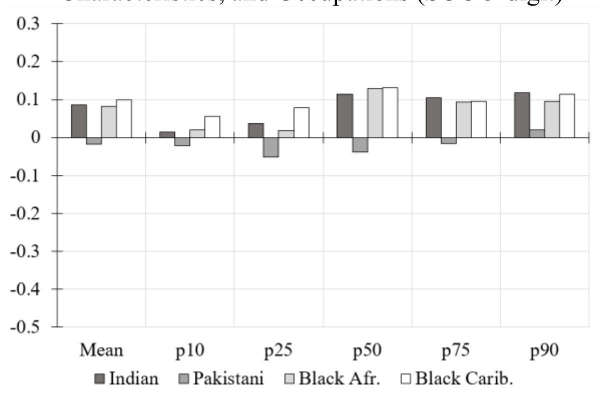
Focusing on men, Table 6 and Figure 4 show the decomposition results comparable to those described for women above. As among women, the individual and family characteristics of ethnic minority men would generally predict significantly higher employee wages than for white men, except for Pakistani men. The observed firm characteristics contribute minimally to the total raw wage gaps. Occupations tend to explain larger negative ethnic minority wage gaps among men than women, especially for high-earning Black African and Black Caribbean men, but not for Indian men. Even so, these decomposition results show starkly that the observed ethnic minority wage gaps among male employees are not only substantively accounted for by the unexplained differences between high earners but that this occurs within firms, rather than being accounted for by ethnic segregation across firms.

FIGURE 4: Estimated gender-ethnic log basic hourly wage gaps at the mean and unconditional quantiles, England and Wales, 2011: ***female*** employees, ethnic minority group minus white

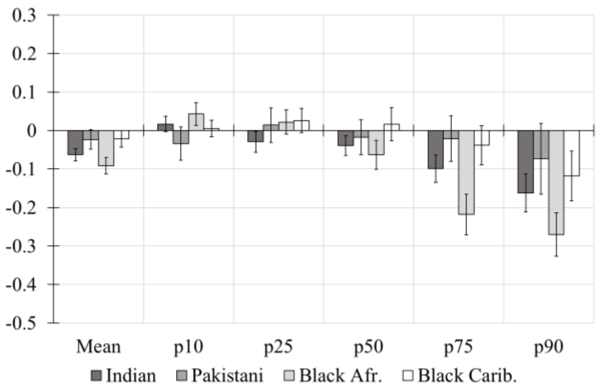
(a) Total raw gap



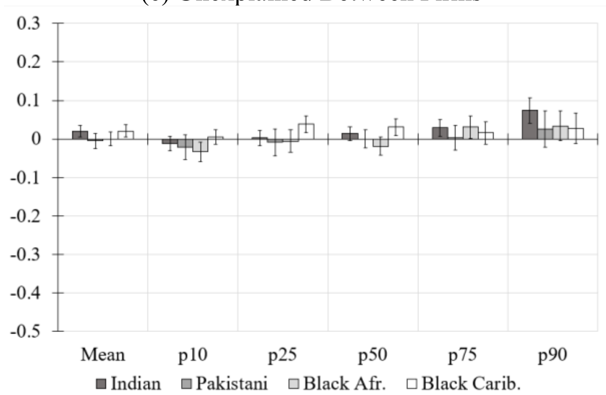
(b) Explained – Individual, Family, and Firm Characteristics, and Occupations (SOC 3-digit)



(c) Unexplained Within Firms



(e) Unexplained Between Firms



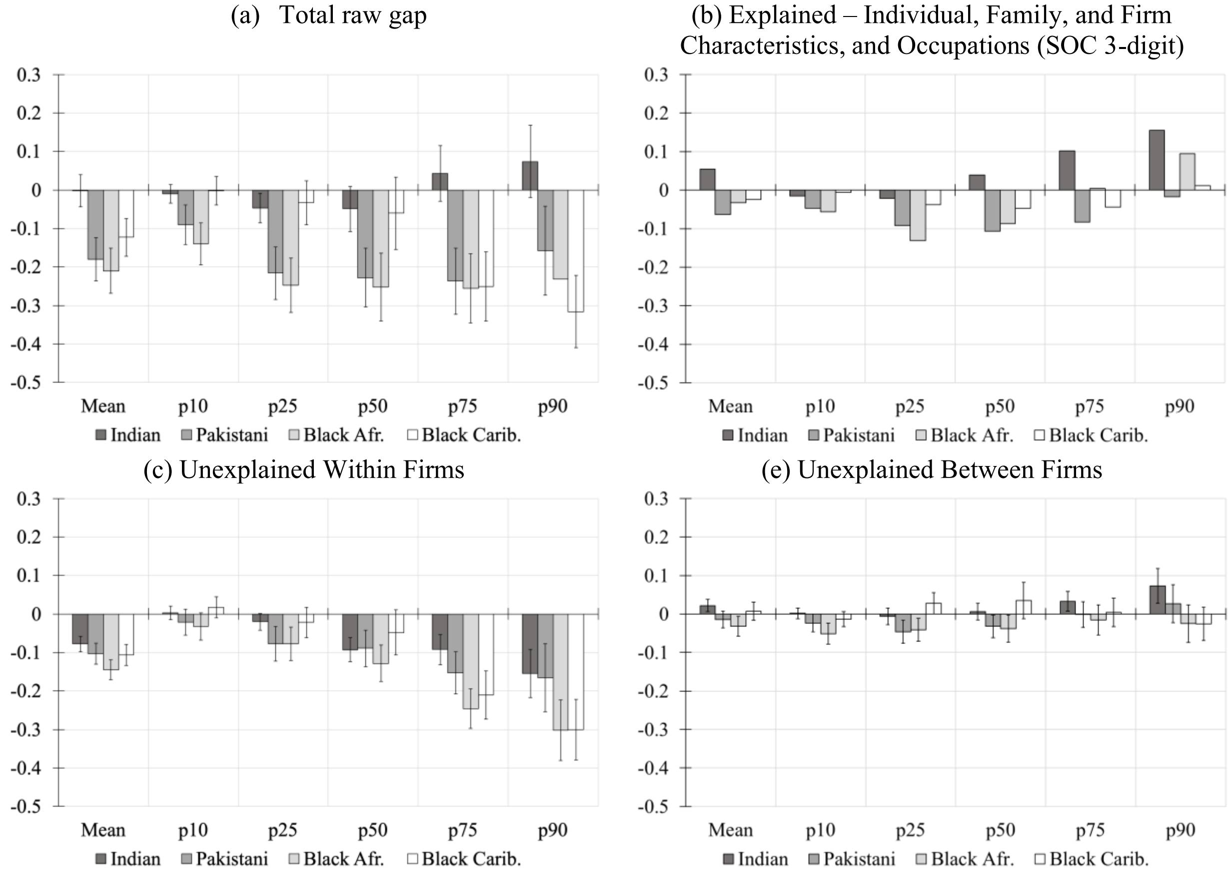
Notes: author calculations using ASHE-Census 2011 dataset. See Tables 4 & 5 for model estimates and sample sizes. 95% confidence intervals are displayed, estimated with standard errors that are robust to firm-level clusters.

TABLE 5: Oaxaca-Blinder decomposition results for the log basic hourly wage gaps between ethnic minority and white employees, ***female*** only, at the mean and unconditional quantiles, England and Wales, 2011

		Mean (I)	p10 (II)	p25 (III)	p50 (IV)	p75 (V)	p90 (VI)
Indian	**Total (N=1,014)**	**0.043****	**0.020**	**0.011**	**0.089*****	**0.034**	**0.030**
	= Expl. Indiv. & Fam. char's	0.078***	0.030***	0.042***	0.093***	0.101***	0.110***
	+ Expl. Occ's (SOC 3-digit)	0.011	-0.013**	-0.002	0.024	0.007	0.011
	+ Expl. Firm char's	-0.003	-0.002	-0.003	-0.003	-0.004**	-0.003
	+ Unexplained within firms	-0.063***	0.017*	-0.029**	-0.039***	-0.099***	-0.162***
	+ Unexplained between firms	0.020***	-0.012	0.003	0.014	0.029***	0.074***
Pakistani	**Total (N=272)**	**-0.047**	**-0.075****	**-0.046**	**-0.057**	**-0.035**	**-0.028**
	= Expl. Indiv. & Fam. char's	0.004	0.001	-0.006	0.018	-0.000	-0.007
	+ Expl. Occ's (SOC 3-digit)	-0.023	-0.023**	-0.047***	-0.058**	-0.017	0.026
	+ Expl. Firm char's	0.001	0.001	0.002	0.001	0.001	0.001
	+ Unexplained within firms	-0.023*	-0.034	0.014	-0.017	-0.021	-0.073
	+ Unexplained between firms	-0.005	-0.021	-0.009	-0.000	0.003	0.026
Black Afr.	**Total (N=450)**	**-0.007**	**0.031**	**0.033**	**0.046**	**-0.092****	**-0.142*****
	= Expl. Indiv. & Fam. char's	0.109***	0.034***	0.033***	0.115***	0.158***	0.197***
	+ Expl. Occ's (SOC 3-digit)	-0.028**	-0.015**	-0.017	0.013	-0.066***	-0.104***
	+ Expl. Firm char's	0.002	0.001	0.002	0.002	0.002	0.002
	+ Unexplained within firms	-0.091***	0.043***	0.022	-0.063***	-0.218***	-0.270***
	+ Unexplained between firms	0.000	-0.033***	-0.006	-0.019*	0.031**	0.034*
Black Carib.	**Total (N=534)**	**0.098*****	**0.066*****	**0.143*****	**0.179*****	**0.075***	**0.022**
	= Expl. Indiv. & Fam. char's	0.104***	0.045***	0.057***	0.117***	0.133***	0.164***
	+ Expl. Occ's (SOC 3-digit)	-0.006	0.010	0.020*	0.014	-0.037*	-0.051**
	+ Expl. Firm char's	0.001	0.001	0.002	0.001	0.000	0.001
	+ Unexplained within firms	-0.021*	0.005	0.026	0.017	-0.038	-0.118***
	+ Unexplained between firms	0.021***	0.005	0.038***	0.031***	0.016	0.027
Non-white	**Total (N=2,514)**	**0.042*****	**0.024****	**0.044*****	**0.086*****	**0.024**	**0.001**
	= Expl. Indiv. & Fam. char's	0.080***	0.031***	0.037***	0.093***	0.105***	0.122***
	+ Expl. Occ's (SOC 3-digit)	-0.002	-0.009***	-0.005	0.011	-0.015	-0.018*
	+ Expl. Firm char's	-0.000	0.000	0.011	-0.000	-0.001	-0.000
	+ Unexplained within firms	-0.051***	0.014**	0.000	-0.032***	-0.093***	-0.154***
	+ Unexplained between firms	0.017***	-0.012*	0.011	0.014**	0.027***	0.051***

Notes: author calculation using ASHE-Census 2011 dataset. See Equation (4), as well as Tables 3 & 4, and Figures 4 & 5 for more details and results of the underlying regression models. Note the explanation in the text about why our preferred estimates for the 'Unexplained' parts at percentiles are shown in Table 4.
***, **, * indicate significant differences from zero, two-sided tests, at the 1%, 5%, and 10% levels, respectively, with standard errors robust to firm-level clustering in parentheses.

FIGURE 5: Estimated gender-ethnic log basic hourly wage gaps at the mean and unconditional quantiles, England and Wales, 2011: ***male*** employees, ethnic minority group minus white



Notes: author calculations using ASHE-Census 2011 dataset. See Tables 4 & 5 for model estimates and sample sizes. 95% confidence intervals are displayed, estimated with standard errors that are robust to firm-level clusters.

TABLE 6: Oaxaca-Blinder decomposition results for the log basic hourly wage gaps between ethnic minority and white employees, ***male*** only, at the mean and unconditional quantiles, England and Wales, 2011

		Mean (I)	p10 (II)	p25 (III)	p50 (IV)	p75 (V)	p90 (VI)
Indian	**Total (N=934)**	**-0.002**	**-0.010**	**-0.047****	**-0.049**	**0.043**	**0.074**
	= Expl. Indiv. & Fam. char's	0.052***	0.009***	0.008**	0.052***	0.081***	0.104***
	+ Expl. Occ's (SOC 3-digit)	0.008	-0.020***	-0.022***	-0.008	0.027	0.056***
	+ Expl. Firm char's	-0.005**	-0.004*	-0.007*	0.001	-0.006**	-0.005**
	+ Unexplained within firms	-0.078***	0.003	-0.020*	-0.093***	-0.092***	-0.155***
	+ Unexplained between firms	0.022***	0.002	-0.006	0.006	0.033**	0.073***
Pakistani	**Total (N=366)**	**-0.180*****	**-0.090*****	**-0.216*****	**-0.228*****	**-0.237*****	**-0.157*****
	= Expl. Indiv. & Fam. char's	-0.017*	-0.009**	-0.026***	-0.020**	-0.026*	-0.014
	+ Expl. Occ's (SOC 3-digit)	-0.043***	-0.036***	-0.063***	-0.084***	-0.052**	-0.000
	+ Expl. Firm char's	-0.003**	-0.002	-0.003	-0.003*	-0.005**	-0.003*
	+ Unexplained within firms	-0.103***	-0.021	-0.078***	-0.089***	-0.153***	-0.166***
	+ Unexplained between firms	-0.014	-0.023*	-0.046***	-0.032**	-0.001	0.027
Black Afr.	**Total (N=389)**	**-0.210*****	**-0.140*****	**-0.248*****	**-0.253*****	**-0.256*****	**-0.232*****
	= Expl. Indiv. & Fam. char's	0.078***	0.005	-0.013*	0.060***	0.138***	0.200***
	+ Expl. Occ's (SOC 3-digit)	-0.108***	-0.059***	-0.114***	-0.144***	-0.130***	-0.102***
	+ Expl. Firm char's	-0.003*	-0.002	-0.004	-0.003*	-0.004**	-0.003*
	+ Unexplained within firms	-0.145***	-0.032*	-0.077***	-0.128***	-0.246***	-0.302***
	+ Unexplained between firms	-0.032**	-0.051***	-0.041***	-0.038**	-0.015	-0.025
Black Carib.	**Total (N=326)**	**-0.123*****	**-0.002**	**-0.033**	**-0.060**	**-0.251*****	**-0.316*****
	= Expl. Indiv. & Fam. char's	0.051***	0.018***	0.008	0.042***	0.072***	0.116***
	+ Expl. Occ's (SOC 3-digit)	-0.074***	-0.024***	-0.046***	-0.088***	-0.113***	-0.103***
	+ Expl. Firm char's	-0.001	-0.000	-0.000	-0.001	-0.003	-0.001
	+ Unexplained within firms	-0.106***	0.017	-0.022	-0.048	-0.211***	-0.301***
	+ Unexplained between firms	0.007	-0.013	0.028**	0.035	0.004	-0.026
Non-white	**Total (N=2,236)**	**-0.080*****	**-0.045*****	**-0.111*****	**-0.104*****	**-0.093*****	**-0.070****
	= Expl. Indiv. & Fam. char's	0.048***	0.009***	0.000	0.043***	0.075***	0.107***
	+ Expl. Occ's (SOC 3-digit)	-0.030***	-0.030***	-0.048***	-0.053***	-0.029**	-0.001
	+ Expl. Firm char's	-0.004***	-0.003*	-0.005*	-0.004**	-0.005***	-0.004**
	+ Unexplained within firms	-0.101***	-0.006	-0.045***	-0.090***	-0.157***	-0.213***
	+ Unexplained between firms	0.007	-0.016***	-0.014*	-0.000	0.022**	0.040**

Notes: author calculation using ASHE-Census 2011 dataset. See Equation (4), as well as Tables 3 & 4, and Figures 4 & 5 for more details and results of the underlying regression models. Note the explanation in the text about why our preferred estimates for the 'Unexplained' parts at percentiles are shown in Table 4.
***, **, * indicate significant differences from zero, two-sided tests, at the 1%, 5%, and 10% levels, respectively, with standard errors robust to firm-level clustering in parentheses.

5. Summary and further discussion

We use a newly-linked dataset - the ASHE-Census - which matches a large sample of accurate employer-employee payroll-based data about earnings and jobs to the detailed personal characteristics of employees recorded in the Census, for England and Wales in 2011. This linked dataset has allowed us to investigate whether unexplained wage disparities between ethnic groups occur within or between firms, and to do so throughout the wage distribution. In general, there are some significant unexplained between-firm differences in wages for particular ethnic groups, both at the mean and across the distribution. However, we have found that gender-ethnic wage gaps predominantly occur within firms, especially among men and for higher earners. Some ethnic minority groups appear to be more disadvantaged than others by unexplained pay gaps relative to their white coworkers.

The payroll data on employee earnings have confirmed findings from previous household-survey based analyses for England and Wales, that the wage gaps between white and ethnic minority employees vary greatly, according to which groups are considered, whether men or women are compared, and which portion of the overall wage distribution is studied. There is substantial heterogeneity that is overlooked or masked by the average gaps between white and non-white employees. For example, compared to white employees, there are positive observed wage gaps in favour of Indian and Chinese employees, which increase between higher percentiles of the respective wage distributions. The equivalent wage gaps tend to be in favour of white employees when compared with Pakistani, Bangladeshi and Black African employees, particularly among higher earners. The observed wage gaps between Black Caribbean and white male employees are insignificant among lower earners, but they turn significantly negative and in favour of white employees among higher earners.

Our study is reminiscent of earlier work for Britain (Forth et al., 2023a) and for the United States (Troske & Carrington, 1998) in suggesting that the ethnic segregation of workers over employers contributes relatively little to ethnic wage gap estimates at the mean. However, our study is the first to explore whether firm-specific effects can play an important role in understanding the size and direction of gender-ethnic wage gaps vis-à-vis white employees across the wage distribution. In doing so, we would like to place the employer centre-stage in future efforts to understand further why it is that employees from different ethnic backgrounds are paid differently within the firm. Due to the nature of our dataset, we could not identify firm-specific wage premiums (fixed effects) fully, because we cannot reliably observe the mobility of large numbers of ethnic minority workers between firms over a reasonable period. An obvious question remains though as to whether the extent of assortative matching between high-wage workers and high-wage firms may differ by gender-ethnicity (e.g., see the literature begun largely by Abowd et al., 1999). Further, our sample sizes have not allowed us to delve more deeply into patterns of segregation of workers by gender-ethnicity across employers, as well as the different occupations and levels of jobs within firms. However, those patterns must matter, since otherwise we ought not to have seen our estimates of wage penalties and what explains wage gaps being sensitive to whether firm-specific wage effects were modelled. This perhaps has to be taken forward further using field studies where company payrolls and the mechanics of talent markets are open to researchers.[12] Another natural step forward from our analysis in this paper would be to look further beneath the firm-specific wage effects, especially at whether they reflect firm-level productivity and profitability. This is an avenue that is theoretically possibly to pursue in the UK, since the ASHE payroll dataset can be linked to firm-level surveys and administrative data sources (including even the Bureau van Dijk's Financial Analysis Made Easy (FAME) – see Bell et al., 2022). But at present, the data owners of ASHE-Census have not yet facilitated such linkages.

An alternative model, in which non-white employees face hiring discrimination – either on taste-based or statistical grounds - and thus need to signal greater productivity than their white counterparts to enter a firm, might also partially align with some of our results. The less important role of unexplained within firm wages at or between the 10th percentiles of the ethnic minority and white wage distributions may also relate to the bite of the National Minimum Wage, which sets a wage floor for such low-paid employees. This could plausibly limit opportunities for low-wage employers to exercise wage setting power to the detriment of ethnic minority workers (see Clark & Nolan, 2021, for some analysis of the differential effects of minimum wages in the UK on ethnic minority workers, and Derenoncourt & Montialoux, 2021, for evidence on such effects in the US).

Further research might use the ASHE-Census to explore the importance of other employee attributes that are both plausibly relevant to pay determination and the likelihood of working for relatively high or low wage firms, and which are partially correlated with ethnicity. These include migration background and status (e.g., Algan et al., 2010; Kaya, 2024) and religion (e.g., Longhi et al., 2013). Education and human capital are coarsely dealt with by the UK census and thus our analysis. While we can observe standard levels of education, there is good evidence now in the UK, using administrative data sources, specifically the Longitudinal Education Outcomes dataset, that the subject, location, and attainment levels of qualifications are important in determining life-long labour market outcomes (e.g., Battiston et al., 2019; Britton et al., 2020). We also must acknowledge that our findings refer to a single point in time, 2011, when the UK unemployment rate was approximately at its height following the Great Recession. A lot has changed in Great Britain and its labour market since, with austerity, Brexit, and record low unemployment rates just before Covid-19 struck the

[12] See Roussille, 2024, for a recent example of innovative field study work, gaining access to the talent market for engineers in the US, and uncovering that women asking for lower salaries than men could account for their lower starting salaries at firms.

economy. It will be important to revisit our findings once the 2021 Census has been linked to ASHE as well. That may also allow some longitudinal wage analysis for employees linked between 2011 and 2021. We are currently scoping out these linkages and extensions of the ASHE-Census dataset with the Office for National Statistics, but it will be some time yet before they are delivered and research-ready.

We also think that there could be great value in designing studies that can uncover why ethnic wage penalties appear in some firms but not others. For instance, Forth et al. (2023a) found some evidence that ethnic minorities tend to experience skills mismatches due to employer practices, and that job evaluation schemes were associated with smaller ethnic wage penalties. Such practices, by promoting equal treatment in the workplace and decreasing within-employer wage gaps, may help to tackle the ethnic wage gaps we have estimated in this paper, especially if they are addressed in high-wage jobs and careers.

One way to incentivise employers to examine their practices is to introduce legislation on gender-ethnic pay gap reporting. Greater transparency about differentials in pay by ethnicity, perhaps combined with gender as well, may uncover previously hidden problems or systematic disadvantages within a firm. This could prompt decision makers to seek out and address the underlying origins or causes of wage inequality between the groups within their workforce. A few countries have already introduced laws requiring large employers to report transparently and periodically on their own gender pay gaps. Evaluations of these policies have so far indicated that increased transparency has led to reduced wage differentials between men and women within firms (Bennedsen et al., 2023). Given our findings indicate that much of gender-ethnic wage gaps exist within organisations, requiring firms to report on their ethnic wage gaps may yield similar benefits.

References

Abowd, J., Kramarz, F., & Margolis, D. (1999). High Wage Workers and High Wage Firms. *Econometrica*, 67(2), 251-333.

Algan, Y., Dustmann, C., Glitz, A., & Manning, A. (2010). The Economic Situation of First and Second-Generation Immigrants in France, Germany and the United Kingdom. *The Economic Journal*, 120(542), F4-F30.

Avery, D. R., Volpone, S. D., Stewart, R. W., Luksyte, A., Hernandez, M., McKay, P. F., & Hebl, M. M. R. (2013). Examining the draw of diversity: How diversity climate perceptions affect job-pursuit intentions. *Human Resource Management*, 52(2), 175-193.

Barth, E., Bryson, A., Davis, J. C., & Freeman, R. (2016). It's Where You Work: Increases in the Dispersion of Earnings across Establishments and Individuals in the United States. *Journal of Labor Economics*, 34(S2), S67-S97.

Battiston, A., Patrignani, P., Hedges, S., & Conlon, G. (2019). Labour market outcomes disaggregated by subject area using the Longitudinal Education Outcomes (LEO) data (No. 021). Centre for Vocational Education Research.

Bell, B., Bloom, N., & Blundell, J. (2022). Income dynamics in the United Kingdom and the Covid-19 recession. *Quantitative Economics*, 13(4), 1849-1878.

Bennedsen, M., Simintzi, E., Tsoutsoura, M., & Wolfenzon, D. (2022). Do Firms Respond to Gender Pay Gap Transparency? *The Journal of Finance*, 77(4), 2051-2091.

Bennedsen, M., Larsen, B. & Wei, J. (2023). Gender wage transparency and the gender pay gap: A survey. *Journal of Economic Surveys,* 37(5), 1743-1777.

Blackaby, D. H., Clark, K., Leslie, D. G., & Murphy, P. D. (1994). Black-white male earnings and employment prospects in the 1970s and 1980s evidence for Britain. *Economics Letters*, 46(3), 273-279.

Blackaby, D. H., Leslie, D. G., Murphy, P. D., & O'Leary, N. C. (1998). The ethnic wage gap and employment differentials in the 1990s: Evidence for Britain. *Economics Letters*, 58(1), 97-103.

Blackaby, D. H., Leslie, D. G., Murphy, P. D., & O'Leary, N. C. (2002). White/ethnic minority earnings and employment differentials in Britain: evidence from the LFS. *Oxford Economic Papers*, 54(2), 270-297.

Blinder, A. S. (1973). Wage Discrimination: Reduced Form and Structural Estimates. *Journal of Human Resources*, 8(4), 436-455.

Britton, J., Dearden, L., van der Erve, L., & Waltmann, B. (2020). The impact of undergraduate degrees on lifetime earnings (No. R167). IFS Report.

Brown, W., Marginson, P., & Walsh, J. (2003). The management of pay as the influence of collective bargaining diminishes. *Industrial Relations, Theory and Practice*, 2, 189-213.

Card, D., Cardoso, A. R., & Kline, P. (2016). Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women. *The Quarterly Journal of Economics*, 131(2), 633-686.

Card, D., Cardoso, A. R., Heining, J., & Kline, P. (2018). Firms and Labor Market Inequality: Evidence and Some Theory. *Journal of Labor Economics*, 36(S1), S13-S70.

Card, D., Heining, J., & Kline, P. (2013). Workplace Heterogeneity and the Rise of West German Wage Inequality. *The Quarterly Journal of Economics*, 128(3), 967-1015.

Carrington, W. J., & Troske, K. R. (1998). Interfirm Segregation and the Black/White Wage Gap. *Journal of Labor Economics*, 16(2), 231-260.

Clark, K., & Nolan, S. (2021). The Changing Distribution of the Male Ethnic Wage Gap in Great Britain. IZA Discussion Papers 14276, Institute of Labor Economics (IZA).

Costa Dias, M., Joyce, R., & Parodi, F. (2020). The gender pay gap in the UK: children and experience in work. *Oxford Review of Economic Policy*, 36(4), 855-881.

Derenoncourt, E., & Montialoux, C. (2021). Minimum Wages and Racial Inequality. *The Quarterly Journal of Economics*, 136(1), 169-228.

Duchini, E., Simion, S., Turrell, A., & Blundell, J. (2024). Pay transparency and gender equality. *American Economic Journal: Economic Policy*.

Firpo, S., Fortin, N. M., & Lemieux, T. (2009). Unconditional Quantile Regressions. *Econometrica*, 77(3), 953-973.

Firpo, S. P., Fortin, N. M., & Lemieux, T. (2018). Decomposing Wage Distributions Using Recentered Influence Function Regressions. *Econometrics*, 6(2), 28.

Forth, J., Theodoropoulos, N., & Bryson, A. (2023a). The role of the workplace in ethnic wage differentials. *British Journal of Industrial Relations*, 61(2), 259-290.

Forth, J., Bryson, A., Phan, V., Ritchie, F., Singleton, C., Stokes, L., & Whittard, D. (2023b). *Data Explained: Annual Survey of Hours and Earnings linked to 2011 Census – England and Wales*, Swindon: ADR England.

Forth, J., & Jones, M. K. (2025). The Disability Pay Gap Within and Across Firms. IZA Discussion Papers 17679, Institute of Labor Economics (IZA).

Giuliano, L., Levine, D. I. & Leonard, J. (2011). Racial Bias in the Manager-Employee Relationship: An Analysis of Quits, Dismissals, and Promotions at a Large Retail Firm. *Journal of Human Resources*, 46(1), 26-52.

Gulyas, A., Seitz, S., & Sinha, S. (2023). Does Pay Transparency Affect the Gender Wage Gap? Evidence from Austria. *American Economic Journal: Economic Policy*, 15(2), 236-255.

Hall, T., Manning, A., & Rose, R. (2024). Ethnic minority and migrant pay gaps over the life-cycle. *Oxford Review of Economic Policy*, 40(3), 556-578.

Handwerker, E. W. (2023). Outsourcing, Occupationally Homogeneous Employers, and Wage Inequality in the United States. *Journal of Labor Economics*, 41(S1), S173-S203.

Heath, A., & Cheung, S. (2006). *Ethnic Penalties in the Labour Market: Employers and Discrimination*, Department for Work and Pensions Research Report No. 341.

Heath, A. F., & Di Stasio, V. (2019). Racial discrimination in Britain, 1969–2017: a meta-analysis of field experiments on racial discrimination in the British labour market. *The British Journal of Sociology*, 70(5), 1774-1798.

Jewell, S. L., Razzu, G., & Singleton, C. (2020). Who Works for Whom and the UK Gender Pay Gap. *British Journal of Industrial Relations*, 58(1), 50-81.

Jones, M., Kaya, E., & Papps, K. L. (2022). The Ongoing Impact of Gender Pay Gap Transparency Legislation. IZA Discussion Papers 15817, Institute of Labor Economics (IZA).

Kaya, E. (2021). Gender wage gap across the distribution: What is the role of within-and between-firm effects? *IZA Journal of Development and Migration*, 12(1).

Kaya, E. (2024). Labour market performance of immigrants: New evidence from linked administrative data. GLO Discussion Paper Series 1418, Global Labor Organization (GLO).

Li, Y., & Heath, A. (2020). Persisting disadvantages: a study of labour market dynamics of ethnic unemployment and earnings in the UK (2009–2015). *Journal of Ethnic and Migration Studies*, 46(5), 857-878.

Longhi, S., & Brynin, M. (2017). The Ethnicity Pay Gap. Equality and Human Rights Commission.

Longhi, S., Nicoletti, C., & Platt, L. (2013). Explained and unexplained wage gaps across the main ethno-religious groups in Great Britain. *Oxford Economic Papers*, 65(2), 471-493.

Oaxaca, R. (1973). Male-Female Wage Differentials in Urban Labor Markets. *International Economic Review*, 693-709.

Office for National Statistics. (2020). 2011 Census: Aggregate Data. [data collection]. UK Data Service. SN: 7427, DOI: 10.5257/census/aggregate-2011-2.

Office for National Statistics. (2021). Annual Survey of Hours and Earnings, 1997-2021: Secure Access. [data collection]. 19th Edition. UK Data Service. SN: 6689, DOI: 10.5255/UKDA-SN-6689-18.

Office for National Statistics, Social Survey Division. (2022). Annual Population Survey, January - December, 2011. [data collection]. 5th Edition. UK Data Service. SN: 7059, DOI: 10.5255/UKDA-SN-7059-5.

Office for National Statistics. (2023a), Annual Survey of Hours and Earnings linked to 2011 Census - England and Wales, dataset, ONS SRS Metadata Catalogue, https://doi.org/10.57906/80f7-te97 , released 03 July 2023

Office for National Statistics. (2023b) Annual Population Survey - UK, dataset, ONS SRS Metadata Catalogue, https://doi.org/10.57906/0qp1-6k77, released 08 September 2023.

Parker, J. (2017). A report into the ethnic diversity of UK boards. Independent Report. London: EY.

Pham, T., Schaefer, D., & Singleton, C. (2024). Unequal Hiring Wages and Their Impact on the Gender Pay Gap. IZA Discussion Papers 17285, Institute of Labor Economics (IZA).

Phan, V., Singleton, C., Bryson, A., Forth, J., Ritchie, F., Stokes, L., & Whittard, D. (2022). Accounting for firms in ethnicity wage gaps throughout the earnings distribution. IZA Discussion Papers 15284, Institute of Labor Economics (IZA).

Rios-Avila, F. (2020). Recentered influence functions (RIFs) in Stata: RIF regression and RIF decomposition. *The Stata Journal*, 20(1), 51-94.

Rios-Avila, F., & Maroto, M. L. (2022). Moving beyond linear regression: Implementing and interpreting quantile regression models with fixed effects. *Sociological Methods & Research*, 00491241211036165.

Roussille, N. (2024). The role of the ask gap in gender pay inequality. *The Quarterly Journal of Economics*, 139(3), 1557-1610.

Schaefer, D., & Singleton, C. (2020). Recent Changes in British Wage Inequality: Evidence from Large Firms and Occupations. *Scottish Journal of Political Economy*, 67(1), 100-125.

Singleton, C. (2019). The public–private sector wage differential in the UK: Evidence from longitudinal employer–employee data. *Economics Letters*, 174, 109-113.

Song, J., Price, D. J., Guvenen, F., Bloom, N., & Von Wachter, T. (2019). Firming Up Inequality. *The Quarterly Journal of Economics*, 134(1), 1-50.

Stewart, M. B. (1983). Racial Discrimination and Occupational Attainment in Britain. *The Economic Journal*, 93(371), 521-541.

Stokes, L., Bryson, A., Forth, J., & Weale, M. (2017). Who Fared Better? The Fortunes of Performance Pay and Fixed Pay Workers through Recession. *British Journal of Industrial Relations*, 55(4), 778-801.

Wheatley, D., & Gifford, J. (2019). *UK Working Lives: Survey Report 2019*, London: CIPD.

Accounting for firms in ethnic wage gaps across the earnings distribution

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Online Appendix

A. Further details on the ASHE-Census 2011 dataset

In what follows, we give some additional details regarding the datasets we have used and how we have constructed the analysis sample. The main data source is the Annual Survey of Hours and Earnings (ASHE), which is based on a 1% random sample of UK employees, drawn from Pay As You Earn (PAYE) records of Her Majesty's Revenue and Customs (HMRC). The survey is conducted and administrated by the Office for National Statistics (ONS). The survey collects information on employees' earnings, paid hours, occupations, along with some employer characteristics, for a reference period in April, either by a questionnaire issued to employers or by an automatic reporting system from company payrolls for larger firms. However, ASHE contains relatively few personal characteristics for employees, limited to age, gender, and residential location. To expand the number of personal characteristics and family characteristics (e.g., ethnicity, education, marital status, dependent children, etc.) observed for the employees in ASHE, ONS has linked the personal details of the employees in the 2011 ASHE to those of individuals observed in the 2011 Census for England and Wales. The overall linkage rate between the ASHE and the 2011 Census for England and Wales is around 74% of ASHE job observations.

It is common to find that linkage rates vary across subsets of the population, and this case is no different. Table A1 presents odds ratio estimates from logit models, where the dependent indicator variable is whether a worker observation in ASHE was linked (matched) with the 2011 Census, and the independent variables are several characteristics about workers and jobs recorded by the ASHE. Column (I) reports unweighted estimates for the likelihood of linkage, while column (II) reports the result after applying the standard ASHE-cross section population weights provided by the ONS. Linkage rates are substantially and significantly lower for older and younger workers than middle-aged workers, conditional on other characteristics. Similarly, linkage rates are generally greater among employees with middling amounts of tenure in their current job. The linkage rates are also higher among male employees than female employees, and lower for those working in London than in the other regions of England and Wales. The effect of the differential linkage rates is to skew the profile of the ASHE-Census sample away from the profile of the full ASHE sample to some extent. However, the overall fit of this model is fairly low, indicating that although some characteristics do significantly predict linkage, there is still a relatively large amount of randomness in terms of which

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employees were linked between ASHE and Census in 2011. Nevertheless, we have generated some adjusted sampling weights (called 'ASHE-Census weights') to address at least partially the extent to which the non-random linkage of ASHE-Census could substantively bias estimates of descriptive statistics about the employee population in England and Wales in 2011. These weights were generated by predicting the probabilities of employees in ASHE being linked with the 2011 Census, after already applying the standard ASHE 2011 cross-section sample weights that are generated by ONS. We estimate a probit model to predict the probabilities of a job observations in ASHE being linked with the 2011 Census. The inverse of the predicted linkage probability for a job observation is then used to adjust the standard ASHE weights. This procedure and the new derived sample weights make sample descriptive statistics obtained from the ASHE-Census less biased representations of all jobs held by employees in England and Wales in 2011, by removing (or at least substantially reducing) observable linkage biases.

In the analysis and estimation samples described within the main text, we only keep job observations in ASHE-Census where an employee is aged 25-64, which have not been marked as having incurred a loss of pay during the pay period, and which are not paid at an apprenticeship rate. We also drop any worker observations for years with non-main job holdings (if employees in ASHE have records for more than one job, we define their main job as the one with the most hours worked, and the one with the highest earnings if there is a tie in hours worked), drop observations with basic weekly hours worked records equal to 0 or greater than 99, and trim the top and the bottom 0.5 percentile of the basic hourly wage distribution, as these could reflect measurement error. We use two pay variables from the ASHE: (i) basic hourly wages, which is the ratio of the employee basic weekly earnings to the total number of basic weekly paid hours; and (ii) gross earnings per hour, which is derived by dividing gross weekly pay by the combined number of weekly basic and overtime hours worked. In the ASHE, basic hours are intended by the survey to be a record for an employee in a normal week, excluding overtime and meal breaks. Gross weekly pay recorded in the reference period includes basic pay, incentive-related pay, any premiums for weekend or night work, and other sources of pay, such as meal and travel allowances. The ASHE also contains other basic information about employees (e.g., age, gender, home postcode), their jobs (an identifier for who they work for, employment start date, occupation, part-time/fulltime status), and employers (e.g., workplace postcode, industry sector), along with a unique employer identifier which derives from the UK's official business register (the IDBR). To create a tenure variable, we use the recorded employment start date of individuals. We drop a tiny number of unrealistic entry dates, where the start date lies in the future or where it implies an employee started working aged fifteen or younger. Linking the ASHE with the 2011 Census allows us to bring more information about individual characteristics which cannot be observed in ASHE (e.g., ethnicity, education, marital status, language, etc.) and family characteristics (e.g., number of children, age of the children, etc.). A list and details of all variables used in our analysis can be found in Table A2.

To provide some sort of benchmark for the ASHE-Census 2011, we use the 2011 Annual Population Survey (APS), a household survey, comprising a selectively boosted version of four consecutive quarters of the UK's Quarterly Labour Force Survey (Office for National Statistics, 2023b). The APS contains many similar variables to the ASHE-Census but has approximately half the sample size for employees. It is not possible with the APS to identify co-workers, as the datasets contain no employer identifier. The pay and hours worked data in the APS are self-reported by household representatives and are thus considered much less reliable than the records in ASHE. For the APS, we use an employee's gross hourly pay, which is calculated by dividing gross weekly pay by reported basic actual hours worked. We then mirror the analysis sample selection steps that we applied to the ASHE-Census: we restrict the sample to those aged 25-64, drop observations with reported basic actual work hours equal to 0 or greater than 99, and trim the top and the bottom 0.5 percentiles of the gross hourly pay distribution.

Figure A1 illustrates the distributions of log gross hourly earnings for white employees and other ethnic minority groups, by gender, from our ASHE-Census sample. Each of the six panels of Figure A1 overlays the male and female distributions of white employees with those for one other ethnic minority group. In panel (a), Indian women's hourly earnings are more dispersed than those of white women. Men's hourly earnings are more dispersed than women's but, again, that dispersion is greater for Indian men than it is for white men. Panel (b) depicts the distributions for Pakistani employees. Again, white women's hourly earnings are a little less dispersed than for Pakistani women, especially in the left-tail of the distribution. The distribution of white men's hourly earnings is generally to the right of that for Pakistani men and is more right skewed. From panel (c), it is apparent that the hourly earnings of Bangladeshi women are a little more compressed than for white women, and Bangladeshi men's hourly earnings are more compressed than for white men. In panel (d), we see that Chinese women's and men's hourly earnings are more dispersed and their distributions lie to the right of their white counterparts. In panel (e), Black African women's hourly earnings are a little more dispersed than white women's, whereas Black African men's hourly earnings are more compressed than for white men. Finally, in panel (f), Black Caribbean women's hourly earnings are more compressed than white women's and, on average, they are paid more per hour. The hourly earnings profile of Black Caribbean men is like that of white men, though the former is a little more compressed.

Figure A2 presents distributions of log gross hourly wages across different ethnic minority groups, compared to white employees, by gender, in the APS for 2011. Figure A3 illustrates distributions of log gross hourly wages by ethnicity and gender in the APS for 2011, overlaid be comparable estimates from the ASHE-Census. Even without applying any sample weights for either dataset, it is reassuring that the distributions of wages within and between ethnic-gender groups in the APS are remarkably like those that we have estimated from the linked ASHE-Census.

TABLE A1: Logistic regression – Which employees in ASHE 2011 are matched with the Census 2011 in England and Wales?

	Unweighted (I)	Weighted (II)
Male	0.938***	0.955***
	[0.015]	[0.015]
Age (years)	1.303***	1.301***
	[0.006]	[0.006]
Age squared (years^2/ 100)	0.725***	0.725***
	[0.004]	[0.004]
Tenure (years)	1.065***	1.065***
	[0.002]	[0.003]
Tenure squared (years^2/ 100)	0.841***	0.840***
	[0.006]	[0.006]
Gross hourly pay (£)	1.000	1.000
	[0.001]	[0.001]
Basic weekly hours worked	1.003***	1.003***
	[0.001]	[0.001]
Govt. office region at workplace (excl. cat., North East):		
+ North West	0.880***	0.883***
	[0.032]	[0.032]
+ Yorkshire	0.933*	0.947
	[0.035]	[0.036]
+ East Midlands	1.027	1.033
	[0.040]	[0.041]
+ West Midlands	0.907***	0.913**
	[0.034]	[0.034]
+ South West	1.022	1.033
	[0.039]	[0.040]
+ East of England	1.019	1.031
	[0.038]	[0.039]
+ London	0.619***	0.629***
	[0.022]	[0.022]
+ South East	0.982	0.987
	[0.035]	[0.036]
N of employees	148,912	148,912
Pseudo-R^2	0.200	0.200

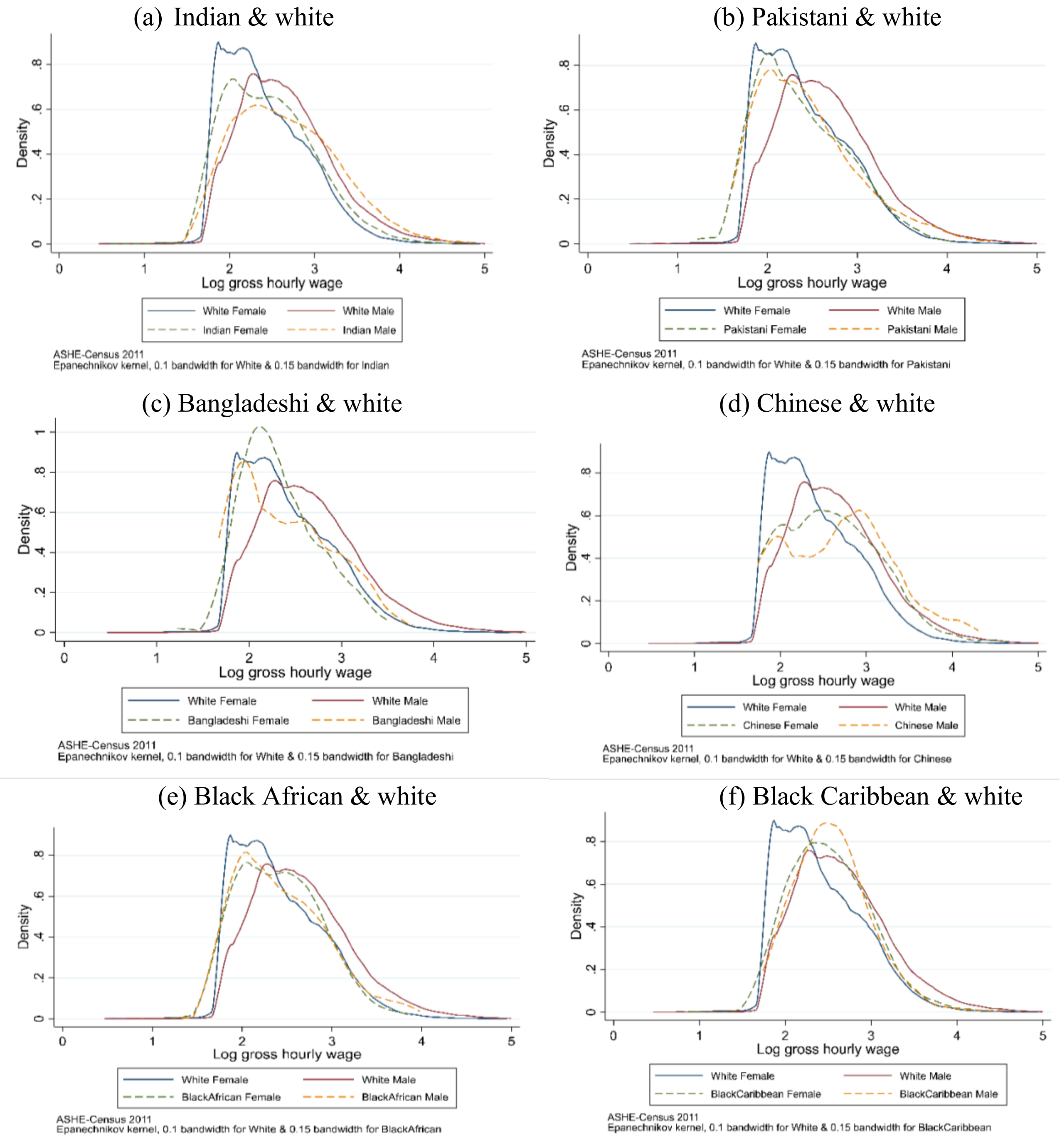
Notes: presents estimates of log odd ratios from logit models where the dependent variables are whether an employee observation in ASHE 2011 was successfully linked to the Census 2011. Column (I) reports unweighted estimates. Column (II) reports estimates weighting observations using the standard ASHE cross-section sample weights). Other control variables included in the models: occupation (SOC10, 1-digit), industry (SIC07, 1 digit).
***,**,* indicate significant differences from zero, two-sided tests, at the 1%, 5% and 10% levels, respectively, with robust standard errors in parentheses.

Table A2: List of variables used in the linked ASHE-Census 2011 dataset and Annual Population Survey

Panel (a): ASHE	Description	Variables
Basic hourly wage	Basic hourly pay is a continuous variable, calculated by the ratio of the basic weekly earnings to the total number of basic weekly paid hours (Unit: £)	bpay/bhr
Gross hourly earnings	Gross hourly earnings is a continuous variable, derived by ONS. It is calculated by the ratio of the gross weekly earnings to the total number of basic weekly paid hours (Unit: £)	he/100
Age	Employee's age (years)	age
Male	Dummy variable indicating whether the employee is male.	sex
Tenure	Employment tenure (years), derived from when an employee started working for their employer and the known reference period of the ASHE in April 2011.	empsta
Work region	The region of the workplace, NUTS1 level: North East, North West, Yorkshire, East Midlands, West Midlands, South West, East, London, South East, Wales). We drop those working outside England, and Wales.	wgor
Part-time	Dummy variable whether the job is part-time. It is derived from basic weekly hours worked. It takes the value of 1 if weekly hours are less than 30.	bhr
Occupation	3-digit classification of employee's occupation (SOC10)	occ10
Industry	1-digit classification of employee's job (SIC07: (i) Agriculture, forestry, and fishing, (ii) Mining, and quarrying, (iii) Manufacturing, (iv) Electricity, gas, air conditioner supply, (v) Water supply, sewerage, and waste, (vi) Construction, (vii) Wholesale, retail, repair of vehicles, (viii) Transport, and storage, (ix) Accommodation, and food service, (x) Information, and communication, (xi) Financial and insurance activities, (xii) Real estate activities, (xiii) Professional, scientific, and technical activities, (xiv) Admin and support services, (xv) Public admin and defence, (xvi) Education, (xvii) Health and social work, (xviii) Art, entertainment, and recreation, (xix) Other service activities, (xx) Activities of households as employers, (xxi) Activities of extraterritorial organisations.	sic07
Private Sector	Dummy variable for whether the employer (enterprise) is recorded as a private sector organisation as per the UK's Inter-Departmental Business Register (IDBR).	idbrsta
Firm Size	The number of employees working for the firm (enterprise) according to the IDBR.	idbrnemp
Panel (b): Census	**Description**	**Variables**
Ethnicity	Employee's ethnicity: white, Indian, Pakistani, Bangladeshi, Chinese, Black Caribbean, Black African. Observations in the Mixed and Other categories are not considered due to small sample sizes.	ethpuk11
Education	Employee's qualifications: (i) No qualification, (ii) GCSEs, apprenticeship, (iii) A-level, (iv) Degree, and (v) Other/vocational qualification.	hlqpuk11

Marital status	Dummy variable of whether the employee is married or registered in a same-sex civil partnership.	marstat
General Health problem	Dummy variable whether the employee' health was very good, good, or fair (self-assessment).	health
Non-UK born	Dummy variable of whether the employee was not born in the UK. It is derived from the length of residence in the UK, calculated from the date when the employee last arrived to live in the UK.	lrespuk
Number of dependent children	The number of dependent children aged 0 to 15 in the household of the employee. It is derived from the dependent children in the family and the number of adults in the household. The missing values are replaced with 0 when there is only one adult in the household.	dpcfamuk, adthuk
Age of the youngest child	It is a categorical variable indicating age ranges of the youngest dependent child of the employee: (i) under 4 years old, (ii) 5-7 years old, (iii) 8-9 years old, (iv) 10-11 years old, (v) 12-15 years old, (vi) 16-18 years old.	dpcfamuk
Panel (b): APS	**Description**	**Variables**
Gross hourly pay	Gross hourly pay is a continuous variable It is calculated by the ratio of the gross weekly earnings to the total number of usual (basic + overtime) weekly paid hours (Unit: £)	hourpay
Male	Dummy variable indicating whether the employee is male.	sex
Tenure	Employment tenure (years). This is derived from when an employee started working for their current employer.	conmpy
Work region	The region of the workplace, NUTS1: East, North West, Yorkshire, East Midlands, West Midlands, South West, East, London, South East, Wales). We drop those working outside England and Wales.	gorwkr
Part-time	Dummy variable, self-reported, whether the job is part-time.	ftptwk
Occupation	Major groups of the SOC10 occupation classification	nsecmj10
Industry	Major groups of the SIC07 industry classifications	inde07m
Ethnicity	Employee's ethnicity: White, Indian, Pakistani, Bangladeshi, Chinese, Black, Caribbean, Black Africa. Observations in the Mixed and Other categories are not considered.	ethew18
Age	Age ranges of the employee aged 25 or over.	ages
Education	Employee's qualifications:(i) no qualification, (ii) other qualification, (iii) below National Qualifications Framework (NQF) level 2, (iv) NQF level 2, (v)Trade apprenticeships, (vi) NQF level 3, (v) NQF level 4 and above.	levqul11
Marital status	Dummy variables of whether the employee is married or registered in a same-sex civil partnership.	marsta
UK national identity	Dummy variable of whether the employee has UK national identity	natide11
Number of children under 19	A count variable, indicating the number of children under 19 years old in the family	fdpch19
Age of the youngest child	It is a categorical variable indicating age ranges of the youngest dependent child of the employee: (i) under 2 years old, (ii) 2-4years old, (iii) 5-9 years old, (iv) 10-15 years old, (v) 16-under 19 years old, (vi) 19+years old or no dependent children. It is derived from the number children in the family.	fdpch2, fdpch4, fdpch9, fdpch15, fdpch16, fdpch19

FIGURE A1: Estimated distributions of log gross hourly earnings, comparing white and ethnic minority employees, ASHE-Census 2011

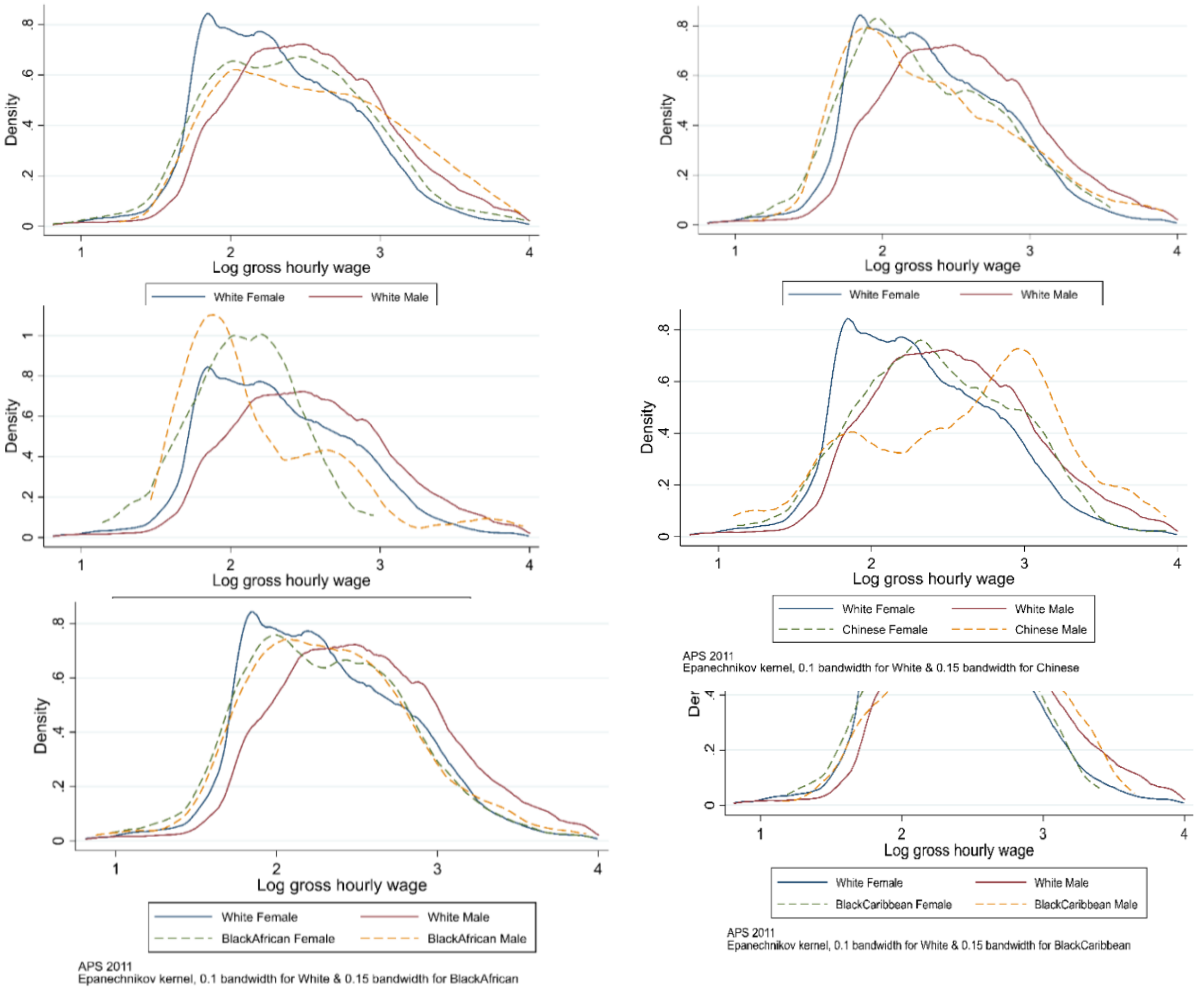


Notes: author calculations using ASHE-Census 2011 dataset. See Figure 1 for sample sizes by gender. See Figure A2 for equivalent kernel density estimates from the Annual Population Survey (APS) 2011, and Figure A3 for the ASHE-Census and APS distributions overlaid.

FIGURE A2: Estimated distributions of log gross hourly earnings, comparing white and other ethnic minority employees, Annual Population Survey 2011

(a) Indian & white

(b) Pakistani & white

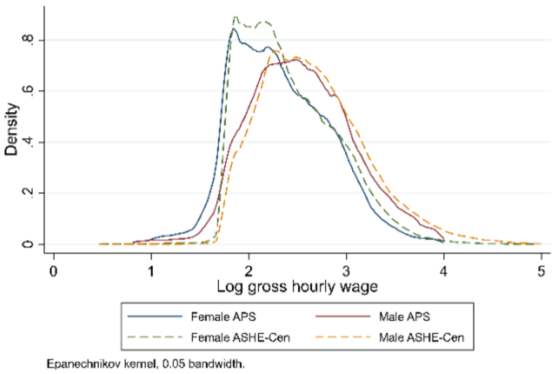


Notes: author calculations using ASHE-Census 2011 dataset. See Figure A3 for the ASHE-Census distributions overlaid.

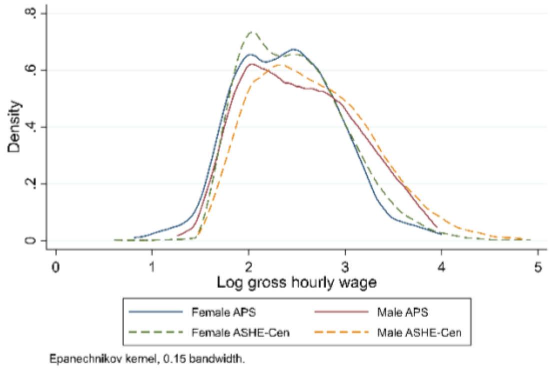
For the APS 2011, N_White (F=37,964 and M=38,130), N_Indian (F=1,176 and M=1,189), N_Pakistani (F=314 and M=514), N_Bangladeshi (F=98 and M=171), N_Chinese (F=208 and M=172), N_Black African (F=557 and M=487), and N_Black Caribbean (F=599 and M=396).

FIGURE A3: Distributions of log gross hourly earnings, by ethnicity and gender, in ASHE-Census 2011 and APS 2011, England and Wales

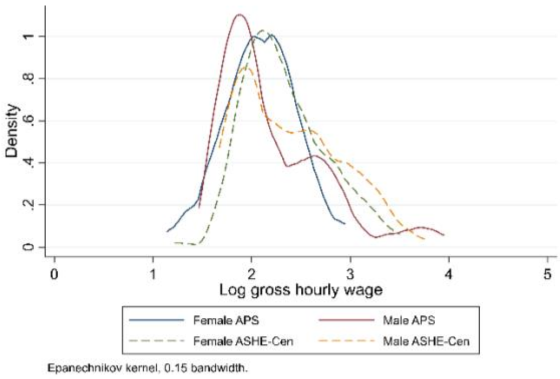
(a) White



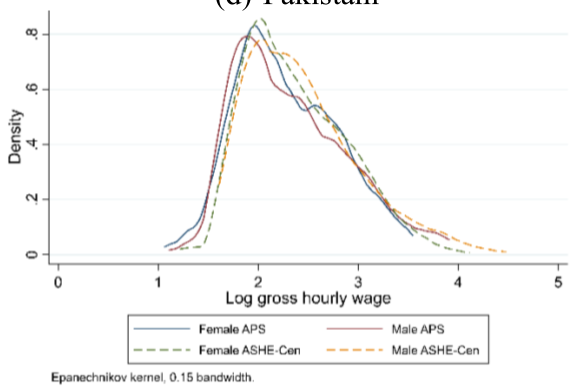
(b) Indian



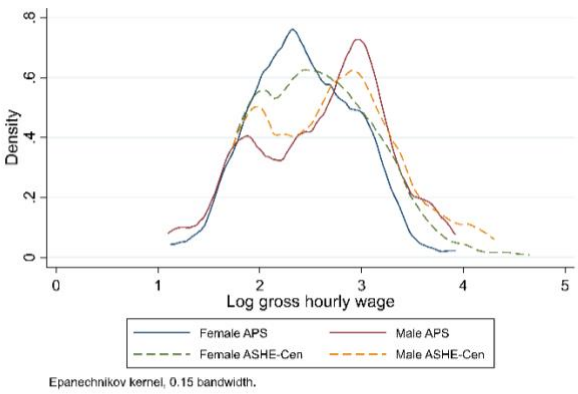
(c) Bangladeshi



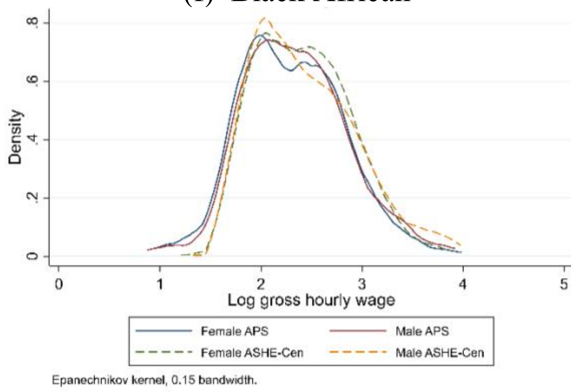
(d) Pakistani



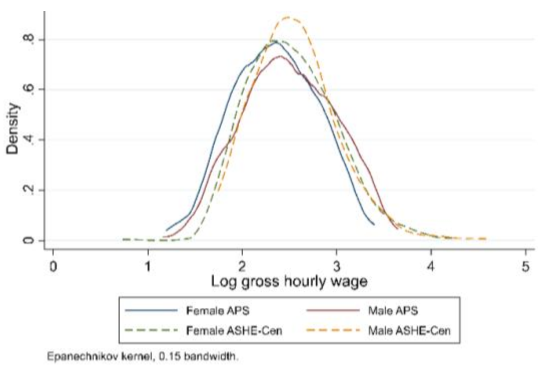
(e) Chinese



(f) Black African



(g) Black Caribbean



Notes: author calculations using ASHE-Census 2011 dataset and Annual Population Survey.

B. Additional Tables and Figures

TABLE B1: Estimates of gender-ethnicity log gross hourly wage gaps at the mean, employees in England and Wales, 2011

	(I)	(II)	(III)	(IV)	(V)	(VI)
Male	0.232***	0.245***	0.155***	0.167***	0.132***	0.131***
	(0.008)	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)
Ethnicity (excl. cat., white):						
Indian	0.060***	0.072***	-0.110***	-0.103***	-0.072***	-0.070***
	(0.017)	(0.018)	(0.015)	(0.015)	(0.010)	(0.011)
Pakistani	-0.038	-0.045	-0.093***	-0.094***	-0.035**	-0.037**
	(0.028)	(0.030)	(0.023)	(0.025)	(0.018)	(0.018)
Bangladeshi	-0.073*	-0.070	-0.127***	-0.124***	-0.059**	-0.061**
	(0.042)	(0.046)	(0.034)	(0.035)	(0.026)	(0.028)
Chinese	0.164***	0.169***	-0.039	-0.036	-0.006	-0.011
	(0.038)	(0.040)	(0.028)	(0.030)	(0.022)	(0.024)
Black African	0.000	-0.012	-0.213***	-0.213***	-0.115***	-0.110***
	(0.022)	(0.023)	(0.016)	(0.016)	(0.012)	(0.012)
Black Caribbean	0.109***	0.111***	-0.083***	-0.086***	-0.038***	-0.042***
	(0.021)	(0.022)	(0.016)	(0.016)	(0.013)	(0.013)
Interaction terms:						
Indian × Male	-0.034	-0.010	0.007	0.025	0.005	0.014
	(0.023)	(0.024)	(0.019)	(0.020)	(0.015)	(0.015)
Pakistani × Male	-0.150***	-0.120***	-0.097***	-0.080**	-0.089***	-0.083***
	(0.038)	(0.041)	(0.031)	(0.032)	(0.024)	(0.025)
Bangladeshi × Male	-0.150***	-0.144**	-0.175***	-0.163***	-0.150***	-0.149***
	(0.054)	(0.061)	(0.046)	(0.051)	(0.036)	(0.041)
Chinese × Male	-0.103*	-0.102	-0.053	-0.046	-0.069*	-0.058
	(0.061)	(0.064)	(0.047)	(0.047)	(0.037)	(0.038)
Black African × Male	-0.192***	-0.174***	-0.138***	-0.139***	-0.068***	-0.074***
	(0.034)	(0.035)	(0.026)	(0.027)	(0.020)	(0.020)
Black Caribbean × Male	-0.225***	-0.218***	-0.098***	-0.096***	-0.085***	-0.082***
	(0.029)	(0.032)	(0.024)	(0.025)	(0.019)	(0.020)
Individual characteristics	N	N	Y	Y	Y	Y
Family characteristics	N	N	Y	Y	Y	Y
Occupation (3-digit) effects	N	N	N	N	Y	Y
ASHE-Census weighted	N	Y	N	Y	N	Y
N of employees	90,486	89,883	90,486	89,883	90,486	89,883
R^2	0.051	0.055	0.428	0.437	0.611	0.614

Notes: author calculations using ASHE-Census 2011 dataset. See notes to Table 2 in the main text. The regression models (and columns) described here are equivalent to those in Table 2 except that the dependent variable is the log of gross hourly earnings rather than the log of basic hourly wages.
***, **, * indicate significant differences from zero, two-sided tests, at the 1%, 5%, and 10% levels, respectively, with standard errors robust to firm-level clustering in parentheses.

TABLE B2: Estimated gender-ethnicity log gross hourly earnings gaps at the mean, employees in England and Wales, 2011: Unexplained Gaps Within vs Between Firms

	Adjusted: employer characteristics		Adjusted: within firms	Adjusted: between firm	Adjusted: within firms	Adjusted: between firms
	(I)	(II)	(III)	(IV)	(V)	(VI)
Male	0.134***	0.134***	0.116***	0.056***	0.117***	0.055***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Ethnicity (excl. cat., white):						
Indian	-0.072***	-0.071***	-0.060***	0.023***	-0.059***	0.025***
	(0.010)	(0.011)	(0.010)	(0.008)	(0.011)	(0.008)
Pakistani	-0.037**	-0.039**	-0.028*	-0.004	-0.028*	-0.005
	(0.017)	(0.018)	(0.017)	(0.011)	(0.017)	(0.011)
Bangladeshi	-0.065**	-0.067**	-0.070**	0.019	-0.072**	0.021
	(0.025)	(0.027)	(0.029)	(0.017)	(0.033)	(0.018)
Chinese	-0.004	-0.008	-0.010	0.070***	-0.009	0.073***
	(0.022)	(0.023)	(0.025)	(0.019)	(0.026)	(0.020)
Black African	-0.113***	-0.109***	-0.086***	-0.010	-0.078***	-0.011
	(0.012)	(0.012)	(0.013)	(0.009)	(0.014)	(0.009)
Black Caribbean	-0.041***	-0.045***	-0.023*	0.016*	-0.026**	0.017*
	(0.012)	(0.013)	(0.013)	(0.009)	(0.013)	(0.009)
Interaction terms:						
Indian × Male	0.005	0.014	-0.002	-0.002	0.001	0.007
	(0.015)	(0.015)	(0.014)	(0.010)	(0.014)	(0.011)
Pakistani × Male	-0.087***	-0.082***	-0.068***	-0.012	-0.067***	-0.004
	(0.024)	(0.024)	(0.023)	(0.015)	(0.024)	(0.016)
Bangladeshi × Male	-0.149***	-0.148***	-0.078**	-0.007	-0.079*	0.008
	(0.035)	(0.040)	(0.040)	(0.025)	(0.044)	(0.028)
Chinese × Male	-0.067*	-0.056	-0.054	0.006	-0.040	0.001
	(0.037)	(0.038)	(0.040)	(0.033)	(0.041)	(0.035)
Black African × Male	-0.068***	-0.075***	-0.061***	-0.039***	-0.068***	-0.037**
	(0.019)	(0.020)	(0.019)	(0.014)	(0.020)	(0.015)
Black Caribbean × Male	-0.084***	-0.082***	-0.088***	-0.018	-0.087***	-0.016
	(0.019)	(0.020)	(0.020)	(0.013)	(0.021)	(0.014)
Individual characteristics	Y	Y	Y	Y	Y	Y
Family characteristics	Y	Y	Y	Y	Y	Y
Occupation (3-digit) effects	Y	Y	Y	Y	Y	Y
Employer characteristics	Y	Y	Y	Y	Y	Y
ASHE-Census weighted	N	Y	N	N	Y	Y
N of employees	90,120	89,523	68,218	68,218	67,748	67,748
R^2	0.638	0.640	0.745	0.034	0.744	0.029

Notes: author calculations using ASHE-Census 2011 dataset. See notes to Table 3 in the main text. The regression models (and columns) described here are equivalent to those in Table 3 except that the dependent variable is the log of gross hourly earnings rather than the log of basic hourly wages.
***, **, * indicate significant differences from zero, two-sided tests, at the 1%, 5%, and 10% levels, respectively, with standard errors robust to firm-level clustering in parentheses.

TABLE B3: Estimated gender-ethnic log gross hourly earnings at the mean and unconditional quantiles, England and Wales, 2011

	Unexplained Within Firms						Unexplained Between Firms					
	Mean	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)
Male	0.116***	0.034***	0.062***	0.104***	0.148***	0.217***	0.056***	0.055***	0.085***	0.084***	0.038***	0.024***
	[0.005]	[0.005]	[0.006]	[0.007]	[0.009]	[0.013]	[0.004]	[0.007]	[0.011]	[0.006]	[0.007]	[0.008]
Indian	-0.002	-0.007	-0.008	-0.043*	0.026	0.061	-0.002	0.006	-0.020*	-0.017	0.012	0.015
	[0.014]	[0.016]	[0.023]	[0.025]	[0.027]	[0.046]	[0.010]	[0.011]	[0.012]	[0.013]	[0.015]	[0.024]
Pakistani	-0.068***	0.024	-0.019	-0.090**	-0.138***	-0.076	-0.012	-0.016	-0.023	-0.024	-0.008	0.004
	[0.023]	[0.041]	[0.036]	[0.041]	[0.045]	[0.073]	[0.015]	[0.020]	[0.020]	[0.020]	[0.021]	[0.032]
Bangladeshi	-0.078**	0.014	-0.029	0.070	-0.219***	-0.233*	-0.007	-0.049**	-0.045*	-0.057*	0.052	0.076
	[0.040]	[0.065]	[0.069]	[0.062]	[0.081]	[0.126]	[0.025]	[0.023]	[0.026]	[0.030]	[0.038]	[0.063]
Chinese	-0.054	-0.002	-0.064*	-0.015	-0.065	-0.226	0.006	-0.008	-0.030	-0.014	-0.002	0.116
	[0.040]	[0.035]	[0.036]	[0.066]	[0.094]	[0.171]	[0.033]	[0.027]	[0.024]	[0.030]	[0.051]	[0.098]
Black Afr.	-0.061***	-0.036	-0.074**	-0.068*	-0.091**	-0.070	-0.039***	-0.030	-0.054***	-0.036*	-0.046**	-0.035
	[0.019]	[0.027]	[0.031]	[0.036]	[0.043]	[0.053]	[0.014]	[0.019]	[0.020]	[0.020]	[0.021]	[0.027]
Black Carib.	-0.088***	0.005	-0.056*	-0.071	-0.124***	-0.123**	-0.018	-0.030**	-0.011	-0.003	-0.025	-0.075***
	[0.020]	[0.022]	[0.029]	[0.048]	[0.042]	[0.058]	[0.013]	[0.012]	[0.016]	[0.024]	[0.020]	[0.028]
Indian × Male	-0.060***	0.007	-0.014	-0.044***	-0.107***	-0.142***	0.023***	-0.005	0.012	0.015	0.025**	0.071***
	[0.010]	[0.013]	[0.016]	[0.016]	[0.021]	[0.032]	[0.008]	[0.010]	[0.010]	[0.010]	[0.011]	[0.015]
Pakistani× Male	-0.028*	-0.033	-0.003	0.008	-0.017	-0.070	-0.004	-0.020	-0.025	-0.017	0.006	0.025
	[0.017]	[0.033]	[0.022]	[0.030]	[0.033]	[0.055]	[0.011]	[0.016]	[0.016]	[0.014]	[0.015]	[0.022]
Bangladeshi× Male	-0.070**	0.035	-0.032	-0.147***	-0.029	-0.128*	0.019	-0.004	-0.006	0.051**	0.020	0.025
	[0.029]	[0.043]	[0.054]	[0.044]	[0.057]	[0.067]	[0.017]	[0.018]	[0.021]	[0.024]	[0.030]	[0.037]
Chinese× Male	-0.010	0.012	0.046*	-0.015	-0.021	-0.037	0.070***	0.002	0.063***	0.080***	0.100***	0.095*
	[0.025]	[0.025]	[0.024]	[0.047]	[0.057]	[0.091]	[0.019]	[0.018]	[0.017]	[0.020]	[0.030]	[0.053]
Black Afr. × Male	-0.086***	0.043**	0.022	-0.065***	-0.160***	-0.254***	-0.010	-0.031**	-0.010	-0.033***	0.026*	0.019
	[0.013]	[0.019]	[0.021]	[0.024]	[0.032]	[0.036]	[0.009]	[0.013]	[0.014]	[0.012]	[0.015]	[0.018]
Black Carib. × Male	-0.023*	0.009	0.041**	0.008	-0.054*	-0.127***	0.016*	0.013	0.021*	0.018	0.018	0.047**
	[0.013]	[0.014]	[0.018]	[0.024]	[0.029]	[0.037]	[0.009]	[0.008]	[0.011]	[0.011]	[0.014]	[0.021]

Notes: author calculations using ASHE-Census 2011 dataset. See notes to Table 4 in the main text. The regression models (and columns) described here are equivalent to those in Table 3 except that the dependent variable is the log of gross hourly earnings rather than the log of basic hourly wages.
***, **, * indicate significant differences from zero, two-sided tests, at the 1%, 5%, and 10% levels, respectively, with standard errors robust to firm-level clustering in parentheses.

TABLE B4: Oaxaca-Blinder decomposition results for the log gross hourly earnings gaps between ethnic minority and white employees, ***female*** only, at the mean and unconditional quantiles, England and Wales, 2011

		Mean (I)	p10 (II)	p25 (III)	p50 (IV)	p75 (V)	p90 (VI)
Indian	**Total (N=1,020)**	**0.051*****	**0.014**	**0.036**	**0.087*****	**0.028**	**0.066****
	= Expl. Indiv. & Fam. char's	0.077***	0.031***	0.048***	0.092***	0.095***	0.113***
	+ Expl. Occ's (SOC 3-digit)	0.015	-0.012*	-0.000	0.026*	0.016	0.021
	+ Expl. Firm char's	-0.003**	-0.003**	-0.004**	-0.002	-0.003*	-0.002
	+ Unexplained within firms	-0.060***	0.007	-0.014	-0.043***	-0.109***	-0.142***
	+ Unexplained between firms	0.022***	-0.009	0.006	0.014	0.029***	0.076***
Pakistani	**Total (N=276)**	**-0.051***	**-0.079***	**-0.076****	**-0.043**	**-0.030**	**-0.024**
	= Expl. Indiv. & Fam. char's	0.003	0.000	-0.003	0.018	-0.002	-0.005
	+ Expl. Occ's (SOC 3-digit)	-0.023	-0.029***	-0.050***	-0.054**	-0.015	0.031
	+ Expl. Firm char's	0.001	-0.001	0.000	0.001	0.001	0.001
	+ Unexplained within firms	-0.028*	-0.033	-0.004	0.007	-0.018	-0.070
	+ Unexplained between firms	-0.004	-0.016	-0.019	-0.016	0.004	0.019
Black Afr.	**Total (N=452)**	**0.001**	**0.025**	**0.043**	**0.057**	**-0.028**	**-0.128*****
	= Expl. Indiv. & Fam. char's	0.110***	0.032***	0.042***	0.117***	0.149***	0.197***
	+ Expl. Occ's (SOC 3-digit)	-0.014	-0.018**	-0.007	0.039*	-0.046***	-0.095***
	+ Expl. Firm char's	0.002	0.002	0.002	0.001	0.002	0.001
	+ Unexplained within firms	-0.086***	0.043**	0.022	-0.066***	-0.160***	-0.254***
	+ Unexplained between firms	-0.010	-0.034**	-0.015	-0.034***	0.028**	0.023
Black Carib.	**Total (N=540)**	**0.097*****	**0.088*****	**0.157*****	**0.166*****	**0.058**	**0.026**
	= Expl. Indiv. & Fam. char's	0.108***	0.048***	0.065***	0.118***	0.132***	0.165***
	+ Expl. Occ's (SOC 3-digit)	-0.004	0.011	0.020*	0.018	-0.033*	-0.049**
	+ Expl. Firm char's	-0.000	-0.002	-0.001	0.000	0.001	0.001
	+ Unexplained within firms	-0.023**	0.009	0.040**	0.010	-0.056**	-0.127***
	+ Unexplained between firms	0.017**	0.022**	0.032***	0.020*	0.014	0.035
Non-white	**Total (N=2,533)**	**0.046*****	**0.024***	**0.056*****	**0.086*****	**0.030**	**0.019**
	= Expl. Indiv. & Fam. char's	0.080***	0.032***	0.045***	0.093***	0.100***	0.124***
	+ Expl. Occ's (SOC 3-digit)	0.002	-0.010***	-0.003	0.017*	-0.007	-0.011
	+ Expl. Firm char's	-0.001	-0.002	-0.001	-0.000	-0.001	-0.000
	+ Unexplained within firms	-0.051***	0.011	0.008	-0.033***	-0.089***	-0.144***
	+ Unexplained between firms	0.015***	-0.007	0.008	0.009	0.027***	0.051***

Notes: author calculation using ASHE-Census 2011 dataset. See Equation (4), as well as Tables B2 & B3, for more details and results of the underlying regression models.
***, **, * indicate significant differences from zero, two-sided tests, at 1%, 5%, and 10% level, respectively.

TABLE B5: Oaxaca-Blinder decomposition results for the log gross hourly earnings gaps between ethnic minority and white employees, ***male*** only, at the mean and unconditional quantiles, England and Wales, 2011

		Mean (I)	p10 (II)	p25 (III)	p50 (IV)	p75 (V)	p90 (VI)
Indian	**Total (N=937)**	**0.014**	**-0.014**	**-0.046****	**-0.047**	**0.052**	**0.167*****
	= Expl. Indiv. & Fam. char's	0.051***	0.006**	0.011***	0.053***	0.076***	0.106***
	+ Expl. Occ's (SOC 3-digit)	0.009	-0.022***	-0.024***	-0.008	0.027	0.064***
	+ Expl. Firm char's	-0.004**	-0.002	-0.005	-0.003**	-0.006**	-0.004*
	+ Unexplained within firms	-0.063***	-0.000	-0.023*	-0.087***	-0.083***	-0.082**
	+ Unexplained between firms	0.020**	0.004	-0.006	-0.001	0.037***	0.083***
Pakistani	**Total (N=367)**	**-0.180*****	**-0.105*****	**-0.165*****	**-0.228*****	**-0.238*****	**-0.131****
	= Expl. Indiv. & Fam. char's	-0.019**	-0.013***	-0.027***	-0.019*	-0.028**	-0.015
	+ Expl. Occ's (SOC 3-digit)	-0.044***	-0.042***	-0.063***	-0.083***	-0.048**	0.004
	+ Expl. Firm char's	-0.004**	-0.005***	-0.006**	-0.002	-0.004**	-0.002
	+ Unexplained within firms	-0.096***	-0.009	-0.022	-0.082***	-0.156***	-0.147***
	+ Unexplained between firms	-0.016	-0.036**	-0.048***	-0.041***	-0.002	0.029
Black Afr	**Total (N=389)**	**-0.224*****	**-0.132*****	**-0.235*****	**-0.269*****	**-0.266*****	**-0.243*****
	= Expl. Indiv. & Fam. char's	0.078***	-0.004	-0.007	0.064***	0.129***	0.201***
	+ Expl. Occ's (SOC 3-digit)	-0.104***	-0.074***	-0.114***	-0.128***	-0.120***	-0.099***
	+ Expl. Firm char's	-0.003**	-0.002	-0.003	-0.002*	-0.003*	-0.002
	+ Unexplained within firms	-0.148***	0.007	-0.049**	-0.134***	-0.252***	-0.326***
	+ Unexplained between firms	-0.048***	-0.059***	-0.062***	-0.069***	-0.021	-0.017
Black Carib	**Total (N=327)**	**-0.132*****	**-0.010**	**-0.031**	**-0.083***	**-0.228*****	**-0.273*****
	= Expl. Indiv. & Fam. char's	0.054***	0.016***	0.014*	0.047***	0.072***	0.115***
	+ Expl. Occ's (SOC 3-digit)	-0.072***	-0.028***	-0.048***	-0.082***	-0.107***	-0.096***
	+ Expl. Firm char's	-0.002	-0.004**	-0.004*	-0.001	-0.002	-0.001
	+ Unexplained within firms	-0.111***	0.014	-0.016	-0.063*	-0.178***	-0.251***
	+ Unexplained between firms	-0.001	-0.007	0.022*	0.017	-0.013	-0.041*
Non-white	**Total (N=2,243)**	**-0.079*****	**-0.048*****	**-0.097*****	**-0.111*****	**-0.089*****	**-0.027**
	= Expl. Indiv. & Fam. char's	0.048***	0.004*	0.004	0.045***	0.071***	0.108***
	+ Expl. Occ's (SOC 3-digit)	-0.030***	-0.035***	-0.049***	-0.051***	-0.027**	0.004
	+ Expl. Firm char's	-0.003***	-0.002	-0.005*	-0.002**	-0.004***	-0.003
	+ Unexplained within firms	-0.095***	0.005	-0.028***	-0.088***	-0.146***	-0.183***
	+ Unexplained between firms	0.001	-0.019***	-0.019***	-0.014	0.018*	0.046***

Notes: author calculation using ASHE-Census 2011 dataset. See Equation (4), as well as Tables B2 & B3 for more details and results of the underlying regression models. The numbers in parentheses
***, **, * indicate significant differences from zero, two-sided tests, at 1%, 5%, and 10% level, respectively.