Oxford Review of Economic Policy, 2024, **40**, 556–578
https://doi.org/10.1093/oxrep/grae030
Article

Ethnic minority and migrant pay gaps over the life-cycle

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Many thanks to Carlos Vargas-Silva and a referee for comments on an earlier draft. The ERC funded part of this project under grant LPIGMANN 834455.

Abstract

It is well-known that ethnic minority and migrant workers have lower average pay than the White UK-born workforce. However, we know much less about how these gaps vary over the life-cycle because of data limitations. We use new data that combine a 1999–2018 panel from the Annual Survey of Hours and Earnings (ASHE) with individual characteristics from the 2011 Census in England and Wales. We investigate pay gaps on labour market entry and differences in pay growth. We find that differences in entry pay gaps are more important than differences in pay growth. The entry pay gaps are large, though vary across groups. The pay penalties on labour market entry can, to a considerable degree, be explained by over-representation in lower-paying firms and, within firms, in lower-paying occupations. For most groups, the pay gaps at entry seem to be largely preserved over the life-cycle, neither narrowing nor widening. For migrants, we find that the extra pay penalty is concentrated almost exclusively in those who arrived in the UK at later ages.

Keywords: wage gaps, ethnicity, migration, wage growth, ASHE-Census.

JEL codes: J31, J15, J61, J71

I. Introduction

It is well known that ethnic minorities are paid less than similar White British workers (see Clark and Shankley (2020) for a recent review) though the magnitude of the pay gaps varies a lot by ethnicity. Differences in personal characteristics such as age, education, or region of work cannot fully explain these pay gaps (Brynin and Güveli, 2012). There are also large differences in unemployment rates (Clark and Shankley, 2020). Field experiments, where researchers send sets of fictitious job applications to employers which have the same level of education and skill but differ in the ethnicity of the applicant, find evidence of direct discrimination against ethnic minorities in hiring (Wood *et al*., 2009; Heath and Di Stasio, 2019).

There is also not much evidence that these pay gaps have declined, despite policy initiatives aimed at improving the situation of minority workers in the labour market. Manning and Rose (2021) find that pay gaps between Black, Pakistani, and Bangladeshi groups and the White majority in the UK have widened in the past decade.

Existing research on ethnic pay penalties primarily uses cross-sectional data and estimates a single pay gap between ethnic groups.[1] There is little research on how differences in career progression contribute to observed pay gaps.[2] This is surprising considering that divergent wage progression plays a crucial role in explaining the gender

[1] Though Clark and Nolan (2021) investigate how the gaps vary across the pay distribution. They find that Black men face a glass-ceiling barring access to high paid jobs, which has worsened over time, driving an increase in their wage gap. At the bottom of the pay distribution, the introduction of national minimum wages in 1998 helped to reduce the pay gap between ethnic minorities and White workers.

[2] In surveys, workers from minority backgrounds report that this hinders their opportunities for career progression (McGregor-Smith, 2017).

pay gap (Manning and Swaffield, 2008; Blau and Kahn, 2017). Men and women enter the labour market with similar wages, but women average slower pay growth in their twenties and thirties, mainly due to the responsibilities that come with raising children. As a result, there has been a growing interest in understanding the role of career progression, or the lack thereof, in the discussion of labour market inequalities.

The study of ethnic differences in pay progression by ethnicity has been hampered by poor availability of data. The Labour Force Survey (LFS), commonly used to analyse labour market disparities, has, at most, two observations on individual earnings, one year apart. The Annual Survey of Hours and Earnings (ASHE) alone follows individuals for their entire career but lacks much information on individual characteristics, notably ethnicity. Other longitudinal data sets have either too small a sample of ethnic minorities for analysis (e.g. the British Household Panel Survey) or only a short sample period (e.g. the UK Household Longitudinal Survey). As a result of these data deficiencies the best that could be done with available data is to estimate how earnings gaps vary over the life-cycle using repeated cross-sections. However, these estimates may be contaminated with cohort effects and selection into employment that varies with age.

This paper uses new panel data to provide timely evidence on the distinct career dynamics experienced by ethnic minority and migrant groups. ASHE is the most reliable source of wage information in the UK and follows the same individuals over a long period. Our sample covers the years from 1999 to 2018. This has been linked to a rich set of individual characteristics from the 2011 Census in England and Wales, including ethnicity, education, country of birth, and year of entry to the UK. We use these data to understand how pay gaps by ethnicity evolve over the life-cycle. Using the ASHE–2011 Census panel data, we can fully account for individual characteristics and thus accurately isolate the effects of differential wage growth from cohort effects.

The paper investigates pay gaps on labour market entry and differences in pay growth to explore intersectional gaps in career dynamics. We find that differences in entry pay gaps are more important than differences in pay growth. The entry pay gaps are large; after accounting for region of work and educational level, ethnic minority groups face an average wage penalty at entry compared to the White UK-born of 0.23 log points (~23 per cent) for men and 0.17 log points (~17 per cent) for women. This entry gap varies across groups, being widest for Black African migrant men who face a penalty of 0.41 log points. For ethnic minority women, fixed wage gaps are smaller, and again largest for Black African migrant women who face a 0.32 log point penalty. The pay penalties on labour market entry can, to a considerable degree, be explained by over-representation in lower-paying firms and, within firms, in lower-paying occupations (as in Phan *et al.*, 2022). Without considering the role of firms, most of these wage differences would have been attributed to individual characteristics like education and location.

For most groups, the sizeable pay gaps at entry seem to be largely preserved over the life-cycle, neither narrowing nor widening. UK-born ethnic minority men also generally experience slower wage growth throughout their career, but this contributes less to the overall wage gap than the pay gap at entry. The largest growth penalty is for Black Caribbean migrant men: at age 45 around two-thirds of the pay penalty they experience is due to slower wage growth. On the other hand, UK-born women exhibit more pay convergence throughout their career. None of the UK-born women ethnic minority groups experience slower wage growth than Whites. Black African, Indian, Pakistani, and Bangladeshi women experience faster wage growth.

We find that migrants face an extra pay penalty on top of ethnicity but that this is concentrated almost exclusively in those who arrived in the UK at later ages. We argue this is because migrant status will often be invisible to employers while ethnicity rarely is.

The UK is actively engaged in policy discussions aimed at addressing the challenges faced by ethnic minority workers and the disadvantages they encounter. Our research provides policy-makers with a more comprehensive understanding of the evolving inequalities within the labour market for different groups in the UK. By identifying the specific groups that experience significant disparities and pinpointing the specific stages in their careers when these disparities occur, we can develop more targeted and effective policies.

The remainder of the paper is structured as follows: section II describes the data and provides descriptive evidence of ethnic minority and migrant pay gaps across the career; section III presents our empirical strategy to decompose fixed and dynamic pay gaps; section IV outlines results; and in section V we conclude and discuss policy implications.

II. Data and descriptive evidence

Our analysis primarily relies on the Annual Survey of Hours and Earnings (ASHE) matched to the 2011 Census in England and Wales. The ASHE dataset is derived from a 1 per cent sample of employee jobs, extracted randomly from the Pay as You Earn (PAYE) register.

This survey encompasses both the public and private sectors but excludes the self-employed who make up on average 12 per cent of the UK workforce in our sample period. As shown in Table 1, Pakistani and Bangladeshi groups have considerably higher rates of self-employment than the White majority, especially among migrant men for which around 30 per cent are self-employed. Much of the solo self-employment undertaken by this group in the UK is low-pay work with little opportunity for career progression; in 2018 around half of self-employed Pakistanis in the UK were taxi drivers. And the solo self-employed in the UK on average earn less than employees (Giupponi and Xu, 2020). Clark and Drinkwater (2000) suggest that the high rates of self-employment for Pakistani and Bangladeshi men in the UK are partly due to these workers being deterred from paid employment by discrimination. Boeri *et al*. (2020) highlight that for many minority groups solo self-employment is often a transitory state between unemployment and paid work. Although self-employment plays an important role in the career dynamics of ethnic minority and migrant workers, due to the nature of our data, the remainder of this paper is focused on pay gaps over the career for paid employees.

Each year, ASHE provides information on approximately 140,000 to 180,000 employees. As workers are tracked throughout their entire careers based on their NINO (National Insurance Number), multiple years can be combined to create a panel dataset. The ASHE study has been extensively used for research on inequality and wage rigidities, thanks to its comprehensive earnings data and long panel (Elsby *et al*., 2016; Bell *et al*., 2022). Additionally, the inclusion of firm identifiers in the dataset has allowed for investigations into within and between-firm inequality (Schaefer and Singleton, 2020).

The ASHE dataset provides valuable information on employees' hourly earnings, paid hours, occupation as well as a limited number of personal characteristics: gender, age, and location of work. To include a richer set of personal characteristics, the ASHE dataset has been merged with the 2011 Census in England and Wales. The merged dataset includes additional personal characteristics such as educational and vocational qualifications, health status, migration status, country of birth, year of arrival to the UK, and ethnicity.

The dataset linking was done by identifying individuals in ASHE from either 2010, 2011, or 2012 in the 2011 Census by matching on a combination of name, sex, age, and residential postcode. Approximately 62 per cent of eligible ASHE records (2010–12) were matched in this way. The linked panel follows this subset of ASHE individuals with a successful Census match in the period from 1999 to 2018. Hence, only individuals who appeared in the 2011 Census can appear in this panel. We further restrict our sample to those aged 20–50.[3] Figure 1 shows the sample size of each year. As expected, this is highest in 2011 when the linkage was performed.

Table 1: Self-employment rates in England and Wales by migrant status and ethnicity.

	UK-born		Migrant	
Men	**Self-employed %**	**Of which solo %**	**Self-employed %**	**Of which solo %**
White	15.30	77.89	17.06	83.23
Black Caribbean	15.05	91.65	16.35	85.32
Black African	13.20	83.51	11.83	84.76
Indian	14.89	63.95	15.20	67.96
Pakistani/Bangladeshi	21.70	74.54	30.89	78.39
Women	**Self-employed %**	**Of which solo %**	**Self-employed %**	**Of which solo %**
White	7.26	81.85	10.99	88.77
Black Caribbean	4.56	89.20	4.82	91.18
Black African	5.49	89.89	4.95	85.65
Indian	6.35	73.59	8.34	69.34
Pakistani/Bangladeshi	6.55	74.29	10.57	75.75

Source: LFS, 1999–2018, aged 20–50.

[3] This is done because there are fewer than 40 observations for Black African and Pakistani/Bangladeshi migrants past the age of 50, since these are relatively recent migrant cohorts. Similarly, there are insufficient observations for UK-born teenagers (aged 16–19) in most ethnic minority groups. Since our main regression specification involves separately estimating ethnic and migrant pay gaps at each age group with individual fixed effects, we drop age ranges where there is insufficient sample size.

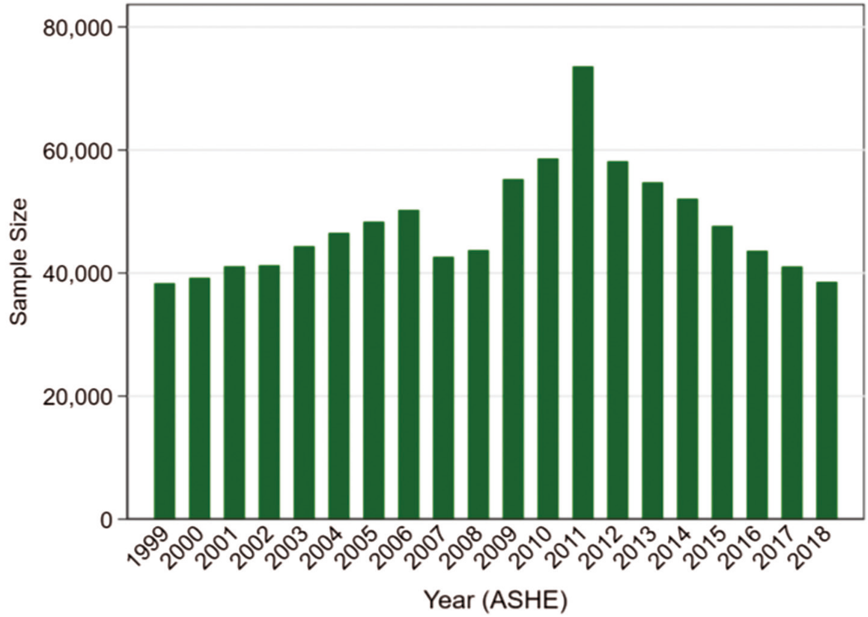

Figure 1: Sample size by ASHE year.
Source: Office for National Statistics (ONS) ASHE–2011 Census.

The quality of linkage between ASHE records (2010–12) and the 2011 Census varies by employee, job, and employer characteristics. Linkage rates are lower for older and younger workers, greater for male employees, and lower for those living in high density areas like London (Forth *et al*., 2022). Since linkage rates are lower in London, ethnic minorities and migrants are under-represented in the ASHE–2011 Census sample (see Appendix). This non-random sampling has the potential to bias our pay gap estimates if, for example, linkage quality by ethnicity also correlates with hourly pay. However, in the Appendix we show that the relationship between linkage quality and hourly pay is weak with the inclusion of region and age controls (included in all our main regressions), which absorb the variation in linkage quality. Furthermore, our results are robust to applying sample weights designed by the ONS to make the ASHE–2011 Census sample representative of all jobs held by employees in England and Wales in 2011.

Also, in the Appendix we repeat our analysis using the Quarterly Labour Force Survey (QLFS) to check the representativeness of the ASHE–2011 Census sample. Population characteristics and cross-sectional pay gaps in the QLFS are similar to those in the ASHE–2011 Census sample, providing further evidence that the sample selection issue does not massively skew our results.

The study of ethnic pay gaps in the UK has made significant progress by acknowledging the diverse nature of Britain's ethnic minority population, resulting in varying average earnings outcomes compared to the White population. Indian men and women tend to have lower wage gaps, while those with Black or Pakistani/Bangladeshi heritage face the largest pay gaps. Ethnic minority women, on average, face smaller pay penalties compared to White women. However, it is important to note that White women already face significant penalties compared to White men. Migrant workers face an additional pay penalty when compared to UK-born of the same ethnicity. In light of this, we examine career wage gaps from an intersectional perspective, considering how gender, migrant status, and ethnicity interact in the labour market.

In our analysis, we study the following ethnic groups: Black Caribbean, Black African, Indian, and Pakistani/Bangladeshi. We chose these groupings based on a combination of previous research documenting differences in pay gaps across ethnic groups and the need to have enough observations for reliable analysis. Some groups (Chinese, Arab, and those of other or mixed heritage) are excluded because of small sample sizes. Even the groups we use are themselves heterogeneous; Black African groups together Nigerians and Somalis, countries separated by 6,000 kilometres.

Figure 2 breaks down the 2011 maximum sample into each ethnic group by migrant status and gender. This figure makes it clear why we've decided to separate Black African and Black Caribbean groups. They display very

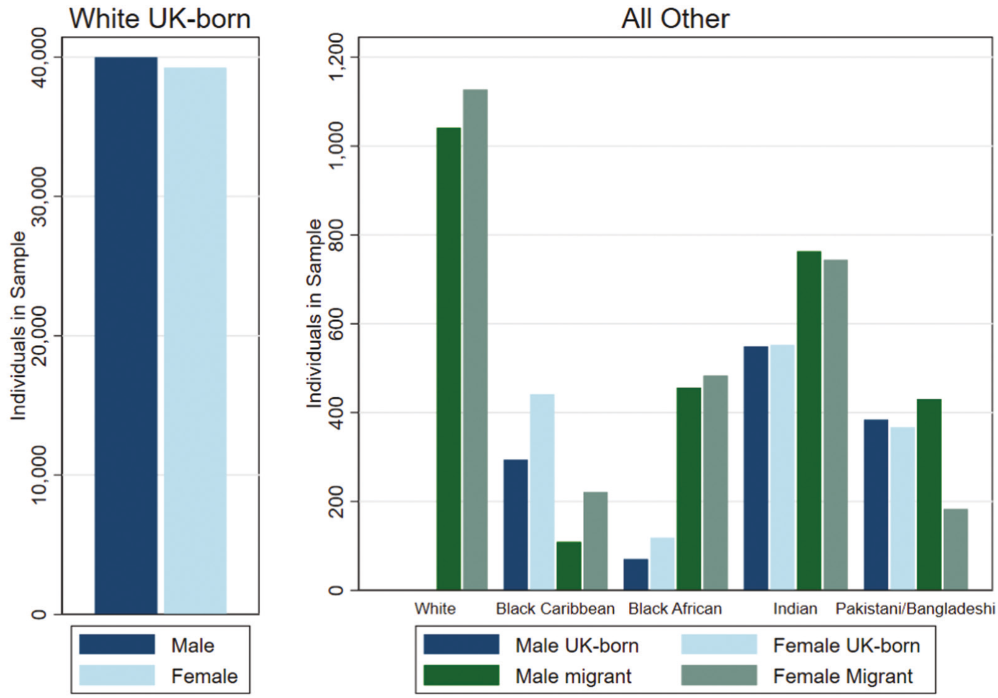

Figure 2: The distribution of the sample by ethnicity, gender, and migration status.
Source: ONS ASHE–2011 Census.

different characteristics in terms of migrant composition: Black African are a much more recent cohort while Black Caribbean are mostly UK-born (e.g. children of the Windrush generation).

A drawback of our data is that while the matched sample covers up to 19 years of an individual's work history (from 1999 to 2018), key demographic variables are only observed at one point in time (in 2011). However, the variables from the 2011 Census which we use in our analysis (ethnicity, country of birth, year of entry to the UK, qualification level) are likely to be fixed after entering the labour market.

(i) Descriptive evidence

Table 2 shows the characteristics of ethnic minority and migrant groups in the ASHE–2011 Census sample, pooling the years 1999–2018. Table 2 illustrates the dangers of simply looking at headline pay gaps. For UK-born men, Black Africans and Indians earn more, on average, than White men, and for UK-born women average hourly earnings are lowest for the White group. But this is not comparing like with like. All ethnic minority and migrant groups are more likely to live in London, where average wages in the UK are highest, and hold at least a bachelor's degree compared to the White UK born majority. This is starkest for the Black African UK born, of which 75 per cent of men and 78 per cent of women in our sample hold a degree.[4] Women all earn less than men of the same ethnicity, and the spread of their average wages by ethnicity is smaller. The most recent migrant cohort are Black Africans while the oldest are Black Caribbeans.

These differences highlight the necessity to control for region of work and qualification level when measuring ethnic and migrant pay gaps. While some minority groups may earn more than the White UK born on average—the highest earning men are White and Indian migrants and women are Black African UK born—they experience a pay penalty when we control for educational level and region of work.

Table 3 presents cross-sectional estimates of the average difference in log hourly wage between each ethnicity/migrant status group and the White UK born majority of the same gender. Even when we look at the pay gap within

[4] This is a bit higher than appears in other sources e.g. the Census and the LFS. But those other sources also find that the UK-born with Black African ethnicity are very highly educated.

Table 2: Sample characteristics (means shown and standard deviation in brackets) by sex, ethnicity, and migrant status.

UK born	Hourly wage	Age	% degree	% in London	N	Hourly wage	Age	% degree	% in London	N
	Men					Women				
White	14.34 (10.79)	39.16 (9.99)	36	11	513,668	11.33 (7.63)	40.27 (9.96)	36	9	518,318
Black Caribbean	12.57 (6.64)	39.72 (8.91)	33	49	3,888	12.46 (7.18)	39.58 (9.19)	38	59	5,674
Black African	15.19 (8.57)	37.28 (9.20)	75	76	793	13.60 (7.54)	37.42 (9.22)	78	69	1,209
Indian	14.58 (11.83)	32.96 (7.77)	57	33	5,793	13.13 (8.94)	33.42 (8.05)	63	33	5,861
Pakistani/ Ban-gladeshi	12.24 (8.43)	30.92 (6.99)	48	27	3,758	11.91 (7.14)	31.26 (7.38)	51	30	3,473
Total	14.32 (10.76)	39.03 (9.98)	36	12	527,900	11.37 (7.65)	40.12 (9.97)	37	10	534,535

Migrant	Hourly wage	Age	% degree	% in London	Time in UK	N	Hourly wage	Age	% degree	% in London	Time in UK	N
	Men						Women					
White	18.16 (16.06)	40.46 (9.38)	51	23	29.66 (14.23)	12,672	13.34 (8.76)	41.39 (9.75)	49	20	29.78 (14.32)	14,253
Black Caribbean	12.26 (7.15)	44.06 (9.76)	27	53	25.73 (15.66)	1,349	10.91 (5.43)	45.27 (9.34)	34	57	27.66 (14.68)	2,719
Black African	12.32 (8.02)	40.51 (9.12)	55	52	14.08 (8.18)	4,599	11.62 (7.26)	40.67 (9.48)	57	56	14.64 (8.47)	5,040
Indian	15.93 (13.49)	41.74 (9.05)	53	37	22.20 (14.60)	8,779	11.93 (8.82)	42.64 (8.89)	45	42	23.76 (13.63)	8,957
Pakistani/ Ban-gladeshi	13.46 (12.40)	37.47 (9.19)	50	40	20.35 (12.48)	4,482	10.98 (6.65)	37.15 (9.18)	42	36	24.54 (11.39)	1,907
Total	15.79 (13.82)	40.55 (9.36)	51	35	23.88 (14.52)	31,881	12.36 (8.27)	41.69 (9.56)	48	36	25.34 (14.25)	32,876

Source: ONS ASHE–2011 Census.

Table 3: Cross-sectional regression table of log hourly wage gap with White UK born, various controls

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Men				**Women**			
White	0.0910***	0.0351***	0.0225***	0.00319	0.0955***	0.0367***	0.0143***	0.00908**
Migrant	(0.00485)	(0.00427)	(0.00476)	(0.00384)	(0.00396)	(0.00345)	(0.00388)	(0.00309)
Black Caribbean	–0.329***	–0.229***	–0.145***	–0.0875***	–0.160***	–0.153***	–0.122***	–0.0731***
Migrant	(0.0113)	(0.0112)	(0.0116)	(0.00874)	(0.00768)	(0.00686)	(0.00702)	(0.00556)
Black Caribbean	–0.259***	–0.217***	–0.185***	–0.113***	–0.0506***	–0.0497***	–0.0544***	–0.0237***
UK born	(0.00680)	(0.00638)	(0.00655)	(0.00532)	(0.00570)	(0.00527)	(0.00569)	(0.00434)
Black African	–0.378***	–0.434***	–0.302***	–0.156***	–0.176***	–0.251***	–0.193***	–0.101***
Migrant	(0.00724)	(0.00671)	(0.00652)	(0.00478)	(0.00627)	(0.00554)	(0.00576)	(0.00450)
Black African	–0.169***	–0.301***	–0.193***	–0.112***	–0.0314**	–0.201***	–0.183***	–0.0911***
UK born	(0.0167)	(0.0160)	(0.0154)	(0.0126)	(0.0117)	(0.0119)	(0.0125)	(0.00944)
Indian	–0.113***	–0.155***	–0.0989***	–0.0831***	–0.117***	–0.134***	–0.105***	–0.0662***
Migrant	(0.00640)	(0.00552)	(0.00590)	(0.00424)	(0.00537)	(0.00467)	(0.00492)	(0.00359)
Indian	–0.0478***	–0.117***	–0.131***	–0.0794***	0.0541***	–0.0475***	–0.0818***	–0.0388***
UK born	(0.00634)	(0.00576)	(0.00585)	(0.00458)	(0.00599)	(0.00547)	(0.00622)	(0.00473)
Pakistani/Bangladeshi	–0.254***	–0.257***	–0.165***	–0.110***	–0.150***	–0.144***	–0.126***	–0.0565***
Migrant	(0.00838)	(0.00724)	(0.00753)	(0.00563)	(0.0106)	(0.00914)	(0.0104)	(0.00722)
Pakistani/Bangladeshi	–0.137***	–0.164***	–0.154***	–0.102***	–0.0346***	–0.0848***	–0.0866***	–0.0457***
UK born	(0.00731)	(0.00663)	(0.00659)	(0.00530)	(0.00756)	(0.00682)	(0.00735)	(0.00558)
Cons	2.510***	2.513***	2.556***	2.552***	2.306***	2.310***	2.354***	2.351***
	(0.000661)	(0.000577)	(0.000491)	(0.000395)	(0.000625)	(0.000533)	(0.000475)	(0.000374)
N	555,925	555,848	483,829	483,828	557,545	557,510	490,130	490,124
r2	0.253	0.433	0.688	0.796	0.211	0.431	0.634	0.772
Controls								
Region - year	X	X	X	X	X	X	X	X
Age	X	X	X	X	X	X	X	X
Educ - year		X	X	X		X	X	X
Firm			X	X			X	X
Occupation				X				X

Notes: Robust standard errors in parentheses. $^{*}P < .05$, $^{**}P < .01$, $^{***}P < .001$.
Source: ONS ASHE–2011 Census.

occupations, firms, regions, education levels, and age, the results show that penalties persist. These estimates are in line with the literature (Clark and Shankley, 2020).

Raw gaps with only region, year, and age controls (column 1) are largest for Black African migrants for both men and women. These gaps generally increase when we control for education, reflecting the fact that minority groups tend to be better educated than the White UK born majority. Further controlling for occupation and firm effects, gaps decrease. However, there are still significant pay gaps within the same firm and occupation for all groups (apart from White migrants).

The pay gaps reported in Table 3 are averages across the life-cycle. While these cross-sectional estimates give a good overview of average pay gaps in the UK, they do not tell us at which point in the career pay penalties arise.

The main interest in this paper is whether these gaps vary with age. As a first look at this, Figure 3 shows estimated earnings profiles by ethnicity, migrant status, and gender, controlling for region of work and year effects.

The main takeaway is that most of the pay gaps are on labour market entry and do not noticeably widen or narrow over the career. For UK-born men, all ethnic minorities enter the labour market at a statistically significant lower wage than Whites. The entry gap is largest for Black minorities and smallest for Indian minorities. On the whole, these gaps don't close over the career cycle, except for Indian UK-born men who earn the same as White UK-born in the same region between the ages of 40 and 50. For UK-born women, the pay gaps at entry are smaller. Women display more convergence in pay throughout their careers. All migrant men and women from ethnic minority groups face an additional penalty compared to UK-born of the same ethnicity. This is highest for Black African male migrant minorities. The Appendix shows that the estimated effects are similar to those found in repeated cross-sections of the LFS, providing reassurance that the unusual nature of the ASHE–2011 Census matched data does not lead to very different conclusions.

The estimates in Figure 3 might also reflect changing cohort characteristics or changing selection into work over the life-cycle. Our main estimates exploit our panel data to account for these possibilities; we now turn to this.

III. Estimation methodology

First, we use our panel data to disaggregate observed wage gaps at each age into the contribution of a fixed pay gap at labour market entry and pay growth gaps. To do this we regress log basic hourly pay from ASHE on a set of dummies $\beta^{g,A}$ that represent each 5-year age category A for distinct groups g, defined by the combination of ethnicity, migrant status, and sex.

With panel data we can follow workers over time and can control for individual fixed effects α_i; this controls for changing selection into work over the life-cycle. For individual i belonging to group g in year t and age category A, log hourly wages w_{it} are given by

$$w_{it} = \beta^{g,A} + \alpha_i + \epsilon_{it} \tag{1}$$

All the regression specifications also control for region of work, time trends, and regional time trends but omit them from the notation in the interests of simplicity. We chose to use dummy coefficients $\beta^{g,A}$ for each age category instead of specifying a functional form in age (e.g. quadratic or quintic). This more flexible specification bypasses the debate over which functional form is best when analysing how wages evolve over the career (Murphy and Welch, 1990). Because of the inclusion of individual fixed effects, we can set $\beta^{g,entry} = 0$ without any loss of generality.

IV. Results

(i) Entry pay and pay growth gaps

The pay on entry is captured by the individual fixed effects. To investigate how these vary with ethnicity we take the estimated fixed effects and regress them on ethnicity. We further look at how much of the fixed effect is explained by education by adding controls for highest qualification level (at a detailed 16-level description from the 2011 Census).

The first two columns of Table 4 show estimates of the entry pay gaps for men (relative to White UK-born), while the fifth and sixth columns show the entry gap for women. Except for the White migrant groups, all the estimated entry pay gaps are negative, implying that all non-White groups earn less than the White UK-born population. For all non-White groups, the entry pay gaps for men are over 10 log points; for women they are generally smaller. Some of the entry pay gaps are very large (41 log points for Black African migrants). Controlling for an individual's highest qualification level widens the pay gap at labour market entry for most groups. This is especially true for

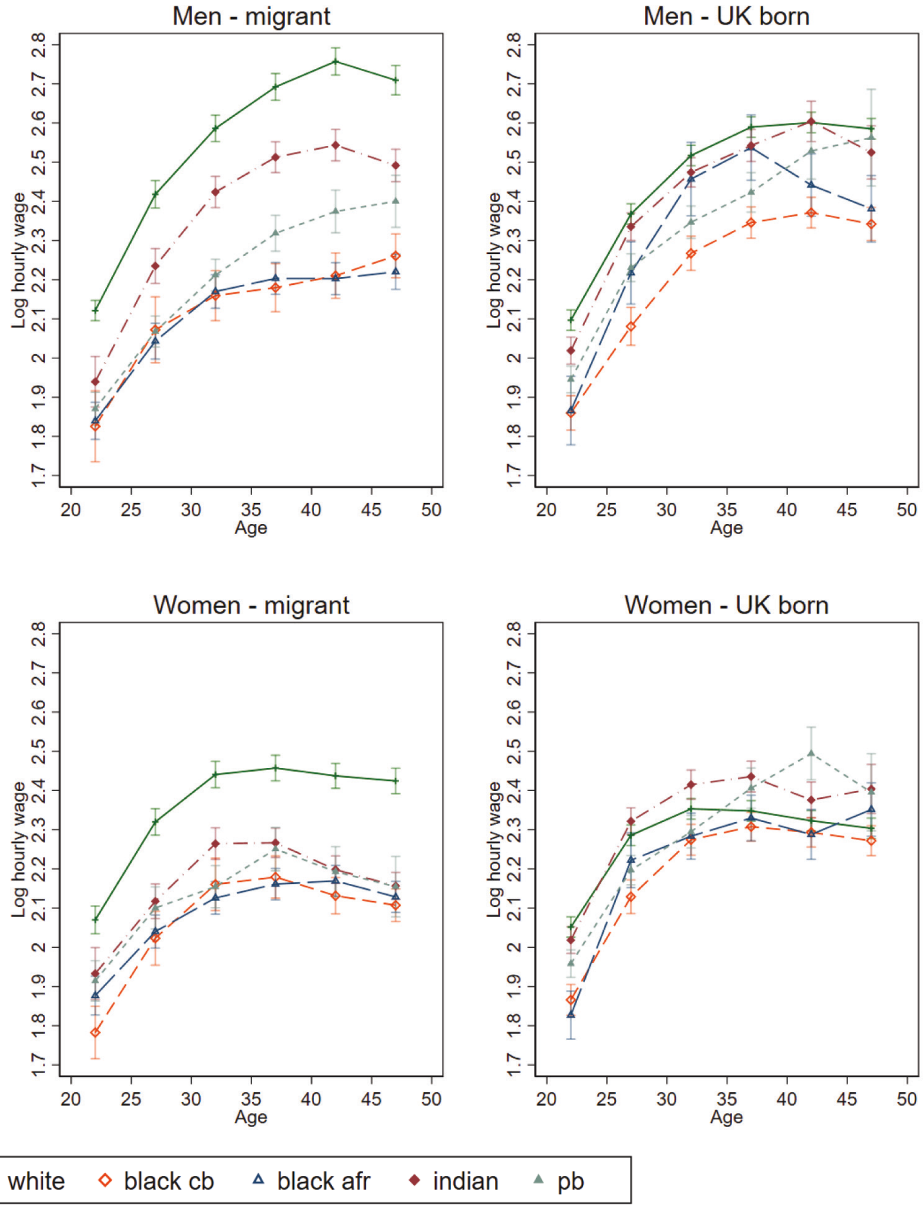

Figure 3: Log hourly wages by ethnic group and age group; year-region controls.
Source: ONS ASHE–2011 Census.

Black African UK-born minorities for whom the pay gap increased by 0.18 log points for women and 0.14 log points for men with the addition of educational controls. This is in line with Clark and Nolan (2021), who also observe that all ethnic groups experience lower earnings compared to the White majority than they would if their qualifications were equally valued and rewarded. For migrants, this might be because foreign qualifications are not equally regarded in the UK. For ethnic minorities, entry pay gaps among those with the same level of education might reflect differences in human capital developed in the labour market (Tomaskovic-Devey *et al.*, 2005) or unmeasured differences in educational quality, like university and subject prestige (Gaddis, 2015). Another possibility, which is supported by field experiments which find evidence of direct labour market discrimination (Wood *et al.*, 2009; Heath and Di Stasio, 2019), is that ethnic minorities with the same human capital are treated unequally by employers.

Table 4: Decomposition entry and growth gaps in log hourly wages. Region-year full interaction controls.

	Men				Women			
	Entry gap		Growth gap		Entry gap		Growth gap	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Entry Gap	Control for education	Growth gap: Entry to 35	Growth gap: 35 to 45	Entry Gap	Control for education	Growth gap: Entry to 35	Growth gap: 35 to 45
White	0.0292	–0.0254	0.0527***	0.0445***	0.0382	–0.0168	0.0579***	0.0191*
Migrant	(0.0207)	(0.0207)	(0.0147)	(0.00839)	(0.0203)	(0.0203)	(0.0151)	(0.00934)
Black CB	–0.103	–0.0126	–0.137**	–0.0498	–0.165***	–0.138**	–0.0416	0.0937***
Migrant	(0.0547)	(0.0547)	(0.0419)	(0.0377)	(0.0434)	(0.0434)	(0.0362)	(0.0234)
Black Caribbean	–0.136***	–0.0931**	–0.0775***	–0.0471***	–0.0870**	–0.0862**	0.0325	0.0237
UK born	(0.0321)	(0.0321)	(0.0201)	(0.0136)	(0.0306)	(0.0306)	(0.0205)	(0.0123)
Black African	–0.413***	–0.471***	–0.00557	0.0548***	–0.322***	–0.400***	0.0568*	0.150***
Migrant	(0.0366)	(0.0366)	(0.0255)	(0.0164)	(0.0356)	(0.0356)	(0.0278)	(0.0175)
Black African	–0.293***	–0.428***	0.136**	–0.0349	–0.197	–0.372***	0.166***	0.00880
UK born	(0.0690)	(0.0690)	(0.0511)	(0.0335)	(0.107)	(0.107)	(0.0419)	(0.0296)
Indian	–0.141***	–0.190***	0.0391	0.0555***	–0.132***	–0.150***	0.0302	0.0152
Migrant	(0.0284)	(0.0284)	(0.0234)	(0.0107)	(0.0309)	(0.0309)	(0.0278)	(0.0111)
Indian	–0.191*	–0.270***	0.0560***	–0.00929	–0.0626	–0.185***	0.109***	0.00233
UK born	(0.0816)	(0.0816)	(0.0142)	(0.0141)	(0.0510)	(0.0510)	(0.0151)	(0.0134)
Pakistani/Bangladeshi	–0.270***	–0.293***	0.00297	–0.00941	–0.0925*	–0.107*	–0.0788**	–0.0349
Migrant	(0.0401)	(0.0401)	(0.0183)	(0.0142)	(0.0438)	(0.0438)	(0.0281)	(0.0248)
Pakistani/Bangladeshi	–0.292	–0.336	0.0108	0.0193	–0.105	–0.182*	0.000517	0.0802***
UK born	(0.215)	(0.215)	(0.0142)	(0.0186)	(0.0809)	(0.0809)	(0.0162)	(0.0201)
N	555,492				557,154			
r2	0.8644				0.8267			

Notes: Robust standard errors in parentheses. *$P < .05$, **$P < .01$, ***$P < .001$.
Source: ONS ASHE–2011 Census.

Table 4 also shows the pay growth gaps in the early career (between entry and 35), and mid-career (between 35 and 45). The estimates for men are in columns 3 and 4 and for women in columns 7 and 8. These pay growth gaps should be added to the entry growth gaps to give the total pay gap at age 35 or 45. In contrast to the entry pay gaps, the pay growth gaps are not always significantly different from zero and are not always negative. For example, Indian UK-born men are estimated to have pay growth 0.056 log points (~5.6 per cent) higher than White UK-born men. The main conclusion is that most of the pay gaps are on labour market entry and persist through the life-cycle.

(ii) The role of firms and occupation

Segregation by ethnicity into lower-paying occupations or firms could also account for some of the ethnic and migrant pay gap. Evidence for firm-specific wage effects is found by Phan *et al.* (2022) who, using the same ASHE–2011 Census linked sample as we do, find that the concentration of ethnic minorities into lower-paying firms accounts for sizeable parts of estimated wage gaps. Zwysen and Demireva (2020) find that UK-born ethnic minorities are less likely to work in the highest-paying occupations, but the type of disadvantage differs strongly between groups.

To explore labour market entry and growth gaps within and between firms and occupations, we add firm (establishment identifier) fixed effects $\eta_{k(i,t)}$ and occupation (4-digit SIC 2010 codes) fixed effects $\phi_{j(i,t)}$ to our regression.

$$w_{it} = \beta^{g,A} + \alpha_i + \phi_{j(i,t)} + \eta_{k(i,t)} + \epsilon_{it} \qquad (2)$$

This specification is used to decompose the fixed entry wage gap into the contribution of:

(i) fixed entry gap within firm and occupation (differences in the individual fixed effects),
(ii) over-representation of minorities in low-paying occupations at labour market entry,
(iii) over-representation of minorities in low-paying firms at labour market entry.

Likewise, the dynamic growth gap can be decomposed into the contribution of:

(iv) minority groups facingdifferential growth within firm and occupation,
(v) differential occupational upgrading for minority groups,
(vi) differential firm switching behaviour for minority groups.

For simplicity we do not control for education in reporting the average gap in fixed effects. Table 5 decomposes the fixed gap and growth penalty gap (from entry to age 45) for men into the within firm-occupation effects and the between firm-occupation effects.

One systematic finding is that, at labour market entry, all non-White groups are over-represented in low-wage firms and, within those firms, low-wage occupations. The magnitude of this effect is quite similar across groups. One consequence of this is that controlling for firm and occupation fixed effects reduces the gaps in the average fixed effects and most are no longer significantly different from zero. This means that a large part of the entry gaps come from minority groups being concentrated in firms and occupations which pay lower wages at labour market entry. A notable exception are Black African migrants, who still experience large entry gaps within firm and occupation.

For the growth gaps, most, but not all, of the groups seem to have modest firm and occupation upgrading over their careers but not enough to surmount the initial entry gaps faced. Pay gaps remain very substantial at age 45.

Table 6 shows the same results for women. For women, the patterns are similar to those for men; over-representation of non-White groups into low-paying firms and occupations on labour market entry, differences that are partially undone over the course of the career.

The overall conclusion is that the pay penalties experienced by non-White groups are present on labour market entry and largely persist through the life-cycle without either narrowing or widening.

(iii) Migrant wage penalties

Finally, we explore further the pay penalties suffered by migrants. In particular, we investigate different pay gaps by age of arrival in the UK. Migrant workers who arrived at older ages may face extra challenges such as limited English proficiency, qualifications that may not be universally recognized by employers, and unfamiliarity with the cultural norms of the UK. These factors may directly impact their earnings. Our empirical specification differs from the way migrant 'assimilation' effect was initially explored by Chiswick (1978) who revealed a positive correlation between the length of time migrants spent in a host country and their wages.[5]

Length of time in the UK can be inferred from the difference between age and age at arrival. Conditioning on age of arrival has the advantage that it allows a natural comparison with the UK-born as we might expect migrants who arrived at very young ages to be treated similarly to those born in the UK.

Table 7 investigates the impact of age at arrival. The reported migrant wage penalties are in addition to the ethnic wage gaps reported in the first row.

Migrants face an average additional penalty of 0.02 for women and 0.08 log points for men compared to UK-born of the same ethnicity (region, year, age, education controls). Decomposing the migrant penalty by age of arrival group, we find that it is mostly migrants who arrive at older ages that face the largest penalties. For migrants who arrived as children (before age 10), no pay penalty is experienced, and in some cases a pay advantage. This suggests assimilation effects: migrants who arrived older have less UK labour-market-specific knowledge or qualifications and hence experience pay disadvantages; those who arrived young don't face these barriers. This is not that surprising; applications for jobs typically do not ask for country of birth, so a migrant who has been in the UK almost their whole life will seem indistinguishable from someone born in the UK. Their ethnicity will, however, remain visible.

[5] Borjas (1985) pointed out the limitation of the pioneering cross-sectional regression analysis in distinguishing between the influence of time spent in the host country and the different characteristics among different migrant cohorts. Put simply, the presence of strong assimilation in a cross-section could potentially be attributed to the fact that previous migrant cohorts were more skilled. Later studies (Borjas, 1995, 2015) use longitudinal data to address this issue. Selective outmigration of less successful migrants can also bias cross-sectional estimates of migrant assimilation (see Dustmann and Görlach (2015) for a review). Lubotsky (2007) uses longitudinal earnings data to show that selective emigration leads to an overestimation of wage growth for migrants who stay. The size and direction of this bias has been recently debated (Akee and Jones, 2019; Rho and Sanders, 2021).

Table 5: Decomposition entry and growth gaps in log hourly wages. Within and between firm and occupation effects: Men.

MEN	Entry gaps			Growth gaps		
	Individual FE gap	Firm FE gap	Occupation FE gap	Within firm and occ wage growth to 45	Firm switching wage growth to 45	Occupation upgrading wage growth to 45
White Migrant	0.0192 (0.0214)	–0.0125 (0.00955)	0.0108** (0.00349)	0.0848*** (0.0180)	0.0209* (0.0106)	0.0116** (0.00406)
Black Caribbean Migrant	–0.0303 (0.0545)	–0.0629** (0.0242)	–0.0615*** (0.0102)	–0.215*** (0.0483)	0.0373 (0.0270)	–0.00748 (0.0135)
Black Caribbean UK born	–0.0494 (0.0320)	–0.0336** (0.0122)	–0.0468*** (0.00433)	–0.175*** (0.0225)	0.0305* (0.0140)	0.0166** (0.00541)
Black African Migrant	–0.256*** (0.0356)	–0.0331** (0.0107)	–0.0552*** (0.00400)	–0.0202 (0.0291)	–0.00112 (0.0123)	–0.0182*** (0.00523)
Black African UK born	–0.124 (0.0660)	–0.0438* (0.0222)	–0.0273** (0.00914)	–0.0283 (0.0582)	–0.0143 (0.0285)	0.00651 (0.0115)
Indian Migrant	–0.0691* (0.0297)	–0.0497*** (0.0115)	–0.0370*** (0.00594)	0.0323 (0.0272)	0.0475*** (0.0129)	0.0267*** (0.00663)
Indian UK born	–0.143 (0.0958)	–0.0178** (0.00622)	–0.0169*** (0.00240)	0.0388* (0.0173)	0.0320** (0.0106)	0.0107* (0.00486)
Pakistani/Bangladeshi Migrant	–0.221*** (0.0421)	–0.0442*** (0.00839)	–0.0354*** (0.00434)	0.0113 (0.0242)	0.0259* (0.0114)	–0.00272 (0.00627)
Pakistani/Bangladeshi UK born	–0.173 (0.233)	–0.0292*** (0.00574)	–0.0343*** (0.00274)	–0.0748*** (0.0201)	0.0245* (0.0101)	0.0218** (0.00690)

Notes: Regression N = 483,425. Regression r2 = 0.923. Standard errors in parentheses. *P < .05, **P < .01, ***P < .001.
Source: ONS ASHE–2011 Census.

Table 6: Decomposition entry and growth gaps in log hourly wages. Within and between firm and occupation effects: Women.

WOMEN	Entry gaps			Growth gaps		
	Individual FE gap	Firm FE gap	Occupation FE gap	Within firm and occ wage growth to 45	Firm switching wage growth to 45	Occupation upgrading wage growth to 45
White Migrant	0.0248 (0.0208)	–0.00693 (0.00842)	0.00781* (0.00380)	0.0431* (0.0173)	0.0246** (0.00916)	0.0116** (0.00406)
Black Caribbean Migrant	–0.122** (0.0455)	–0.0796*** (0.0130)	–0.0309** (0.00946)	0.00765 (0.0428)	0.0857*** (0.0159)	–0.00748 (0.0135)
Black Caribbean UK born	–0.0462 (0.0315)	–0.0196* (0.00951)	–0.0332*** (0.00354)	0.00836 (0.0247)	0.0258* (0.0107)	0.0166** (0.00541)
Black African Migrant	–0.201*** (0.0350)	–0.0332*** (0.00828)	–0.0316*** (0.00566)	0.0988** (0.0311)	0.0212* (0.0101)	–0.0182*** (0.00523)
Black African UK born	–0.0917 (0.0727)	–0.0498** (0.0174)	–0.0471*** (0.00557)	0.0355 (0.0452)	0.0479* (0.0220)	0.00651 (0.0115)
Indian Migrant	–0.108*** (0.0284)	–0.0278* (0.0126)	–0.0220*** (0.00651)	0.0464 (0.0258)	0.0142 (0.0136)	0.0267*** (0.00663)
Indian UK born	–0.0236 (0.0365)	–0.00579 (0.00619)	–0.00368 (0.00306)	0.0571** (0.0182)	0.00646 (0.00867)	0.0107* (0.00486)
Pakistani/Bangladeshi Migrant	–0.0556 (0.0430)	–0.0431*** (0.00937)	–0.0370*** (0.00690)	–0.102** (0.0321)	0.0480*** (0.0131)	–0.00272 (0.00627)
Pakistani/Bangladeshi UK born	–0.0619 (0.0687)	0.00717 (0.00594)	–0.0109** (0.00348)	0.0199 (0.0240)	0.00877 (0.0131)	0.0218** (0.00690)

Notes: Regression N = 489,675. Regression r2 = 0.890. Standard errors in parentheses. *$P < .05$, **$P < .01$, ***$P < .001$.
Source: ONS ASHE–2011 Census

Table 7: Decomposition of the migrant gap in log hourly wages by age of arrival

	White	Black Caribbean	Black African	Indian	Pakistani/Bangladeshi
			MEN		
Ethnic gap	0	–0.217***	–0.300***	–0.116***	–0.164***
	(.)	(0.00638)	(0.0160)	(0.00576)	(0.00663)
Migrant penalty					
Before age 10	0.0225***	0.0190	0.0581	0.0299**	–0.0000344
	(0.00526)	(0.0207)	(0.0341)	(0.0114)	(0.0133)
Age 10–18	–0.0141	–0.120***	–0.0335	–0.0380***	–0.0593**
	(0.0133)	(0.0249)	(0.0237)	(0.0112)	(0.0184)
Age 19–30	0.0532***	–0.0104	–0.0703***	–0.118***	–0.168***
	(0.0111)	(0.0253)	(0.0212)	(0.0119)	(0.0142)
Age 31–40	0.133***	0.0311	–0.173***	0.0399*	–0.156***
	(0.0174)	(0.0462)	(0.0207)	(0.0160)	(0.0192)
After age 40	0.0821***	–0.0979***	–0.215***	–0.124***	–0.176***
	(0.0178)	(0.0255)	(0.0191)	(0.0176)	(0.0301)
N	555,848	555,848	555,848	555,848	555,848
r2	0.434	0.434	0.434	0.434	0.434
			WOMEN		
Ethnic gap	0	–0.0493***	–0.201***	–0.0476***	–0.0850***
	(.)	(0.00527)	(0.0119)	(0.00547)	(0.00682)
Migrant penalty					
Before age 10	0.0296***	0.0201	0.0310	0.0499***	–0.00460
	(0.00449)	(0.0138)	(0.0295)	(0.0105)	(0.0139)
Age 10–18	0.0249**	–0.0991***	–0.00370	–0.0557***	–0.0948***
	(0.00812)	(0.0122)	(0.0188)	(0.00978)	(0.0222)
Age 19–30	0.0735***	–0.105***	–0.0888***	–0.202***	–0.107***
	(0.00893)	(0.0203)	(0.0155)	(0.00957)	(0.0221)
Age 31–40	0.00336	–0.171***	–0.0284	–0.0494**	–0.0851**
	(0.0163)	(0.0270)	(0.0170)	(0.0167)	(0.0328)
After age 40	0.0477***	–0.208***	–0.0632***	–0.141***	—
	(0.0128)	(0.0158)	(0.0148)	(0.0151)	—
N	557,510	557,510	557,510	557,510	557,510
r2	0.432	0.432	0.432	0.432	0.432

Notes: Fixed-effects controls for: age, region-year, arrival cohort, and highest qualification.
Robust standard errors in parentheses. *P < .05, **P < .01, ***P < .001.
Source: ONS ASHE–2011 Census.

V. Conclusion and policy implications

The UK has large pay gaps between ethnic minorities and the White population. Non-White migrants typically face an additional pay penalty. This paper explores these pay penalties over the life-cycle by gender, ethnicity, and migrant status for the UK using a new data set that links the longitudinal Annual Survey of Hours and Earnings with the 2011 Census. This combines high-quality longitudinal earnings information with individual characteristics that are often missing from employer–employee data sets.

The paper investigates the disparity in wages when individuals enter the labour market, as well as the differences in wage growth. We find that differences in entry pay gaps are more important than differences in pay growth. The entry pay gaps are large, though vary across groups. For most groups, the pay gaps at entry seem to be preserved over the life-cycle, neither narrowing nor widening. For migrants, we find that the extra pay penalty is primarily concentrated among those who arrived in the UK at a later age. We have argued that this is because for migrants who arrived as children migrant status will often be invisible to employers while ethnicity rarely is.

The pay penalties on labour market entry can, to a considerable degree, be explained by over-representation in lower-paying firms and, within firms, in lower-paying occupations. A significant body of literature explores how wage-setting behaviour by firms contributes to inequality in the labour market (Card *et al*., 2013; Song *et al*., 2019). Differences in wage levels among employers may arise due to labour market frictions, monopolistic behaviour on the part of employers, and variations in rent sharing. Ethnic differences can arise, for example, if ethnic minority and migrant groups have lower ability to extract rent (Card *et al*., 2018), or if minority groups have lower reservation wages, strengthening the monopsony power of firms to suppress wages (Amior and Stuhler, 2024).

Occupational segregation of ethnic minorities and migrants into lower paying jobs, within the same firm and education level, can arise as a result of discriminatory practices in hiring (Heath and Di Stasio, 2019) or historical and cultural ties between ethnic groups and certain occupations (Engstrom, 1997). The influence of social networks can also contribute to occupational segregation (Calvó-Armengol and Jackson, 2004; Ioannides and Loury, 2004). If workers are more likely to refer people from their own ethnic group, networks of individuals of the same ethnicity can increase the chances of finding a job through informal referrals. However, if these networks consist mostly of people in low-paying occupations, they can exacerbate occupational segregation.

The pay gaps we have estimated may also be influenced by geographical factors we're unable to capture in our data. Many ethnic minorities live in London, and we have accounted for this by including regional controls. However, labour markets may be more local than broad region (Manning and Petrongolo, 2017) and ethnic minorities are often overrepresented in more deprived urban areas (Clark and Drinkwater, 2002) where job opportunities and average wages are lower.

There are limitations to our research caused by the limitation of the data to employees, omitting those who are self-employed or unemployed. Black Caribbean and African men in particular experience large unemployment gaps, even after controlling for age, region, education, and marriage status (Clark and Shankley, 2020). Pakistani and Bangladeshi men, especially migrants, are more likely to be self-employed (see Table 1). Self-employment often serves as a middle ground between unemployment and traditional employment. In 2019, approximately 25 per cent of newly self-employed individuals were previously unemployed, while an additional 31 per cent were inactive (Giupponi and Xu, 2020). Career dynamics in self-employment and unemployment may be important for a comprehensive understanding of career dynamics but are beyond the scope of this paper.

Moreover, ethnic minorities are disproportionately represented in precarious work arrangements involving 'gig' economy jobs and zero-hours contracts which have rapidly increased over the past decades. Bowyer and Henderson (2020) analyse data from the Next Steps, a longitudinal study of the millennial generation in England, and find that millennials from Black and Asian minority ethnic backgrounds are 47 per cent more likely to be on a zero-hours contract. This suggests that hourly earnings may mask additional pay gaps on the intensive margin, particularly on labour market entry. The scope for promotion and pay progression in these precarious jobs is also limited, therefore pay growth gaps could also widen in the future as these cohorts age.

Our findings, which suggest that there remains widespread disadvantage among non-White groups in the UK labour market, are consistent with evidence from audit studies of employer discrimination (Wood *et al*., 2009; Heath and Di Stasio, 2019). This contrasts with the more optimistic conclusion of the Sewell Report on Race and Ethnic Disparities (Commission on Race and Ethnic Disparities, 2021) which implies that gaps are small and falling. There is an urgent need to develop policies to address this injustice. The finding that most ethnic and migrant pay gaps are incurred at labour market entry suggests that this is a key time for policy intervention. Possible initiatives include providing better career information in schools, improving student–university matching, and ensuring equal access to vocational training for ethnic minorities. It is also essential to address the issues on the employers' side. This involves analysing recruitment procedures and closely examining hiring discrimination, especially in specific occupations where ethnic minorities are under-represented.

Appendix: Addressing potential selection in the ASHE–Census 2011 dataset

In Table A1, we compare the entire population of employees aged 20–50 in the 2011 Census to the sub-set of those in the 2011 Census which have been matched to ASHE records. Migrants and ethnic minority workers are under-represented in the ASHE–2011 Census sub-sample. This is because linkage quality is lower in London.

Non-random linkage between ASHE and the 2011 Census might bias our estimated pay gaps, particularly if linkage quality is also correlated with our outcome variable, basic hourly pay. To explore this, we estimate a probit model for employees aged 20–50 in the 2011 ASHE in which a dummy variable identifying Census linkage is regressed on basic log hourly pay. Linkage rates tend to rise with basic hourly pay, but this correlation is only modest with a marginal effect of log hourly pay on the probability of Census linkage of 0.114 and overall pseudo-R-squared of 0.0119. If we include the controls we use in our main regressions (year, region, age fixed effects) in this probit model, the marginal effect falls to 0.0616.

Furthermore, our results are robust to applying sample weights which have been constructed by the Office for National Statistics to adjust the earnings profile of the linked ASHE–Census to match the profile of the full ASHE sample.

As a further indication that the sample selection problem is not severe, we use the Quarterly Labour Force Survey (QLFS) to check the representativeness of our ASHE–2011 Census sample. We replicate our results using the Labour Force Survey (LFS) from 1999 to 2018 using the same population sub-samples. Black Caribbean and Black African groups have been merged in order to maintain consistent ethnicity definitions across the sample years. In Table A4 we find that compared to the ASHE–Census sample, the LFS sample is on average younger with lower pay. Some migrant groups also have markedly different shares of people holding degrees or living in London.

The analysis in Table 3 is replicated in Table A5, with the exclusion of firm-level controls. Most wage gaps in column 1 are within 3 per cent of their previous estimate apart from White migrants whose wage gaps are over 10 per cent larger in this sample. Male UK-born Indians have an estimated gap 7 per cent smaller than estimated in

Table A1: Descriptive statistics and balance. All employees aged 20–50.

	2011 Census	2011 Census linked with ASHE
	%	%
Male	47.88	50.17
UK born	82.39	93.73
Bachelor's degree (or higher)	35.55	36.42
White	85.19	93.12
Black Caribbean	1.24	1.21
Black African	2.04	1.26
Indian	3.10	2.92
Pakistani / Bangladeshi	2.40	1.49

Source: 2011 Census in England and Wales and ASHE–Census linked sample in England and Wales.

Table A2: Probit regression for census linkage on log hourly pay.

	(1)	(2)
	Census link	Census link
Log hourly pay (marginal effect at mean)	0.114***	0.0616***
	(0.00056)	(0.00703)
N	2577835	2031094
Pseudo r2	0.0119	0.0380
FE		
Region – year		X
Age		X

Notes: Standard errors in parentheses. *P < .05, **P < .01, ***P < .001.
Source: ASHE–2011 Census linked sample in England and Wales.

Table A3: Pooled cross-sectional wage penalty regression with various controls and using sample weights.

MEN	(1)	(2)	(3)	(4)
	log_w	log_w	log_w	log_w
White migrant	0.0993***	0.0415***	0.0276***	0.00755
	(0.00543)	(0.00480)	(0.00514)	(0.00428)
Black Caribbean migrant	–0.319***	–0.216***	–0.133***	–0.0868***
	(0.0142)	(0.0137)	(0.0133)	(0.00990)
Black Caribbean UK	–0.267***	–0.221***	–0.197***	–0.123***
	(0.00795)	(0.00732)	(0.00744)	(0.00614)
Black Afr migrant	–0.358***	–0.414***	–0.308***	–0.165***
	(0.00837)	(0.00761)	(0.00738)	(0.00546)
Black Afr UK	–0.157***	–0.279***	–0.195***	–0.121***
	(0.0196)	(0.0188)	(0.0176)	(0.0145)
Indian migrant	–0.0720***	–0.124***	–0.0851***	–0.0833***
	(0.00738)	(0.00635)	(0.00665)	(0.00490)
Indian UK	–0.0230**	–0.0978***	–0.129***	–0.0836***
	(0.00717)	(0.00653)	(0.00658)	(0.00523)
Pakistani/Bangladeshi migrant	–0.231***	–0.239***	–0.149***	–0.109***
	(0.00996)	(0.00838)	(0.00869)	(0.00665)
Pakistani/Bangladeshi UK	–0.114***	–0.151***	–0.155***	–0.110***
	(0.00855)	(0.00774)	(0.00743)	(0.00606)
Cons	2.626***	2.630***	2.633***	2.630***
	(0.000767)	(0.000670)	(0.000528)	(0.000431)
N	437,587	437,522	427,293	427,292
r2	0.224	0.415	0.697	0.801
FE				
Region - year	X	X	X	X
Age	X	X	X	X
Educ - year		X	X	X
Firm			X	X
Occupation				X

WOMEN	(1)	(2)	(3)	(4)
	log_w	log_w	log_w	log_w
White migrant	0.0928***	0.0316***	0.0120**	0.00791*
	(0.00453)	(0.00391)	(0.00424)	(0.00334)
Black Caribbean migrant	–0.174***	–0.160***	–0.127***	–0.0762***
	(0.00883)	(0.00785)	(0.00797)	(0.00620)
Black Caribbean UK	–0.0569***	–0.0493***	–0.0499***	–0.0235***
	(0.00663)	(0.00602)	(0.00623)	(0.00470)
Black Afr migrant	–0.171***	–0.252***	–0.196***	–0.106***
	(0.00675)	(0.00575)	(0.00615)	(0.00470)
Black Afr UK	–0.0364**	–0.202***	–0.188***	–0.101***
	(0.0129)	(0.0129)	(0.0131)	(0.0100)

Table A3. Continued

WOMEN	(1)	(2)	(3)	(4)
	log_w	log_w	log_w	log_w
Indian migrant	–0.104***	–0.133***	–0.102***	–0.0667***
	(0.00625)	(0.00531)	(0.00541)	(0.00384)
Indian UK	0.0667***	–0.0384***	–0.0765***	–0.0351***
	(0.00672)	(0.00606)	(0.00668)	(0.00499)
Pakistani/Bangladeshi M migrant	–0.143***	–0.131***	–0.112***	–0.0510***
	(0.0125)	(0.0103)	(0.0116)	(0.00759)
Pakistani/Bangladeshi UK	–0.0279***	–0.0779***	–0.0834***	–0.0461***
	(0.00837)	(0.00742)	(0.00800)	(0.00580)
Cons	2.407***	2.412***	2.416***	2.413***
	(0.000732)	(0.000614)	(0.000518)	(0.000399)
N	440,365	440,334	430,321	430,317
r2	0.165	0.416	0.649	0.792
FE				
Region - year	X	X	X	X
Age	X	X	X	X
Educ - year		X	X	X
Firm			X	X
Occupation				X

Notes: Standard errors in parentheses. $*P < .05$, $**P < .01$, $***P < .001$.
Source: ASHE–2011 Census linked sample in England and Wales.

the ASHE–Census sample. Controlling for education in column 2 reduces the disparity for all groups, excluding the male UK-born Pakistani–Bangladeshi and Indian groups, where the difference is a similar magnitude. Column 3 has larger disparities due to the absence of firm controls.

Figure A1 demonstrates similar patterns in wage progression compared to Figure 3, particularly the UK-born groups. Within the male migrant group, the combined Black group has more positive wage growth relative to the Pakistani and Bangladeshi group. The Indian migrant group shows more wage growth at earlier ages, but a pronounced wage cut after age 30 for both men and women. The Bangladeshi and Pakistani male migrant group also experience wage stagnation in later years.

In summary, the ASHE–Census findings are generally consistent with those produced using the LFS. The largest differences can be found when comparing migrant results. This suggests that the ASHE–Census could contain a more representative and reliable resource for analysis of migrant and groups.

Table A4: Sample characteristics (means shown and standard deviation in brackets) by sex, ethnicity, and migrant status.

UK Born	Hourly wage	Age	% degree	% in London	N	Hourly wage	Age	% degree	% in London	N
	MEN					WOMEN				
White	13.10	36.53	36	8	262,503	10.29	36.69	37	7	287,396
	(8.58)	(8.41)				(6.77)	(8.45)			
Black	11.90	36.02	36	49	2.320	11.50	36.23	46	55	3,456
	(7.01)	(7.88)				(6.48)	(7.89)			
Indian	14.38	32.45	58	31	2,511	12.17	32.11	60	33	2,762
	(9.89)	(7.26)				(7.33)	(7.32)			
Pakistani/ Bangladeshi	11.65	30.30	50	22	1,573	10.23	30.19	50	24	1,588
	(8.58)	(7.02)				(6.31)	(7.19)			
Total	13.10	36.45	36	8	268,907	10.32	36.60	38	8	295,202
	(8.59)	(8.41)				(6.77)	(8.45)			

Migrant	Hourly wage	Age	% degree	% in London	N	Hourly wage	Age	% degree	% in London	N
	MEN					WOMEN				
White	14.71	35.20	42	26	20,285	9.87	37.29	48	27	22,918
	(10.80)	(7.68)				(5.38)	(7.71)			
Black	11.00	37.34	47	44	3,721	9.87	37.29	47	51	4,515
	(6.49)	(7.70)				(5.38)	(7.71)			
Indian	14.79	37.44	53	37	4,853	11.24	37.77	47	39	4,298
	(10.25)	(7.29)				(7.71)	(7.38)			
Pakistani/ Bangladeshi	9.52	35.40	34	33	3,258	9.67	35.23	37	22	1,278
	(7.14)	(7.54)				(6.94)	(7.88)			
Total	13.77	35.81	43	30	32,117	11.38	35.76	47	32	33,009
	(10.15)	(7.67)				(7.68)	(7.95)			

Source: LFS Individual, 1999–2018.

Table A5: Cross-sectional regression table of log hourly wage gap with White UK born, various controls.

	Male			Female		
VARIABLES	(1)	(2)	(3)	(1)	(2)	(3)
White migrant	–0.0393***	0.0135***	–0.114***	–0.0161***	0.00490	–0.0287***
	(0.00419)	(0.00402)	(0.00848)	(0.00376)	(0.00361)	(0.00665)
Black migrant	–0.342***	–0.314***	–0.0663***	–0.235***	–0.207***	–0.0373***
	(0.00862)	(0.00810)	(0.00860)	(0.00751)	(0.00687)	(0.00742)
Black UK born	–0.219***	–0.184***	–0.102***	–0.0556***	–0.0626***	–0.0802***
	(0.0105)	(0.00960)	(0.0108)	(0.00836)	(0.00768)	(0.0101)
Indian migrant	–0.0810***	–0.0815***	0.0145***	–0.0941***	–0.0746***	0.00236
	(0.00884)	(0.00792)	(0.00331)	(0.00865)	(0.00788)	(0.00298)
Indian UK born	0.0199*	–0.0545***	–0.155***	0.0719***	–0.00865	–0.105***
	(0.0107)	(0.00965)	(0.00669)	(0.00925)	(0.00843)	(0.00591)
Pakistani/Bangladeshi migrant	–0.451***	–0.342***	–0.0857***	–0.222***	–0.158***	–0.0651***
	(0.00997)	(0.00885)	(0.00621)	(0.0152)	(0.0135)	(0.00625)
Pakistani/Bangladeshi UK born	–0.115***	–0.153***	–0.214***	–0.0768***	–0.104***	–0.0853***
	(0.0133)	(0.0119)	(0.00752)	(0.0125)	(0.0114)	(0.0119)
Constant	2.421***	2.418***	2.413***	2.190***	2.189***	2.187***
	(0.000999)	(0.000908)	(0.000794)	(0.000946)	(0.000841)	(0.000716)
Observations	301,024	298,353	298,256	328,211	326,000	325,944
R-squared	0.213	0.356	0.520	0.178	0.353	0.535
Controls						
Region-Year	X	X	X	X	X	X
Age	X	X	X	X	X	X
Education-Year		X	X		X	X
Occupation			X			X

Notes: Robust standard errors in parentheses. ***$P < .01$, **$P < .05$, *$P < .1$.
Source: LFS Individual, 1999–2018.

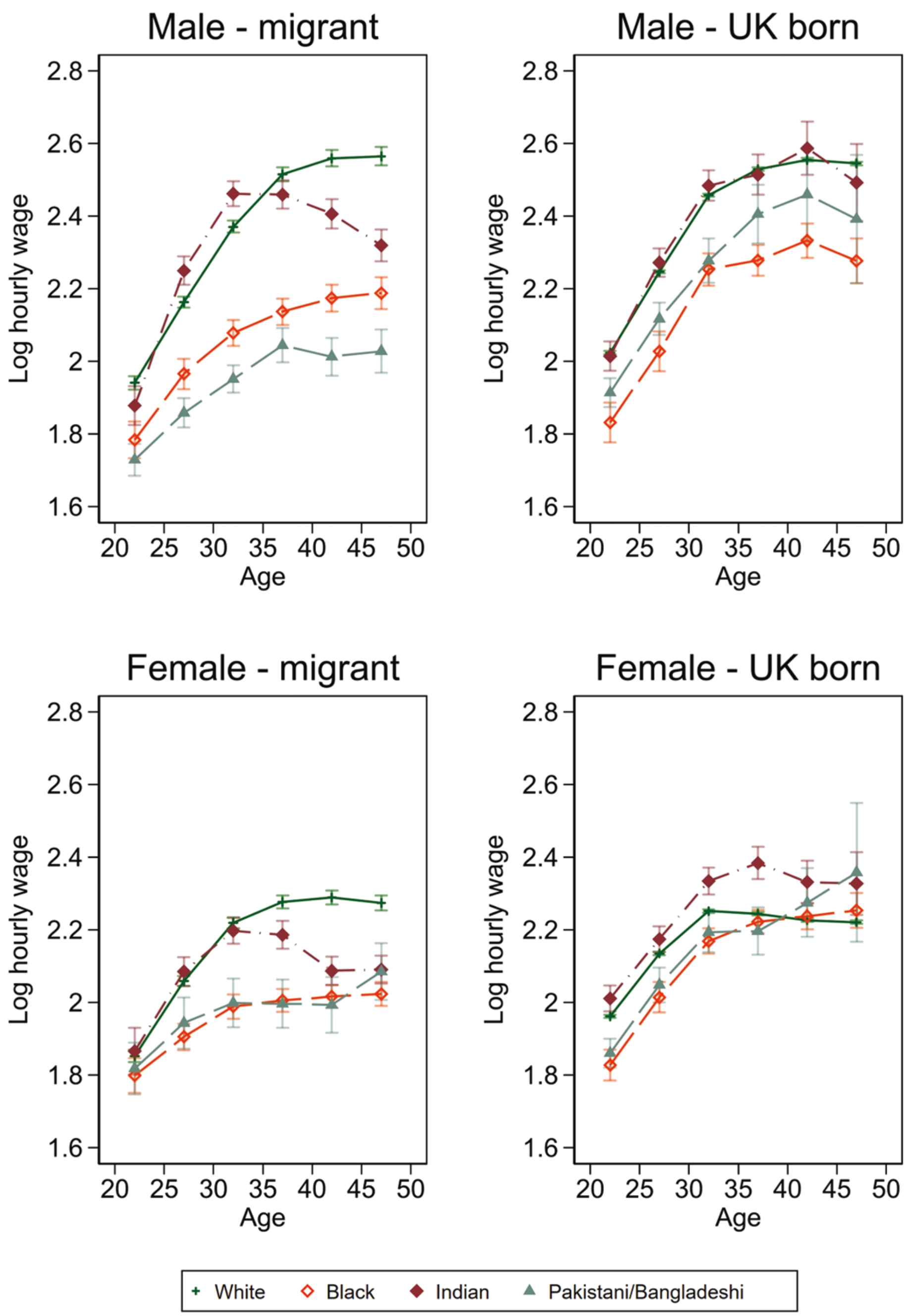

Figure A1: Log hourly wages by ethnic group and age group. Year-region controls.
Source: LFS Individual, 1999–2018.

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