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Abstract

Ethnicity wage gaps in Great Britain are large and have persisted over time. Previous studies of these gaps have been almost exclusively confined to analyses of household data, so they could not account for the role played by individual employers, despite growing evidence of their wage-setting power. We study ethnicity wage gaps using high quality employer-employee payroll data on jobs, hours, and earnings, linked with the personal and family characteristics of workers from the national 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, there are substantial gaps between the wage structures of white and ethnic minority employees which cannot be accounted for by who people work for or other attributes, especially among higher earners.

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

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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., 1998; Longhi et al., 2013; Stewart, 1983). The gaps vary across ethnic 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 rely on household survey data, they cannot address the potential contribution of the firm to ethnicity wage gaps. Yet, there is increasing recognition that firms influence wage determination, contrary to standard assumptions in labour economics that see most employers as wage takers. A large proportion of the 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).

It is, therefore, conceivable that ethnicity wage gaps are driven in part by differences across employers in Britain. 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 also know from field experiments that hiring discrimination on racial grounds persists in the British labour market (Heath & Di Stasio, 2019). If this discrimination is more prevalent among firms that tend to pay relatively high wages, then this could help to explain earnings disparities by ethnicity. However, the evidence for the United States suggests 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) found that within-plant racial wage gaps are generally accounted for by observed characteristics, such as education or experience, but a significant component (around five percentage points for men and around two percentage points for women) remained on average unaccounted for.

Forth et al. (2021) is the only study for Britain that has used linked employer-employee data (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. (2021) concluded that average ethnicity wage gaps in Britain predominantly occur within workplaces, rather than between workplaces, suggesting that the sorting of ethnicities across employers does not appear to play a large role in accounting for these gaps. This might occur if, for example, employers discriminate based on race in the pay of new hires or in the promotion of employees, either statistically or on grounds of taste. Whilst such discrimination within firms would be illegal under UK equalities legislation, this is also the case for 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 at 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. (2021), is poorer quality matches between jobs and skills among ethnic minority workers, leading to skills underutilisation.

In this paper, we contribute to the literature by using a new employer-employee dataset for England and Wales to study the distribution of ethnicity wage gaps, addressing the influence of firm-specific wages. As noted above, the only other study that has done this for Britain is Forth et al. (2021). However, their sample sizes were relatively small, such that they focused on the gap between white and non-white employees, only offering limited analysis hinting at the heterogeneity in gaps between different ethnic minority groups and white workers. Our sample sizes allow us to overcome this problem, as well as to look at wage gaps at different parts of the earnings distribution, whereas Forth et al. (2021) could only recover differences at the mean. Further, the wage data used by Forth et al. (2021) are based on banded self-reported information, whereas our wage and hours data are reported by employers from payrolls, in response 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) of 2011 to the Census of England and Wales carried out among the general population in the same year. Thus, we can 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 a first look at how much of the distribution of ethnic wage gaps can be accounted for by firm-specific wages, as opposed to the traditional characteristics, such as education and experience.[2] To decompose the distributions of ethnicity wage gaps, we apply an extension of the Oaxaca-Blinder (O-B) wage decomposition method to unconditional quantile

[2] This first look is limited because of the small samples of workers observed within firms, 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).

regression (Firpo et al., 2009, Firpo et al., 2018; Rios-Avila, 2018).[3] We compare the results between wage models estimated with and without firm-specific wage effects.

We find that employee ethnicity wage gaps vary substantially, both on average and throughout the wage distribution, depending on which minority group is compared with white workers. Accounting for firm-specific wage effects tends to reduce the contributions to these gaps made by other factors, such as education, occupation, and region, because these are correlated with entry into relatively high or low-wage firms. Therefore, studies which are unable to account for the influence of firm-specific wage determination are prone to bias when estimating the amounts contributed to ethnicity pay differences by some characteristics of workers, including their locations, education levels, and occupations.

After accounting for the firm-specific wages and other worker characteristics, significant unexplained (or residual) penalties occur even where the explained wage gaps would be in favour of ethnic minority employees (e.g., for high earning Indian and low earning Black Caribbean employees). Furthermore, these unexplained penalties between some ethnic minority and white wage distributions are at least as large as the explained penalties (e.g., for high earning Black Caribbean employees). Our findings are consistent with 'glass ceilings', potentially linked to discriminatory practices, which would make it hard for ethnic minorities to reach the higher echelons of firms unless they possess higher earning attributes than their white co-workers. We also show that there is substantial heterogeneity in what accounts for ethnic minority wage gaps, across groups and across the wage distribution, which would otherwise be obscured by either pooling non-white employees or only focusing on the central tendency of these gaps.

The findings from this analysis have potentially important implications for policy, since they highlight the important role played by the employer in the existence and size of ethnicity wage gaps in Britain, both positively and negatively, and not only on average but to a greater extent among higher earning workers. Our results suggest that policy makers need to consider the substantial influence that some employers are probably having on the likelihood of ethnic minorities working for them, as also evidenced by the discriminatory hiring practices that have been persistently implicated by field experiments.

The remainder of the paper proceeds as follows: Section 2 describes the ASHE-Census dataset; Section 3 explains the estimation and decomposition methods; Section 4 shows the main results; and

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

Section 5 concludes. The Online Appendix contains further details about the ASHE-Census dataset and more detailed estimates concerning the distributions of 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 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) with the accurate components of pay and employer identification coming from the ASHE. We call this new dataset the ASHE-Census. It contains wage observations for around 0.5 percent of the population of employees in England and Wales. The ASHE has been used in the 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., 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 studies. By identifying the ethnicity of employees in ASHE, we can take a first look at whether the distribution of ethnicity wage gaps in England and Wales is accounted for by firm-specific wages, as opposed to the traditional explanatory characteristics, such as education and labour market experience. Online Appendix A gives extended details about the ASHE-Census dataset and descriptions for all the variables used throughout our analysis, including their categories and transformations as used in the regression models described later.

In examining the pay differences between ethnic groups, we focus on basic hourly wages (henceforth just the "wage"), derived by dividing an employee's basic weekly earnings by the 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 wage effects and the amount of wage variation by ethnicity within firms.[4]

[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. This second wage measure is like the gross hourly pay reported by the household respondents in the UK Labour Force Survey, which is employed in Clark and Nolan (2021) in their analysis of ethnicity wage distributions.

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 1 and no more than 99 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 hourly wages, followed by Indian employees 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). This is a boosted and combined version of the household-based Quarterly Labour Force Survey that is used for most national labour market statistics. Average hourly wages in the APS for 2011 show a similar pattern across ethnic groups to what we observe in the ASHE-Census, including the same ranking 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 Online Appendix A, as well as more comparisons to equivalent statistics and distributions obtained from the APS. Specifically, Appendix Figure A1 expands on Table 1, by showing raw ethnicity wage gaps from ASHE-Census for men and women separately. Appendix Figures A2-A4 show kernel density estimates of employee hourly wages, by ethnicity and gender, and comparing the ASHE-Census and APS datasets.

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

Ethnicity	ASHE-Census 2011						APS 2011		
	Gross hourly earnings			Basic hourly wage			Hourly wage		
	N	Mean	Premium (+)/ Penalty (-)	*N*	Mean	Premium (+)/ Penalty (-)	*N*	Mean	Premium (+)/ Penalty (-)
Chinese	380	£17.25	£2.31	379	£16.65	£2.47	177	£14.51	£1.46
Indian	2,365	£16.13	£1.20	2,352	£15.07	£0.88	1,283	£13.99	£0.94
white	**76,094**	**£14.93**	-	**75,786**	**£14.18**	-	**46,128**	**£13.05**	-
Black Car.	995	£14.02	-£0.91	989	£13.50	-£0.69	419	£12.35	-£0.71
Pakistani	828	£13.52	-£1.42	824	£12.78	-£1.41	473	£11.96	-£1.09
Black Afr.	1,044	£12.79	-£2.14	1,041	£12.23	-£1.95	659	£11.71	-£1.34
Bangladeshi	269	£12.52	-£2.41	268	£11.93	-£2.25	174	£10.30	-£2.76

Notes: author calculations using the ASHE-Census 2011 and Annual Population Survey 2011 datasets. These are unweighted sample statistics.

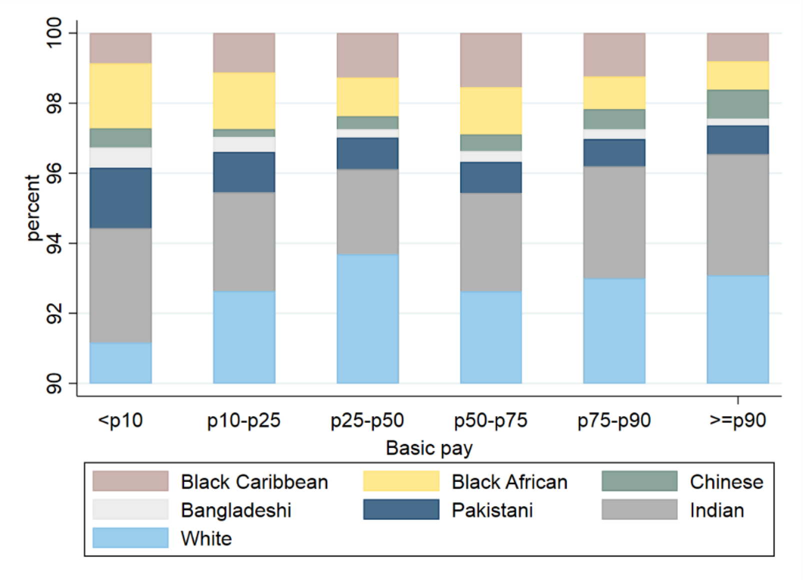
Figure 1 gives an overview of the ethnicity distribution of employees at different parts of the overall basic hourly wage distribution for our analysis sample in 2011. White workers make up more than 90 percent of the employees in every part of this overall wage distribution, but their presence varies 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.

The employers (or firms) that we study in the ASHE are observed at the enterprise level, which is a specific administrative definition of employers. An enterprise can contain several local units (or plants). We believe this is the appropriate level to study firm-specific wages, because many smaller organisations consist of a single enterprise with only one local unit, and pay-setting practices in larger organisations tend to be determined at the enterprise level.[5] Ethnic minority employees are segregated over different firms in the ASHE-Census, although the following statistics are surely biased overestimates, since on average we only randomly observe very small proportions of employees within any given firm. For a white employee in the ASHE-Census, on average 94 percent of the employees observed working in the same firm are also white. For an Indian, Pakistani, Bangladeshi, or Black African employee, on average, around 29-32 percent of the employees observed working in the same firm are also Indian, Pakistani, Bangladeshi, or Black African, respectively. This measure

[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.

of segregation over firms is slightly lower for Black Caribbean employees (around 26 percent), but moderately higher for Chinese employees (around 42 percent). These patterns are likely to in part reflect segregation by ethnicity between local areas and labour markets, as opposed to purely segregation between firms within an area or labour market.[6] However, in what follows, we can control for any general wage differences between regional labour markets because some firms have employees who are dispersed throughout England and Wales.

FIGURE 1: 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.

Before decomposing more fully the differences between the wage distributions of ethnic minority and white employees, in Online Appendix B we investigate whether addressing firm-specific wage effects alters some basic estimates of adjusted (or conditional, or residual) ethnic-minority-gender wage gaps. Even after conditioning on occupations, regions, education levels, age, job tenure, and other worker characteristics, these results generally show that addressing firm-specific wages tends to reduce the adjusted gender wage gap throughout the employee wage distribution. For most ethnic minority groups and comparing to white employees of the same gender, adjusted ethnicity wage gap estimates are not substantially different depending on whether firm-specific wage factors are included in the regression models. However, adjusted wage penalties for Pakistani and Bangladeshi men, compared to white men, tend to be notably smaller after addressing firm-specific wage effects. This is also the case for higher earning Black Caribbean men and women, whereas adjusted wage penalty

[6] See also Forth et al. (2011) for estimates on the segregation of employees over workplaces and regions in Great Britain using information collected from managers responding to the Workplace Employment Relations Survey.

estimates among higher earning Chinese men are substantially increased after addressing their greater tendency to work for high wage paying firms than white men.

3. Decomposition Methodology

To account for the role of employers in the wage gaps between ethnic minority and white employees, we estimate regression models for log basic hourly wages and apply an Oaxaca-Blinder-style decomposition method (Blinder, 1973). We carry out these decompositions both for the gaps between the sample mean log wages of ethnic minority and 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).

3.1 Decomposing differences between average wages

For the decomposition of differences in mean log wages, starting with the sample of white workers, W, and with parameter estimates obtained from the white wage models indicated by a w subscript, we estimate the following wage equation using OLS:

$$y_i = \alpha_w + \gamma_w G_i + \mathbf{x}_i \boldsymbol{\beta}_w + \varphi_{J(i),w} + \varepsilon_i \, , \;\; i \in W \, . \qquad (1)$$

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, NUTS1 region of work, whether working part-time, occupation (SOC10, 1-digit), highest qualification level, whether married, number of children, age of youngest child, and whether non-UK born; see Online Appendix A for details of all these variables. $\boldsymbol{\beta}_w$ is a column vector containing the parameters for each of these control variables, as estimated over white employees only, and α_w is a constant. $\varphi_{J(i),w}$ are firm-specific wage effects (fixed over white 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. We can only estimate these parameters where at least two white 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 75,234 ASHE-Census ethnic minority and white employee observations (see Online Appendix Table B1). When we introduce firm-specific wage effects that are estimated jointly over firms in ASHE-Census where at least two white or ethnic minority employees are observed, the estimation sample drops size to 55,818 employees over 6,012 distinct firms (see Online Appendix Table B2).[7] For the decomposition analysis, where we must impose the restriction on the

[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 (III) of Online Appendix Table B1 and the first "Mean" column of Online Appendix Table B2. These estimates are

estimation sample that firms are observed with at least two white employees, this sample size drops 523 employees or approximately one percent to 55,295: the estimation sample numbers of {white, Indian, Pakistani, Bangladeshi, Chinese, Black African, Black Caribbean} employees are {51,435, 1,571, 523, 175, 189, 666, 736}. G_i is a dummy variable indicating whether an employee is male, with associated parameter γ_w. Although we provide some separate estimates by gender and ethnicity in the descriptive statistics and adjusted wage gap regressions described in the Online Appendices, for the wage gap decompositions we pool male and female employees. We do so to maximise the available employee sample sizes from ASHE-Census to obtain estimates of the firm-specific wage effects, which are our focus. The remaining wage heterogeneity is captured by the error term, ε_i.

Having estimated the firm-specific wage effects over white employees, we then subtract these from the observed log wages of ethnic minority workers observed in the same firms, and then use this remaining wage variation to estimate the other parameters of the wage regression for ethnic minority employees, using OLS, where $m = M(i)$ is a subscript indicating a parameter specific to an employee from the set of employees in ethnic minority group M:

$$y_i - \hat{\varphi}_{J(i),w} = \tilde{y}_i = \alpha_{M(i)} + \gamma_{M(i)} G_i + \mathbf{x}_i \boldsymbol{\beta}_{M(i)} + \varepsilon_i\,, \quad i \notin W\,. \qquad (2)$$

Finally, we gather all these estimates to decompose into three parts the difference in the average log wages of white workers and those in ethnic minority group M:

$$\begin{aligned} E[y_i \mid i \in M] - E[y_i \mid i \in W] = {} & \{E[\hat{\varphi}_{J(i),w} \mid i \in M] - E[\hat{\varphi}_{J(i),w} \mid i \in W]\} \\ & +\{\hat{\gamma}_w(E[G_i \mid i \in M] - E[G_i \mid i \in W]) + (E[\mathbf{x}_i\widehat{\boldsymbol{\beta}}_w \mid i \in M] - E[\mathbf{x}_i\widehat{\boldsymbol{\beta}}_w \mid i \in W]\} \\ & + \{(\hat{\alpha}_m - \hat{\alpha}_w) + (\hat{\gamma}_m - \hat{\gamma}_w)E[G_i \mid i \in M] + E[\mathbf{x}_i(\widehat{\boldsymbol{\beta}}_m - \widehat{\boldsymbol{\beta}}_w) \mid i \in M]\}\,. \qquad (3) \end{aligned}$$

The first part of the decomposition, on the RHS of the first line of Equation (3), accounts for how much of the average log wage gap is due to the difference in the average firm-specific wage effects that white and ethnic minority workers received in the labour market. It can also be interpreted as a counterfactual, conditional on all the other factors including in the wage models, for how different the ethnic minority wage gap would be if white and ethnic minority employees were equally distributed over employers that tended to pay relatively high or low wages to their white employees.

The second line of Equation (3) provides the amount of the average log wage gap that is accounted for by the other differences in characteristics between white and ethnic minority employees that can explain wages, such as education levels, age and tenure, and occupations, where the wage returns of these factors are evaluated according to how they explain the variation in white employee

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.

wages. This is the part of a wage gap that is often referred to in the literature as the 'Explained' amount from an Oaxaca-Blinder-style decomposition. The third line of Equation (3) then provides 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 who they work for or their other observed characteristics, but instead from the different estimated labour market returns to those characteristics according to ethnicity. We estimate standard errors for these three different parts of the wage gap decompositions using bootstrapping.

3.2 Decomposing differences between the quantiles of wage distributions

To decompose the estimated gaps between quantiles of ethnic minority and white employee wage distributions, we use unconditional quantile regression models (UQR) (Firpo et al., 2009) and apply to these Oaxaca-Blinder-style methods (Firpo et al., 2018; Rios-Avila, 2020). Figure 2 gives an illustration of the wage gaps that we can decompose using these methods, specifically 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 only a matter of changing the dependent variables of the linear regression models. For quantile τ_w of the log wages of white employees, we estimate the following using least squares:

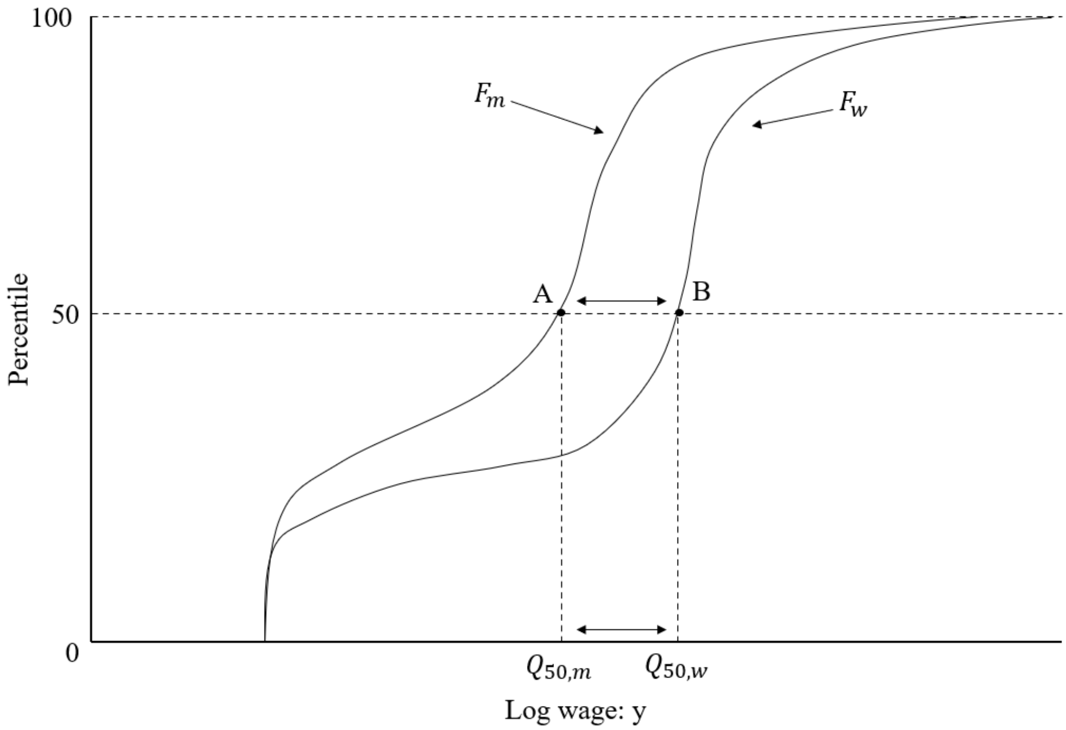
$$\widehat{RIF}\left(y_i, \hat{Q}_{\tau_w}\right) = \hat{Q}_{\tau_w} + \frac{\tau_w - \mathbb{1}\{y_i \leq \hat{Q}_{\tau_w}\}}{f_{y_w}(\hat{Q}_{\tau_w})} = \alpha_{\tau_w} + \gamma_{\tau_w} G_i + \mathbf{x}_i \boldsymbol{\beta}_{\tau_w} + \varphi_{J(i),\tau_w} + \varepsilon_i\,,\ i \notin W. \qquad (4)$$

$\hat{Q}_{\tau_w}$ is the log wage at quantile τ_w of the white employees in the 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, estimated using a Gaussian kernel and Silverman plugin bandwidth. We then use the estimated firm-specific 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 (2) above. Gathering up these estimates, we can decompose the differences between quantiles of ethnic minority and white employee wages into the equivalent three parts as described for the average gaps in Equation (3):

$$\begin{aligned}\hat{Q}_{\tau_m} - \hat{Q}_{\tau_w} = {} & \{E\left[\hat{\varphi}_{J(i),\tau_w} \mid i \in M\right] - E\left[\hat{\varphi}_{J(i),\tau_w} \mid i \in W\right]\} \\ & +\{\hat{\gamma}_{\tau_w}(E[G_i \mid i \in M] - E[G_i \mid i \in W]) + (E\left[\mathbf{x}_i \widehat{\boldsymbol{\beta}}_{\tau_w} \mid i \in M\right] - E\left[\mathbf{x}_i \widehat{\boldsymbol{\beta}}_{\tau_w} \mid i \in W\right]\} \\ & + \{(\hat{\alpha}_{\tau_m} - \hat{\alpha}_{\tau_w}) + (\hat{\gamma}_{\tau_m} - \hat{\gamma}_{\tau_w})E[G_i \mid i \in M] + E\left[\mathbf{x}_i\left(\widehat{\boldsymbol{\beta}}_{\tau_m} - \widehat{\boldsymbol{\beta}}_{\tau_w}\right) \middle| i \in M\right]\}, \qquad (5)\end{aligned}$$

where the expected values of the RIFs over ethnic minority and white employees are the estimation sample log wage quantiles of the respective distributions. The interpretations of the three parts (lines) of the quantile wage gap decompositions given by Equation (5) are equivalent to those described above for average wage gaps. In particular, and with reference back to Figure 2, the firm-specific wage effects contribution 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 firms that tend to pay relatively high or low wages to their white employees.

FIGURE 2: 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.

It is clear from Equations (3) and (5) that the overall unexplained parts of the decompositions are in effect residual amounts within our methodology, left over after projecting the model parameters from the white employee wage regression, obtained from Equations (1) and (4), onto the samples of ethnic minority employees. Nonetheless, we still estimate Equation (2) for each ethnic minority group and its UQR equivalents so that we can provide divisions of the unexplained part of the wage gaps, which could relate to differences either in returns to education, occupation, job tenure, etc. Likewise, in Online Appendix C we also show the results from partialling out of the estimated firm-specific parts of the wage gaps the effects of working in the private sector and for larger firms (using a quadratic in the administrative record of the number of employees). However, these particular firm-level factors contribute very little to the overall estimates of the firm-specific parts of ethnicity wage gaps and, therefore, we do not dwell on them in what follows.

4. Main Results

The results of decomposing ethnicity wage gaps in England and Wales in 2011, using the methods outlined in the preceding section, are summarised in Table 2, and represented in Figures 3 & 4. We focus on the three main parts that can explain the total wage gaps: 1) who people work for – firm-specific wage effects; 2) the differences in observed wage-relevant personal and job characteristics of employees (e.g., education levels, occupation, regions) (shown only in the LHS panels of Figures 3 & 4); 3) the differences according to ethnicity in how the labour market tends to reward those characteristics in terms of hourly wages – the unexplained or residual part of the wage gap, that tends to exist within firms and isn't accounted for by other worker and job characteristics (shown only in the RHS panels of Figures 3 & 4). Sub-divisions of these different estimated parts of the wage gaps are presented in more detailed tables in Online Appendix C. In what follows, we describe in turn the results from comparing the distributions of basic hourly wages among white employees and one of the six ethnic minority groups that we can analyse using ASHE-Census, before summarising and discussing our results further in the following section. In Figures 3 & 4 and Online Appendix C, we also show wage gap decomposition results where we omit the firm-specific effects from the regression models, in effect constraining or assuming that the contributions from whom people work for are zero. These results demonstrate the magnitudes and directions of the biases in the other parts of the ethnicity wage gap decomposition estimates when the influences of specific firms are omitted from the models.

To provide a benchmark, before comparing the wages of white and ethnic minority employees as individual groups, we consider the gaps in hourly wages between white and all non-white employees.[8] The first portion of Table 2 summarises the decomposition results for these gaps. Column (I) shows results for the gap between average log wages, and columns (II)-(VI) consider gaps between the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles of the observed wage distributions. On average, there is no significant log wage gap between white and non-white employees in our estimation sample. However, the three overall parts of the decomposition are all significantly different from zero. Firm-specific wage effects and the characteristics of employees would each on average lead to a significant wage gap in favour of non-white employees, of approximately one and three percent, respectively. However, there is no significant overall wage gap on average between white and non-

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

white employees because of the off-setting negative unexplained penalty. The white and non-white specific returns to the wage-relevant characteristics included in our models account on average for a five percent hourly wage penalty for non-white employees. Table 2 also shows significant total wage gaps in favour of white employees at the 25th, 75th, and 90th percentiles, of between one and two percent. At the 90th percentile, the firm-specific wage effects are generally in favour of non-white employees, accounting for almost a positive four percent wage gap. The other personal and job characteristics account for an approximate four percent positive wage gap in favour of non-white employees from the median up to the 90th percentile. The unexplained wage penalty for non-white employees rises significantly moving up the hourly wage distribution, being three percent at the 25th percentile, four percent at the 50th percentile, eight percent at the 75th percentile, and nine percent at the 90th percentile. Overall, these results show that, when comparing white employees with non-white employees, an insignificant overall wage gap at the mean not only masks significant total wage penalties for higher earning non-white employees but also significant unexplained penalties throughout the wage distribution. These unexplained penalties are increasing with the level of hourly wages. However, they are moderated – particularly at higher wage levels – by the greater tendency of non-white employees to work for relatively high wage paying firms.

Indian-white wage gaps

The second portion of Table 2 and Figure 3(a) summarise the decomposition results for the wage gaps between Indian and white employees. On average this gap is significantly positive, with firm-specific wage effects and the other characteristics in the models contributing two and four percentage points, respectively, which are offset by a negative unexplained average wage penalty of three percentage points. Across the selected percentiles, the observed gap to the white employee wage distribution is only statistically significant from zero at the 90th percentile, being at that point approximately seven percent. The firm-specific wage effects increase in magnitude across the percentiles – seen from the blue line in Figure 3a. At the 90th percentile, these effects provide the only statistically significant part of the decomposition, contributing six percentage points of the overall wage gap.. High Indian earners tend to receive higher wage rates than high white earners for the most part due to the former group being more likely to work at firms that pay high wages, conditional on the influence of education, occupations, location, etc. There is an unexplained wage penalty across all the selected percentiles for Indian employees – shown by the solid red line in the right-hand panel of Table 3a - but it is greatest and only statistically significant at the 75th percentiles of the wage distributions. The dashed lines in Figure 3(a) show the remaining parts of the wage gap decomposition when we omit firm-specific effects from the models. The contributions of the other worker characteristics to the positive wage gaps at higher percentiles – shown by the solid red line in the left-hand panel of Figure

3a - would have been substantially biased upwards without accounting for firm specific wage effects. This is mainly because the contributions of a worker's home region, occupation, and age would have been overestimated (see Online Appendix Table C1), suggesting that these factors most positively correlate with entry into relatively high-wage firms among Indian employees, conditional on all the other factors in the models.

Pakistani-white wage gaps

The third portion of Table 2 and Figure 3(b) summarise the decomposition results for the wage gaps between Pakistani and white employees. The observed gap between the average wages of these two groups of workers is significantly negative, with Pakistani employees tending to earn almost eight percent less. However, none of the three major parts of the decomposition are statistically significant for the average wage gap, though the negative characteristics part is largest. The total wage gaps relative to white employees are also significantly negative at the 10^{th}, 25^{th}, 50^{th} and 75^{th} percentiles, rising from a four percent penalty at the 10^{th} percentile to eleven percent at the 75^{th} percentile. The firm-specific wage effects tend to contribute to these overall wage gaps, though not significantly, except for three percentage points at the 25^{th} percentile. These firm-specific wage effects are thus less important for Pakistani employees than for Indian employees, and where they do prove to be informative, they are disadvantageous. The negative contributions of the other worker characteristics to the differences from the wage distribution of white employees become larger and statistically significant with the level of pay, with the biggest contributing factors being the age, tenure & part-time status, and occupations of employees (see Online Appendix Table C2). The dashed lines in Figure 3(b) show that the decomposition results for wage gaps between Pakistani and white employees are approximately robust to whether firm-specific wage effects are included in the models.

Bangladeshi-white wage gaps

The fourth portion of Table 2 and Figure 3(c) summarise the decomposition results for the wage gaps between Bangladeshi and white employees. The overall wage gaps at the mean and selected percentiles are similar for Bangladeshi and Pakistani employees. There is a significant negative eight percent total gap between the average wages of Bangladeshi and white employees. Across the respective wage distributions of these two groups, the gap is smallest and insignificant at the 10^{th} percentile, and largest and statistically significant at the 75^{th} percentile. Among higher earning workers, firm-specific wage effects, however, significantly offset these overall wage penalties, and would by themselves instead account for positive wage gaps for Bangladeshi employees of six and eight percent at the 75^{th} and 90^{th} percentiles, respectively. The other estimated components of the decompositions are large for Bangladeshi employees, particularly the overall unexplained parts of the gaps, but none of these are statistically significant.

TABLE 2: 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	Total	-0.002	0.009	**-0.014**	0.009	**-0.021**	**-0.013**
	Firm wage effects	**0.011**	**-0.007**	-0.001	**0.013**	**0.018**	**0.036**
	Characteristics	**0.032**	**0.025**	0.016	**0.038**	**0.041**	**0.040**
	Coefficients (Unexplained)	**-0.046**	-0.010	**-0.030**	**-0.043**	**-0.080**	**-0.090**
2. Indian	Total	**0.030**	0.018	-0.011	0.038	0.040	**0.073**
	Firm wage effects	**0.016**	0.001	-0.002	0.012	**0.023**	**0.062**
	Characteristics	**0.044**	0.024	0.013	**0.067**	**0.074**	0.035
	Coefficients (Unexplained)	**-0.031**	-0.008	-0.022	-0.042	**-0.056**	-0.024
3. Pakistani	Total	**-0.077**	**-0.042**	**-0.097**	**-0.088**	**-0.105**	-0.090
	Firm wage effects	-0.002	-0.012	**-0.029**	-0.011	0.007	0.031
	Characteristics	-0.048	-0.018	-0.009	-0.063	**-0.113**	-0.183
	Coefficients (Unexplained)	-0.028	-0.012	-0.059	-0.013	0.001	0.063
4. Bangladeshi	Total	**-0.080**	0.001	**-0.089**	-0.054	**-0.123**	-0.115
	Firm wage effects	0.027	-0.026	-0.010	0.032	**0.060**	**0.084**
	Characteristics	0.018	0.048	0.100	-0.067	-0.103	-0.004
	Coefficients (Unexplained)	-0.125	-0.020	-0.180	-0.020	-0.080	-0.195
5. Chinese	Total	**0.277**	**0.215**	**0.253**	**0.349**	**0.293**	**0.353**
	Firm wage effects	**0.095**	0.008	**0.059**	**0.101**	**0.117**	**0.207**
	Characteristics	**0.177**	**0.234**	0.222	**0.294**	**0.234**	-0.022
	Coefficients (Unexplained)	0.005	-0.027	-0.028	-0.046	-0.059	0.168
6. Black African	Total	**-0.085**	-0.015	**-0.062**	**-0.064**	**-0.118**	**-0.145**
	Firm wage effects	**-0.019**	**-0.034**	**-0.021**	-0.017	-0.007	**-0.038**
	Characteristics	-0.008	0.020	-0.008	-0.048	0.040	-0.058
	Coefficients (Unexplained)	**-0.058**	0.002	-0.031	0.002	**-0.150**	-0.049
7. Black Caribbean	Total	0.003	**0.055**	**0.064**	**0.046**	**-0.061**	**-0.114**
	Firm wage effects	**0.012**	0.007	**0.028**	**0.031**	0.000	0.001
	Characteristics	**0.062**	0.054	**0.102**	**0.057**	0.016	0.005
	Coefficients (Unexplained)	**-0.070**	-0.007	**-0.066**	-0.042	**-0.078**	**-0.121**

Notes: author calculations using ASHE-Census 2011 dataset. *N* of white employees =51,435 for all models. *N* of {Indian, Pakistani, Bangladeshi, Chinese, Black African, Black Caribbean} employees ={1,571, 523, 175, 189, 666, 736}. Each set of values across rows and columns show contributions to the O-B decomposition from a single model using OLS or UQR, all with 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 Figures 3 & 4 and Online Appendix Tables C1-C6 for more detailed decomposition results, as well as equivalent estimates that don't admit firm-specific wage effects.
Bold values indicate significant differences from zero, two-sided tests, at the 5% level, with standard errors computed using 200 bootstrap replications.

Chinese-white wage gaps

The fifth portion of Table 2 and Figure 4(a) summarise the decomposition results for the wage gaps between Chinese and white employees. On average, Chinese employees earn significantly and substantially more than white employees in England and Wales, by almost twenty-eight log points (over thirty percent). Approximately one third of this gap is accounted for by the firm-specific wage effects, with the remainder explained by the other worker and job characteristics in the models, especially due to occupations, education levels, and locations (see Online Appendix Table C4). The positive overall wage gap for Chinese employees increases moving up the wage distribution, from twenty-two log points (twenty-four percent) at the 10th percentile to thirty-five log points at the 90th percentile (forty-two percent). These gaps are also increasingly accounted for, moving up the wage distribution, by the greater tendency of Chinese employees to work for relatively high wage paying firms, which accounts for as much as twenty-one log points of the gap at the 90th percentile. The unexplained parts of the wage gaps for Chinese employees are generally negative but not significantly different from zero. As for Indian employees, Figure 4(a) shows that omitting the firm-specific wage effects would have resulted in substantial overestimates of the contributions to the positive wage gaps from the other worker characteristics in the model, especially among higher earners and for the influences of occupations, tenure and part-time status, locations, and education levels (see Online Appendix Table C4).

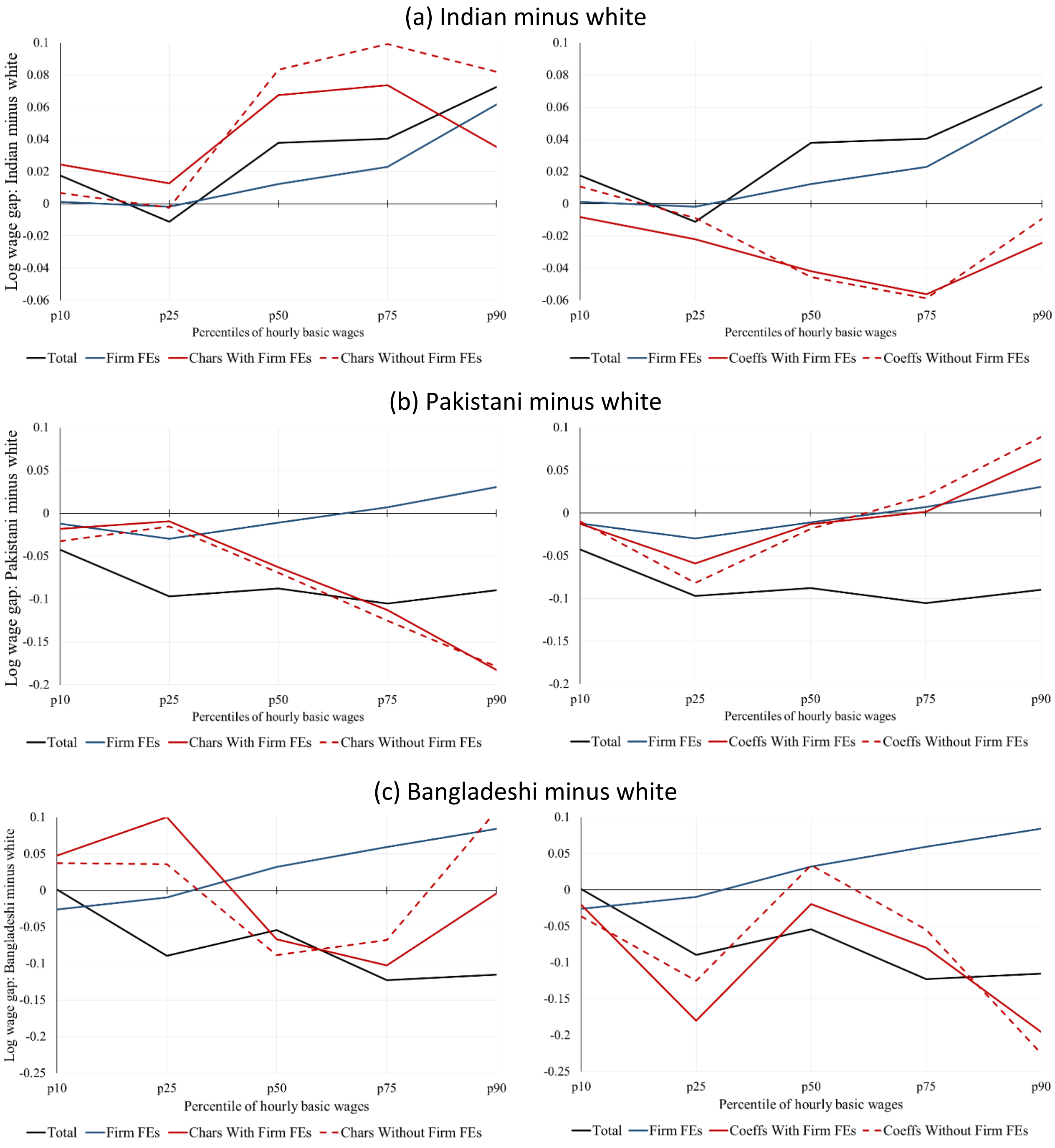
Black African-white wage gaps

The sixth portion of Table 2 and Figure 4(b) summarise the decomposition results for the wage gaps between Black African and white employees. The overall average and percentile wage gaps for Black African employees are like those described above for Bangladeshi and Pakistani employees. The average total wage gap in favour of white employees is approximately nine percent, at the 10th percentile it is statistically insignificant, but rises substantially to twelve and fifteen percent by the 75th and 90th percentiles. The firm-specific wage effects generally contribute significantly to these total gaps throughout the wage distributions, accounting for two percentage points on average and up to four percentage points for the 90th percentile. The other worker characteristics in the models do not account for statistically significant parts of the gaps between the Black African and white employee wage distributions. The unexplained part accounts for a significant six percentage points penalty on average and is greatest between the 75th percentiles of the wage distributions, accounting there for a sixteen percent penalty for Black African employees. Figure 4(b) shows that omitting the firm-specific effects from the models would have led to those unexplained wage penalties being marginally overestimated.

Black Caribbean-white wage gaps

The seventh portion of Table 2 and Figure 4(c) summarise the decomposition results for the wage gaps between Black Caribbean and white employees. The gap between the average wages of these two groups of workers is statistically insignificant from zero. However, the three main parts of the wage gap decomposition at the mean are all significant. The firm-specific effects and the other worker characteristics would each account for positive wage gaps in favour of Black Caribbean employees of one and six percent, respectively. Thus, there is an unexplained wage penalty on average of seven percent compared to white employees. The overall wage gap for Black Caribbean employees is significantly positive, around five to six percent, at the 10^{th}, 25^{th} and 50^{th} percentiles. However, this turns significantly negative by the 75^{th} and 90^{th} percentiles, being 6 and 12 percent, respectively. The firm-specific wage effects contribute nothing to these wage gaps among higher earners, nor for the positive gap at the 10^{th} percentile, but they do explain approximately half (three percentage points) of the positive gaps at the 25^{th} and 50^{th} percentiles. The other worker characteristics in the wage models also contribute substantial positive amounts at these percentiles, such that there remains a negative unexplained wage penalty of four to seven percent, which increases further to 12 percent by the 90^{th} percentile, where it accounts for approximately all the observed differences between the Black Caribbean and white employee wage distributions. Figure 4(c) shows that omitting the firm-specific effects from these decompositions would have led to overestimates of the positive contributions that other worker characteristics make to offset the negative unexplained wage penalties experienced by Black Caribbean employees, particularly the amounts due to locations (see Online Appendix Table C6).

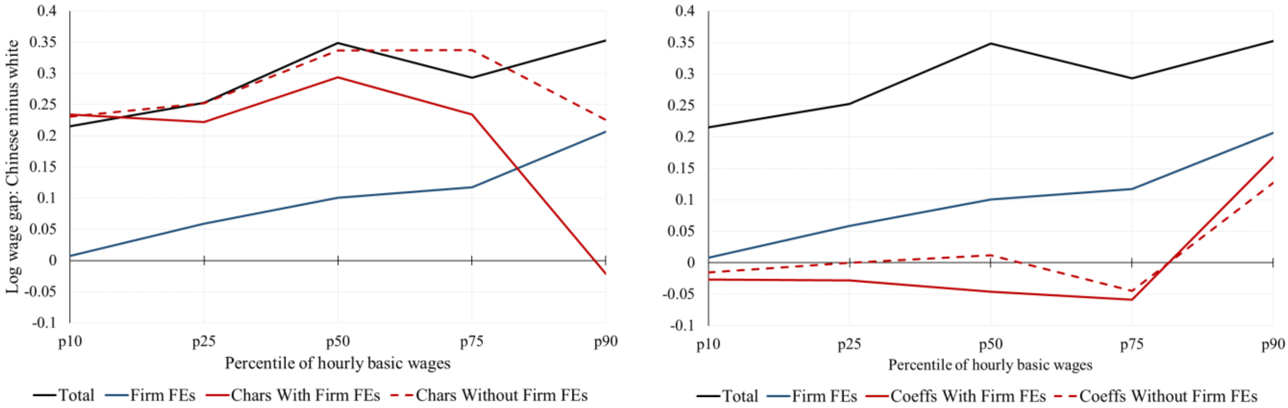
FIGURE 3: Summary of Oaxaca-Blinder decompositions of ethnicity log hourly basic wage gaps, ordinary least squares and unconditional quantile regression estimates, England and Wales, 2011 **(Part 1)**



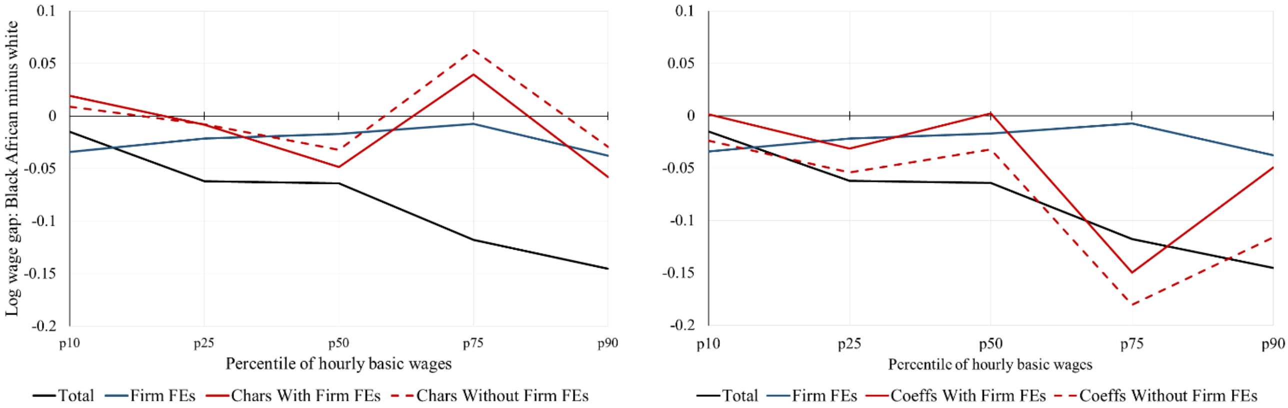
Notes: author calculations using ASHE-Census 2011 dataset. See Table 2 and Online Appendix Tables C1-C3 for the displayed estimates and indications of statistical significance. We present two separate figures for each group, so they are not too cluttered. “Total” gives the overall wage gap estimate at the mean or between respective percentiles of the wage distributions, shown in both figures for each group. “Firm FEs shows the contribution of the firm-specific wage effects, also shown in both figures for each group. “Chars” show the contributions of differences in characteristic, shown only in the LHS figures. “Coeffs” show the contributions from differences in coefficients in the models, i.e., the unexplained component, shown only in the RHS figures. The dashed lines show comparable estimates when firm-specific wage effects are not included in the wage models.

FIGURE 4: Summary of Oaxaca-Blinder decompositions of ethnicity log hourly basic wage gaps, ordinary least squares and unconditional quantile regressions estimates, England and Wales, 2011 **(Part 2)**

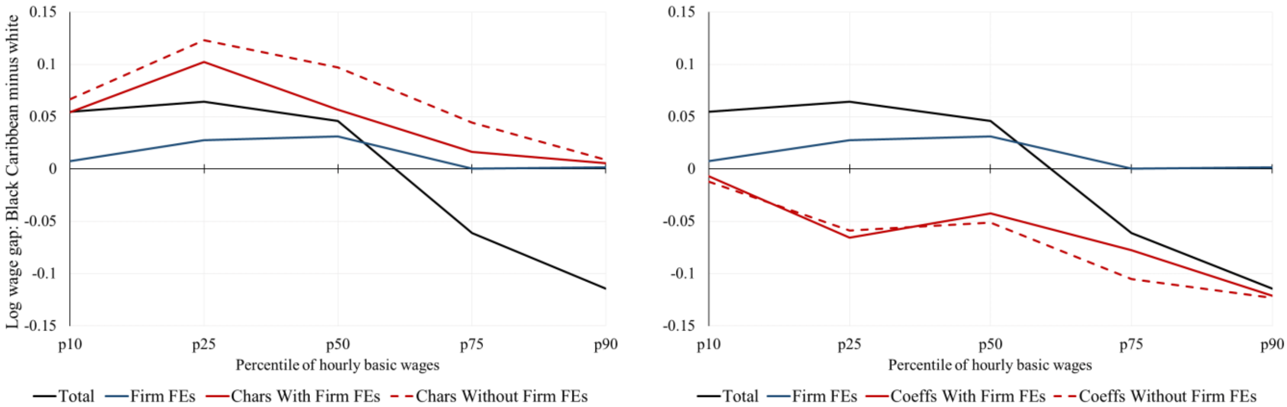
(a) Chinese minus white



(b) Black African minus white



(c) Black Caribbean minus white



Notes: author calculations using ASHE-Census 2011 dataset. See Table 2 and Online Appendix Tables C4-C6 for the displayed estimates and indications of statistical significance. We present two separate figures for each group, so they are not too cluttered. "Total" gives the overall wage gap estimate at the mean or between respective percentiles of the wage distributions, shown in both figures for each group. "Firm FEs shows the contribution of the firm-specific wage effects, also shown in both figures for each group. "Chars" show the contributions of differences in characteristic, shown only in the LHS figures. "Coeffs" show the contributions from differences in coefficients in the models, i.e., the unexplained component, shown only in the RHS figures. The dashed lines show comparable estimates when firm-specific wage effects are not included in the wage models.

5. Summary and further discussion

In this paper, 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 account for the influence of firm-specific wages throughout the distribution of ethnicity wage gaps. The influence of which employee works for which employer 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 firm-specific wage effects play an important and significant role in accounting for ethnicity wage gaps. This role would otherwise have been attributed either to other worker characteristics that corelate with firm-specific pay rates, such as education levels, workplace location and occupations, or to the unexplained part of these wage gaps.

Using payroll data on the components of employee earnings, we have confirmed previous household-survey based analyses for England and Wales that the wage gaps between white and ethnic minority employees vary greatly, according to which group is considered 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 employees are significantly positive among lower earners but turn even more significantly negative and in favour of white employees among higher earners.

We have also found that firm-specific wage effects contribute to ethnicity wage gaps differently across the groups that we have looked at. The fact that Indian and Chinese employees are more likely than white employees to work for firms who tend to offer relatively high wages, even after controlling for other worker and job characteristics, can account for large parts of why these groups have positive wage gaps towards the top of the overall wage distribution, to the extent that the role of those other characteristics in explaining those gaps would be substantially overestimated if firm-specific wages were not accounted for. In contrast, firm-specific wage effects do not tend to contribute to the differences between the Pakistani and white employee wage distributions; they contribute positively for relatively high earning Bangladeshi employees; they tend to significantly favour white employees over Black African employees; and vice versa for Black Caribbean employees, except in this latter case among higher earners, where they account for none of the significant total wage penalty to white employees at the 75th and 90th percentiles of those two respective wage distributions.

In general, we would conclude that who people work for is an important dimension of ethnicity wage gaps, even after also addressing the influence of factors such as education levels and occupations. Furthermore, we have shown that the estimated influences of those other factors tend to be overestimated when firm-specific wage effects are ignored, since they correlate with whether somebody works for a relatively high wage paying firm. Nonetheless, there are significant negative unexplained wage penalties between ethnic minority and white employee wage distributions, after controlling for who works where and other worker characteristics, with these penalties being especially large among higher wage earners.

Our study is reminiscent of earlier work for Britain (Forth et al., 2021) and for the United States (Troske and Carrington, 1998) in identifying considerable ethnic segregation of employees across employers, and in showing that this contributes relatively little to ethnicity wage gaps at the mean. However, our study is the first to demonstrate that firm effects play an important role in understanding the size and direction of ethnicity wage gaps vis-à-vis white employees across the wage distribution, and in identifying the heterogeneity in those firm-specific wage effects across different ethnic groups. In doing so, it places the employer centre-stage in efforts to understand further why it is that employees from different ethnic backgrounds are paid differently. Substantial positive firm wage effects in the upper part of the wage distribution benefit Indian, Chinese and Bangladeshi employees, partially offsetting lower wage returns of those ethnic groups relative to whites from their characteristics. But it remains unclear why it is that Indian and Chinese employees should be able to sort into firms which pay higher wages, whereas Pakistani, Bangladeshi, Black African and Black Caribbean employees do not benefit significantly from positive firm wage effects in the top half of the wage distribution. It is possible that Indian and Chinese employees possess unobserved earnings-enhancing traits which complement production in high wage firms, generating wage offers from those firms that other ethnic groups do not receive. This sort of assortative matching has been observed in the literature, beginning with Abowd et al. (1999), but it is not something we can test for directly in our data since we do not follow employees over time, something we would need to do in order to identify the role of worker sorting.

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 the firm, might also partially explain some of our results. The insignificant contributions of firm-specific effects to gaps between the 10th percentiles of the ethnic minority and white wage distributions may be related 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 powers to the detriment of ethnic minority workers (see Clark & Nolan, 2021, for 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 utilise ASHE-Census to explore the importance of other employee attributes which might be 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 (Algan et al., 2010) and religion (Longhi et al, 2013). There could also be great value in designing studies that can uncover why ethnicity wage penalties appear in some firms. For example, Forth et al. (2021) found some evidence that ethnic minorities experience skills mismatches as a result of firm employment practices, and that job evaluation schemes were associated with smaller ethnic wage penalties. Such practices, by promoting equal treatment in the workplace, may help tackle the ethnicity wage gaps we have estimated in this paper.

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Accounting for employers in the distribution of ethnic pay gaps

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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 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 62% of ASHE job observations. However, this linkage rate varies by employee, job, and employer characteristics.

Table A1 presents odds ratio estimates from logit models, where the dependent indicator 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 much higher among male employees than female employees, and lower for those working in London than in the other regions of England and Wales. The effect of the differential linkage rates is to skew the profile of the ASHE-Census sample away from the profile of the full ASHE sample to some extent. However, the overall fit of this model is fairly low, indicating that although some

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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 adjusted with the standard ASHE weights. In theory, this procedure and the new derived sample weights should make sample descriptive statistics obtained from the ASHE-Census less biased representations of all jobs held by employees in England and Wales in 2011.

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 the following 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). 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. It is worth noting that many more relevant socio-economic variables than these have been added or can now be derived for employees in ASHE through the ASHE-Census linkage.

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. 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. 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 or over, 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 shows mean absolute wage gap estimates from ASHE-Census by ethnicity and gender. Figure A2 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 A2 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 A3 presents distributions of log gross hourly wages across different ethnic minority groups, compared to white employees, by gender, in the APS for 2011. Figure A4 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	1.227***	1.250***
	(0.018)	(0.018)
Age (years)	1.510***	1.508***
	(0.007)	(0.008)
Age squared (years^2/ 100)	0.597***	0.597***
	(0.003)	(0.003)
Tenure (years)	1.057***	1.058***
	(0.002)	(0.002)
Tenure squared (years^2/ 100)	0.845***	0.843***
	(0.006)	(0.006)
Gross hourly pay (£)	0.999*	0.999**
	(0.001)	(0.001)
Basic weekly hours worked	1.005***	1.005***
	(0.001)	(0.001)
Govt. office region at workplace (excl. cat., North East):		
+ North West	0.938*	0.944*
	(0.031)	(0.032)
+ Yorkshire	0.924**	0.938*
	(0.032)	(0.033)
+ East Midlands	1.002	1.010
	(0.036)	(0.036)
+ West Midlands	0.962	0.974
	(0.033)	(0.034)
+ South West	0.966	0.978
	(0.033)	(0.034)
+ East of England	0.958	0.973
	(0.033)	(0.034)
+ London	0.687***	0.697***
	(0.022)	(0.023)
+ South East	0.917***	0.926**
	(0.030)	(0.030)
N of employees	135,118	135,118
Pseudo-R^2	0.085	0.085

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.

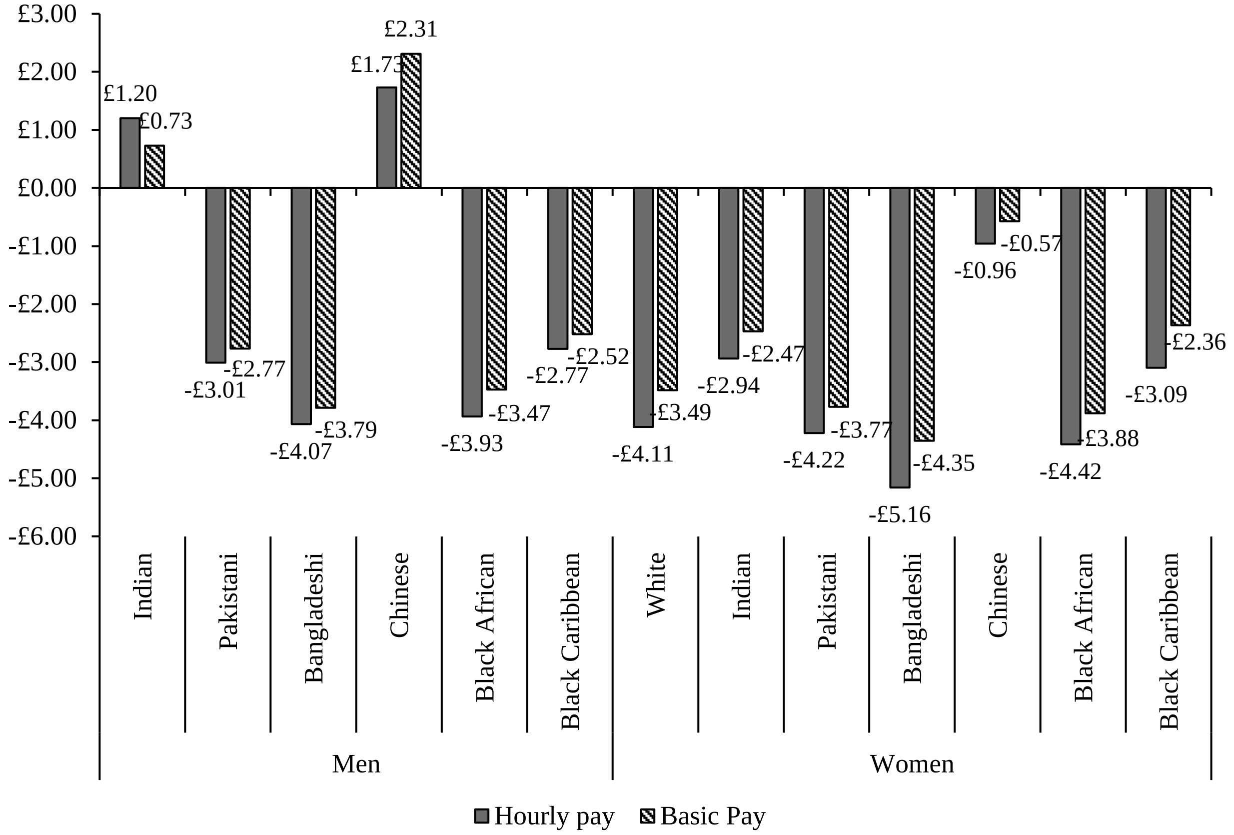
Table A2: List of variables used in the linked ASHE-Census 2011 dataset and Annual Population Survey

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

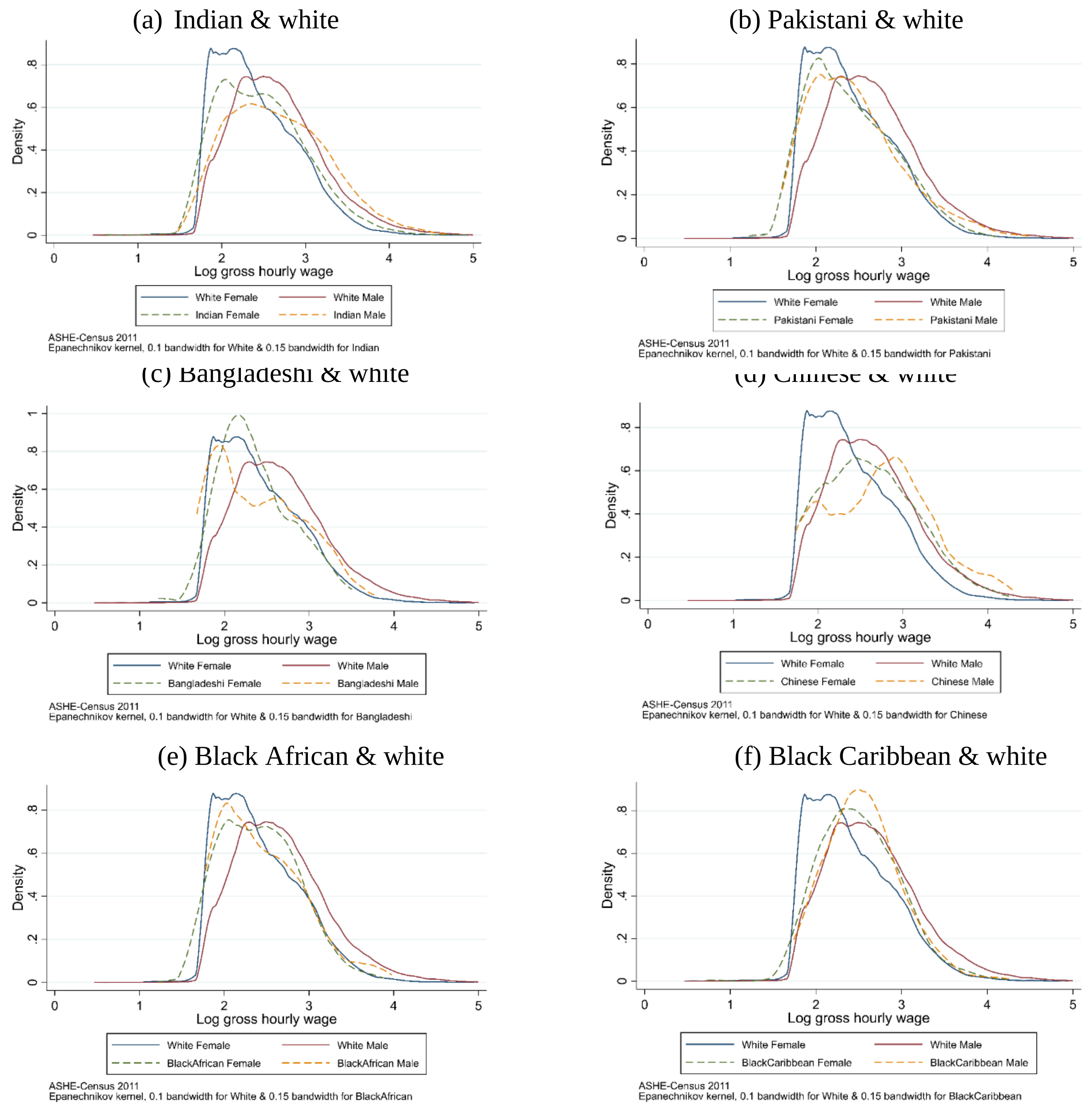
Panel (b): APS	Description	Variables
Gross hourly pay	Gross hourly pay is a continuous variable. It is calculated by the ratio of the gross weekly earnings to the total number of basic week paid hours (Unit: £)	hourpay
Male	Dummy variable indicating whether the employee is male.	sex
Tenure	Employment 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 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 DDA disability, or work-limiting disability.	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: Raw average ethnicity hourly wage gaps among male and female employees in England and Wales, relative to white men, ASHE-Census 2011



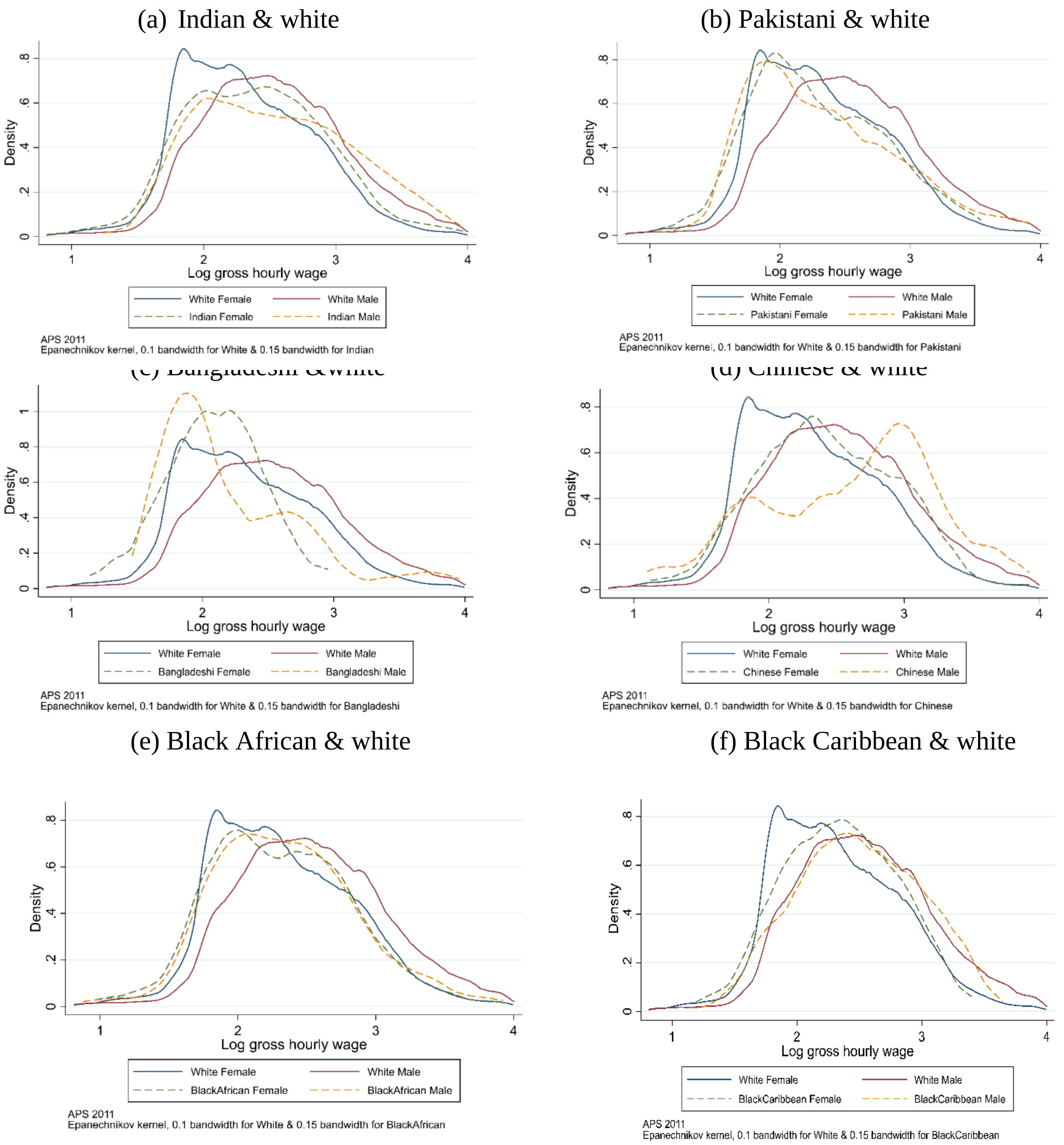
Notes: author calculations using ASHE-Census 2011 dataset. The raw ethnicity wage gap is calculated by the average wage of ethnic minority M minus the average wage for white men. These are unweighted sample statistics. "Hourly pay" refers to Earnings per hour. "Basic pay" refers to Basic hourly wages. Sample sizes of employees for Hourly pay: *N* white (*F*=37,964 and *M*=38,130), *N* Indian (*F*=1,176 and *M*=1,189), *N* Pakistani (*F*=314 and *M*=514), *N* Bangladeshi (*F*=98 and *M*=171), *N* Chinese (*F*=208 and *M*=172), *N* Black African (*F*=557 and *M*=487), and *N* Black Caribbean (*F*=599 and *M*=396). For the Basic pay, *N* white (*F*=37,765 and *M*=38,021), *N* Indian (*F*=1,165 and *M*=1,187), *N* Pakistani (*F*=311 and *M*=513, *N* Bangladeshi (*F*=97 and *M*=171), *N* Chinese (*F*=208 and *M*=171), *N* Black African (*F*=554 and *M*=487), and *N* Black Caribbean (*F*=594 and *M*=395).

FIGURE A2: Estimated distributions of log gross hourly earnings, comparing white and ethnic minority employees, ASHE-Census 2011



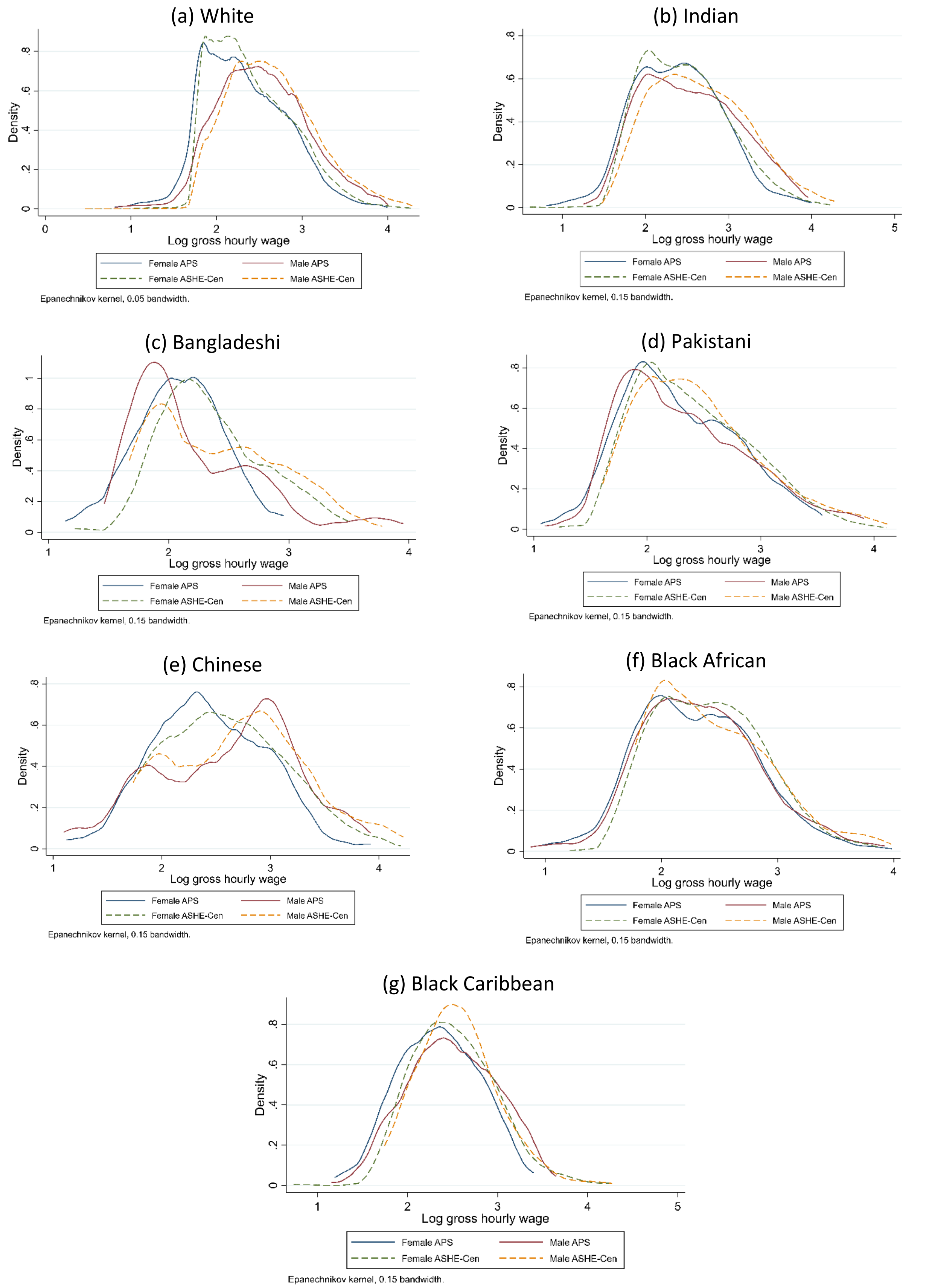
Notes: author calculations using ASHE-Census 2011 dataset. See Figure A1 for sample sizes by gender. See Figure A3 for equivalent kernel density estimates from the Annual Population Survey (APS) 2011, and Figure A4 for the ASHE-Census and APS distributions overlaid.

FIGURE A3: Estimated distributions of log gross hourly earnings, comparing white and other ethnic minority employees, Annual Population Survey 2011



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

FIGURE A4: Distributions of log gross hourly earnings, by ethnicity and gender, in ASHE-Census 2011 and APS 2011, England and Wales



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

B. Estimates of Adjusted Ethnicity Wage Gaps using ASHE-Census

In this Appendix, we present the estimates of adjusted (or residual) ethnicity wage gaps for employees in England and Wales, using the linked 2011 ASHE-Census. For the mean adjusted (log) wage gaps, we estimate wage equations using Ordinary Least Squares (OLS). These equations are given by variants on the following:

$$y_i = \alpha + \theta_{Z(i)} + \mathbf{x}_i\boldsymbol{\beta} + \varphi_{J(i)} + \varepsilon_i \qquad \text{(B1)}$$

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, NUTS1 region of work, whether working part-time, occupation (SOC10, 1-digit), highest qualification level, whether married, number of children, age of youngest child, and whether non-UK born; see 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 ethnicity-gender of an employee, where $z = Z(i)$ is an indicator function that person i is in ethnic-minority-gender 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 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.

To estimate the influence of ethnicity and gender throughout the wage distribution, and not just at the mean, we use Unconditional Quantile Regression (UQR) (see also the methods described in Section 3 in the main text). This is equivalent to estimating the Recentred Influence Function (RIF) of log wages in the estimation sample 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:

$$\widehat{RIF}(y_i, \hat{Q}_\tau) = \hat{Q}_\tau + \frac{\tau - \mathbb{1}\{y_i \le \hat{Q}_\tau\}}{f_y(\hat{Q}_\tau)} = \alpha_\tau + \theta_{Z(i),\tau} + \mathbf{x}_i\boldsymbol{\beta}_\tau + \varphi_{J(i),\tau} + \varepsilon_i\ , \qquad \text{(B2)}$$

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.

To estimate Equations (B1) and (B2) 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 other sample selection described in Appendix A). Before considering that more selected sample, which will be inevitably somewhat biased towards larger firms compared with the whole of ASHE-Census, Table B1 shows estimates of Equation (B1) using the all the employee observations described in Section 2 and Appendix A. Columns (I) and (III) provide the model estimates without using any sample weighting, whereas columns (II) and (IV) provide comparable estimates applying the ASHE-Census weights. In general, male employees in 2011 earned on average significantly higher residual hourly wages than female employees. Among women, Indian, Bangladeshi, Black African, and Black Caribbean employees tended to experience on average significant adjusted wage penalties. Among men, Pakistani, Bangladeshi, Black African and Black Caribbean employees had on average significant residual wage penalties compared to white male employees. After controlling for the influences of occupation and industry on wages, these average residual wage gap estimates are approximately robust to using the ASHE-Census sample weights described in Appendix A.

Henceforth, we restrict our focus on the sub-sample of ASHE-Census where employees can be observed with at least one co-worker in the dataset. Figure B1 shows the regression-adjusted differences in log hourly wages between white men and women computed at selected percentiles of the wage distribution, comparing estimates obtained from specifications of Equation (B2) with and without firm-specific wages. At the 10th percentile, the darker line shows that white women in 2011 earned around 5 log points less than their male counterparts, conditional on other personal and job-related characteristics. This gap rises increasingly as one moves up the earnings distribution, such that at the 90th percentile of the overall wage distribution the adjusted gender wage gap was close to 25 log points – five times greater than the gap at the 10th percentile.

The lighter line that sits beneath the darker line in Figure B1 traces out estimates of the adjusted wage gap in log points between white men and women once we additionally account for firm-specific wage effects. After doing so, the estimated adjusted wage gaps drop quite considerably throughout the overall employee wage distribution. This indicates that a sizeable part of the earnings differentials between white men and women in England and Wales that existed in 2011 can be linked to the fact that men were more likely to work for firms that tended to pay relatively high wages to their employees, thus mirroring similar results in Jewell et al., (2020). Including firm-specific effects in the wage equation leads to a reduction of about 2-4 log points in the adjusted white gender wage gaps throughout the overall basic hourly wage distribution in England and Wales. This reduction is greatest at the median, where the adjusted white gender wage gap drops from 11.4 to 7.8 log points after addressing the influence of firm-specific effects.

Figure B2 shows adjusted ethnicity-gender wage gaps from the estimates of Equation (B2), with and without firm fixed effects. Table B2 summarises the parameter estimates shown in Figures B1 & B2 for the selected percentiles, with standard errors, as well as showing the equivalent mean adjusted differences in log wages in the same estimation samples. Panel (a) of Figure B2 compares the adjusted log hourly wage gaps between white and Indian employees with and without firm-specific wage effects for women and men separately. For Indian women, the incorporation of firm-specific wage effects makes little difference to the adjusted wage gap estimates: Indian women have no significant residual wage penalty compared with white women at the 10th percentile of the overall wage distribution, but they are earning 16 log points less at the 90th percentile, even conditioning on factors such as education and occupation. For Indian men, the adjusted wage gaps to white men are statistically insignificant throughout the wage distribution.

In panel (b) of Figure B2, we can see that the adjusted wage penalty estimates for Pakistani men relative to white men are increasing moving up the wage distribution – to 14 log points at the 90th percentile of the wage distribution – but across the whole wage distribution the incorporation of firm-specific wages in the models reduces the size of this gap. Pakistani women do not experience a significant adjusted wage gap compared to white women either at the mean or at the selected points of the overall distribution.

In panel (c) of Figure B2, 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 11 log points at the 50th percentile to 18 log points at the 90th percentile. These patterns are apparent whether one conditions on firm-specific wage effects or not. Among men, the patterns of Bangladeshi adjusted wage penalty estimates are similar to among women.

In panel (d) of Figure B2, there is a significant adjusted wage premium for Chinese women relative to white women towards the bottom of the overall wage distribution. Chinese men have an adjusted wage penalty compared to white men, which is particularly large among high earners after firm-specific wage effects are controlled for. However, due to the relatively small samples of Chinese employees these estimated wage penalties are not statistically significant despite being large.

In panel (e) of Figure B2, 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 ameliorated somewhat with the introduction of firm-specific wage effects, it remains at 35 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 concentrated in the bottom half of the wage distribution, are much smaller than among women, and are largely unaffected by conditioning on firm-specific wage effects.

In panel (f) of Figure B2, 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, those gaps become significant and substantial moving up the wage distribution. At the 90^{th} percentile of hourly wages and conditioning on firm-specific wage effects, the adjusted wage penalties for Black Caribbean men and women are 13 and 17 log points, respectively.

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 region. These adjusted wage gaps also vary a great deal by gender and the level of hourly pay even within the same ethnic minority groups. Our ability to control for the influence of firm-specific wage effects, using the ASHE-Census, can either exacerbate or ameliorate estimates of adjusted wage gaps by ethnicity, gender, and the level of hourly pay.

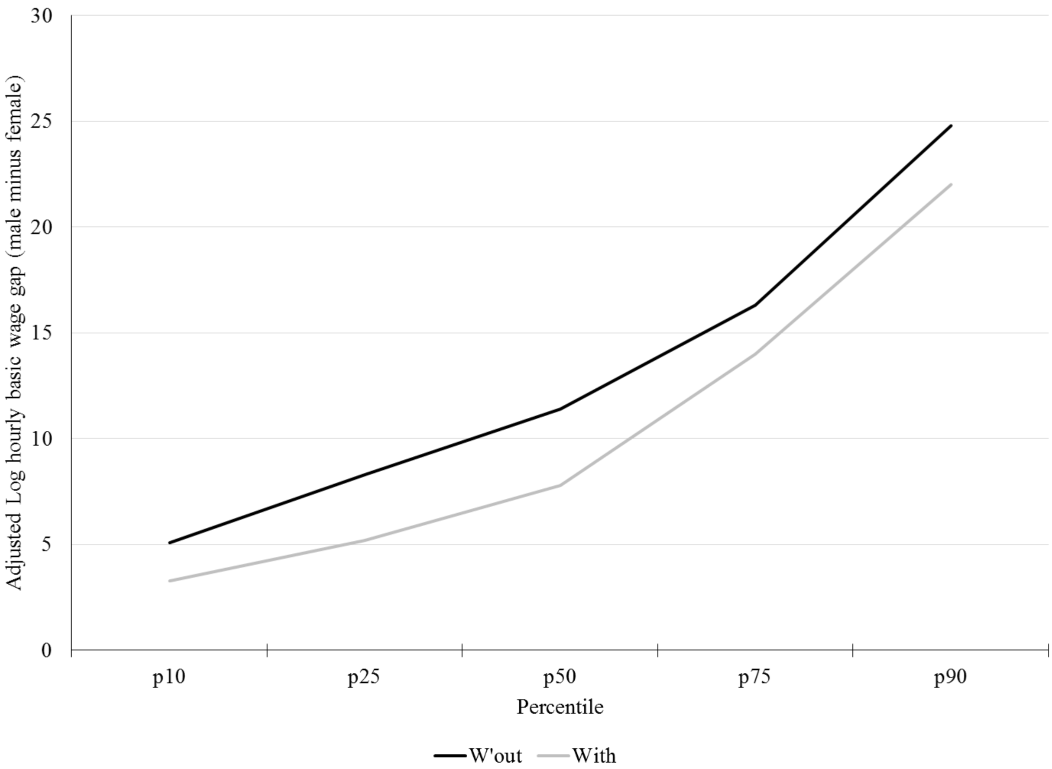
As a robustness check, we estimate Equations (B1) and (B2) applying the adjusted ASHE-Census sample weight, the results of which are summarised in Table B3. We also show in Table B4 comparable unweighted estimates after replacing the basic hourly wage dependent variable with gross hourly earnings. Finally, 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 B5. 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 B2 with Tables B3-B5).

TABLE B1: Wage regressions for employees in England and Wales, 2011, comparing weighted and estimates

	(I)	(II)	(III)	(IV)
Male	0.158***	0.173***	0.132***	0.135***
	(0.003)	(0.004)	(0.003)	(0.004)
Ethnicity (excl. cat., white):				
Indian	-0.073***	-0.059***	-0.054***	-0.039***
	(0.013)	(0.017)	(0.010)	(0.014)
Pakistani	-0.038	-0.039	-0.003	-0.005
	(0.024)	(0.025)	(0.019)	(0.020)
Bangladeshi	-0.065*	-0.067*	-0.048*	-0.054*
	(0.034)	(0.036)	(0.029)	(0.032)
Chinese	0.027	0.026	0.031	0.023
	(0.031)	(0.032)	(0.026)	(0.027)
Black African	-0.189***	-0.187***	-0.117***	-0.110***
	(0.016)	(0.017)	(0.013)	(0.014)
Black Caribbean	-0.093***	-0.098***	-0.060***	-0.063***
	(0.016)	(0.018)	(0.013)	(0.015)
Interaction terms:				
Indian × Male	-0.001	0.001	0.004	0.001
	(0.020)	(0.025)	(0.016)	(0.020)
Pakistani × Male	-0.130***	-0.111***	-0.110***	-0.098***
	(0.031)	(0.034)	(0.025)	(0.028)
Bangladeshi × Male	-0.177***	-0.176***	-0.119***	-0.127***
	(0.046)	(0.051)	(0.039)	(0.046)
Chinese × Male	-0.062	-0.054	-0.072*	-0.052
	(0.049)	(0.051)	(0.041)	(0.045)
Black African × Male	-0.150***	-0.164***	-0.081***	-0.093***
	(0.026)	(0.030)	(0.021)	(0.023)
Black Caribbean × Male	-0.096***	-0.102***	-0.079***	-0.082***
	(0.025)	(0.027)	(0.021)	(0.022)
Individual characteristics	Y	Y	Y	Y
Family characteristics	Y	Y	Y	Y
Occ. & Industry effects	N	N	Y	Y
ASHE-Census weighted	N	Y	N	Y
N of employees	75,234	75,234	75,165	75,165
R^2	0.425	0.439	0.578	0.585

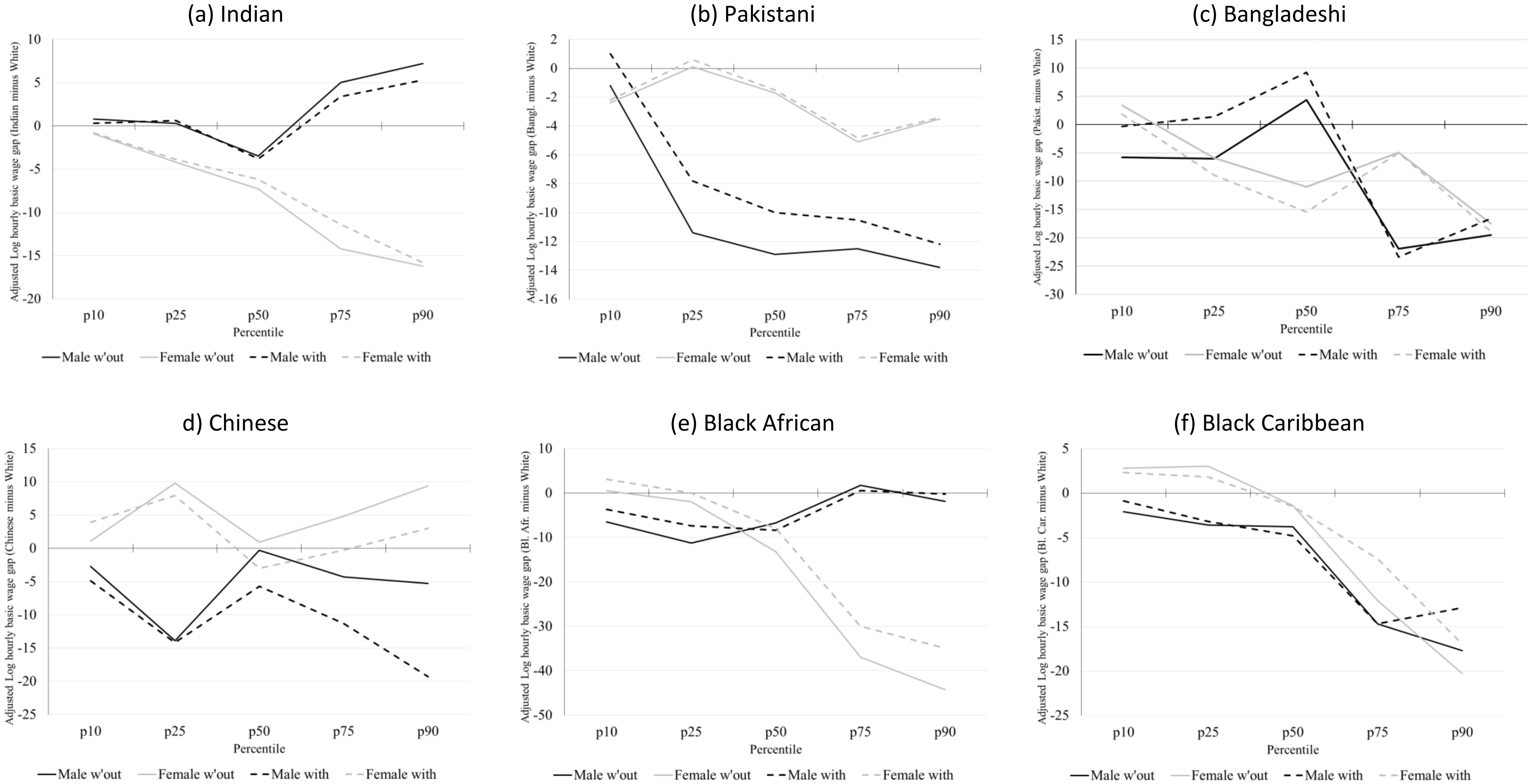
Notes: author calculations using ASHE-Census 2011 dataset. This table reports wage equation estimates for employees in England and Wales, 2011. Columns (I) and (III) report results without applying any weights, while columns (II) and (IV) report comparable results using ASHE-Census weights that look to address the non-random linkage probabilities between the two datasets. The control variables include individual characteristics (age, age squared, education, tenure, tenure squared, disability, non-UK born, English language, health status, workplace region), family characteristics (number of children, age of the youngest child), and occupation and industry characteristics (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.

FIGURE B1: Estimated difference 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 B2 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.

FIGURE B2: 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 B2 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 fixed effects in the models.

TABLE B2: Estimated 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 (excl. white)	Indian	0.005	0.008	0.003	-0.035	0.050	0.072	-0.000	0.003	0.006	-0.038	0.034	0.053
		(0.018)	(0.020)	(0.027)	(0.028)	(0.032)	(0.053)	(0.015)	(0.017)	(0.025)	(0.026)	(0.031)	(0.052)
	Pakistani	**-0.104*****	-0.012	**-0.114*****	**-0.129*****	**-0.125****	-0.138*	**-0.086*****	0.010	**-0.078****	**-0.100****	**-0.105****	-0.122
		(0.026)	(0.043)	(0.037)	(0.044)	(0.052)	(0.075)	(0.024)	(0.039)	(0.035)	(0.045)	(0.052)	(0.077)
	Bangladeshi	**-0.119*****	-0.058	-0.060	0.044	**-0.219*****	-0.195	**-0.093****	-0.003	0.014	0.092	**-0.234****	-0.166
		(0.042)	(0.060)	(0.069)	(0.070)	(0.079)	(0.121)	(0.040)	(0.054)	(0.058)	(0.065)	(0.094)	(0.132)
	Chinese	-0.030	-0.027	**-0.139*****	-0.003	-0.043	-0.053	-0.081	-0.049	**-0.142*****	-0.057	-0.113	-0.193
		(0.053)	(0.039)	(0.040)	(0.064)	(0.104)	(0.199)	(0.050)	(0.038)	(0.039)	(0.071)	(0.103)	(0.193)
	Black Afr.	**-0.055****	**-0.065***	**-0.113*****	**-0.067***	0.017	-0.019	**-0.042***	-0.037	**-0.074****	**-0.084****	0.005	-0.002
		(0.024)	(0.034)	(0.039)	(0.040)	(0.047)	(0.062)	(0.022)	(0.029)	(0.034)	(0.039)	(0.046)	(0.062)
	Black Car.	**-0.077*****	-0.021	-0.036	-0.038	**-0.147*****	**-0.177*****	**-0.073*****	-0.009	-0.032	-0.048	**-0.147*****	**-0.129****
		(0.023)	(0.027)	(0.032)	(0.045)	(0.045)	(0.059)	(0.022)	(0.025)	(0.031)	(0.046)	(0.042)	(0.061)
Female (excl. white)	Indian	**-0.079*****	-0.009	**-0.042****	**-0.073*****	**-0.142*****	**-0.162*****	**-0.069*****	-0.008	**-0.039****	**-0.062*****	**-0.114*****	**-0.158*****
		(0.013)	(0.016)	(0.020)	(0.021)	(0.023)	(0.033)	(0.011)	(0.014)	(0.018)	(0.019)	(0.022)	(0.034)
	Pakistani	-0.025	-0.024	0.001	-0.017	-0.051	-0.035	-0.019	-0.022	0.006	-0.015	-0.048	-0.034
		(0.018)	(0.035)	(0.026)	(0.034)	(0.038)	(0.055)	(0.016)	(0.031)	(0.023)	(0.036)	(0.038)	(0.059)
	Bangladeshi	**-0.059****	0.034	-0.059	**-0.110****	-0.049	**-0.175****	**-0.070****	0.018	**-0.089***	**-0.154*****	-0.050	**-0.189****
		(0.027)	(0.047)	(0.058)	(0.050)	(0.054)	(0.076)	(0.029)	(0.044)	(0.050)	(0.048)	(0.072)	(0.088)
	Chinese	0.040	0.011	**0.098*****	0.009	0.048	0.094	0.007	**0.039***	**0.079*****	-0.030	-0.003	0.030
		(0.034)	(0.029)	(0.030)	(0.051)	(0.069)	(0.114)	(0.031)	(0.023)	(0.029)	(0.055)	(0.068)	(0.108)
	Black Afr.	**-0.175*****	0.005	-0.020	**-0.132*****	**-0.370*****	**-0.443*****	**-0.130*****	0.031	-0.000	**-0.080*****	**-0.300*****	**-0.349*****
		(0.015)	(0.020)	(0.022)	(0.024)	(0.037)	(0.041)	(0.015)	(0.019)	(0.020)	(0.026)	(0.036)	(0.043)
	Black Car.	**-0.058*****	0.028	0.030	-0.014	**-0.121*****	**-0.203*****	**-0.042*****	0.023	0.018	-0.015	**-0.074****	**-0.170*****
		(0.015)	(0.018)	(0.021)	(0.025)	(0.033)	(0.040)	(0.013)	(0.017)	(0.020)	(0.024)	(0.030)	(0.039)
GPG (Male-Female)	white	**0.128*****	**0.051*****	**0.083*****	**0.114*****	**0.163*****	**0.248*****	**0.103*****	**0.033*****	**0.052*****	**0.078*****	**0.140*****	**0.220*****
		(0.005)	(0.007)	(0.009)	(0.008)	(0.010)	(0.014)	(0.005)	(0.006)	(0.006)	(0.008)	(0.009)	(0.015)

Notes: author calculations using ASHE-Census 2011 dataset. See Section 2 & Appendix A for data description. N=55,818 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 6,320. 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, 1-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 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 (excl. white)	Indian	0.008	0.008	0.003	-0.035	0.050	0.072	-0.002	0.003	0.006	-0.038	0.034	0.053
		(0.020)	(0.020)	(0.027)	(0.028)	(0.032)	(0.053)	(0.017)	(0.017)	(0.025)	(0.026)	(0.031)	(0.052)
	Pakistani	-0.088***	-0.012	-0.114***	-0.129***	-0.125**	-0.138*	-0.086***	0.010	-0.078**	-0.100**	-0.105**	-0.122
		(0.027)	(0.043)	(0.037)	(0.044)	(0.052)	(0.075)	(0.025)	(0.039)	(0.035)	(0.045)	(0.052)	(0.077)
	Bangladeshi	-0.122***	-0.058	-0.060	0.044	-0.219***	-0.195	-0.107**	-0.003	0.014	0.092	-0.234**	-0.166
		(0.045)	(0.060)	(0.069)	(0.070)	(0.079)	(0.121)	(0.046)	(0.054)	(0.058)	(0.065)	(0.094)	(0.132)
	Chinese	-0.007	-0.027	-0.139***	-0.003	-0.043	-0.053	-0.084*	-0.049	-0.142***	-0.057	-0.113	-0.193
		(0.057)	(0.039)	(0.040)	(0.064)	(0.104)	(0.199)	(0.050)	(0.038)	(0.039)	(0.071)	(0.103)	(0.193)
	Black Afr.	-0.068***	-0.065*	-0.113***	-0.067*	0.017	-0.019	-0.050**	-0.037	-0.074**	-0.084**	0.005	-0.002
		(0.026)	(0.034)	(0.039)	(0.040)	(0.047)	(0.062)	(0.024)	(0.029)	(0.034)	(0.039)	(0.046)	(0.062)
	Black Car.	-0.083***	-0.021	-0.036	-0.038	-0.147***	-0.177***	-0.079***	-0.009	-0.032	-0.048	-0.147***	-0.129**
		(0.024)	(0.027)	(0.032)	(0.045)	(0.045)	(0.059)	(0.024)	(0.025)	(0.031)	(0.046)	(0.042)	(0.061)
Female (excl. white)	Indian	-0.072***	-0.009	-0.042**	-0.073***	-0.142***	-0.162***	-0.063***	-0.008	-0.039**	-0.062***	-0.114***	-0.158***
		(0.015)	(0.016)	(0.020)	(0.021)	(0.023)	(0.033)	(0.013)	(0.014)	(0.018)	(0.019)	(0.022)	(0.034)
	Pakistani	-0.027	-0.024	0.001	-0.017	-0.051	-0.035	-0.017	-0.022	0.006	-0.015	-0.048	-0.034
		(0.018)	(0.035)	(0.026)	(0.034)	(0.038)	(0.055)	(0.016)	(0.031)	(0.023)	(0.036)	(0.038)	(0.059)
	Bangladeshi	-0.059**	0.034	-0.059	-0.110**	-0.049	-0.175**	-0.064**	0.018	-0.089*	-0.154***	-0.050	-0.189**
		(0.028)	(0.047)	(0.058)	(0.050)	(0.054)	(0.076)	(0.032)	(0.044)	(0.050)	(0.048)	(0.072)	(0.088)
	Chinese	0.025	0.011	0.098***	0.009	0.048	0.094	0.010	0.039*	0.079***	-0.030	-0.003	0.030
		(0.039)	(0.029)	(0.030)	(0.051)	(0.069)	(0.114)	(0.032)	(0.023)	(0.029)	(0.055)	(0.068)	(0.108)
	Black Afr.	-0.169***	0.005	-0.020	-0.132***	-0.370***	-0.443***	-0.127***	0.031	-0.000	-0.080***	-0.300***	-0.349***
		(0.017)	(0.020)	(0.022)	(0.024)	(0.037)	(0.041)	(0.017)	(0.019)	(0.020)	(0.026)	(0.036)	(0.043)
	Black Car.	-0.058***	0.028	0.030	-0.014	-0.121***	-0.203***	-0.041***	0.023	0.018	-0.015	-0.074**	-0.170***
		(0.016)	(0.018)	(0.021)	(0.025)	(0.033)	(0.040)	(0.015)	(0.017)	(0.020)	(0.024)	(0.030)	(0.039)
GPG (Male-Female)	white	0.135***	0.051***	0.083***	0.114***	0.163***	0.248***	0.109***	0.033***	0.052***	0.078***	0.140***	0.220***
		(0.005)	(0.007)	(0.009)	(0.008)	(0.010)	(0.014)	(0.005)	(0.006)	(0.006)	(0.008)	(0.009)	(0.015)

Notes: See Table B2. The estimates here instead apply ASHE-Census probability weights, as described in Appendix A. *N*=55,818 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 6,320. 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, 1-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: 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	0.017	-0.002	-0.012	-0.058**	0.050	0.107*	0.005	-0.008	-0.004	-0.066**	0.030	0.086
		(0.022)	(0.024)	(0.027)	(0.028)	(0.032)	(0.055)	(0.019)	(0.021)	(0.025)	(0.027)	(0.031)	(0.053)
	Pakistani	-0.089***	-0.027	-0.060	-0.155***	-0.162***	-0.087	-0.096***	0.007	-0.034	-0.125***	-0.124***	-0.106
		(0.029)	(0.050)	(0.041)	(0.045)	(0.047)	(0.078)	(0.030)	(0.044)	(0.041)	(0.047)	(0.047)	(0.079)
	Bangladeshi	-0.113**	-0.110	-0.078	-0.033	-0.161*	-0.286**	-0.094**	-0.039	-0.014	0.016	-0.156*	-0.258*
		(0.045)	(0.067)	(0.068)	(0.073)	(0.086)	(0.140)	(0.044)	(0.066)	(0.058)	(0.069)	(0.092)	(0.150)
	Chinese	-0.035	-0.048	-0.112**	-0.060	-0.045	-0.261	-0.093*	-0.062	-0.131***	-0.086	-0.114	-0.431**
		(0.057)	(0.046)	(0.046)	(0.066)	(0.105)	(0.191)	(0.051)	(0.047)	(0.045)	(0.070)	(0.103)	(0.192)
	Black Afr.	-0.096***	-0.079*	-0.162***	-0.108***	-0.039	-0.053	-0.068***	-0.036	-0.109***	-0.098**	-0.031	-0.033
		(0.026)	(0.043)	(0.041)	(0.040)	(0.042)	(0.061)	(0.024)	(0.037)	(0.035)	(0.039)	(0.042)	(0.060)
	Black Car.	-0.090***	-0.028	-0.063*	-0.038	-0.144***	-0.118*	-0.083***	-0.008	-0.062*	-0.047	-0.144***	-0.064
		(0.024)	(0.033)	(0.033)	(0.043)	(0.046)	(0.063)	(0.024)	(0.032)	(0.033)	(0.043)	(0.043)	(0.065)
Female (excl. white)	Indian	-0.060***	-0.004	-0.031	-0.056***	-0.119***	-0.124***	-0.053***	0.002	-0.031*	-0.042**	-0.090***	-0.120***
		(0.016)	(0.019)	(0.021)	(0.021)	(0.023)	(0.036)	(0.014)	(0.015)	(0.018)	(0.019)	(0.024)	(0.038)
	Pakistani	-0.019	-0.015	-0.028	-0.004	-0.029	-0.043	-0.009	-0.010	-0.010	0.000	-0.037	-0.022
		(0.020)	(0.041)	(0.029)	(0.035)	(0.035)	(0.056)	(0.018)	(0.035)	(0.029)	(0.037)	(0.035)	(0.059)
	Bangladeshi	-0.065**	0.099**	-0.042	-0.090*	-0.065	-0.135	-0.064**	0.075*	-0.066	-0.116**	-0.053	-0.125
		(0.029)	(0.048)	(0.054)	(0.049)	(0.060)	(0.086)	(0.032)	(0.045)	(0.047)	(0.049)	(0.069)	(0.092)
	Chinese	0.028	0.020	0.084**	0.028	0.031	0.115	0.003	0.050*	0.075**	-0.016	-0.021	0.040
		(0.040)	(0.034)	(0.037)	(0.046)	(0.066)	(0.113)	(0.032)	(0.028)	(0.035)	(0.048)	(0.064)	(0.109)
	Black Afr.	-0.160***	0.004	0.000	-0.110***	-0.315***	-0.437***	-0.120***	0.032	0.019	-0.067**	-0.251***	-0.346***
		(0.017)	(0.026)	(0.024)	(0.026)	(0.031)	(0.041)	(0.017)	(0.024)	(0.023)	(0.027)	(0.032)	(0.041)
	Black Car.	-0.064***	0.027	0.063***	-0.042	-0.128***	-0.231***	-0.044***	0.010	0.056***	-0.031	-0.080***	-0.190***
		(0.016)	(0.022)	(0.022)	(0.027)	(0.030)	(0.041)	(0.016)	(0.020)	(0.021)	(0.026)	(0.028)	(0.039)
GPG (Male-Female)	white	0.159***	0.074***	0.107***	0.147***	0.185***	0.269***	0.126***	0.047***	0.067***	0.106***	0.155***	0.237***
		(0.005)	(0.008)	(0.010)	(0.008)	(0.010)	(0.014)	(0.005)	(0.007)	(0.007)	(0.007)	(0.009)	(0.014)

Notes: See Table B2. The estimates here are equivalent but using log earnings per hour as the dependent variables instead of log hourly basic wages, N=55,818 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 6,320. 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, 1-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 B5: 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. W. Brit.)	Indian	0.005	0.007	0.000	-0.035	0.051	0.074	0.000	-0.002	0.003	-0.039	0.038	0.062
		(0.018)	(0.020)	(0.027)	(0.028)	(0.032)	(0.053)	(0.015)	(0.017)	(0.025)	(0.025)	(0.031)	(0.053)
	Pakistani	-0.103***	-0.018	-0.114***	-0.129***	-0.114**	-0.153**	-0.087***	0.003	-0.078**	-0.099**	-0.094*	-0.138*
		(0.026)	(0.043)	(0.037)	(0.043)	(0.051)	(0.076)	(0.024)	(0.040)	(0.035)	(0.045)	(0.052)	(0.079)
	Bangladeshi	-0.119***	-0.059	-0.061	0.041	-0.222***	-0.201*	-0.089**	-0.000	0.017	0.093	-0.234**	-0.177
		(0.042)	(0.060)	(0.069)	(0.069)	(0.079)	(0.122)	(0.040)	(0.055)	(0.058)	(0.065)	(0.092)	(0.132)
	Chinese	-0.029	-0.026	-0.137***	-0.004	-0.046	-0.114	-0.085*	-0.059	-0.141***	-0.069	-0.124	-0.245
		(0.053)	(0.039)	(0.040)	(0.064)	(0.103)	(0.201)	(0.050)	(0.037)	(0.040)	(0.070)	(0.103)	(0.195)
	Black Afr.	-0.056**	-0.067*	-0.115***	-0.068*	0.021	-0.021	-0.040*	-0.036	-0.067**	-0.081**	0.005	-0.002
		(0.024)	(0.034)	(0.039)	(0.040)	(0.047)	(0.062)	(0.023)	(0.029)	(0.034)	(0.039)	(0.046)	(0.064)
	Black Car.	-0.077***	-0.016	-0.038	-0.038	-0.144***	-0.184***	-0.068***	-0.003	-0.028	-0.039	-0.146***	-0.133**
		(0.023)	(0.027)	(0.032)	(0.045)	(0.045)	(0.060)	(0.022)	(0.025)	(0.031)	(0.046)	(0.042)	(0.062)
Female (excl. W. Brit.)	Indian	-0.080***	-0.007	-0.044**	-0.076***	-0.148***	-0.162***	-0.068***	0.002	-0.035*	-0.063***	-0.120***	-0.163***
		(0.014)	(0.017)	(0.020)	(0.021)	(0.023)	(0.034)	(0.011)	(0.014)	(0.019)	(0.019)	(0.022)	(0.035)
	Pakistani	-0.026	-0.022	0.001	-0.019	-0.056	-0.027	-0.018	-0.018	0.011	-0.015	-0.055	-0.026
		(0.018)	(0.035)	(0.026)	(0.034)	(0.038)	(0.056)	(0.017)	(0.032)	(0.023)	(0.036)	(0.038)	(0.060)
	Bangladeshi	-0.062**	0.039	-0.056	-0.113**	-0.057	-0.182**	-0.070**	0.023	-0.085*	-0.150***	-0.046	-0.202**
		(0.027)	(0.048)	(0.058)	(0.049)	(0.053)	(0.076)	(0.029)	(0.045)	(0.050)	(0.049)	(0.067)	(0.089)
	Chinese	0.038	0.011	0.097***	0.005	0.038	0.140	0.007	0.041*	0.080***	-0.029	-0.017	0.058
		(0.034)	(0.029)	(0.030)	(0.050)	(0.069)	(0.117)	(0.031)	(0.023)	(0.028)	(0.055)	(0.068)	(0.111)
	Black Afr.	-0.177***	0.006	-0.020	-0.135***	-0.374***	-0.454***	-0.132***	0.038*	0.001	-0.085***	-0.300***	-0.364***
		(0.016)	(0.020)	(0.022)	(0.024)	(0.037)	(0.042)	(0.016)	(0.020)	(0.021)	(0.026)	(0.037)	(0.045)
	Black Car.	-0.059***	0.024	0.033	-0.017	-0.125***	-0.205***	-0.045***	0.022	0.020	-0.021	-0.073**	-0.172***
		(0.015)	(0.019)	(0.020)	(0.025)	(0.033)	(0.041)	(0.014)	(0.017)	(0.020)	(0.025)	(0.031)	(0.041)
GPG (Male-Female)	white	0.128***	0.051***	0.081***	0.113***	0.165***	0.252***	0.103***	0.033***	0.052***	0.078***	0.143***	0.222***
		(0.005)	(0.007)	(0.010)	(0.008)	(0.010)	(0.015)	(0.005)	(0.006)	(0.006)	(0.008)	(0.010)	(0.015)

Notes: See Table B2. 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*=53,330 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 6,014. 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, 1-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.

C. Additional Tables and Figures

TABLE C1: Oaxaca-Blinder decompositions of the log hourly basic wage gap for INDIAN compared to white employees, 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	**0.030**	0.018	-0.011	0.038	0.040	**0.073**	**0.030**	0.018	-0.011	0.038	0.040	**0.073**
	Firm effects – Total							**0.016**	0.001	-0.002	0.012	**0.023**	**0.062**
	Private sector							0.000	0.001	0.001	0.000	0.000	-0.001
	Firm size							-0.006	-0.006	-0.006	-0.006	-0.007	-0.004
	Residual							0.022	0.006	0.003	0.018	0.030	0.066
Characteristics:	Total	**0.056**	0.007	-0.002	**0.083**	**0.099**	**0.082**	**0.044**	0.024	0.013	**0.067**	**0.074**	0.035
	Age	-0.009	0.003	0.009	-0.001	-0.026	-0.046	-0.014	0.004	0.007	-0.005	-0.030	-0.058
	Tenure & Part-time	-0.007	-0.008	-0.018	-0.017	-0.003	0.019	-0.006	-0.007	-0.015	-0.015	-0.003	0.018
	Highest qualification	0.026	0.007	0.000	0.028	0.056	0.051	0.026	0.008	0.004	0.026	0.054	0.050
	Non-UK born	-0.001	-0.007	-0.009	-0.002	0.005	0.007	-0.003	-0.004	-0.007	-0.003	0.002	-0.006
	Family chars	-0.004	-0.003	-0.004	-0.003	-0.009	-0.005	-0.001	-0.002	-0.003	-0.002	-0.006	0.004
	Region (NUTS1)	0.053	0.023	0.037	0.082	0.067	0.046	0.036	0.030	0.038	0.059	0.037	0.006
	Occupation (1-digit)	-0.001	-0.007	-0.017	-0.002	0.011	0.011	0.006	-0.004	-0.010	0.009	0.020	0.022
	Male	0.000	0.000	0.000	0.000	-0.001	-0.001	0.000	0.000	0.000	0.000	-0.001	-0.001
Coefficients:	Total	-0.026	0.011	-0.009	-0.045	-0.059	-0.009	**-0.031**	-0.008	-0.022	-0.042	**-0.056**	-0.024
	Age	0.069	0.151	-0.258	-0.275	0.158	0.576	0.292	0.095	-0.115	-0.105	0.402	1.113
	Tenure & Part-time	-0.018	0.010	0.028	-0.028	-0.083	-0.117	-0.026	0.014	0.024	-0.034	-0.097	-0.152
	Highest qualification	-0.036	0.041	0.172	-0.124	-0.092	-0.115	-0.005	0.068	0.170	-0.061	-0.044	-0.111
	Non-UK born	0.000	0.000	-0.001	0.000	0.000	0.000	-0.001	-0.001	-0.001	-0.001	0.000	-0.002
	Family chars	-0.044	-0.021	-0.026	-0.031	-0.083	-0.065	-0.029	-0.011	-0.014	-0.020	-0.068	-0.035
	Region (NUTS1)	-0.033	0.088	0.015	0.083	0.026	-0.005	-0.068	0.135	0.043	0.019	-0.096	-0.106
	Occupation (1-digit)	-0.116	-0.004	-0.078	-0.145	-0.364	-0.102	-0.063	0.030	-0.044	-0.107	-0.293	-0.036
	Male	-0.001	0.000	-0.003	-0.015	0.032	0.013	-0.002	0.008	0.003	-0.013	0.022	-0.001
	Constant	0.153	-0.255	0.142	0.490	0.348	-0.194	-0.130	-0.347	-0.088	0.279	0.118	-0.695

Notes: See Table 2 and Figure 3 in the main text. *N* of white employees =51,435 for all models. *N* of Indian employees =1,571. 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 5% level – tests only for 'Total' components.

TABLE C2: Oaxaca-Blinder decompositions of the log hourly basic wage gap for PAKISTANI compared to white employees, 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	**-0.077**	**-0.042**	**-0.097**	**-0.088**	**-0.105**	-0.090	**-0.077**	**-0.042**	**-0.097**	**-0.088**	**-0.105**	-0.090
	Firm effects – Total							-0.002	-0.012	**-0.029**	-0.011	0.007	0.031
	Private sector							0.000	0.003	0.003	0.000	-0.001	-0.003
	Firm size							-0.001	-0.004	-0.002	-0.001	-0.002	0.002
	Residual							0.000	-0.011	-0.030	-0.010	0.010	0.032
Characteristics:	Total	**-0.059**	-0.033	-0.015	-0.069	**-0.125**	-0.179	-0.048	-0.018	-0.009	-0.063	**-0.113**	-0.183
	Age	-0.049	0.006	0.011	-0.047	-0.062	-0.189	-0.035	0.015	0.023	-0.041	-0.052	-0.178
	Tenure & Part-time	-0.024	-0.026	-0.038	-0.021	-0.036	-0.003	-0.020	-0.023	-0.033	-0.007	-0.032	-0.002
	Highest qualification	0.017	0.010	0.016	0.014	0.015	0.033	0.017	0.008	0.012	0.018	0.020	0.029
	Non-UK born	0.000	-0.001	-0.003	-0.001	0.001	0.000	-0.002	0.001	-0.003	-0.001	-0.002	-0.005
	Family chars	-0.003	0.007	-0.002	-0.003	-0.009	-0.015	-0.004	0.002	-0.001	-0.003	-0.007	-0.017
	Region (NUTS1)	0.032	-0.017	0.036	0.050	-0.005	0.011	0.026	-0.013	0.032	0.028	-0.011	0.014
	Occupation (1-digit)	-0.035	-0.016	-0.038	-0.063	-0.026	-0.033	-0.032	-0.013	-0.040	-0.058	-0.021	-0.033
	Male	0.004	0.004	0.001	0.002	-0.003	0.017	0.002	0.004	0.000	0.001	-0.007	0.011
Coefficients:	Total	-0.019	-0.010	-0.082	-0.019	0.020	0.089	-0.028	-0.012	-0.059	-0.013	0.001	0.063
	Age	0.006	-0.468	-0.144	0.280	-0.134	-0.262	0.225	-0.318	-0.303	0.215	-0.074	0.529
	Tenure & Part-time	-0.001	0.040	0.032	-0.039	-0.039	0.031	0.009	0.044	0.055	-0.050	-0.023	0.018
	Highest qualification	-0.045	-0.020	-0.027	-0.120	-0.075	0.087	-0.043	0.000	-0.013	-0.117	-0.060	0.094
	Non-UK born	0.000	0.001	0.000	0.000	0.000	-0.001	-0.001	0.001	-0.001	0.000	-0.002	-0.004
	Family chars	-0.037	0.005	-0.029	-0.049	-0.035	-0.083	-0.033	0.000	-0.020	-0.038	-0.029	-0.104
	Region (NUTS1)	0.002	0.034	0.042	-0.146	-0.122	-0.081	-0.012	0.018	0.010	-0.122	-0.147	-0.116
	Occupation (1-digit)	0.004	0.015	0.040	0.024	-0.106	-0.081	-0.019	-0.003	-0.051	-0.040	-0.123	-0.072
	Male	-0.042	-0.003	-0.035	-0.045	-0.092	-0.038	-0.041	0.005	-0.026	-0.031	-0.097	-0.052
	Constant	0.095	0.387	0.039	0.078	0.623	0.518	-0.112	0.241	0.291	0.170	0.558	-0.229

Notes: See Table 2 and Figure 3 in the main text. *N* of white employees =51,435 for all models. *N* of Pakistani employees =523. 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 5% level – tests only for 'Total' components.

TABLE C3: Oaxaca-Blinder decompositions of the log hourly basic wage gap for BANGLADESHI compared to White employees, 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	**-0.080**	0.001	**-0.089**	-0.054	**-0.123**	-0.115	**-0.080**	0.001	**-0.089**	-0.054	**-0.123**	-0.115
	Firm effects – Total							0.027	-0.026	-0.010	0.032	**0.060**	**0.084**
	Private sector							0.001	0.009	0.010	0.001	-0.004	-0.011
	Firm size							-0.010	-0.019	-0.022	-0.012	-0.007	0.003
	Residual							0.036	-0.017	0.002	0.043	0.071	0.092
Characteristics:	Total	0.013	0.037	0.036	-0.088	-0.068	0.110	0.018	0.048	0.100	-0.067	-0.103	-0.004
	Age	-0.040	-0.002	0.050	-0.075	-0.065	-0.120	-0.034	-0.007	0.081	-0.049	-0.063	-0.155
	Tenure & Part-time	-0.069	-0.017	-0.058	-0.137	-0.096	-0.046	-0.042	0.019	0.004	-0.097	-0.095	-0.059
	Highest qualification	0.003	0.014	0.005	-0.002	0.002	-0.007	-0.002	0.003	-0.001	-0.001	-0.001	-0.016
	Non-UK born	0.004	0.003	0.009	0.006	0.000	0.003	0.003	0.001	0.006	0.005	-0.003	0.003
	Family chars	0.030	-0.021	0.003	0.061	0.062	0.023	0.012	-0.035	-0.015	0.036	0.041	-0.011
	Region (NUTS1)	0.104	0.042	0.039	0.115	0.061	0.243	0.102	0.041	0.030	0.102	0.048	0.224
	Occupation (1-digit)	-0.023	0.023	-0.010	-0.067	-0.029	-0.009	-0.023	0.024	-0.005	-0.072	-0.025	-0.008
	Male	0.003	-0.003	-0.002	0.009	-0.003	0.023	0.003	0.001	0.000	0.009	-0.005	0.018
Coefficients:	Total	-0.093	-0.036	-0.125	0.034	-0.055	-0.225	-0.125	-0.020	-0.180	-0.020	-0.080	-0.195
	Age	0.618	1.820	0.488	-1.127	-0.590	0.925	0.682	1.974	0.234	-1.444	-0.226	1.562
	Tenure & Part-time	-0.052	-0.060	-0.045	0.044	-0.058	-0.182	-0.048	-0.075	-0.040	0.029	-0.076	-0.169
	Highest qualification	-0.064	-0.131	-0.182	-0.167	-0.223	0.162	-0.106	-0.017	-0.143	-0.160	-0.355	-0.094
	Non-UK born	0.003	0.003	0.006	0.004	-0.001	0.000	0.002	0.001	0.004	0.003	-0.002	0.001
	Family chars	-0.045	-0.034	0.016	-0.014	0.039	-0.162	-0.030	-0.043	0.068	-0.005	0.030	-0.165
	Region (NUTS1)	0.141	-0.133	0.198	0.268	0.243	-0.092	0.072	-0.150	0.210	0.198	0.131	-0.295
	Occupation (1-digit)	0.449	0.220	0.142	0.099	0.678	1.325	0.352	0.186	0.107	-0.055	0.630	1.245
	Male	-0.043	-0.042	-0.053	-0.001	-0.094	0.015	-0.032	-0.009	-0.024	0.013	-0.096	0.005
	Constant	-1.098	-1.678	-0.695	0.928	-0.049	-2.216	-1.016	-1.887	-0.596	1.403	-0.116	-2.286

Notes: See Table 2 and Figure 3 in the main text. *N* of White employees =51,435 for all models. *N* of Bangladeshi employees =175. 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 5% level – tests only for 'Total' components.

TABLE C4: Oaxaca-Blinder decompositions of the log hourly basic wage gap for CHINESE compared to white employees, 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	**0.277**	**0.215**	**0.253**	**0.349**	**0.293**	**0.353**	**0.277**	**0.215**	**0.253**	**0.349**	**0.293**	**0.353**
	Firm effects – Total							**0.095**	0.008	**0.059**	**0.101**	**0.117**	**0.207**
	Private sector							-0.001	-0.006	-0.006	-0.001	0.003	0.007
	Firm size							0.005	0.010	0.013	0.006	0.002	-0.003
	Residual							0.091	0.003	0.052	0.095	0.112	0.203
Characteristics:	Total	**0.261**	0.231	0.252	**0.336**	**0.338**	0.225	**0.177**	**0.234**	0.222	**0.294**	**0.234**	-0.022
	Age	-0.003	-0.007	0.013	0.015	-0.007	-0.024	0.000	0.001	0.018	0.013	0.007	-0.007
	Tenure & Part-time	0.014	0.077	-0.013	-0.038	0.048	0.037	-0.034	0.047	-0.064	-0.062	-0.006	-0.066
	Highest qualification	0.047	-0.018	0.057	0.134	0.041	-0.029	0.033	-0.022	0.069	0.120	0.032	-0.062
	Non-UK born	0.003	-0.048	0.004	0.010	0.019	0.013	0.007	-0.044	0.010	0.019	0.016	0.010
	Family chars	0.012	0.033	0.021	-0.007	0.009	0.017	0.011	0.041	0.022	-0.008	0.003	0.012
	Region (NUTS1)	0.078	0.001	0.040	0.088	0.139	0.158	0.057	0.018	0.036	0.056	0.124	0.078
	Occupation (1-digit)	0.116	0.195	0.136	0.140	0.098	0.060	0.106	0.196	0.135	0.159	0.060	0.012
	Male	-0.006	-0.003	-0.006	-0.006	-0.009	-0.006	-0.003	-0.002	-0.005	-0.003	-0.002	0.002
Coefficients:	Total	0.016	-0.016	0.000	0.012	-0.045	0.127	0.005	-0.027	-0.028	-0.046	-0.059	0.168
	Age	-0.143	1.056	-0.489	-0.281	-0.439	0.675	0.162	1.041	-0.312	-0.008	-0.669	0.784
	Tenure & Part-time	-0.129	0.168	0.097	-0.078	-0.245	-0.613	-0.036	0.189	0.129	-0.070	-0.040	-0.324
	Highest qualification	0.214	1.152	0.768	-0.089	-0.225	-0.123	0.119	1.160	0.770	-0.013	-0.172	-0.265
	Non-UK born	0.001	-0.006	0.002	0.002	0.002	0.000	0.001	-0.006	0.002	0.003	0.002	0.001
	Family chars	-0.027	-0.096	-0.057	-0.049	-0.005	-0.062	-0.019	-0.084	-0.055	-0.022	-0.024	-0.007
	Region (NUTS1)	0.029	-0.161	-0.164	0.042	0.141	0.120	0.018	-0.130	-0.193	0.106	0.217	0.132
	Occupation (1-digit)	-0.385	-0.221	-0.276	-0.243	-0.573	-1.038	-0.271	-0.213	-0.216	-0.179	-0.395	-0.804
	Male	0.002	0.005	0.027	0.008	0.016	-0.056	-0.020	0.005	0.035	-0.002	-0.040	-0.121
	Constant	0.453	-1.912	0.092	0.699	1.283	1.224	0.051	-1.988	-0.187	0.139	1.063	0.772

Notes: See Table 2 and Figure 4 in the main text. *N* of white employees =51,435 for all models. *N* of Chinese employees =189. 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 5% level – tests only for 'Total' components.

TABLE C5: Oaxaca-Blinder decompositions of the log hourly basic wage gap for BLACK AFRICAN compared to white employees, 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	**-0.085**	-0.015	**-0.062**	**-0.064**	**-0.118**	**-0.145**	**-0.085**	-0.015	**-0.062**	**-0.064**	**-0.118**	**-0.145**
	Firm effects – Total							**-0.019**	**-0.034**	**-0.021**	-0.017	-0.007	**-0.038**
	Private sector							0.000	0.004	0.004	0.000	-0.002	-0.005
	Firm size							-0.002	-0.006	-0.006	-0.002	-0.001	0.003
	Residual							-0.017	-0.032	-0.020	-0.015	-0.005	-0.036
Characteristics:	Total	0.004	0.009	-0.008	-0.032	0.063	-0.029	-0.008	0.020	-0.008	-0.048	0.040	-0.058
	Age	-0.001	0.000	-0.002	0.001	0.003	-0.010	-0.003	-0.004	-0.005	0.000	0.001	-0.010
	Tenure & Part-time	-0.034	-0.004	-0.012	-0.076	-0.037	-0.004	-0.035	-0.001	0.000	-0.077	-0.038	-0.024
	Highest qualification	0.031	0.012	0.028	0.030	0.043	0.036	0.018	0.000	0.018	0.019	0.023	0.019
	Non-UK born	-0.009	-0.020	-0.025	-0.013	0.003	0.001	-0.008	-0.013	-0.019	-0.013	0.001	-0.002
	Family chars	-0.008	0.004	0.009	-0.011	-0.016	-0.024	-0.004	0.008	0.008	-0.009	-0.011	-0.021
	Region (NUTS1)	0.063	0.030	0.037	0.100	0.093	0.031	0.051	0.041	0.025	0.077	0.073	0.021
	Occupation (1-digit)	-0.037	-0.014	-0.042	-0.062	-0.023	-0.056	-0.026	-0.012	-0.034	-0.047	-0.007	-0.038
	Male	-0.001	0.000	0.000	-0.001	-0.003	-0.004	-0.001	0.000	0.000	0.000	-0.002	-0.004
Coefficients:	Total	**-0.089**	-0.024	-0.054	-0.032	**-0.180**	-0.116	**-0.058**	0.002	-0.031	0.002	**-0.150**	-0.049
	Age	-0.453	0.400	0.348	-0.193	-1.527	-1.482	-0.398	0.437	0.260	-0.387	-1.390	-0.958
	Tenure & Part-time	0.040	-0.041	-0.070	0.022	0.095	0.107	0.019	-0.066	-0.095	0.014	0.056	0.082
	Highest qualification	-0.143	-0.188	-0.169	-0.087	-0.140	-0.126	-0.103	-0.138	-0.029	0.014	-0.225	-0.270
	Non-UK born	-0.001	-0.001	-0.002	-0.001	0.000	-0.001	-0.001	-0.001	-0.002	-0.001	0.000	-0.001
	Family chars	-0.034	-0.022	-0.029	-0.033	-0.041	-0.062	-0.034	-0.028	-0.031	-0.036	-0.038	-0.070
	Region (NUTS1)	-0.077	0.202	0.106	-0.117	-0.115	-0.143	-0.077	0.294	0.170	-0.206	-0.090	-0.268
	Occupation (1-digit)	-0.047	0.035	0.033	0.021	-0.057	-0.237	-0.037	0.087	0.062	-0.027	-0.060	-0.170
	Male	-0.025	-0.027	-0.039	-0.040	-0.003	0.000	-0.018	-0.018	-0.017	-0.041	-0.010	0.002
	Constant	0.652	-0.381	-0.233	0.396	1.609	1.827	0.591	-0.566	-0.350	0.672	1.609	1.605

Notes: See Table 2 and Figure 4 in the main text. *N* of white employees =51,435 for all models. *N* of Black African employees = 666. 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 5% level – tests only for 'Total' components.

TABLE C6: Oaxaca-Blinder decompositions of the log hourly basic wage gap for BLACK CARIBBEAN compared to white employees, 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	0.003	**0.055**	**0.064**	**0.046**	**-0.061**	**-0.114**	0.003	**0.055**	**0.064**	**0.046**	**-0.061**	**-0.114**
	Firm effects – Total							0.012	0.007	**0.028**	**0.031**	0.000	0.001
	Private sector							0.001	0.013	-0.002	0.002	-0.006	-0.015
	Firm size							0.000	-0.013	-0.002	-0.002	0.004	0.014
	Residual							0.011	0.008	0.031	0.031	0.002	0.002
Characteristics:	Total	**0.081**	0.067	**0.123**	**0.097**	0.044	0.009	**0.062**	0.054	**0.102**	**0.057**	0.016	0.005
	Age	0.014	0.008	0.018	0.013	0.015	0.005	0.014	0.007	0.016	0.011	0.017	0.013
	Tenure & Part-time	0.005	0.010	0.011	0.006	0.001	-0.003	0.004	0.010	0.010	0.006	-0.001	-0.006
	Highest qualification	-0.007	-0.005	-0.006	-0.007	-0.010	-0.007	-0.006	-0.004	-0.005	-0.006	-0.009	-0.006
	Non-UK born	0.000	-0.001	0.000	0.000	0.000	0.001	0.000	-0.001	0.000	0.001	-0.001	-0.001
	Family chars	-0.009	0.001	-0.001	-0.006	-0.009	-0.021	-0.014	0.003	-0.005	-0.011	-0.014	-0.029
	Region (NUTS1)	0.094	0.057	0.111	0.104	0.068	0.065	0.082	0.050	0.101	0.071	0.046	0.068
	Occupation (1-digit)	-0.013	0.000	-0.004	-0.011	-0.021	-0.027	-0.017	-0.008	-0.011	-0.015	-0.023	-0.027
	Male	-0.002	-0.004	-0.005	-0.002	-0.001	-0.005	-0.001	-0.003	-0.003	0.001	0.000	-0.006
Coefficients:	Total	**-0.078**	-0.012	-0.059	-0.051	**-0.105**	**-0.123**	**-0.070**	-0.007	**-0.066**	-0.042	**-0.078**	**-0.121**
	Age	0.465	0.382	1.540	0.088	-0.122	-0.664	0.510	0.400	1.482	-0.054	-0.140	-0.152
	Tenure & Part-time	-0.046	-0.012	-0.034	-0.065	-0.029	-0.042	-0.050	-0.023	-0.037	-0.074	-0.029	-0.016
	Highest qualification	-0.121	-0.085	-0.024	-0.122	-0.122	-0.167	-0.086	-0.036	0.017	-0.064	-0.123	-0.165
	Non-UK born	0.000	-0.002	0.001	0.001	-0.001	0.000	0.000	-0.002	0.001	0.002	-0.002	-0.004
	Family chars	-0.009	-0.008	0.001	-0.032	-0.016	0.016	0.011	-0.011	0.011	-0.003	0.015	0.042
	Region (NUTS1)	0.074	0.236	-0.106	0.165	-0.035	-0.323	0.081	0.307	-0.048	0.101	-0.082	-0.292
	Occupation (1-digit)	0.042	-0.019	0.034	0.218	0.063	0.049	0.012	-0.043	0.003	0.155	0.058	0.027
	Male	-0.048	-0.003	-0.011	-0.042	-0.069	-0.090	-0.045	0.003	-0.009	-0.042	-0.067	-0.067
	Constant	-0.434	-0.500	-1.461	-0.263	0.227	1.097	-0.504	-0.602	-1.486	-0.063	0.293	0.505

Notes: See Table 2 and Figure 4 in the main text. *N* of white employees =51,435 for all models. *N* of Black Caribbean employees = 736. 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 5% level – tests only for 'Total' components.