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Accounting for firms in gender-ethnicity wage gaps throughout the earnings distribution

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Abstract

Previous studies of gender-ethnicity wage gaps have almost exclusively been confined to analyses of household data, so do not fully account for employer influence and wage-setting power. Exploiting 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 show that firm-specific wage effects account for sizeable parts of the estimated differences between the wages of white and ethnic minority workers at the mean and other points in the wage distribution, which would otherwise mostly have been attributed to differences in individual worker attributes, such as education levels, occupations, and locations. Nevertheless, substantial gaps persist between the wages of white and ethnic minority employees, especially among higher earners. These patterns differ notably by gender and whichever ethnic minority group is compared with white workers. Since most of the wage disadvantage for ethnic minorities appears to sit within firms, our findings suggest that recent legislative reforms on firm-level gender pay gap transparency could be worth extending in the UK, to encompass gender-ethnicity gaps.

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 describes substantial ethnicity wage gaps in the United Kingdom across the wage 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). Those 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 (Clark & Nolan, 2021; Li & Heath, 2020). Because previous studies relied on household survey data, they could not fully address the contribution of the firm to ethnicity wage gaps. Yet, there is increasing recognition that firms influence wage determination, contrary to the standard assumptions in labour economics that see most employers as wage takers. It is also now well-established that a large proportion of the general growth in wage inequality over the past few decades, in the UK and other countries, can be accounted for by increases to the differences in wages between firms rather than within (e.g., for the US, see Barth et al., 2016, and Song et al., 2019; for Germany, see Card et al., 2013; for the UK, see Schaefer & Singleton, 2020).

Gender-ethnicity wage gaps in Britain may, therefore, be affected by differences across employers in ways and to an extent that is not yet known. This would occur if, for example, there is some degree of segregation by ethnicity over firms, for whatever reason, according to whether those firms tend to pay relatively high or low wages to all their workers, regardless of their ethnicity. We know from field experiments that hiring discrimination on racial grounds persists in the British labour market (Heath & Di Stasio, 2019), which could help to explain earnings disparities by ethnicity. 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 ethnicity wage gaps were generally accounted for by traditional observed characteristics, such as education or experience, even if a significant but smaller component remained unaccounted for.

Forth et al. (2023a) is the only study that has used linked employer-employee data from Britain (the Workplace Employment Relations Survey, for 1998, 2004 and 2011) to examine ethnicity wage differences within workplaces. Although they identified substantial ethnic segregation of employees across workplaces, Forth et al. (2023a) concluded that average ethnicity wage gaps in Britain predominantly occur within workplaces, rather than between, suggesting that the sorting of workers by ethnicity across employers is unlikely to play a large role in accounting for these gaps. This might occur if, for example, employers have unbiased selection practices but discriminate based on ethnicity in new hire pay or promotions, either statistically or based on taste. Although such discrimination within firms would be illegal under UK equalities legislation, that also 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 ethnicity differences in the reporting of unfair treatment in the workplace (Wheatley & Gifford, 2019), in unfair treatment in promotion or job advancement (Heath & Cheung, 2006), and for the US in 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 gender-ethnicity wage gaps, addressing the influence of firm-specific (residual or 'equal treatment') pay effects (i.e., the different amounts of pay that employees get just because they happen to work for one employer or another). The only other study that offers comparable evidence for Britain is Forth et al. (2023a). However, 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 ethnicity groups, and studying only average wage gaps. Our sample sizes allow us to overcome those significant limitations. Further, Forth et al.'s (2023a) analysis was based on banded, self-reported wage data, whereas we can use 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 comes from linking the payroll-based Annual Survey of Hours and Earnings (ASHE) and 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 around 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 gender-ethnicity groups in England and Wales are influenced by firm-specific wages.[1] First, we estimate covariate-adjusted gender-ethnicity wage gaps, both at the mean and selected percentiles of the overall unconditional employee wage distribution. Then, focusing on male employees, and treating the majority white wage distribution as the counterfactual or baseline distribution of earnings in the market, we decompose the distributions of ethnicity wage gaps, by applying an extension of the Oaxaca-Blinder (O-B) wage decomposition

[1] 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.

method to unconditional quantile regression (Firpo et al., 2009, Firpo et al., 2018; Rios-Avila, 2018).[2] We compare both sets of results between wage models estimated with and without firm-specific wage effects. Despite uncovering different ethnicity wage gap patterns by gender in the first analysis, in the decompositions we focus on male employees due to our estimation sample sizes, and because those differences would also make pooling men and women counterproductive.

We find that employee gender-ethnicity wage gap estimates vary substantially, both on average and throughout the wage distribution, depending on which gender or ethnicity group is compared with white employees. There is substantial heterogeneity which 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. Addressing the influence of firm-specific wage effects, thus using wage variation between colleagues within firms, tends to reduce the estimated contributions to gender-ethnicity wage gaps from other factors, such as education, occupation, and region, because these are generally correlated with employment in relatively high or low-wage firms. Therefore, studies which are unable to account for the influence of firm-specific wage determination are potentially prone to some bias when estimating covariate-adjusted gender-ethnicity pay gaps, or when trying to account for how the differences in some set of observable characteristics could 'explain' the observed gaps.

After accounting for firm-specific wages and other worker characteristics among men, we find that significant unexplained (or residual) gaps occur even where the explained parts of wage gaps would be in favour of ethnic minority employees (e.g., for high-earning Indian male employees). Further, these unexplained gaps between some male ethnic minority and white wage distributions are at least as large as the observed gaps (e.g., for high earning Black Caribbean employees). These findings are consistent with the notion of 'glass ceilings', potentially linked to discriminatory pay and promotion practices, which would make it hard 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 what is happening within the employer in the size and persistence of ethnicity wage gaps in Britain, both positive and negative, and not only on average but to a greater extent among higher earning workers. Our results suggest that policy makers may want to consider

[2] 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.

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 ethnicity wage gaps are predominantly a within rather than a between firm phenomenon, there is arguably scope and 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.[3]

The remainder of the paper proceeds as follows: Section 2 describes the ASHE-Census dataset; Section 3 estimates covariate-adjusted gender-ethnicity wage gaps, on average and at selected unconditional quantiles of the overall wage distribution, in England and Wales in 2011; Section 4 focuses on male employees, looking at the influence of observable characteristics on the differences between white and ethnic minority wage distributions, with and without addressing firm-specific wage effects; 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 new employer-employee dataset for England and Wales to study the distribution of gender-ethnicity wage gaps and address the influence of firm-specific wages. 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 new 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 been used in cross-section and longitudinally over employers and employees to study the influence of firm-specific wages effects for various patterns of pay in the UK (e.g., Bell et al., 2022; Jewell et al., 2020; Schaefer and Singleton, 2020; Singleton, 2019; Stokes et al., 2017). The new ASHE-Census dataset adds several well-known covariates of wages that were missing from those

[3] For evidence on the impacts of gender pay reporting: in the UK (introduced in 2017), see Duchini et al. (2020) and Jones et al. (2023); 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).

studies. By identifying the ethnicity of employees in ASHE, we can estimate the distributions of gender-ethnicity wage gaps in England and Wales and, for the first time, we are able to establish whether they are accounted for by firm-specific wages, as opposed to a traditional set of explanatory characteristics, such as education and labour market experience. 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.

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 ethnicity within firms.[4]

We restrict our analysis 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.

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

Table 1 shows raw average ethnicity wage gaps among employees in England and Wales in 2011 from the ASHE-Census data. Among ethnic groups, Chinese employees had the highest average

[4] For completeness, we 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 as in Clark and Nolan (2021).

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 average 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 ethnicity 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). Specifically, Figure 1 expands on Table 1, by showing raw ethnicity wage gaps from ASHE-Census for men and women separately. Appendix Figures A1-A3 show kernel density estimates of employee hourly wages, by ethnicity and gender, and comparing the ASHE-Census and APS datasets. Overall, we reassured by these statistics and comparisons that ASHE-Census can provide reasonably representative descriptions of employee wages for England and Wales.

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

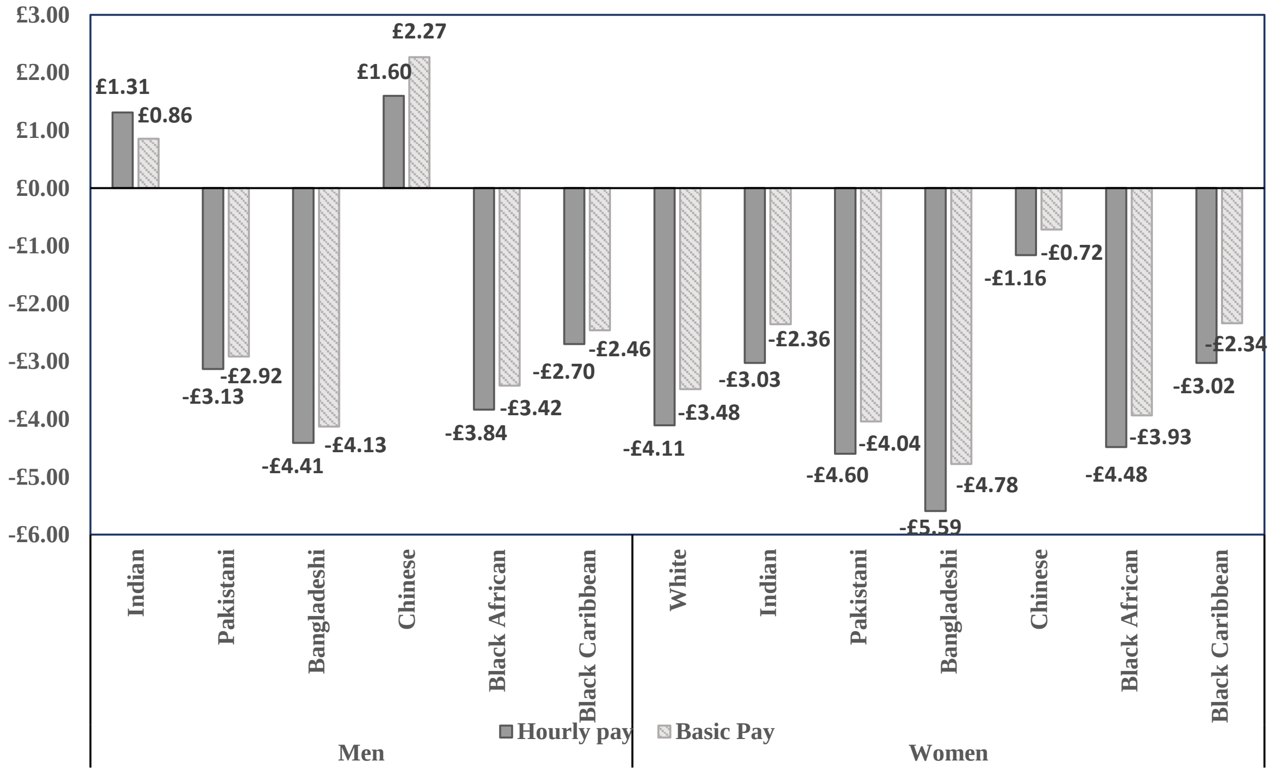
	ASHE-Census 2011						APS 2011		
Ethnicity	Gross hourly earnings			Basic hourly wage			Hourly wage		
	N	Mean	Premium (+)/ Penalty (-)	*N*	Mean	Premium (+)/ Penalty (-)	*N*	Mean	Premium (+)/ Penalty (-)
Chinese	463	£17.04	£2.18	460	£16.53	£2.38	177	£14.51	£1.46
Indian	2703	£16.13	£1.27	2690	£15.20	£1.06	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 2 gives an overview of the ethnicity 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 this 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 1: Raw average ethnicity hourly wage gaps among male and female employees in England and Wales, relative to white men, ASHE-Census 2011

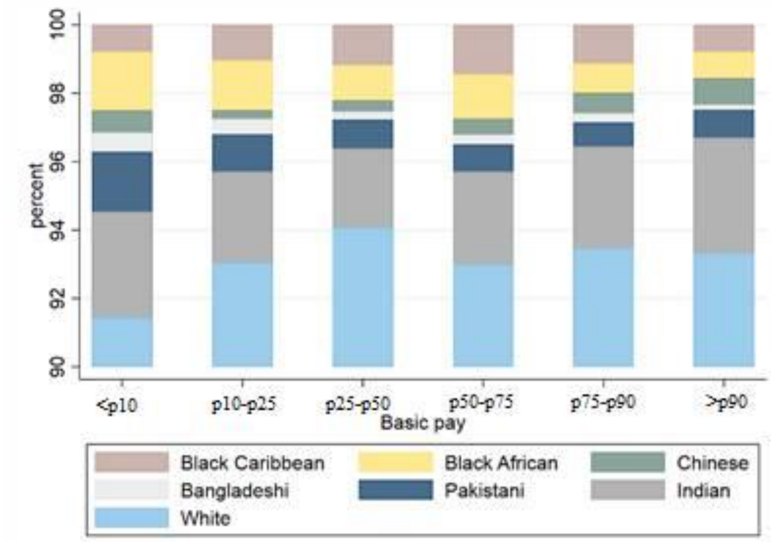


Notes: author calculations using ASHE-Census 2011 dataset. The raw ethnicity wage gap is calculated by the average wage of ethnicity X minus the average White men wage. These figures are unweighted. For hourly pay, *N* White (F=47,938 and M=43,892), *N* Indian (F=1,360 and M=1,343), *N* Pakistani (F=362 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).

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 firm-specific wages, because pay determination systems and practices in multi-plant organisations tend to be determined at the enterprise level.[5] In what follows, we can control for general wage differences between regional labour markets because some firms have employees who are dispersed throughout England and Wales.

[5] 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.

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 adjusted gender-ethnicity wage gaps

In this section, we investigate whether a consideration of firm-specific wage effects alters some basic estimates of adjusted (or conditional, or residual) gender-ethnicity wage gaps. For the mean adjusted (log) gaps, we estimate wage equations of the following form using Ordinary Least Squares (OLS):

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

The dependent variable, $y_i = \ln \omega_i$, is the log wage of employee i. $\mathbf{x}_i$ is a row vector of relevant controls for wage determination: quadratics in individual age and tenure at the current firm; Nomenclature of Territorial Units for Statistics Level 1 (NUTS1; e.g., London, Wales) region of work; highest qualification level; occupation (SOC10, 1-digit or 3-digit); whether working part-time, whether married, number of children, and age of youngest child, which we would expect to all correlate somewhat with unobserved accumulated human capital through general work experience, especially among women (e.g., see for the UK, Costa Dias et al., 2020); and whether non-UK born; see Online Appendix A for details of all these variables. $\boldsymbol{\beta}$ is a column vector containing the parameters for each of these control variables. $\theta_{Z(i)}$ 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 and within and between ethnic minority groups. $\varphi_{J(i)}$ 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.

Moving beyond a study of only the average white and ethnic minority employees, to estimate the influence of ethnicity and gender throughout the log wage distribution, we 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:

$$\widehat{RIF}(y_i, \hat{Q}_\tau) = \hat{Q}_\tau + \frac{\tau - \mathbb{1}\{y_i \leq \hat{Q}_\tau\}}{f_y(\hat{Q}_\tau)} = \alpha_\tau + \theta_{Z(i),\tau} + \mathbf{x}_i \boldsymbol{\beta}_\tau + \varphi_{J(i),\tau} + \varepsilon_i \qquad (2)$$

where $f_y(\cdot)$ is the density of the marginal distribution of log wages, estimated using a Gaussian kernel and Silverman plugin bandwidth. We estimate standard errors for these models using bootstrapping.

The UQR method allows us to study whether the relationship between gender-ethnicity and wages varies for relatively low, middling, or high earners. Rios-Avila & 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 & 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 though 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 can change form one type to another. In other words, the estimates of $\theta_{Z(i),\tau}$ can tell us what difference there would be in the τth quantile of the wage distribution when comparing a case where every person 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 imagine that $\theta_{Z(i),\tau}$ also tell us how quantiles of the unconditional wage distribution are sensitive to small changes in the incidence of different gender-ethnicity groups in the sample, e.g., a one percentage point increase in the share of the population who are Bangladeshi men, offset by a one percentage point decrease in the share of the population who are white men – if being a Bangladeshi man is associated with no wage penalty at some quantile, then the overall wage distribution would not move at that point. This is analogous to the linear regression case in terms of considering whether being Bangladeshi matters for the average person's wages.

To estimate (1) and (2) fully, with the firm-specific wage effects, we must restrict the estimation samples to only employees for whom at least one other co-worker is observed in the ASHE-Census dataset (and no missing values for control variables, and after the other sample selection described in Appendix A). Before considering that more selected sample, which will inevitably be somewhat biased towards larger firms compared with the whole of ASHE-Census, the first four columns of Table 2 show estimates of (1) using all the employee observations described in Section 2 and Online Appendix A, with gross hourly earnings as the dependent variable. Column (I) shows the model estimates without using any sample weights, whereas column (II) provides comparable estimates applying the ASHE-Census weights described in Online Appendix A, in both cases excluding any occupation and firm-specific effects. In general, white male employees in 2011 earned on average significantly higher residual hourly earnings than white female employees, by around 15-16 log points. Among women, residual earnings were significantly lower than those of Whites for all but Chinese employees with the gap being largest with respect to Black African women. Among men, all but Chinese and Indian employees had residual earnings significantly lower than Whites, the gap being largest with respect to Bangladeshis. These baseline average residual wage gap estimates are approximately robust to using the ASHE-Census sample weights.

Columns (III)-(V) of Table 2 show estimates of (1) when, in turn, we control for 1-digit occupations, replace these with 3-digit effects, and further add firm-specific wage effects. The adjusted female wage penalty among white employees attenuates as these extra controls for job types are included in the model estimates, being 11.5 log points in the final column, which conditions for 3-digit occupation and firm-specific effects. The average ethnicity residual wage penalties, also tend to attenuate, somewhat so for Indian employees, more so for Pakistani, Bangladeshi, Black African and Black Caribbean employees, and especially so for Black African and Bangladeshi men. However, the estimates also show that even within quite detailed occupation categories and individual firms, and after also controlling for some standard personal characteristics, ethnic minority employees experienced significant average unexplained hourly earnings penalties compared to their white co-workers.

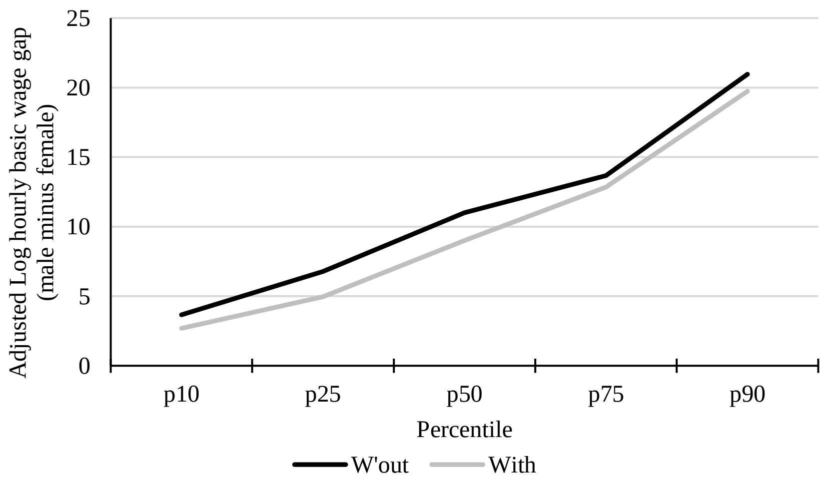
TABLE 2: Log wage regression (gross hourly earnings) estimates for employees in England and Wales, 2011

	(I)	(II)	(III)	(IV)	(V)
Male	0.154***	0.165***	0.144***	0.131***	0.115***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
Ethnicity (excl. cat., white):					
Indian	-0.077***	-0.070***	-0.050***	-0.055***	-0.053***
	(0.012)	(0.013)	(0.010)	(0.009)	(0.010)
Pakistani	-0.070***	-0.070***	-0.023	-0.022	-0.023
	(0.022)	(0.023)	(0.018)	(0.017)	(0.016)
Bangladeshi	-0.078**	-0.073**	-0.047*	-0.033	-0.060**
	(0.032)	(0.033)	(0.027)	(0.027)	(0.030)
Chinese	-0.003	0.001	0.009	0.012	-0.004
	(0.027)	(0.028)	(0.023)	(0.022)	(0.025)
Black African	-0.193***	-0.191***	-0.137***	-0.105***	-0.084***
	(0.015)	(0.016)	(0.013)	(0.012)	(0.013)
Black Caribbean	-0.088***	-0.092***	-0.065***	-0.041***	-0.025**
	(0.015)	(0.016)	(0.013)	(0.012)	(0.013)
Interaction terms:					
Indian × Male	0.006	0.022	0.006	0.004	-0.002
	(0.018)	(0.020)	(0.015)	(0.014)	(0.014)
Pakistani × Male	-0.092***	-0.075**	-0.085***	-0.088***	-0.069***
	(0.030)	(0.031)	(0.024)	(0.022)	(0.023)
Bangladeshi × Male	-0.179***	-0.170***	-0.169***	-0.156***	-0.078*
	(0.043)	(0.047)	(0.038)	(0.038)	(0.040)
Chinese × Male	-0.045	-0.037	-0.082**	-0.064*	-0.054
	(0.045)	(0.045)	(0.039)	(0.036)	(0.040)
Black African × Male	-0.140***	-0.143***	-0.071***	-0.069***	-0.061***
	(0.025)	(0.026)	(0.020)	(0.019)	(0.019)
Black Caribbean × Male	-0.101***	-0.099***	-0.081***	-0.087***	-0.089***
	(0.024)	(0.025)	(0.020)	(0.019)	(0.020)
Individual characteristics	Y	Y	Y	Y	Y
Family characteristics	Y	Y	Y	Y	Y
Occupation (1 digit) effect	N	N	Y	N	N
Occupation (3 digit) effect	N	N	N	Y	Y
Firm effects	N	N	N	N	Y
ASHE-Census weighted	N	Y	N	N	N
N of employees	90,562	89,959	90,562	90,562	68,218
R^2	0.430	0.440	0.564	0.611	0.745

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 without using any weight, while column (II) uses the ASHE-Census weights. Column (III) controls for occupations, SOC10 1 digit, while column (IV) controls for SOC10 3 digit. Employer-specific effects are added in column (V). The other control variables include individual characteristics (age, age square, education, tenure, tenure square, disability, non-UK born, English language, health status, workplace region), family characteristics (number of children, age of the youngest child), and occupation characteristics (SOC10).
***,**,* indicate significant differences from zero, two-sided tests, at the 1%, 5% and 10% levels, respectively, with robust standard errors in parentheses.

Henceforth, we restrict our focus to basic hourly wages and the sub-sample of ASHE-Census where employees can be observed with at least one co-worker in the dataset. Table 3 shows the estimates of (1), at the mean, equivalent to column (V) of Table 2 (which used gross hourly earnings), as well as estimates of (2) for selected percentiles of the overall unconditional wage distribution, comparing with and without allowing for firm-specific wage effects. Figures 3 & 4 summarise the patterns of these gender-ethnicity residual wage penalties across the percentiles. Figure 3 shows the regression-adjusted differences in log hourly basic wages between white men and women computed at selected percentiles of the overall wage distribution, comparing estimates obtained from specifications of (2) with and without firm-specific wages. At the 10th percentile, the darker line shows that white women in 2011 earned around 4 log points less than their male counterparts, controlling for other personal and job-related characteristics. This gap rises moving up the hourly earnings distribution, such that at the 90th percentile of the overall wage distribution the adjusted gender wage gap was close to 21 log points.

FIGURE 3: Estimated differences in log hourly basic wages between white male and white female employees at selected percentiles, unconditional quantile regressions, comparing models with and without firm-specific wage effects, England and Wales, 2011



Notes: author calculations using ASHE-Census 2011 dataset. See Table 3 for the displayed model coefficient estimates and standard errors. Statistics can be interpreted as the influence of gender on wages at the selected percentile of the overall wage distribution, conditional on the influence of the other factors included in the model (e.g., education, occupation, tenure with the firm). “W’out” gives estimates from models that do not control for the influence of firm-specific wage determination, whereas “With” gives estimates that do control for this, i.e., with firm-specific effects in the models.

The lighter line in Figure 3, which sits beneath the darker line, traces out estimates of the adjusted wage gap between white men and women when we additionally account for firm-specific wage effects when estimating (1). These wage gap estimates are smaller throughout the overall employee wage distribution. This suggests that a part of the earnings differentials between white men and women, in England and Wales in 2011 arises because men are more likely to work in firms paying relatively high wages to their employees, thus mirroring some similar results for Great Britain in

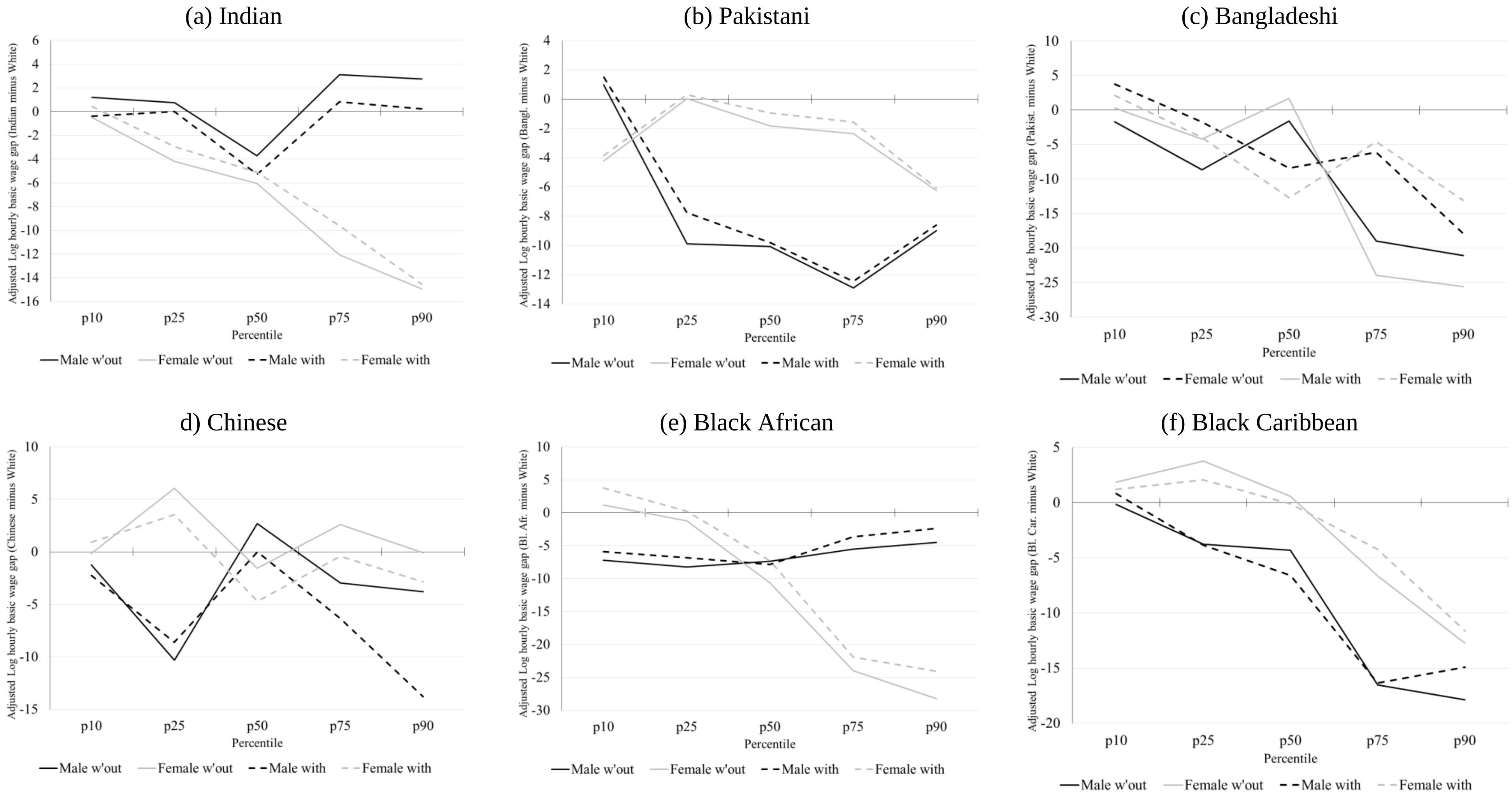
Jewell et al., (2020). After including firm-specific effects in the wage equation, the adjusted white gender gaps are 1-2 percentage points smaller throughout the overall basic hourly wage distribution. This difference is greatest at the median, where the adjusted white gender wage gap drops from 11.0 to 9.0 log points after addressing the influence of firm-specific effects.

Panel (a) of Figure 4 (rows 1 and 7 of Table 3) compares the adjusted log hourly wage gaps estimates between white and Indian employees, with and without addressing firm-specific wage effects, among women and men separately. For Indian women, the incorporation of firm-specific wage effects makes little difference to the adjusted wage gap estimates, marginally leaving them smaller: Indian women have no significant residual wage penalty compared with white women at the 10th percentile of the overall wage distribution. But being Indian is associated with earning an hourly wage that is 15 log points less at the 90th percentile, even conditioning on factors such as education and occupation. For Indian men, the adjusted gaps compared to white men are generally statistically insignificant throughout the wage distribution. A significant adjusted wage penalty of 5 log points though emerges at the median when we control for firm-specific wage effects.

In panel (b) of Figure 4 (row 2 of Table 3), we see that the adjusted wage penalty estimates for Pakistani men relative to white men are increasing moving up the bottom half of the wage distribution – insignificant from zero at the 10^{th} percentile but 10 log points at the median and 13 log points at the 75^{th} percentile. Across the whole wage distribution, the incorporation of firm-specific wages in the models does not notably alter these gaps. Pakistani women do not experience a significant adjusted wage gap compared to white women at any of the selected points of the overall wage distribution (row 8 of Table 3).

In panel (c) of Figure 4 (row 9 of Table 3), Bangladeshi women earn similar adjusted basic hourly wages to white women at the 10th percentile of the wage distribution, but a significant penalty opens moving up the wage distribution, from 8 log points at the 50th percentile to 18 log points at the 90th percentile. These patterns are apparent whether conditioning on firm-specific wage effects or not. Among men (row 3 of Table 3), the patterns of the Bangladeshi adjusted wage penalty estimates are similar to among women.

FIGURE 4: Estimated differences in log hourly basic wages between ethnic minority and white employees, by gender, unconditional quantile regressions, comparing models with and without firm-specific wage effects, England and Wales, 2011



Notes: author calculations using ASHE-Census 2011 dataset. See Table 3 for the displayed model coefficient estimates and standard errors. Statistics can be interpreted as the influence of ethnicity on wages, by gender, at the selected percentile of the overall wage distribution, conditional on the influence of the other factors included in the model (e.g., education, occupation, tenure with the firm). “w’out” gives estimates from models that do not control for the influence of firm-specific wage determination, whereas “with” gives estimates that do control for this, i.e., with firm-specific effects in the models.

TABLE 3: Estimated gender-ethnicity log hourly basic wage penalties at the mean and unconditional quantiles, England and Wales, 2011

		Without firm-specific wage effects						With firm-specific wage effects					
		Mean	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90
Male	1. Indian	0.000	0.012	0.007	-0.037	0.031	0.027	-0.014	-0.004	-0.000	-0.053**	0.008	0.002
(excl. White)		[0.015]	[0.017]	[0.022]	[0.025]	[0.027]	[0.045]	[0.013]	[0.015]	[0.023]	[0.023]	[0.027]	[0.044]
	2. Pakistani	-0.083***	0.010	-0.099***	-0.101**	-0.129***	-0.090	-0.080***	0.015	-0.078**	-0.098**	-0.125***	-0.086
		[0.023]	[0.041]	[0.037]	[0.040]	[0.046]	[0.067]	[0.021]	[0.036]	[0.034]	[0.040]	[0.046]	[0.068]
	3. Bangladeshi	-0.107***	-0.017	-0.086	-0.016	-0.190***	-0.211**	-0.111***	0.003	-0.042	0.017	-0.240***	-0.256**
		[0.038]	[0.055]	[0.062]	[0.066]	[0.072]	[0.099]	[0.037]	[0.050]	[0.055]	[0.062]	[0.084]	[0.103]
	4. Chinese	-0.014	-0.012	-0.103***	0.027	-0.030	-0.038	-0.042	-0.022	-0.086**	-0.000	-0.063	-0.138
		[0.044]	[0.035]	[0.036]	[0.058]	[0.089]	[0.173]	[0.040]	[0.031]	[0.036]	[0.065]	[0.088]	[0.168]
	5. Black Afr.	-0.068***	-0.072**	-0.083**	-0.074**	-0.055	-0.045	-0.054***	-0.059**	-0.068**	-0.079**	-0.036	-0.024
		[0.020]	[0.028]	[0.034]	[0.037]	[0.038]	[0.051]	[0.019]	[0.025]	[0.031]	[0.037]	[0.039]	[0.052]
	6. Black Car.	-0.080***	-0.002	-0.038	-0.043	-0.165***	-0.179***	-0.085***	0.008	-0.039	-0.066	-0.164***	-0.149***
		[0.020]	[0.025]	[0.030]	[0.045]	[0.039]	[0.049]	[0.020]	[0.022]	[0.029]	[0.047]	[0.039]	[0.051]
Female	7. Indian	-0.075***	-0.005	-0.042**	-0.061***	-0.121***	-0.149***	-0.063***	0.004	-0.029*	-0.051***	-0.096***	-0.145***
(excl. White)		[0.011]	[0.016]	[0.017]	[0.018]	[0.019]	[0.027]	[0.009]	[0.013]	[0.016]	[0.016]	[0.019]	[0.029]
	8. Pakistani	-0.032**	-0.042	0.000	-0.018	-0.024	-0.062	-0.025*	-0.038	0.003	-0.010	-0.016	-0.061
		[0.016]	[0.032]	[0.025]	[0.030]	[0.032]	[0.049]	[0.015]	[0.029]	[0.022]	[0.031]	[0.033]	[0.053]
	9. Bangladeshi	-0.052**	0.038	-0.017	-0.084*	-0.061	-0.179***	-0.051**	0.021	-0.040	-0.127***	-0.046	-0.131**
		[0.024]	[0.042]	[0.049]	[0.048]	[0.046]	[0.057]	[0.024]	[0.039]	[0.044]	[0.045]	[0.056]	[0.061]
	10. Chinese	0.008	-0.002	0.060**	-0.016	0.026	-0.001	-0.013	0.009	0.035	-0.047	-0.004	-0.029
		[0.026]	[0.025]	[0.027]	[0.045]	[0.058]	[0.088]	[0.026]	[0.021]	[0.026]	[0.050]	[0.058]	[0.086]
	11. Black Afr.	-0.116***	0.012	-0.012	-0.107***	-0.240***	-0.282***	-0.092***	0.038**	0.002	-0.073***	-0.219***	-0.241***
		[0.013]	[0.018]	[0.021]	[0.022]	[0.030]	[0.031]	[0.013]	[0.017]	[0.019]	[0.023]	[0.031]	[0.035]
	12. Black Car.	-0.028**	0.018	0.038**	0.006	-0.067**	-0.127***	-0.022*	0.012	0.021	-0.001	-0.042	-0.116***
		[0.013]	[0.016]	[0.019]	[0.024]	[0.030]	[0.033]	[0.013]	[0.015]	[0.018]	[0.025]	[0.029]	[0.034]
GPG	13. White	0.110***	0.037***	0.068***	0.110***	0.137***	0.210***	0.098***	0.027***	0.050***	0.090***	0.129***	0.197***
(Male-Female)		[0.005]	[0.005]	[0.006]	[0.007]	[0.008]	[0.012]	[0.004]	[0.005]	[0.006]	[0.007]	[0.008]	[0.013]

Notes: author calculations using ASHE-Census 2011 dataset. See Section 2 & Online Appendix A for data description. *N*=67,932 for all models. Each column shows log wage effects estimated from a single model using OLS or UQR. *N* of distinct firm-specific wage effects estimated is 7,477. Other control variables included in the models: quadratics in individual age and tenure at current firm, NUTS1 region of work, whether working part-time, occupation (SOC10, 3-digit), highest qualification level, whether married, number of children, age of youngest child, and whether non-UK born.

***,**,* indicate significant differences from zero, two-sided tests, at the 1%, 5% and 10% levels, respectively, with standard errors in parentheses robust to firm-level clusters.

In panel (e) of Figure 4 (row 11 of Table 3), there is a substantial and significant adjusted wage penalty for Black African women relative to White women in the top half of the basic hourly wage distribution. Although this penalty is attenuated somewhat with the introduction of firm-specific wage effects to the regression models, it remains even then at 24 log points at the 90th percentile of the wage distribution. In contrast, the significant residual wage penalties for Black African men compared to white men are only significantly different from zero at and below the median, and they are largely unaffected by conditioning on firm-specific wage effects.

In panel (f) of Figure 4, adjusted wage gaps for Black Caribbean men and women, relative to white men and women respectively, are small and insignificant towards the bottom of the overall basic hourly wage distribution. However, these gaps are significant and substantial moving up the wage distribution. At the 90th percentile of hourly wages and conditioning on firm-specific wage effects, the adjusted wage penalties for Black Caribbean men and women are 12 and 15 log points, respectively, even controlling for occupation and looking within employers.

Overall, these estimates show just how heterogeneous ethnic minority wage gaps are relative to white employees, even after controlling for worker characteristics such as education, occupation, age, and the regions of England and Wales. Our ability to control for the influence of firm-specific wage effects, using the ASHE-Census, can either exacerbate or ameliorate the scale of covariate adjusted wage gaps by ethnicity, gender, and the level of hourly pay.

As a robustness check, we estimate (1) and (2) applying the adjusted ASHE-Census sample weights, the results of which are summarised in Appendix Table B1. We also show in Appendix Table B2 comparable unweighted estimates after replacing the basic hourly wage dependent variable with gross hourly earnings. Finally, we restrict the estimation sample to only “White British” within the wider set of white employees, showing a summary of the various model estimates in this case in Table B3. The patterns we have described above, using basic hourly wages, without applying sample weights, and comparing ethnic minority employees to all white employees, are generally robust to the aforementioned variations (comparing results in Table 3 with Appendix Tables B1-B3).

4. Decomposing the gaps between ethnic minority and white male wage distributions

Going a step further than the previous section, we revisit the roles that differences in observable worker and job characteristics have in the observed wage gaps between ethnic minority and white employees. We again estimate regression models for log basic hourly wages, and then apply an Oaxaca-Blinder-style decomposition method (Blinder, 1973; Oaxaca, 1973). We do so both for the gaps between the sample mean log wages of male ethnic minority and male white employees as well as selected quantiles of the respective estimated wage distributions (10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles). Although it is unsatisfactory to focus this part of our analysis on men only, we have to accept that the relatively low labour force participation, high proportion of part-time working, and low sample sizes among some groups of women, would make further analysis of differences between female ethnicity wage distributions impractical or even potentially misleading in terms of any conclusions (i.e., at the minimum, we would need to restrict a women only analysis to firms where we observe at least two white women employed full-time). Further, pooling men and women together, to look at gender neutral ethnicity wage gaps, would be inconsistent with the evidence on the within and between ethnicity gender pay gap patterns described in the previous two sections.

4.1 Methodology

Mean wage gaps

For the decomposition of differences in male mean log wages, we start with the sample of white employees, W, and with parameter estimates obtained from white wage models indicated by a w subscript. We estimate the following variant of (1):

$$y_i = \alpha_w + \tilde{\mathbf{x}}_i \boldsymbol{\beta}_w + \theta_{K(i),w} + \varphi_{J(i),w} + \varepsilon_i \,, \quad i \in W \qquad (3)$$

$\tilde{\mathbf{x}}_i$ contains the same set of observable wage-relevant factors as used in the previous section, excluding minor 3-digit occupation categories. In this section, we specifically denote occupation-specific wage effects by $\theta_{K(i),w}$, where $k = K(i)$ is an indicator function that person i is employed in occupation k. $\varphi_{J(i),w}$ are firm-specific wage effects that are fixed over the white male employees observed in the same firm in 2011. We can only estimate these parameters where at least two white male employees are observed working for the same firm in ASHE-Census in 2011. When we estimate equivalent wage regression models without any firm-specific wage effects, we can use 90,562 ASHE-Census ethnic minority and white employee observations (see Table 2). When we introduce firm-specific wage effects, which are estimated jointly over firms in ASHE-Census where at least two white or ethnic minority employees are observed, the estimation sample drops to 68,218 employees over 7,507 distinct firms (Table 3).[7] For the decomposition analysis, where we focus on men only and must impose the restriction on the estimation sample that firms are observed with at least two white male employees, the sample size drops to 28,982 men over 4,223 distinct firms: the sample numbers of {white, Indian, Pakistani, Bangladeshi, Chinese, Black African, Black Caribbean} employees that can be observed in that set of firms are {27,067, 791, 323, 109, 84, 316, 292}. Due to the especially small sample sizes of Bangladeshi and Chinese men, we do not describe any specific results for these groups, but still include them when comparing the white and pooled ethnic minority wage distributions.

We use our estimates of (3) to decompose the difference in the average log wages of white workers and those in ethnic minority group M into three parts:

$$E[y_i \mid i \in M] - E[y_i \mid i \in W] = \{(E\left[\tilde{\mathbf{x}}_i \widehat{\boldsymbol{\beta}}_w \,\middle|\, i \in M\right] - E\left[\tilde{\mathbf{x}}_i \widehat{\boldsymbol{\beta}}_w \,\middle|\, i \in W\right]\}$$
$$+\{(E\left[\hat{\theta}_{K(i),w} \,\middle|\, i \in M\right] - E\left[\hat{\theta}_{K(i),w} \,\middle|\, i \in W\right]\} + \widehat{U}_m \quad (4)$$

The first two parts on the right-hand-side give the amount of the average log wage gap between white and ethnic minority employees accounted for by differences in some set of traditionally observed, wage-relevant, personal and job characteristics, such as education levels, age and tenure, where the wage returns of these factors are evaluated according to how they explain the variation in white employee wages. In the second of those parts, we specifically denote the contribution of occupations. We focus on this component of the wage gap, and whether its estimation is biased if we do not address firm-specific wages, since we might anticipate that access to high-wage occupations and high-wage firms are correlated or just capture similar patterns of disadvantage. Together, these first two 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 the ethnic minority wage gap would be if white and ethnic minority employees had similar distributions over the observable characteristics. The second part on the RHS of (4) gives the amount of the average observed wage gap that can be accounted for

[7] Adjusted basic hourly wage gap estimates at the mean from the smaller and larger samples of firms, without firm-specific wage effects included in the regression models, can be approximately compared by looking at column (IV) of Table 2 and the first "Mean" column of Table 3. These estimates are quantitatively and qualitatively similar for the most part, except that, in the smaller sample, the wage penalties for ethnic minority women compared with white women are notably smaller for some groups.

by the different occupations that ethnic minority workers are employed in, assuming they would receive the same wages for those jobs as white employees.[8]

The remainder of the average wage gap for group m is in $\widehat{U}_m$. This is typically called the 'Unexplained' or 'Coefficients' amount of the wage gap, which comes from the differences between white and ethnic minority employees that are not on average accounted for by the observed characteristics, but instead by different estimated labour market 'returns' to those characteristics according to ethnicity. Here, $\widehat{U}_m$ also contains any influence of the unobserved firm-specific wage effects from the white employee regression model. However, we cannot further decompose this part to identify how those effects contribute to wage gaps or inequality. Doing so would require panel data and the estimation of an AKM-style wages model (e.g., Card et al., 2018), where more 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). We can though study here how estimates of the 'Explained' amounts of wage gaps depend on whether firm-specific wage effects are controlled for in (3), i.e., when we exploit the within-firm variation in wages.

Gaps between the quantiles of wage distributions

To decompose the estimated gaps between the quantiles of ethnic minority and white employee wage distributions, we again estimate unconditional quantile regression models (UQR) and apply Oaxaca-Blinder-style methods to these (see Firpo et al., 2018; Rios-Avila, 2020). Figure 5 illustrates the wage gaps that we can decompose using these methods, highlighting a hypothetical negative gap between the median wages of some ethnic minority group and white employees. In effect, compared with looking at averages, decomposing wage gaps between selected quantiles of employee wage distributions is just a matter of changing the dependent variables of the linear regression models. For quantile τ_w of the log wages of white male employees, we estimate the following using least squares:

$$\widehat{RIF}\left(y_i, \hat{Q}_{\tau_w}\right) = \hat{Q}_{\tau_w} + \frac{\tau_w - \mathbb{1}\{y_i \leq \hat{Q}_{\tau_w}\}}{f_{y_w}(\hat{Q}_{\tau_w})} = \alpha_{\tau_w} + \tilde{\mathbf{x}}_i \boldsymbol{\beta}_{\tau_w} + \theta_{K(i),\tau_w} + \varphi_{J(i),\tau_w} + \varepsilon_i\,,\ i \in W \qquad (5)$$

$\hat{Q}_{\tau_w}$ is the log wage at quantile τ_w of the white male employee estimation sample. The LHS of the regression model, $\widehat{RIF}\left(y_i, \hat{Q}_{\tau_w}\right)$, is the recentred influence function for this quantile, where $f_{y_w}(\cdot)$ is the density of the marginal distribution of log wages among white male employees, again estimated using a Gaussian kernel and Silverman plugin bandwidth. We then use the estimated firm-specific

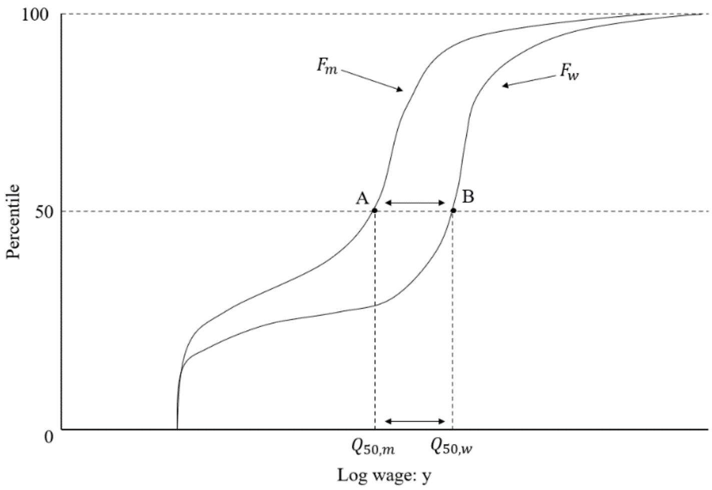
[8] For evidence on how the influence of firm-specific wages in wage inequality patterns, especially changes over time, depend on whether occupation wage effects and segregation across firms are also accounted for see for the US, Handwerker, 2023, and for Great Britain, Schaefer & Singleton, 2020).

wage effects obtained over white employees at some quantile, and the recentred influence function for ethnic minority wages at the same quantile, to estimate the UQR-equivalent of Equation (4) above:

$$\hat{Q}_{\tau_m} - \hat{Q}_{\tau_w} = \{(E[\tilde{\mathbf{x}}_i \hat{\boldsymbol{\beta}}_{\tau_w} \mid i \in M] - E[\tilde{\mathbf{x}}_i \hat{\boldsymbol{\beta}}_{\tau_w} \mid i \in W]\}$$
$$+\{(E[\hat{\theta}_{K(i),\tau_w} \mid i \in M] - E[\hat{\theta}_{K(i),\tau_w} \mid i \in W]\} + \hat{U}_{\tau_m} \qquad (6)$$

The expected values of the RIFs over ethnic minority and white employees are just the estimation sample log wage quantiles of the respective distributions. The interpretation of (6) is equivalent to that described above for average wage gaps. In particular, and with reference to Figure 5, the 'Explained' part can be interpreted as: how much closer or further away would ethnic minority workers be from the white employee wage distribution (quantile), if employees were equally distributed by ethnicity over the observable characteristics contained in $\tilde{\mathbf{x}}$. The unexplained parts of the decompositions in (4) and (6) are in effect residual amounts of the wage gaps, left over after projecting $\hat{\boldsymbol{\beta}}_w$ and $\hat{\boldsymbol{\beta}}_{\tau_w}$ from the white employee wage regression, obtained by estimating (3) and (5), onto the samples of ethnic minority employees.

FIGURE 5: Illustration of the unconditional gap between quantiles of ethnic minority and white wage distributions



Notes: as drawn, the population cumulative density function (CDF) of Ethnic Minority 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.

4.1 Results

Table 4 and Figure 6 summarise the results of decomposing male ethnicity wage gaps in England and Wales in 2011, using the methods outlined above. We focus on what can be accounted for or 'Explained' by differences in the observed wage-relevant personal and job characteristics of employees included in the models (e.g., education levels, regions, occupations) , which are combined in the solid light lines in Figure 6. Table 4 distinguishes the role of occupations, and further sub-divisions of the 'Explained' parts of the wage gaps are presented in more detailed tables in Online Appendix B. We describe in turn the results from comparing the distributions of basic hourly wages among white male employees and each one of the four ethnic minority groups that we can analyse using ASHE-Census. In Table 4, Figure 6 and Online Appendix B, we also show and contrast wage gap decomposition results where we omit the firm-specific effects from the regression models, thus in effect constraining or assuming that the contributions from whom people work for are zero. The comparisons between the two sets of estimates, with vs. without firm-specific wage effects in the white employee regression models, demonstrate the magnitudes and directions of biases to the 'Explained' parts of the male ethnicity wage gaps when the potential influence of firm-specific wages is ignored.

To provide a benchmark, before comparing the wages of white and different groups of ethnic minority employees, we first consider the gaps in basic hourly wages between white and all non-white employees.[9] The first portion of Table 4 summarises the results for these gaps. Column (I) shows results for the gap between average log wages, and columns (II)-(VI) show gaps between the 10th, 25th, 50th, 75th and 90th percentiles of the observed wage distributions. On average, there is a significant eight log point wage gap in favour of white employees in our estimation sample. In the absence of firm-specific wage effects from the white male employee regression model, the total 'Explained' component accounts for 4.0 log points of this 7.7 log point gap, with 1.4 log points due to occupation differences. However, the mean 'Explained' component is only 1.6 log points when we control for firm-specific wage effects, though the 'Occupations' part remains significant at 0.9 log points while the remaining part is then insignificant from zero . This pattern of results is apparent across the wage distribution. It implies that the positive correlation between employment in a relatively high wage firm and having relatively high wage attributes, such as a degree or working in a high-wage occupation, which are on average more common among white employees, would tend to lead to an overestimate of the traditional explained portion of the non-white vs. white wage gap if unaddressed. This is especially the case when comparing the tops of the respective white and non-white wage distributions: at the 90th percentile, the explained part of the gap, without the occupations part, is significantly positive, at nine log points in favour of white employees, but after addressing firm-specific wages this amount is insignificant and negligible.

[9] In practice, we pool the ASHE-Census samples from all six of the considered ethnic minority groups into one non-white group.

TABLE 4: Summary of firm-specific wage effect contributions to Oaxaca-Blinder decompositions of ethnicity log hourly basic wage gaps, ordinary least squares and unconditional quantile regressions at selected percentiles, England and Wales, 2011

		(I) Mean	(II) p10	(III) p25	(IV) p50	(V) p75	(VI) p90
1. Non-white (*N*=1,915)	<u>Total</u>	**-0.077**	**-0.067**	**-0.096**	**-0.093**	**-0.067**	-0.042
w'out firms:	Occupations	**-0.014**	**-0.042**	**-0.033**	**-0.013**	-0.004	-0.004
	Other 'Explained'	**-0.026**	0.013	**0.035**	-0.010	**-0.058**	**-0.090**
with firms:	Occupations	**-0.009**	**-0.035**	**-0.027**	**-0.009**	0.001	-0.004
	Other 'Explained'	-0.007	-0.015	**0.029**	-0.004	-0.023	-0.001
2. Indian (*N*=791)	<u>Total</u>	-0.005	**-0.045**	**-0.036**	-0.020	**0.064**	0.053
w'out firms:	Occupations	-0.009	**-0.053**	**-0.032**	-0.004	0.002	0.000
	Other 'Explained'	**0.051**	-0.028	-0.026	**0.080**	**0.099**	**0.092**
with firms:	Occupations	-0.004	**-0.041**	**-0.024**	0.001	0.004	-0.004
	Other 'Explained'	0.014	-0.002	-0.033	0.058	0.043	-0.027
3. Pakistani (*N*=323)	<u>Total</u>	**-0.168**	**-0.125**	**-0.181**	**-0.210**	**-0.200**	-0.064
w'out firms:	Occupations	**-0.024**	**-0.061**	**-0.043**	**-0.022**	-0.012	-0.007
	Other 'Explained'	-0.059	**-0.093**	0.015	-0.043	-0.121	-0.329
with firms:	Occupations	**-0.017**	**-0.045**	**-0.029**	-0.015	-0.007	-0.005
	Other 'Explained'	-0.064	-0.020	0.016	-0.039	**-0.134**	**-0.403**
4. Black Afr. (*N*=316)	<u>Total</u>	**-0.190**	**-0.121**	**-0.167**	**-0.228**	**-0.205**	**-0.212**
w'out firms:	Occupations	**-0.035**	**-0.063**	**-0.063**	**-0.045**	**-0.019**	-0.013
	Other 'Explained'	0.001	**-0.135**	-0.036	0.024	0.043	-0.012
with firms:	Occupations	**-0.026**	**-0.046**	**-0.052**	**-0.036**	-0.011	-0.008
	Other 'Explained'	-0.031	-0.091	-0.057	-0.018	0.004	-0.096
5. Black Carib. (*N*=292)	<u>Total</u>	**-0.118**	0.010	-0.017	**-0.078**	**-0.200**	**-0.259**
w'out firms:	Occupations	-0.010	0.009	-0.013	-0.023	-0.014	**-0.018**
	Other 'Explained'	**0.065**	**0.067**	**0.090**	**0.065**	0.022	**0.145**
with firms:	Occupations	-0.007	-0.001	-0.018	-0.021	-0.001	-0.004
	Other 'Explained'	**0.064**	0.057	**0.087**	0.052	0.024	**0.135**

Notes: author calculations using ASHE-Census 2011 dataset. *N* of white male employees =27,067. *N* of {Indian, Pakistani, Black African, Black Caribbean} male employees = {791, 323, 316, 292}. Each set of values across rows and columns show the occupations and other combined 'Explained' contributions to the O-B decomposition from models using OLS or UQR, as per Equations (3) and (5), comparing results from specifications with and without firm-specific wage effects estimated over White employees. See Section 2 and Online Appendix A for details of the other variables included in the decompositions. See Figure 6 and Online Appendix Tables B4-B7 for more detailed decomposition results and standard errors.

Bold values indicate significant differences from zero, two-sided tests, at the 10% level, with standard errors computed using 200 bootstrap replications.

Indian-white wage gaps

The second portion of Table 4 and Figure 6(a) summarise the decomposition results for the wage gaps between Indian and white male employees. There is no evidence of a wage gap at the mean. However, Indian men in the bottom quartile of their wage distribution earn significantly less than white men in the bottom quartile of their wage distribution. Differences in occupations account for most of this gap: this remains the case controlling for firm-specific wages, although it is attenuated somewhat. By contrast, comparing the top quartiles of the respective earners, Indian men earn more than white men. In the absence of firm-specific wages this is due to the 'Explained' gap, attributable to Indian top-earners having better individual characteristics such as education (see Online Appendix Table B4). However, these 'Explained' differences are insignificant after conditioning on firm-specific wage effects in the models.

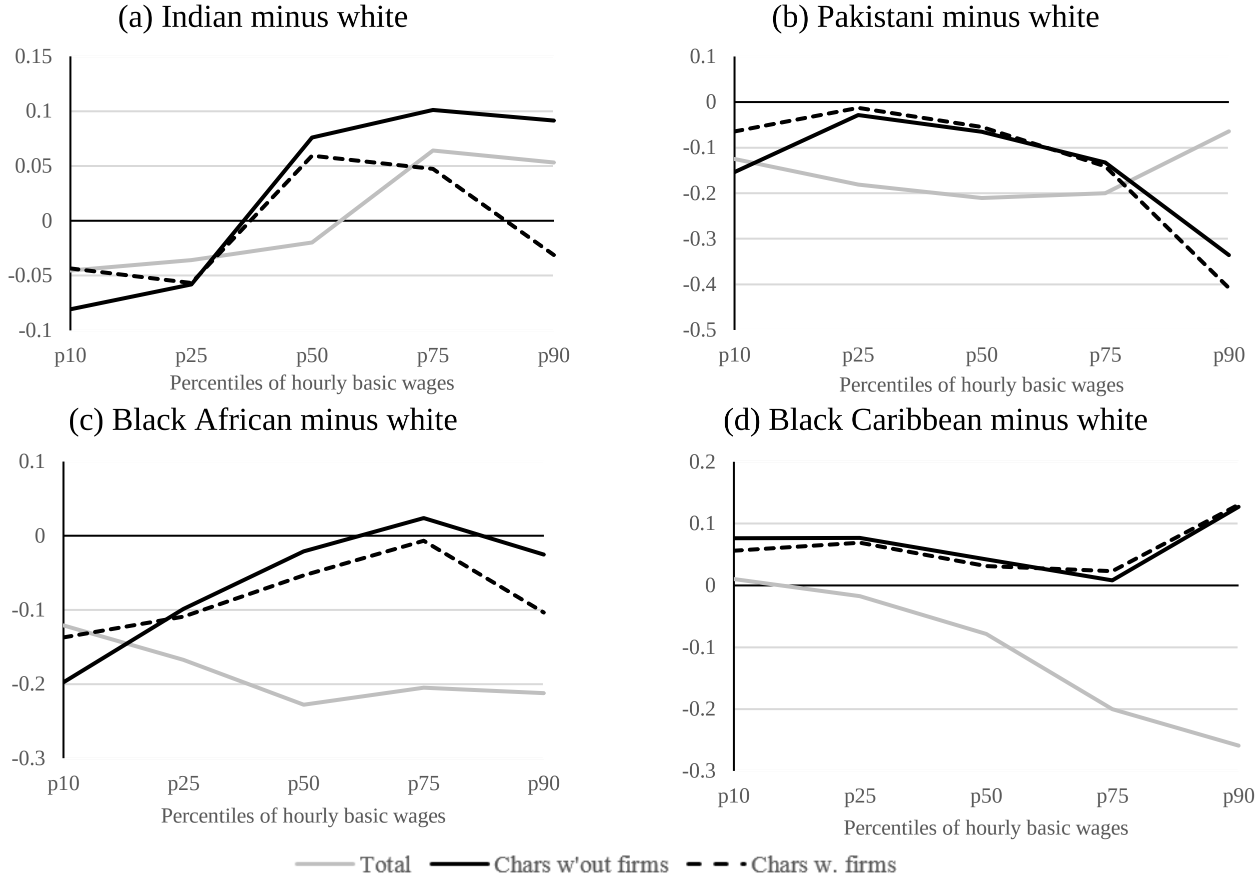
Pakistani-white wage gaps

The third portion of Table 4 and Figure 6(b) summarise the decomposition results for the wage gaps between Pakistani and white employees. Pakistani men earn significantly less than white men comparing up to but not including the 90^{th} percentile of their respective wage distributions. Occupational differences account for much of these gaps, together with differences in age distributions (Online Appendix Table B5). Occupation continues to account for a sizeable part of the wage gaps between the bottom of the wage distributions after controlling for firm-specific wage effects. But when comparing top earners, it is individual characteristics, notably age, which accounts for the lower earnings of Pakistanis, an effect that is partly counteracted by the better qualifications than among white high earners (Online Appendix Table B5).

Black African-white wage gaps

The fourth portion of Table 4 and Figure 6(c) summarise the decomposition results for the wage gaps between Black African and white male employees. Black African employees earn less than white employees comparing across the whole of their respective wage distributions, with this averaging out at nineteen log points. The total wage gap in favour of white men compared with Black African men is twelve log points comparing at the respective 10^{th} percentiles, and rises substantially to seventeen, twenty-three and twenty-one log points moving up to the 25^{th}, 50^{th} and 90^{th} percentiles. Including the firm-specific wage effects in our regression models leads to an attenuation of the 'Explained' and occupations parts of the wage gaps. The more detailed results in Online Appendix Table B6 show that, unlike Pakistani men, it is experience within firms, rather than age per se, that can explain why Black African men tend to earn less than white men (though with the significant caveats that these variables are collinear, and the wage returns for each are not robustly identified). Education levels among Black African male employees are on average higher than among white male employees. This factor on its own would predict a Black African male wage distribution that was significantly to the right of that for white men, rather than being in fact observed significantly to the left. This result holds whether or not we control for firm-specific wage effects.

FIGURE 6: Summary of Oaxaca-Blinder decompositions of ethnicity log hourly basic wage gaps, unconditional quantile regression estimates, England and Wales, 2011



Notes: author calculations using ASHE-Census 2011 dataset. See Table 4 and Online Appendix Tables B4-B7 for the displayed estimates and indications of statistical significance. "Total" gives the overall wage gap estimate between percentiles of the wage distributions. "Chars w'out firms" show the estimated contributions of differences in observed employee and job characteristics (including occupations) when the white employee wage regression models do not include firm-specific effects. "Chars w. firms" shows estimates when those firms are admitted in the regression models. The "Unexpl." or residual parts of the wage gaps are not shown, but they can be read off roughly from the gaps between "Total" and "Chars".

Black Caribbean-white wage gaps

The fifth portion of Table 4 and Figure 6(d) summarise the decomposition results for the wage gaps between Black Caribbean and white employees. The gap between the mean wages of these two groups of workers is significant at twelve log points. However, the gaps between the 10th and 25th percentiles of the respective wage distributions are insignificant, then become significantly negative between the medians (eight log points), before rising sharply when comparing the high wage 90th percentiles of Black Caribbean and white men (twenty-six log points). The occupations contributions to these wage gaps are not significant on the whole, whether we control for firm-specific wages or not. The remaining 'Explained' part of the gap is positive and significant favouring Black Caribbeans and is particularly large for the 90th percentiles, even after addressing firm-specific wages. It is mostly region of employment suggesting that the Black Caribbean male wage distribution ought to be significantly to the right of the one for white men, if both groups earned the same rates of return on their observed characteristics within firms. Unlike the other male ethnic minority groups, Black Caribbean men tend to be at a disadvantage in terms of education levels. Yet overall, the results show that the 'Unexplained' wage gaps between Black Caribbean and white male employees are large even when compared with the apparent disadvantage faced by other ethnic minority men. On average, this unexplained wage gap to white men is eighteen log points, varying between being statistically insignificant from zero for the 10th percentiles and being twenty and thirty-four log points for the 75th and 90th percentiles, respectively.

5. Summary and further discussion

We have introduced a new dataset - the ASHE-Census - which links a large sample of accurate employer-employee payroll-based data about earnings and jobs with the detailed personal characteristics of employees from the Census, for England and Wales in 2011. This linked dataset has allowed us to address the influence of unobserved firm-specific wage effects throughout the distribution of gender-ethnicity wage gaps. The influence of these employer-specific wage effects has typically been an omitted variable in studies of wage gaps, which have tended to rely on self-reported wage and hours data from household surveys. We have found that controlling for firm-specific wage effects seems to have a role when estimating and trying to explain gender-ethnicity wage gaps. This role could otherwise have been attributed to other characteristics that correlate with firm-specific pay rates, such as education levels, workplace location (i.e., a London effect), and occupation.

Using payroll data on employee earnings, we 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 as we consider 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.

We have also found that controlling for firm-specific wage effects changes estimates of gender-ethnicity wage penalties differently depending on which group is considered. In general, the estimated wage penalties are smaller after doing so, and more so when comparing higher earning groups or higher earners within groups. We would conclude from our analysis that addressing who people work for is an important dimension of understanding gender-ethnicity wage gaps, as it can otherwise bias the estimated importance of factors such as education levels, region of a workplace, and occupations. Nonetheless, there are significant negative unexplained wage gaps and penalties associated with ethnicity throughout the overall employee wage distribution, which tend to be larger among higher earners.

Our study is reminiscent of earlier work for Britain (Forth et al., 2023a) and for the United States (Troske and Carrington, 1998) in suggesting that the ethnic segregation of workers over employers contributes relatively little to ethnicity 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-ethnicity 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 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.[10] Another natural step forward from our analysis in this paper would be to look beneath the firm-

[10] See Roussille, 2021, 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.

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 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 controlling for firm-specific effects for gaps 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 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) 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 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 likely be a few years before they are delivered and research-ready.

We also think that there could be great value in designing studies that can uncover why ethnicity wage penalties appear in some firms but not others. For example, 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 ethnicity wage penalties. Such practices, by promoting equal treatment in the workplace and decreasing within-employer wage gaps, may help to tackle the ethnicity 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 ethnicity pay gap reporting. Greater transparency about pay differentials by ethnicity may reveal previously hidden problems to the decision-makers within a firm, prompting them to seek out and address the origins of wage inequality between groups within their workforce. A few countries have introduced laws requiring large employers to report transparently and periodically on their own gender pay gaps. Evaluations of these reforms have so far indicated that this greater level of transparency leads to reduced wage differentials between men and women within firms (Bennedsen et al, 2023). Since our findings indicate that much of the gender-ethnic wage gap exists within organisations, requiring firms to report on their ethnic wage gap 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.

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. and Wei, J. (2023) "Gender wage transparency and the gender pay gap: A survey." *Journal of Economic Surveys*, Advance online publication.

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

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., 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. (2020). Pay transparency and gender equality. arXiv preprint arXiv:2006.16099.

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 and Whittard D (2023b) *Data Explained: Annual Survey of Hours and Earnings linked to 2011 Census – England and Wales*, Swindon: ADR England.

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.

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. and 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).

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

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.

Phan, V., Singleton, C., Bryson, A., Forth, J., Ritchie, F., Stokes, L., & Whittard, D. (2022). Accounting for employers in the distribution of ethnic pay gaps. 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. (2021). The central role of the ask gap in gender pay inequality. University of California, Berkeley.

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.

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).

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

Accounting for firms in gender-ethnicity wage gaps throughout 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.

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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 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, 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.

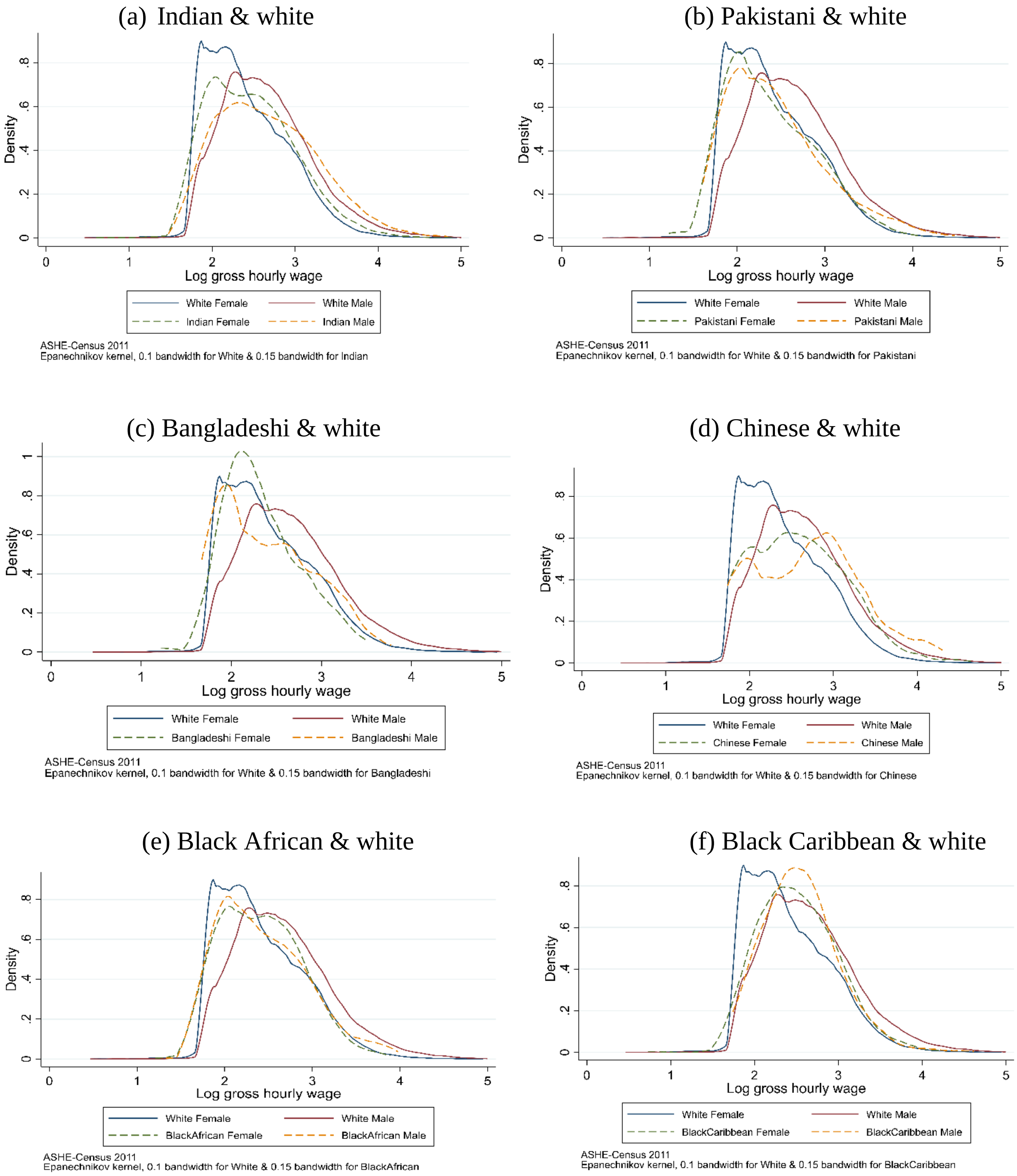
Table A2: List of variables used in the linked ASHE-Census 2011 dataset and Annual Population Survey

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	1-digit classification of employee's occupation (SOC10): (i) Managers, directors, and senior officials, (ii) Science, research, engineering and technology professionals, (iii) Associate professional and technical occupations, (iv) Administrative and secretarial occupations, (v) Skilled trades occupations, (vi) Caring, leisure, and other service occupations, (vii) Sales, and customer service occupations, (viii) Process, plant and machine operatives, (ix) Elementary occupations.	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
Disability	Dummy variable of whether a long-term health problem or disability limits the employee's day-to-day activities and has lasted at least 12 months.	disability
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
Disability	Dummy variable of whether the employee has a long-term disability which substantially limits their daily activities or affects the kind or amount of work they might do.	discurr
UK national identity	Dummy variable of whether the employee has UK national identity	natide11
Health problem	Dummy variable of whether the employee has a longstanding health condition or disease	ehlthm
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

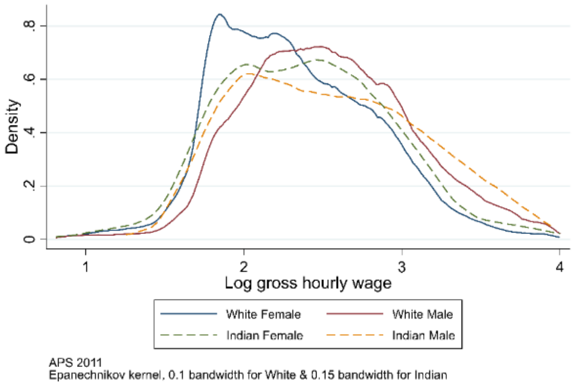
FIGURE A1: Estimated distributions of log gross hourly earnings, comparing white and ethnic minority employees, ASHE-Census 2011



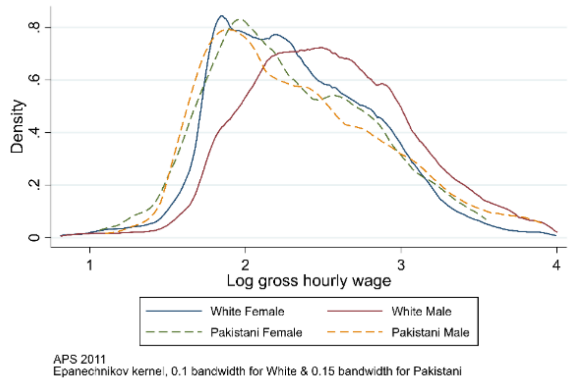
Notes: author calculations using ASHE-Census 2011 dataset. See Figure 1 for sample sizes by gender. See Figure A2 for equivalent kernel density estimates from the Annual Population Survey (APS) 2011, and Figure A3 for the ASHE-Census and APS distributions overlaid.

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

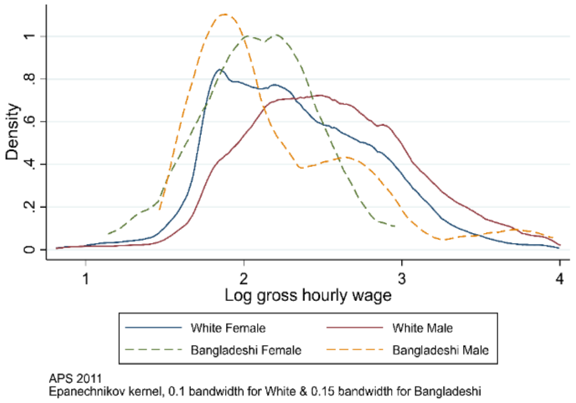
(a) Indian & white



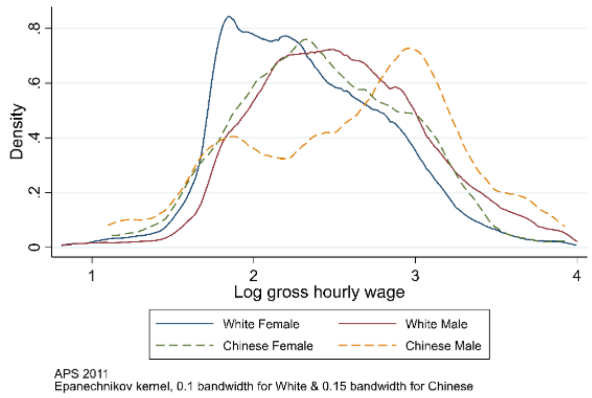
(b) Pakistani & white



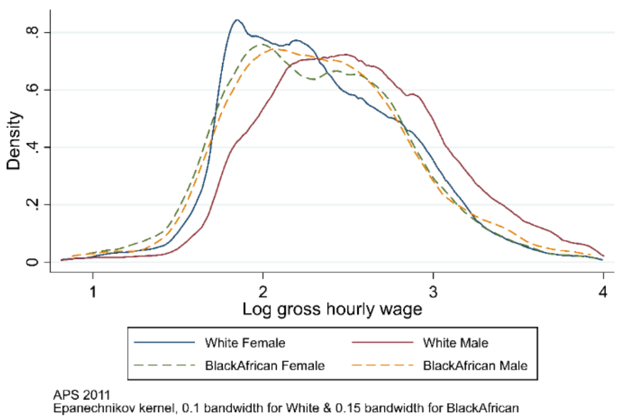
(c) Bangladeshi &white



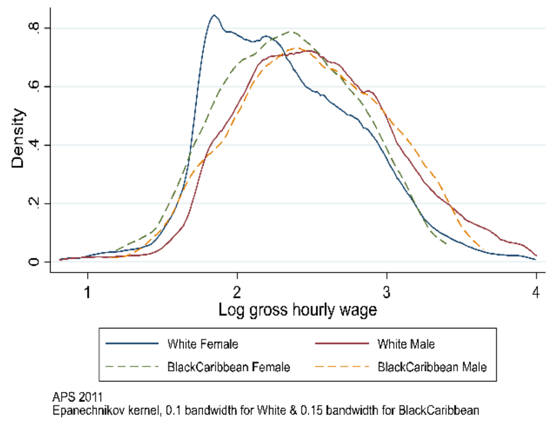
(d) Chinese & white



(e) Black African & white



(f) Black Caribbean & white

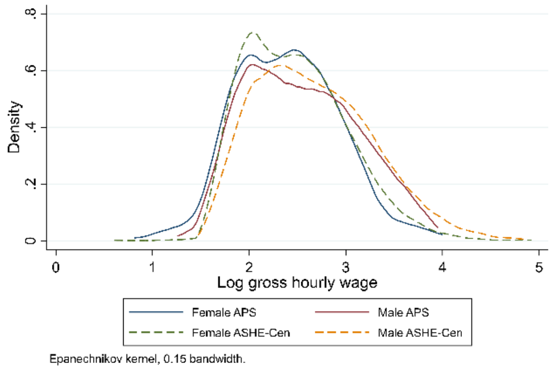


Notes: author calculations using ASHE-Census 2011 dataset. See Figure A3 for the ASHE-Census distributions overlaid.

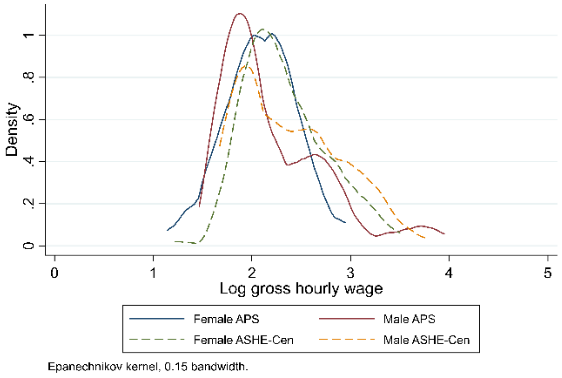
FIGURE A3: Distributions of log gross hourly earnings, by ethnicity and gender, in ASHE-Census 2011 and APS 2011, England and Wales

(a) White

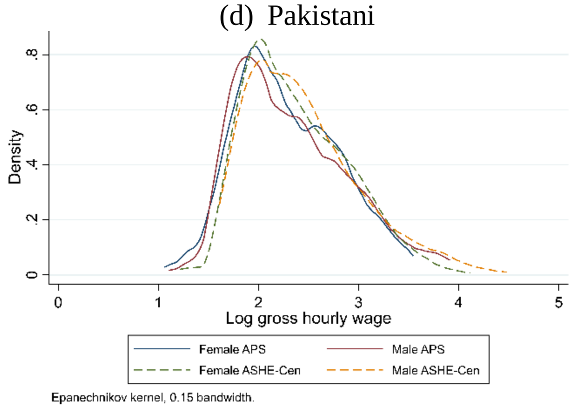
(b) Indian



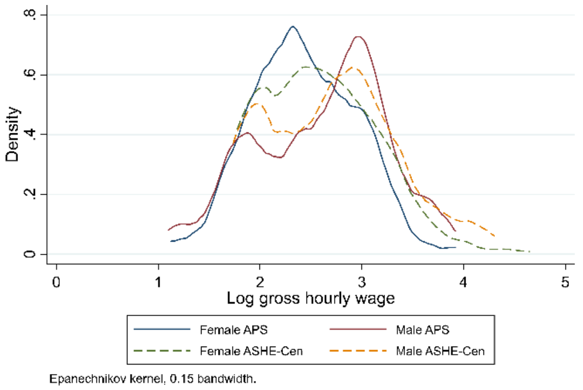
(c) Bangladeshi



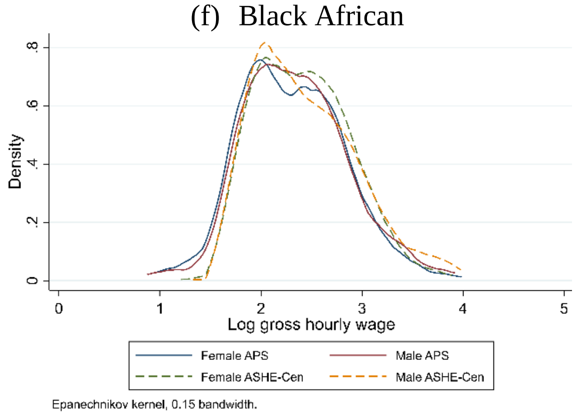
(d) Pakistani



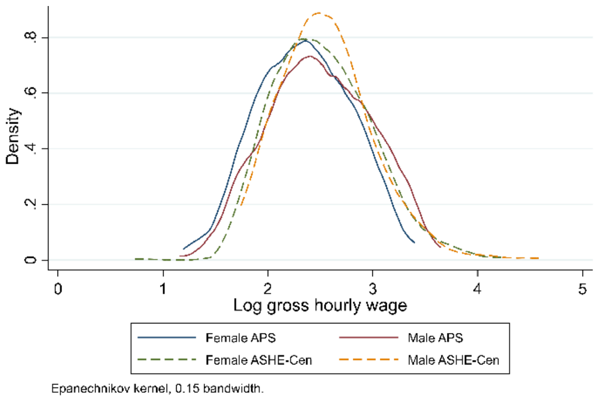
(e) Chinese



(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: Estimated ethnicity log hourly basic wage penalties at the mean and unconditional quantiles, England and Wales, 2011, using ASHE-Census sample probability weights

		Without firm-specific wage effects						With firm-specific wage effects					
		Mean	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90
Male	Indian	0.012	0.013	0.014	-0.018	0.047	0.056	-0.011	-0.006	0.000	-0.043*	0.019	0.013
(excl. White)		[0.015]	[0.017]	[0.021]	[0.024]	[0.030]	[0.052]	[0.014]	[0.015]	[0.020]	[0.022]	[0.029]	[0.051]
	Pakistani	-0.073***	0.016	-0.084**	-0.090**	-0.117**	-0.083	-0.077***	0.020	-0.068**	-0.093**	-0.112**	-0.095
		[0.025]	[0.041]	[0.036]	[0.040]	[0.052]	[0.075]	[0.022]	[0.036]	[0.032]	[0.039]	[0.052]	[0.076]
	Bangladeshi	-0.099**	-0.033	-0.069	0.016	-0.192**	-0.207*	-0.117***	-0.014	-0.041	0.033	-0.254***	-0.296**
		[0.041]	[0.060]	[0.062]	[0.067]	[0.084]	[0.117]	[0.043]	[0.053]	[0.057]	[0.065]	[0.098]	[0.120]
	Chinese	-0.005	-0.004	-0.089***	0.040	-0.025	-0.022	-0.032	-0.019	-0.076**	0.010	-0.049	-0.115
		[0.045]	[0.034]	[0.034]	[0.056]	[0.092]	[0.183]	[0.041]	[0.032]	[0.035]	[0.064]	[0.092]	[0.177]
	Black Afr.	-0.073***	-0.064**	-0.095***	-0.075**	-0.054	-0.060	-0.058***	-0.056**	-0.078**	-0.078**	-0.034	-0.041
		[0.021]	[0.030]	[0.033]	[0.038]	[0.041]	[0.057]	[0.020]	[0.025]	[0.030]	[0.038]	[0.043]	[0.058]
	Black Car.	-0.083***	-0.006	-0.034	-0.038	-0.172***	-0.188***	-0.089***	0.002	-0.040	-0.068	-0.163***	-0.153***
		[0.021]	[0.024]	[0.029]	[0.044]	[0.043]	[0.057]	[0.020]	[0.022]	[0.026]	[0.047]	[0.043]	[0.059]
Female	Indian	-0.075***	-0.008	-0.040**	-0.055***	-0.115***	-0.162***	-0.063***	0.002	-0.025*	-0.044***	-0.092***	-0.160***
(excl. White)		[0.011]	[0.015]	[0.016]	[0.017]	[0.020]	[0.030]	[0.010]	[0.013]	[0.015]	[0.016]	[0.020]	[0.032]
	Pakistani	-0.035**	-0.048	-0.005	-0.014	-0.021	-0.085*	-0.026*	-0.043	0.001	-0.004	-0.014	-0.078
		[0.016]	[0.033]	[0.025]	[0.030]	[0.035]	[0.051]	[0.015]	[0.029]	[0.022]	[0.030]	[0.035]	[0.055]
	Bangladeshi	-0.052**	0.029	-0.022	-0.081	-0.048	-0.194***	-0.050**	0.011	-0.044	-0.118**	-0.038	-0.138*
		[0.024]	[0.043]	[0.050]	[0.052]	[0.049]	[0.064]	[0.025]	[0.038]	[0.044]	[0.049]	[0.059]	[0.072]
	Chinese	0.007	-0.007	0.050**	-0.020	0.037	-0.000	-0.012	0.012	0.031	-0.044	0.004	-0.044
		[0.028]	[0.026]	[0.026]	[0.044]	[0.062]	[0.096]	[0.027]	[0.023]	[0.024]	[0.048]	[0.063]	[0.093]
	Black Afr.	-0.111***	0.007	0.001	-0.095***	-0.239***	-0.284***	-0.087***	0.036**	0.014	-0.062***	-0.222***	-0.232***
		[0.013]	[0.020]	[0.022]	[0.022]	[0.032]	[0.034]	[0.013]	[0.018]	[0.019]	[0.023]	[0.033]	[0.037]
	Black Car.	-0.029**	0.020	0.039**	0.008	-0.064**	-0.141***	-0.022*	0.012	0.022	0.001	-0.044	-0.130***
		[0.014]	[0.015]	[0.018]	[0.024]	[0.032]	[0.036]	[0.013]	[0.014]	[0.018]	[0.025]	[0.032]	[0.037]
GPG	White	0.111***	0.034***	0.064***	0.105***	0.138***	0.222***	0.099***	0.027***	0.048***	0.087***	0.128***	0.210***
(Male-Female)		[0.004]	[0.005]	[0.005]	[0.006]	[0.008]	[0.013]	[0.004]	[0.004]	[0.005]	[0.006]	[0.008]	[0.013]

Notes: See Table 3. The estimates here instead apply ASHE-Census probability weights, as described in Appendix A. *N*=67,932 for all models. Each column shows log wage effects estimated from a single model using OLS or UQR. *N* of distinct firm-specific wage effects estimated is 7,477. Other control variables included in the models: quadratics in individual age and tenure at current firm, NUTS1 region of work, whether working part-time, occupation (SOC10, 3-digit), highest qualification level, whether married, number of children, age of youngest child, and whether non-UK born.
***,**,* indicate significant differences from zero, two-sided tests, at the 1%, 5% and 10% levels, respectively, with standard errors in parentheses robust to firm-level clusters.

TABLE B2: Estimated ethnicity log earnings per hour penalties at the mean and unconditional quantiles, England and Wales, 2011

		Without firm-specific wage effects						With firm-specific wage effects					
		Mean	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90
Male (excl. white)	Indian	0.008	0.016	-0.004	-0.042	0.038	0.072	-0.007	0.001	-0.005	-0.062**	0.013	0.046
		[0.016]	[0.021]	[0.023]	[0.027]	[0.027]	[0.047]	[0.014]	[0.020]	[0.023]	[0.026]	[0.026]	[0.045]
	Pakistani	-0.087***	-0.023	-0.067*	-0.130***	-0.132***	-0.062	-0.080***	0.008	-0.045	-0.117***	-0.111***	-0.079
		[0.024]	[0.048]	[0.039]	[0.042]	[0.040]	[0.068]	[0.023]	[0.042]	[0.037]	[0.041]	[0.041]	[0.069]
	Bangladeshi	-0.103***	-0.063	-0.062	-0.036	-0.151*	-0.199*	-0.099***	-0.024	-0.023	0.005	-0.182**	-0.234**
		[0.037]	[0.063]	[0.065]	[0.065]	[0.079]	[0.109]	[0.036]	[0.062]	[0.058]	[0.062]	[0.086]	[0.114]
	Chinese	-0.035	-0.032	-0.083**	-0.049	-0.019	-0.182	-0.052	-0.033	-0.075*	-0.042	-0.042	-0.340**
		[0.044]	[0.041]	[0.040]	[0.060]	[0.090]	[0.159]	[0.040]	[0.039]	[0.041]	[0.066]	[0.088]	[0.150]
	Black Afr.	-0.076***	-0.044	-0.098***	-0.084**	-0.080**	-0.085*	-0.060***	-0.035	-0.079**	-0.073*	-0.043	-0.069
		[0.021]	[0.036]	[0.037]	[0.038]	[0.036]	[0.049]	[0.019]	[0.031]	[0.033]	[0.037]	[0.037]	[0.051]
	Black Car.	-0.088***	-0.007	-0.063*	-0.040	-0.166***	-0.144***	-0.093***	0.010	-0.063**	-0.066	-0.165***	-0.107*
		[0.020]	[0.029]	[0.033]	[0.042]	[0.041]	[0.054]	[0.020]	[0.029]	[0.031]	[0.044]	[0.040]	[0.056]
Female (excl. white)	Indian	-0.072***	-0.006	-0.033*	-0.058***	-0.112***	-0.127***	-0.059***	0.009	-0.024	-0.045***	-0.083***	-0.121***
		[0.012]	[0.016]	[0.017]	[0.019]	[0.020]	[0.030]	[0.010]	[0.014]	[0.015]	[0.017]	[0.020]	[0.031]
	Pakistani	-0.025	-0.019	-0.007	-0.008	-0.030	-0.070	-0.022	-0.021	-0.002	-0.006	-0.036	-0.053
		[0.017]	[0.039]	[0.026]	[0.030]	[0.029]	[0.048]	[0.015]	[0.033]	[0.024]	[0.031]	[0.031]	[0.052]
	Bangladeshi	-0.055**	0.084*	-0.022	-0.073	-0.078	-0.172***	-0.054**	0.052	-0.049	-0.108**	-0.055	-0.126**
		[0.024]	[0.047]	[0.056]	[0.048]	[0.049]	[0.056]	[0.023]	[0.044]	[0.048]	[0.045]	[0.058]	[0.059]
	Chinese	0.008	0.009	0.068**	0.014	-0.006	0.016	-0.015	0.027	0.046	-0.021	-0.042	0.013
		[0.027]	[0.029]	[0.030]	[0.041]	[0.056]	[0.089]	[0.025]	[0.026]	[0.030]	[0.045]	[0.055]	[0.086]
	Black Afr.	-0.120***	0.015	-0.015	-0.104***	-0.210***	-0.272***	-0.090***	0.050**	0.007	-0.075***	-0.193***	-0.229***
		[0.013]	[0.025]	[0.023]	[0.024]	[0.027]	[0.032]	[0.013]	[0.022]	[0.021]	[0.025]	[0.029]	[0.035]
	Black Car.	-0.031**	0.024	0.066***	-0.011	-0.073***	-0.133***	-0.021*	0.005	0.052***	-0.008	-0.046*	-0.114***
		[0.013]	[0.019]	[0.021]	[0.024]	[0.027]	[0.034]	[0.013]	[0.017]	[0.020]	[0.025]	[0.026]	[0.034]
GPG (Male-Female)	white	0.132***	0.056***	0.087***	0.136***	0.155***	0.227***	0.114***	0.038***	0.060***	0.115***	0.143***	0.213***
		[0.005]	[0.006]	[0.006]	[0.007]	[0.008]	[0.012]	[0.005]	[0.006]	[0.006]	[0.007]	[0.008]	[0.013]

Notes: See Table 3. The estimates here are equivalent but using log earnings per hour as the dependent variables instead of log hourly basic wages, N=67,932 for all models. Each column shows log wage effects estimated from a single model using OLS or UQR. N of distinct firm-specific wage effects estimated is 7,477. Other control variables included in the models: quadratics in individual age and tenure at current firm, NUTS1 region of work, whether working part-time, occupation (SOC10, 3-digit), highest qualification level, whether married, number of children, age of youngest child, and whether non-UK born.
***,**,* indicate significant differences from zero, two-sided tests, at the 1%, 5% and 10% levels, respectively, with standard errors in parentheses robust to firm-level clusters.

TABLE B3: Estimated ethnicity log hourly basic wage gaps at the mean and unconditional quantiles, England and Wales, 2011: White British instead of white

		Without firm-specific wage effects						With firm-specific wage effects					
		Mean	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90
Male (excl. white)	Indian	0.000	0.014	0.007	-0.036	0.038	0.034	-0.015	-0.006	-0.002	-0.052**	0.014	0.009
		[0.015]	[0.017]	[0.022]	[0.024]	[0.027]	[0.045]	[0.013]	[0.015]	[0.022]	[0.022]	[0.027]	[0.044]
	Pakistani	-0.083***	0.007	-0.106***	-0.101**	-0.116**	-0.090	-0.083***	0.008	-0.087**	-0.101**	-0.119**	-0.090
		[0.024]	[0.041]	[0.037]	[0.040]	[0.046]	[0.067]	[0.021]	[0.036]	[0.034]	[0.040]	[0.047]	[0.068]
	Bangladeshi	-0.108***	-0.019	-0.073	-0.018	-0.191***	-0.157	-0.107***	0.004	-0.030	0.022	-0.235***	-0.197*
		[0.038]	[0.055]	[0.063]	[0.066]	[0.072]	[0.105]	[0.037]	[0.051]	[0.055]	[0.062]	[0.083]	[0.113]
	Chinese	-0.014	-0.011	-0.099***	0.025	-0.030	-0.011	-0.052	-0.029	-0.093**	-0.013	-0.077	-0.114
		[0.044]	[0.035]	[0.036]	[0.057]	[0.089]	[0.174]	[0.040]	[0.031]	[0.037]	[0.065]	[0.088]	[0.168]
	Black Afr.	-0.069***	-0.071**	-0.081**	-0.074**	-0.052	-0.055	-0.053***	-0.057**	-0.070**	-0.076**	-0.035	-0.023
		[0.020]	[0.029]	[0.034]	[0.037]	[0.038]	[0.050]	[0.019]	[0.026]	[0.031]	[0.037]	[0.041]	[0.052]
	Black Car.	-0.080***	-0.007	-0.041	-0.043	-0.162***	-0.192***	-0.081***	0.002	-0.032	-0.060	-0.156***	-0.152***
		[0.021]	[0.025]	[0.031]	[0.045]	[0.039]	[0.050]	[0.020]	[0.023]	[0.029]	[0.047]	[0.039]	[0.052]
Female (excl. white)	Indian	-0.077***	-0.005	-0.043***	-0.064***	-0.128***	-0.156***	-0.062***	0.009	-0.027*	-0.054***	-0.100***	-0.150***
		[0.011]	[0.016]	[0.017]	[0.017]	[0.019]	[0.028]	[0.009]	[0.014]	[0.016]	[0.016]	[0.019]	[0.029]
	Pakistani	-0.033**	-0.038	0.002	-0.021	-0.030	-0.069	-0.022	-0.029	0.009	-0.009	-0.015	-0.062
		[0.016]	[0.033]	[0.025]	[0.030]	[0.032]	[0.049]	[0.015]	[0.029]	[0.022]	[0.031]	[0.033]	[0.053]
	Bangladeshi	-0.055**	0.045	-0.028	-0.088*	-0.067	-0.187***	-0.052**	0.027	-0.046	-0.128***	-0.040	-0.154**
		[0.024]	[0.042]	[0.050]	[0.047]	[0.046]	[0.057]	[0.024]	[0.038]	[0.044]	[0.045]	[0.054]	[0.069]
	Chinese	0.006	-0.001	0.059**	-0.018	0.016	-0.011	-0.011	0.012	0.040	-0.044	-0.016	-0.037
		[0.026]	[0.025]	[0.027]	[0.045]	[0.057]	[0.087]	[0.026]	[0.021]	[0.025]	[0.050]	[0.059]	[0.087]
	Black Afr.	-0.119***	0.012	-0.011	-0.110***	-0.250***	-0.283***	-0.093***	0.043**	0.008	-0.076***	-0.223***	-0.247***
		[0.013]	[0.018]	[0.021]	[0.022]	[0.031]	[0.032]	[0.013]	[0.017]	[0.019]	[0.024]	[0.033]	[0.036]
	Black Car.	-0.030**	0.021	0.035*	0.002	-0.068**	-0.123***	-0.024*	0.016	0.016	-0.006	-0.040	-0.116***
		[0.013]	[0.016]	[0.019]	[0.024]	[0.030]	[0.034]	[0.013]	[0.015]	[0.018]	[0.026]	[0.030]	[0.035]
GPG	white	0.111***	0.036***	0.065***	0.110***	0.138***	0.213***	0.099***	0.028***	0.049***	0.090***	0.132***	0.199***
(Male-Female)		[0.005]	[0.005]	[0.006]	[0.007]	[0.009]	[0.013]	[0.005]	[0.005]	[0.006]	[0.007]	[0.009]	[0.013]

Notes: See Table 3. The estimates here are equivalent but instead of using all white observations only those recorded as White British on the 2011 Census are used. *N*=64,849 for all models. Each column shows log wage effects estimated from a single model using OLS or UQR. *N* of distinct firm-specific wage effects estimated is 7,440. Other control variables included in the models: quadratics in individual age and tenure at current firm, NUTS1 region of work, whether working part-time, occupation (SOC10, 3-digit), highest qualification level, whether married, number of children, age of youngest child, and whether non-UK born.
***,**,* indicate significant differences from zero, two-sided tests, at the 1%, 5% and 10% levels, respectively, with standard errors in parentheses robust to firm-level clusters.

TABLE B4: Oaxaca-Blinder decompositions of the log hourly basic wage gap for INDIAN compared to white employees, men only, at the mean and unconditional quantiles, England and Wales, 2011

		Without firm-specific wage effects						With firm-specific wage effects					
		Mean	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90
Overall	Total	-0.005	**-0.045**	**-0.036**	-0.020	**0.064**	0.053	-0.005	**-0.045**	**-0.036**	-0.020	**0.064**	0.053
Characteristics:	Total	**0.051**	-0.028	-0.026	**0.080**	**0.099**	**0.092**	0.014	-0.002	-0.033	0.058	0.043	-0.027
	Age	-0.007	**0.029**	**0.025**	0.001	**-0.032**	**-0.069**	**-0.016**	**0.021**	**0.024**	-0.003	**-0.043**	**-0.092**
	Tenure & Part-time	**-0.034**	**-0.044**	**-0.072**	-0.065	-0.008	**0.033**	**-0.025**	**-0.023**	**-0.066**	**-0.056**	-0.002	**0.034**
	Highest qualification	**0.062**	-0.016	0.012	0.104	**0.094**	**0.085**	**0.056**	-0.006	0.015	**0.105**	**0.082**	**0.055**
	Non-UK born	-0.001	**-0.011**	**-0.012**	-0.003	0.006	0.018	**-0.006**	**-0.010**	**-0.013**	-0.004	-0.002	0.001
	Family chars	0.007	0.016	0.015	0.008	0.004	-0.001	0.002	0.010	0.007	0.000	0.000	0.001
	Region (NUTS1)	0.023	-0.002	0.006	0.035	0.034	0.026	0.003	0.006	0.000	0.016	0.008	-0.026
Occupations:	Total	-0.009	**-0.053**	**-0.032**	-0.004	0.002	0.000	-0.004	**-0.041**	**-0.024**	0.001	0.004	-0.004
Unexplained:	Total	-0.047	0.035	0.023	**-0.096**	-0.037	-0.038	-0.031	0.016	0.043	**-0.096**	-0.022	0.012

Notes: See Table 4 and Figure 6 in the main text. *N* of white employees =27,067 for all models. *N* of Indian employees =791. Each column contributions to the O-B decomposition from a single model using OLS or UQR, all with firm-specific wage effects estimated over White employees.
Bold values indicate significant differences from zero, two-sided tests, at the 10% level.

TABLE B5: Oaxaca-Blinder decompositions of the log hourly basic wage gap for PAKISTANI compared to white employees, men only, at the mean and unconditional quantiles, England and Wales, 2011

		Without firm-specific wage effects						With firm-specific wage effects					
		Mean	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90
Overall	Total	**-0.168**	**-0.125**	**-0.181**	**-0.210**	**-0.200**	-0.064	**-0.168**	**-0.125**	**-0.181**	**-0.210**	**-0.200**	-0.064
Characteristics:	Total	-0.059	**-0.093**	0.015	-0.043	-0.121	-0.329	-0.064	-0.020	0.016	-0.039	**-0.134**	**-0.403**
	Age	**-0.130**	-0.019	**-0.060**	**-0.123**	**-0.230**	**-0.500**	**-0.110**	0.014	-0.043	**-0.091**	**-0.207**	**-0.513**
	Tenure & Part-time	-0.025	-0.035	**-0.041**	-0.033	-0.011	0.052	-0.023	-0.011	**-0.033**	-0.030	-0.014	0.048
	Highest qualification	**0.035**	0.017	0.022	0.028	**0.051**	**0.143**	**0.034**	0.011	0.023	**0.026**	**0.051**	**0.139**
	Non-UK born	0.001	0.002	0.000	-0.001	0.002	0.001	-0.004	0.001	-0.003	-0.004	-0.004	-0.007
	Family chars	-0.001	0.019	0.028	-0.008	-0.027	-0.054	-0.012	0.026	0.003	-0.014	-0.033	-0.081
	Region (NUTS1)	0.062	**-0.077**	0.065	**0.095**	0.093	0.029	**0.051**	**-0.062**	0.070	0.074	0.074	0.011
Occupations:	Total	**-0.024**	**-0.061**	**-0.043**	**-0.022**	-0.012	-0.007	**-0.017**	**-0.045**	**-0.029**	-0.015	-0.007	-0.005
Unexplained:	Total	**-0.084**	0.028	**-0.152**	**-0.145**	-0.067	0.272	**-0.084**	-0.019	**-0.130**	**-0.155**	-0.069	0.311

Notes: See Table 4 and Figure 6 in the main text. *N* of white employees =27,067 for all models. *N* of Pakistani employees =323. Each column contributions to the O-B decomposition from a single model using OLS or UQR, all with firm-specific wage effects estimated over White employees.
Bold values indicate significant differences from zero, two-sided tests, at the 10% level.

TABLE B6: Oaxaca-Blinder decompositions of the log hourly basic wage gap for BLACK AFRICAN compared to white employees, men only, at the mean and unconditional quantiles, England and Wales, 2011

		Without firm-specific wage effects						With firm-specific wage effects					
		Mean	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90
Overall	Total	**-0.190**	**-0.121**	**-0.167**	**-0.228**	**-0.205**	**-0.212**	**-0.190**	**-0.121**	**-0.167**	**-0.228**	**-0.205**	**-0.212**
Characteristics:	Total	0.001	**-0.135**	-0.036	0.024	0.043	-0.012	-0.031	-0.091	-0.057	-0.018	0.004	-0.096
	Age	0.008	0.01	0.019	0.017	-0.001	0.016	0.001	-0.012	0.004	0.016	-0.006	0.017
	Tenure & Part-time	**-0.073**	**-0.07**	**-0.065**	-0.106	-0.057	-0.093	**-0.078**	-0.033	**-0.073**	**-0.116**	-0.052	-0.147
	Highest qualification	**0.055**	-0.022	0.015	**0.093**	**0.085**	0.063	**0.042**	-0.013	0.02	**0.075**	**0.061**	0.039
	Non-UK born	-0.01	0.009	-0.01	**-0.03**	**-0.018**	-0.023	-0.006	0.008	-0.007	-0.022	-0.016	-0.026
	Family chars	-0.003	-0.004	0.011	-0.002	-0.003	-0.016	-0.004	-0.009	0.008	-0.007	0.003	-0.001
	Region (NUTS1)	0.024	**-0.057**	-0.004	0.051	0.037	0.041	0.014	-0.032	-0.011	0.037	0.015	0.022
Occupations:	Total	**-0.035**	**-0.063**	**-0.063**	**-0.045**	**-0.019**	-0.013	**-0.026**	**-0.046**	**-0.052**	**-0.036**	-0.011	-0.008
Unexplained:	Total	**-0.155**	0.076	-0.069	**-0.206**	**-0.229**	-0.187	**-0.097**	0.098	0.003	**-0.146**	**-0.182**	-0.095

Notes: See Table 4 and Figure 6 in the main text. *N* of white employees =27,067 for all models. *N* of Black African employees = 316. Each column contributions to the O-B decomposition from a single model using OLS or UQR, all with firm-specific wage effects estimated over White employees.
Bold values indicate significant differences from zero, two-sided tests, at the 10% level.

TABLE B7: Oaxaca-Blinder decompositions of the log hourly basic wage gap for BLACK CARIBBEAN compared to white employees, men only, at the mean and unconditional quantiles, England and Wales, 2011

		Without firm-specific wage effects						With firm-specific wage effects					
		Mean	p10	p25	p50	p75	p90	Mean	p10	p25	p50	p75	p90
Overall	Total	**-0.118**	0.010	-0.017	**-0.078**	**-0.200**	**-0.259**	**-0.118**	0.010	-0.017	**-0.078**	**-0.200**	**-0.259**
Characteristics:	Total	**0.065**	0.067	**0.090**	**0.065**	0.022	**0.145**	**0.064**	0.057	**0.087**	0.052	0.024	**0.135**
	Age	**0.021**	0.005	**0.020**	**0.022**	**0.031**	**0.023**	**0.015**	0.002	**0.017**	**0.017**	0.023	0.014
	Tenure & Part-time	-0.001	-0.011	-0.013	-0.003	0.003	0.012	-0.001	-0.011	**-0.014**	-0.006	0.005	0.012
	Highest qualification	**-0.031**	-0.009	-0.017	**-0.028**	**-0.045**	**-0.064**	**-0.030**	-0.010	**-0.019**	-0.030	**-0.041**	**-0.051**
	Non-UK born	0.000	0.000	0.001	0.001	0.000	0.002	0.000	-0.001	0.002	0.001	-0.001	-0.001
	Family chars	-0.013	-0.005	-0.003	-0.021	-0.016	-0.008	-0.002	0.002	0.009	-0.009	-0.008	0.000
	Region (NUTS1)	**0.090**	**0.087**	**0.102**	**0.094**	0.048	**0.181**	**0.081**	0.076	**0.090**	0.078	0.045	**0.163**
Occupations:	Total	-0.010	0.009	-0.013	-0.023	-0.014	**-0.018**	-0.007	-0.001	-0.018	-0.021	-0.001	-0.004
Unexplained:	Total	**-0.172**	-0.066	**-0.094**	**-0.120**	**-0.208**	**-0.386**	**-0.177**	-0.071	**-0.099**	**-0.147**	**-0.205**	**-0.336**

Notes: See Table 4 and Figure 6 in the main text. *N* of white employees =27,067 for all models. *N* of Black Caribbean employees = 292. Each column contributions to the O-B decomposition from a single model using OLS or UQR, all with firm-specific wage effects estimated over White employees.
Bold values indicate significant differences from zero, two-sided tests, at the 10% level.