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Understanding pay gaps

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Abstract

In this paper, we use micro-data from the UK Labour Force Survey to estimate unconditional and conditional pay gaps for gender and ethnicity groups since the mid-90s. Both types of gender pay gap have decreased over the sample, but remain in double digits. For ethnicity, the unconditional pay gap has been materially lower, compared to the gender pay gap, while the conditional pay gap is of similar magnitude to the gender one. These trends are apparent not only at the mean but also at the lower and upper ends of the distributions. Interaction effects between gender and ethnicity reveal that female ethnic minority workers experience a larger pay gap than both ethnic minority male, and white female workers. Half of the gender pay gap can be accounted for by compositional effects, such as the individual's age, education, and the nature of their job, such as occupation and sector, while half remains unaccounted for. We find that the minimum wage leads to a decrease in the gender pay gap. Compositional effects for ethnicity suggest that ethnic minorities should be earning more than their white counterparts, with the unaccounted for factors driving the positive ethnicity pay gap. We find that compositional effects are heterogeneous across gender and ethnic minority groups. We assert that there is a strong case to extend compulsory pay gap reporting to ethnicity. There is also a case to extend compulsory reporting from firms with more than 250 employees to those with around 30 or more, to increase the coverage of the UK employed population.

Key words: Gender, ethnicity, pay gap, inequality, minimum wage.

JEL classification: J15, J16, J31, J38.

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Section 1: Introduction

"Pay gaps" measure the difference in pay between people with different demographic characteristics doing identical jobs. They are considered to be a good approximation of inequality in workplace rewards (EHRC (2018)). Under the Equality Act 2010, it is against the law to discriminate on the basis of protected personal characteristics. When it comes to pay, this means people should earn the same wage for the same work, irrespective of their gender, race, religion, disability, or other protected characteristics. In other words, no "pay gap" should exist across any of these characteristics.

Since 2017, it has been compulsory for companies in Great Britain with over 250 employees to report gender pay gaps each financial year. Data for 2018 published earlier this year shows a gender pay gap of around 10% across reporting UK organisations.[1] The UK government has also begun a consultation on requiring companies to publish ethnicity pay gaps on an annual basis.[2] While 63% of employers monitor ethnicity pay gaps, only 31% of employers currently publish them.[3] The Bank of England has published data on its gender pay gap since 2017 and on its ethnicity pay gap since 2018.

While it is widely recognised that these pay gap measures may be imperfect proxies for pay inequality, greater transparency about pay gaps can serve as an important incentive device. Publishing companies' pay gaps encourages them to explain and, with time, close these gaps. The benefits of doing so, for individual companies and the economy at large, have been found to be large. For example, closing the gender pay gap has been estimated to add £600 billion (or 27% of GDP) to UK GDP by 2025 (McKinsey (2016)), while full representation of BAME individuals across the labour market, through improved participation and progression, could add an additional £24 billion (or over 1% of GDP) per year (BEIS (2017)).

Internationally, similar moves to improve pay gap reporting are underway. Iceland has since January 2018 required external auditors to assess pay inequalities among companies with more than 25 employees.[4,5] The Danish Equal Pay Act 2014 requires companies with a minimum of 10 employees to make available gender-disaggregated pay statistics. A number of other EU member states have implemented new reporting standards, including recently in Germany and France. In the US, all employers with more than 100 workers must disclose pay information to the Equal Employment Opportunity Commission.

In this paper, we provide a detailed empirical examination of gender and ethnicity pay gaps in the UK using micro-level survey data. As well as describing the evolution of these pay gaps over time, we identify some of the key explanations and drivers of them over time. This decomposition is important when accurately interpreting data on pay gaps and when deciding where action might best be taken – by companies and/or public policymakers – to close these gaps and harvest some of the benefits this would bring.

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[1] Latest ONS LFS 2019Q1 release.
[2] https://www.gov.uk/government/consultations/ethnicity-pay-reporting
[3] Business in the Community (2019).
[4] Pay in Iceland is assessed using an Equal Pay Standard which highlights four main criteria: expertise, responsibility, effort, and work environment.
[5] Wagner, I (2018), 'Certified Equality: The Icelandic Equal Pay Standard' https://www.researchgate.net/publication/329371051_Certified_Equality_The_Icelandic_Equal_Pay_Standard

Section 2: Literature Review

Gender and ethnicity pay gaps have been studied fairly extensively using US data. In the US, the female/male earnings ratio has increased steadily since the 1980s (Blau and Kahn (2017)). This is typically attributed to improvements in women's levels of education and experience (Stanley and Jarrell (1998), Jarrell and Stanley (2004), Weichselbaumer and Winter-Ebmer (2005)). Alkadry and Tower (2006) find human capital explains over 90% of the gender pay gap. Some studies have also found occupational representation and segregation has been a factor explaining gender pay gaps (Lewis and Soo Oh (2009)).

Goldin (2014) provides one of the most comprehensive studies of the gender pay gap in the US across different age groups. She finds that, while the gap has narrowed for most age groups, the aggregate gap has remained fairly stable. By looking across the life-cycle, she finds that as workers get older the size of the gender pay gap tends to rise. It also differs significantly by occupation, with business occupations having the largest gender pay gaps and technology and science-related occupations the lowest.

Like others, Goldin finds that the narrowing of the gap across age groups is largely due to a rise in the human capital of women relative to men, due to factors such as improved levels of education, experience, and labour force participation. The remaining pay difference can partly be explained by higher-paying occupations in the corporate, financial and legal worlds, especially at later career stages. This is disadvantageous for women who are more likely to work part-time or work fewer hours due to raising children.

The US literature on ethnic minority pay has tended to focus on wage differentials between white and black ethnic groups, the two largest ethnic groups in the US. Studies have tended to find a large wage differential between black and white men, although this does appear to have reduced over time with the black/white earnings ratio increasing from just under 60% in 1967 to around 80% by 2009 (Lang and Lehmann (2012)). This broadly mirrors trends in the gender pay gap. Studies looking at wage gaps over the life-cycle find that there is little evidence of an ethnicity pay gap during early working life, but that this grows to around 14% by age 40 (Tomaskovic-Devey et al (2005)).

Evidence on the role of education on the size of the ethnicity pay gap is mixed. Some studies find that, among young men, the black/white pay differential appears, in part, to be explained by education (O'Neill (1990), Rodgers and Spriggs (1996) and Carneiro, Heckman, and Masterov (2005)). For example, the pay differential decreases when controlling for performance on the Armed Forces Qualifying Test (Neal and Johnson (1996)). Studies also find that, among college-educated men, there is no difference in pay between black and white males (Black et al (2006)). This might suggest the ethnicity pay gap can largely be explained by human capital differences in white-collar sectors, but not in blue-collar jobs (Bjerk (2007)). Other studies, however, have found that human capital differences increase the pay differential (Lang and Manove (2011)).

Wage differentials between black and white women have historically been considerably lower than between men (Lang (2007)) and at times have even reversed. However, Neal (2004) demonstrates that this finding partially reflects the differential selection of black and white women into the labour force. For example, black women face a lower household income than white women, which provides a stronger incentive for them to enter the workforce in the first place.

For the UK, although evidence is more partial, it suggests that both gender and ethnicity pay gaps have fallen over time (ONS (2018), ONS (2019)). For gender, the factors determining these gaps include age, educational background, sector, occupation and part time work (Olsen and Walby (2004), Manning and Swaffield (2005), Mumford and Smith (2007), Brynin (2017), ONS (2018)). Costa Dias et al. (2018) find that differences in years of experience as well as working hours play an important role in explaining the gender pay gap. Similarly, Olsen et al. (2018) identify differences in male-female labour market history to account for 56% of the drivers of the gender pay gap. They note that unobserved components of the gender pay gap, or 'bias', account for another 35%. However, only a small share of what traditionally is referred to as the 'unexplained' part of the pay gap is accounted for by firm-specific wage effects (Jewell et al. 2019). For ethnicity, it includes occupation, being born in the UK and education (ONS (2019), Brynin and Guveli (2012)). As in the US, the UK ethnicity gap appears to be larger for males than females (Longhi and Brynin (2017)).

The gender pay gap differs between the low and high end of the wage distribution. Butcher et al. (2016) find that the unconditional gender pay gap in the UK is commonly close to zero for lower wages and substantially higher from around the 7th percentile. One could argue that institutional policies, such as the introduction of a minimum wage, could be reducing the pay gaps at the lower end of the distribution. Using distribution regression methods, Bargain et al. (2018) find that the gender pay gap at the bottom of the wage distribution has been effectively reduced by the introduction of a national minimum wage in Ireland. However, there is a limited effect on the average wage gap and they do not observe a similar effect in the UK following the introduction of the minimum wage. The initial increase in the minimum wage was very small when it was first introduced in 1999/2000, making the identification of any effects on the pay who difficult. This result has also been corroborated using quantile regression methods by Robinson (2002), which finds no evidence the NMW in the UK affected the gender pay gap at the lower end of the distribution.

When it comes to explaining the sources of pay gaps, three main approaches have typically been used. Regression techniques estimate pay gaps controlling for various characteristics of the individual or job (Goldin (2014), Brynin and Guveli (2012)). Oaxaca-Blinder decompositions account for differences in pay between two groups using an independent set of factors. This is useful for capturing the effects of compositional differences in the characteristics of groups (O'Donnell et al (2008)). Finally, a rich literature uses experiments to assess bias in hiring, promotion and bargaining between groups (Neumark (2018)).

In this paper, we use the first two approaches – regression-based techniques and decompositions – to analyse gender and ethnicity pay gaps in the UK. In the next section we describe the dataset, summarise key trends in the UK labour market over the past 25 years and discuss unconditional pay gaps by gender and ethnicity. In the following section, we provide an explanation of these pay gaps using factor-decomposition and regression-based methods. Section 5 presents our key findings and policy recommendations.

Section 3: Trends in the UK Labour Market

This paper uses quarterly returns from the UK Labour Force Survey (LFS) from 1994 Q1 to 2019 Q1. This gives us a sample of 1,154,759 observations of employed individuals, reduced to 563,353 observations when incorporating pay variables, as there are fewer observations for respondents on pay.[6] There are two main advantages to using the LFS relative to other surveys, such as the British Household Panel Survey (BHPS) and the Annual Survey of Hours and Earnings (ASHE).[7]

First, the LFS has the longest time-series of pay and other work characteristics at a quarterly frequency in the UK. Using it allows us to track the evolution of pay gaps over time. Second, the LFS dataset offers a rich set of information on the characteristics of both workers and their jobs. These controls improve the robustness of the analysis, statistically, and the ability to explain movements in pay gaps behaviourally, using various individual and work-related characteristics.

There have been a number of important changes in the LFS survey population over time. First, female participation has increased from 52% in 1994 to 57% in 2019. Second, the share of ethnic minorities in the workforce has more than doubled, from 4% in 1994 to 10% in 2019. Third, the share of the population in higher education or with a degree has also increased significantly, from 22% to 43%. Fourth, the share of the population not born in the UK has almost tripled, from 6% in 1994 to 17% in 2019. These trends are representative of the composition of the UK population, as reported in the 2011 Census.

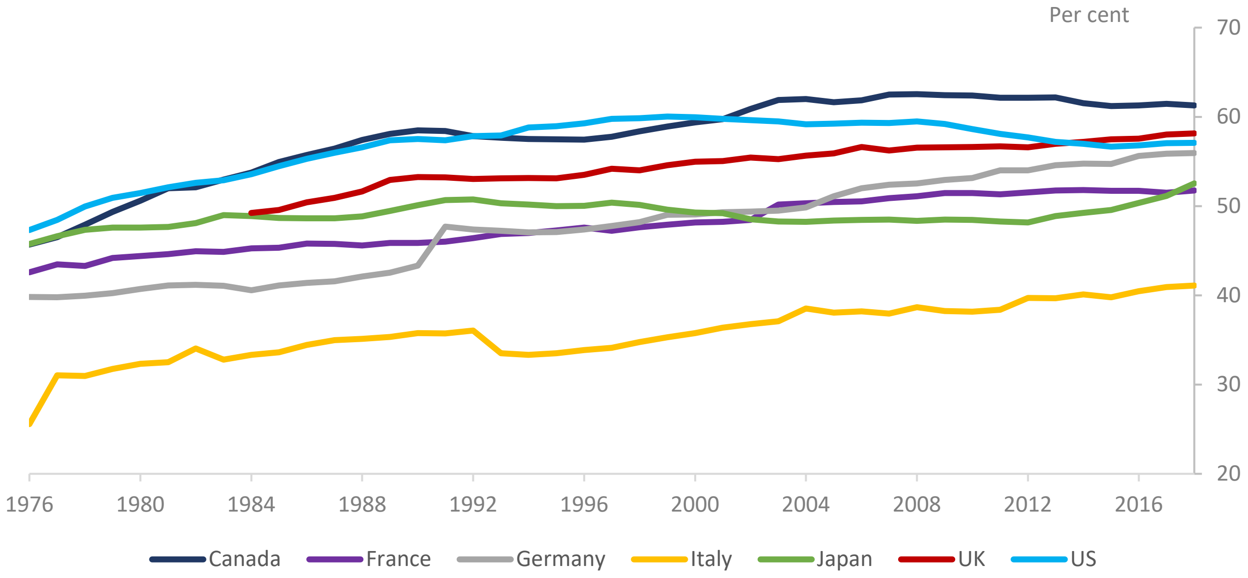
(a) Participation Trends

Female participation in the workforce has been on a broadly upward trend in the UK. Elsewhere across the G7, trends have been more disparate (**Chart 1**). Based on OECD Labour Force Statistics, UK rates of female participation are second only to Canada across the G7, having recently overtaken the US.

[6] Throughout our analysis we only use wave 1 respondents in order to ensure that we are not counting multiple responses from the same individual. In addition to this, we only include workers aged 25 and over in order to remove noise from the data. Most workers under 25 are earning in the minimum wage range which is subject to regulation, and may also particularly represent part-time employment.

[7] This paper does not aim to produce better estimates of the gender and ethnicity pay gaps than the official ones published by the ONS. ASHE data is the best source for estimating the overall gaps, but the LFS has a rich set of individual and job characteristics allowing the type of analysis showcased here.

Chart 1: G7 female participation rates



Sources: ONS Labour Force Survey, OECD Labour Force Statistics and Bank of England calculations.

The increase in female participation has been accompanied by an opposite trend among the male population, which has fallen from 70% to 65% over the sample. In other words, the gender "participation gap" between males and females in the UK has fallen by around 10 percentage points over the past 25 years, though it remains positive at around 8 percentage points.

The participation of ethnic minorities in the UK labour force has also been on an upward trend since the 1990s, reaching around 64% in 2019. Labour participation by the white population was, by contrast, on a slightly downward trend prior to the Global Financial Crisis, after which it has flattened off. That leaves participation rates for ethnic minorities today slightly above the participation levels of the white population.

There have been some striking gender-related shifts in the pattern of work. The share of part-time employment among females has been declining, with a corresponding larger share of females working full-time. The opposite is true among males, with the share of men working part-time increasing by 5 percentage points over the sample. For ethnic minorities, part-time employment has steadily increased, with a pronounced pick up following the Global Financial Crisis.

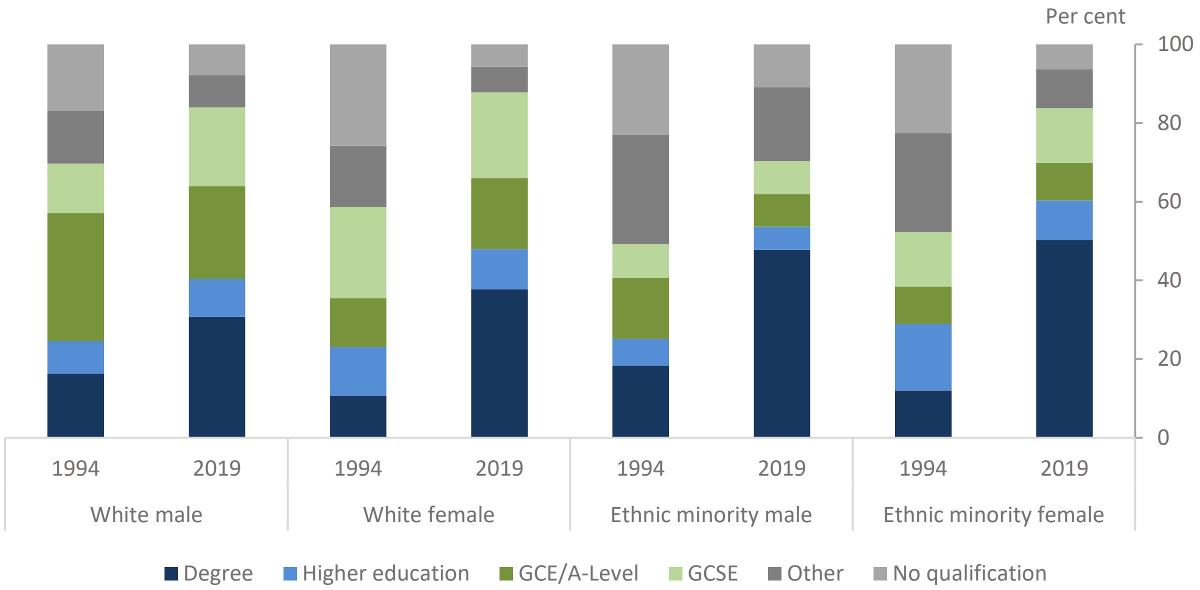
Next, we look at three variables which are often used to capture aspects of "human capital": the highest qualification achieved, the occupation of a person, and the sector in which they are employed. For illustrative purposes, we split the sample into four sub-groups – white men, white women, ethnic minority men, and ethnic minority women – though we also consider more granular sub-sets of these groups.

Chart 2 compares the highest qualification attained among the four sub-samples in 1994 and 2019. The main trend is the same across the board: the share of people with degrees or higher education has almost doubled since 1994. The increases are, however, most pronounced among women and ethnic minorities.

For example, ethnic minority females have seen a 31 percentage point increase between 1994 and 2019. In 2019, around 60% of ethnic minority females had a degree or a higher education qualification.

Conversely, the share of people without a qualification has decreased significantly across all four groups, with the trend for UK-born ethnic minority women reducing at a faster pace than for non-UK born ethnic minorities. Both UK-born and non-UK born workers entering the labour force market in the UK are materially more qualified than in the past.

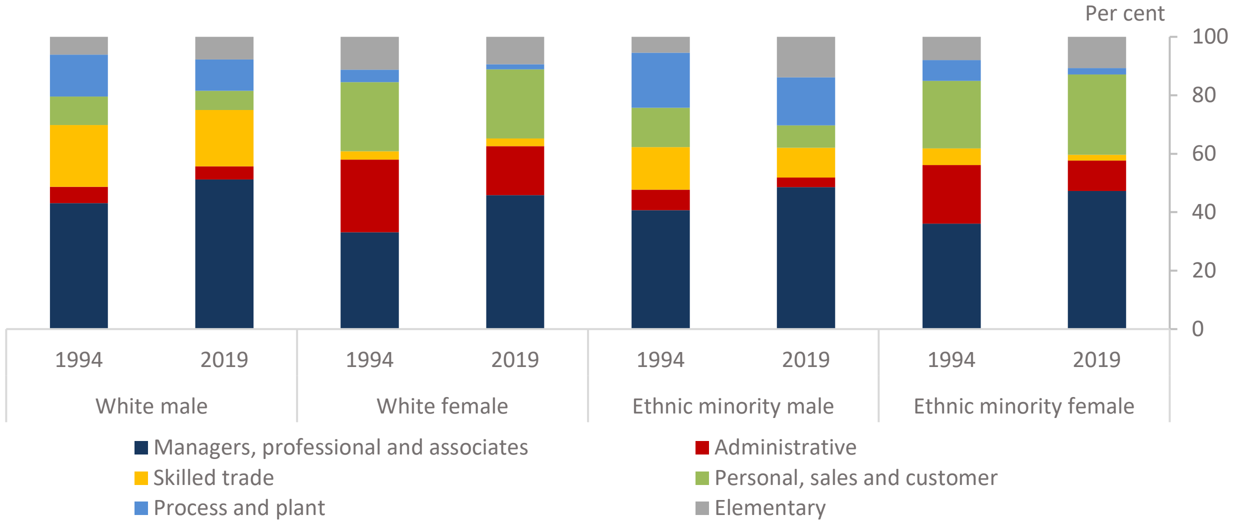
Chart 2: Highest qualification attained



Source: ONS Labour Force Survey and Bank of England calculations.

Chart 3 shows the composition of the labour force by occupation across the four sub-groups. Occupational participation differs strikingly by gender, but less so by ethnicity. There is a higher share of managers, professional, and associate occupations among men than women. Compared to men, women have a larger representation in administrative, and personal, sales and customer service occupations, while men have a larger representation in skilled trades and process and plant occupations. This holds true across ethnicities.

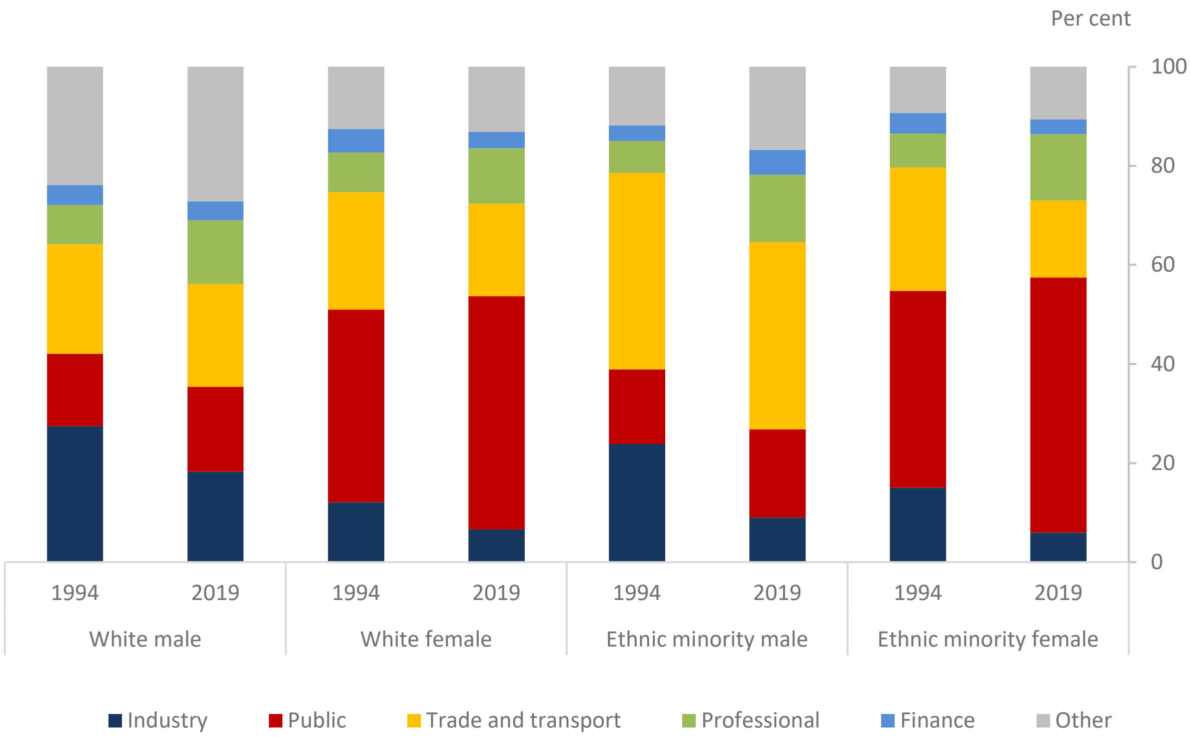
Chart 3: Occupational representation



Source: ONS Labour Force Survey and Bank of England calculations.

Chart 4 shows the composition of the UK labour market by sector. The vast majority of men across both ethnic sub-samples work in the 'industry' sector (including manufacturing, utilities and mining) and trade and transport sectors. The latter is particularly important for ethnic minority males, where close to 40% of this sub-group works. On the other hand, the public sector is dominated by females of both ethnicity backgrounds. The share of people working in professional services and finance is similar across the board.

Chart 4: Sectoral representation



Source: ONS Labour Force Survey and Bank of England calculations.

(b) Pay Trends

Table 1 shows summary statistics of the distribution of hourly earnings across gender and ethnicity. It shows that white men have the highest mean and median hourly earnings, as well as higher earnings at both the higher and the lower end of the pay distribution. Males also have higher earnings than females across the pay distribution for both ethnic groups. Ethnic minority females have higher earnings than white females across the distribution. All distributions have a strong positive skew, though white males have the largest upper tail.

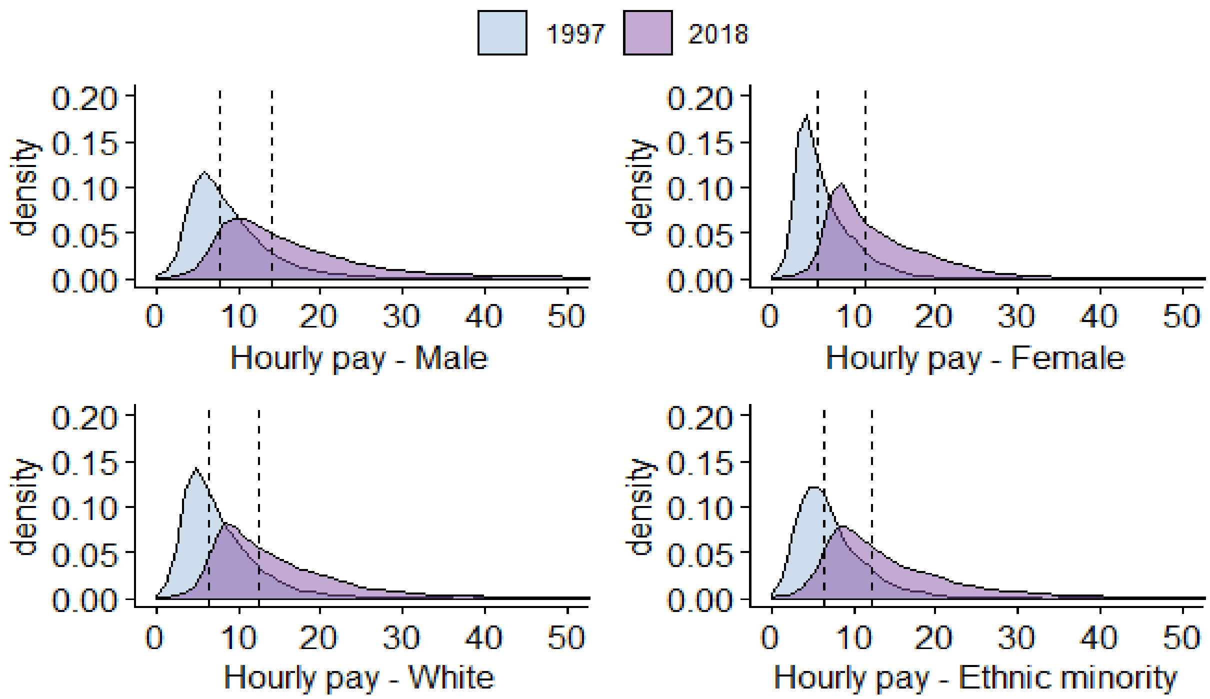
Table 1: Summary statistics for hourly earnings (£) across gender and ethnicity groups

Statistic	**White male**	**White female**	**Ethnic minority male**	**Ethnic minority female**
Mean	13.6	10.4	12.9	11.1
25th percentile	7.6	6.0	6.9	6.4
Median	10.9	8.35	10	9.1
75th percentile	16.4	12.7	15.7	13.6
Standard deviation	14.4	8.6	11.1	8.4
Skewness	46.3	20.4	13.9	16

Source: ONS Labour Force Survey and Bank of England calculations.

Charts 5 plots the distribution of hourly pay in £ for males, females and ethnic minorities separately on two dates: 1997 and 2018. It shows that there is a higher peak of low-paid females in 1997 and, to a lesser extent, in 2018. Put differently, more of the distribution of pay among males is skewed towards the upper tail of higher pay rates. Pay distributions between whites and ethnic minorities show fewer differences.

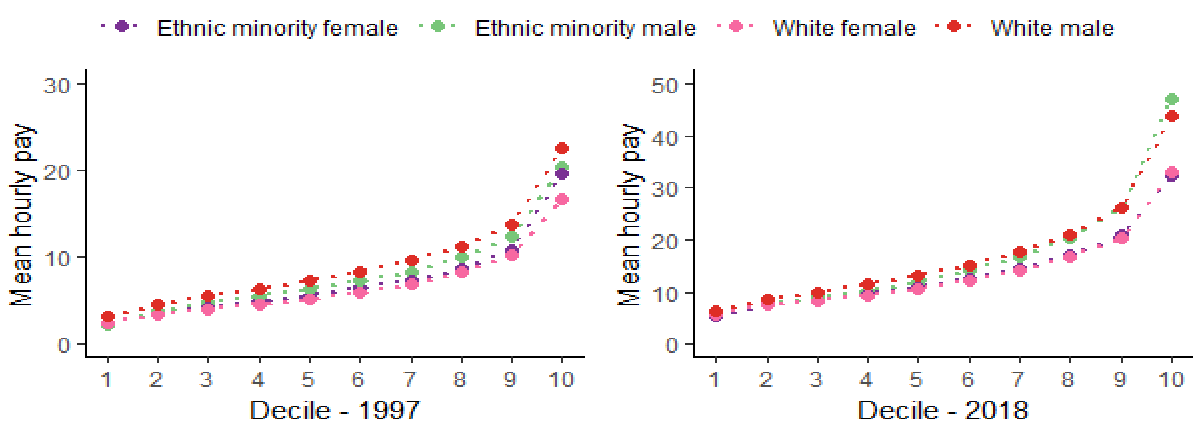
Chart 5: Distribution of hourly pay by gender and ethnicity



Source: ONS Labour Force Survey and Bank of England calculations.

Chart 6 plots the mean hourly pay by decile for different ethnicity and gender groups. In 1997, white males earned more than all other groups, on average, across the entire distribution. The same is broadly true in 2018, except that ethnic minority males now earn more in the top decile. Females continue to earn less than males right across the distribution. The difference between white females and ethnic minority females is relatively small across the distribution. Mean hourly pay has increased at a slower pace for the lower deciles of the pay distribution and mean hourly pay has increased at a noticeably faster pace for the higher deciles of the pay distribution, for both genders and ethnicities.

Chart 6: Mean hourly pay by decile for ethnicity and gender interaction groups



Source: ONS Labour Force Survey and Bank of England calculations.

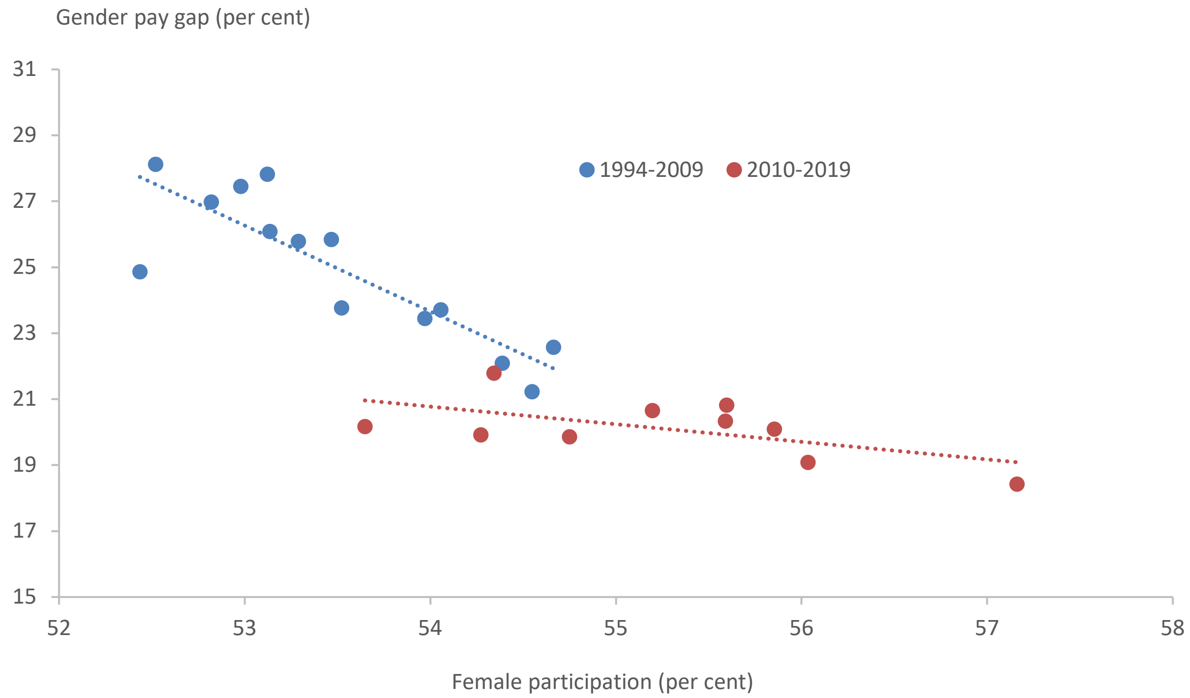
(c) Unconditional gender and ethnicity pay gaps

Unconditional gender and ethnicity pay gaps are calculated as the difference between median male (white) gross hourly earnings and median female (non-white) earnings, divided by median male (white) earnings.[8] As with published pay gaps for companies, these measures make no attempt to control for factors driving or explaining these gaps; they are *unconditional* pay gaps.

The unconditional gender pay gap is large over the sample, averaging just over 22% (**Chart 7**). This gap has shrunk over the past 25 years, from around 30% in the mid-1990s to around 20% in 2018. This downward trend is particularly pronounced between 1994 and 2009, when the pay gap was falling by, on average, around half a percentage point per year. Since the GFC, however, the gender pay gap has flattened-off and has been essentially unchanged since 2007.

At the same time gender pay gaps have been falling, female participation in the workforce has been steadily rising (**Chart 7).** Increased female participation may have contributed to the shrinking of the gender pay gap during the 1990s and early 2000s, as female representation in certain sectors and occupations expanded.[9] But there is little evidence of these effects over the past decade, during which time female participation in the workplace has, if anything, picked up pace but the gender pay gap has been flat.

Chart 7: Female participation rate and unconditional gender pay gap

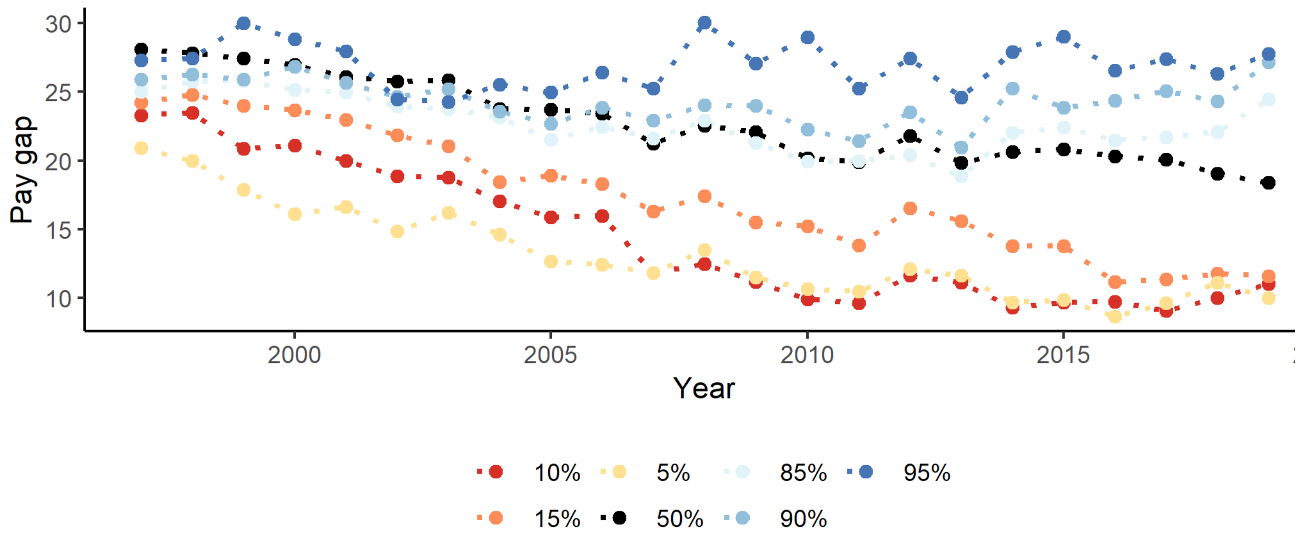


Source: ONS Labour Force Survey and Bank of England calculations.
Note: A positive gender pay gap in this chart means that women earn less than men.

[8] Unconditional gaps are calculated using raw pay data from the LFS and will not attempt to account for individual or job characteristics.
[9] Olivetti, C and Petrongolo, B (2016) show that structural change of the economy becoming more service based, can explain at least half of the overall variation in female hours, both over time and across countries.

The fall observed in the gender pay gap until the early 2000s, can also be observed across the wage distribution, driven by the lower end of this distribution. Ggaps from the 5th to the 15th percentiles have fallen by more than 10pp since the mid-90s (**Chart 8**). The pay gap at the upper end of the distribution, by contrast, has remained broadly unchanged since the start of the sample and is larger than those at the lower end of the distribution.

Chart 8: Unconditional gender pay gap by percentiles

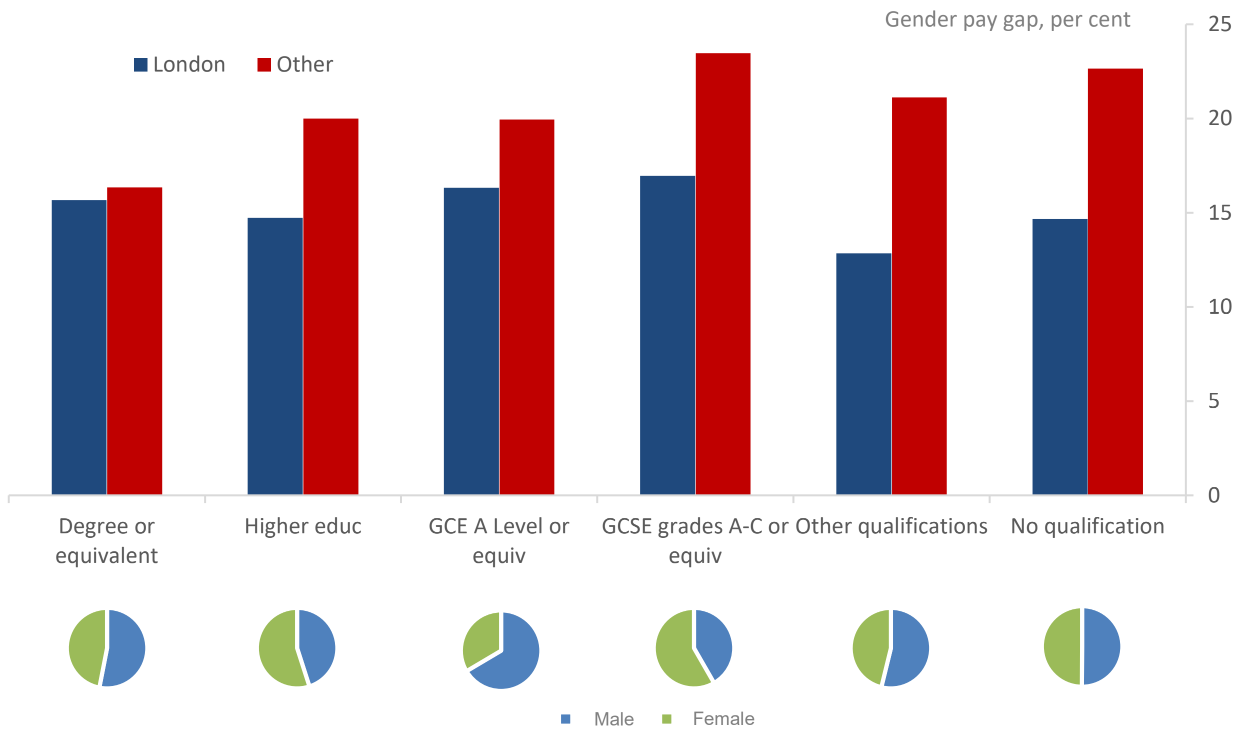


Source: ONS Labour Force Survey and Bank of England calculations.
Note: A positive gender pay gap in this chart means that women earn less than men.

If we assess by qualification, the largest gender pay gaps are observed for people with GCSE or no qualifications, while the lowest gaps are for workers with a degree or equivalent (**Chart 9**). Generally speaking, the higher the qualifications, the lower the gender pay gap.

Location also appears to play an important role. The gender pay gap outside London is consistently higher than in London, across all levels of qualification. The largest gap between London and the rest of the UK is among workers who have no or “other” qualifications. This might be explained by the fact that “other” qualifications includes degrees from outside the UK which may get less recognition.

Chart 9: Median gender pay gap by qualification, sample average

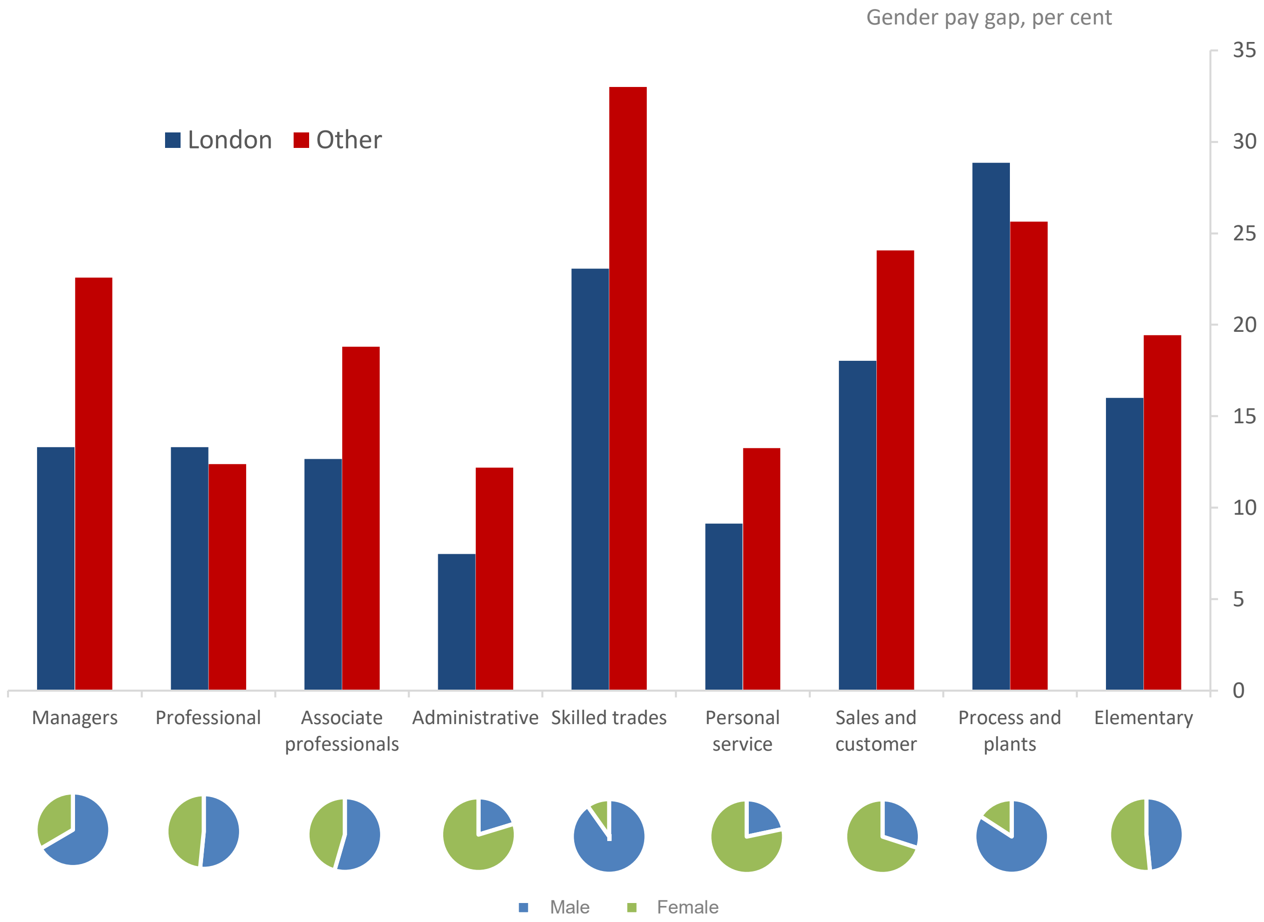


Source: ONS Labour Force Survey and Bank of England calculations.
Note: A positive gender pay gap in this chart indicates that women earn less than men.

By occupation, and consistent with qualifications, the gender pay gap is smaller for professional and administrative occupations than for skilled trades, customer service and plant operatives (**Chart 10**). For almost all occupations, the gender pay gap is higher outside London. In 2018, the gender pay gap outside London remained higher for managers, skilled trades and elementary occupations. For the rest of the occupations, the pay gap in London overtook the respective gap outside London.

Broadly speaking, occupations with median hourly pay of more than £10 (managers, professional, and associate occupations) have lower gender pay gaps than occupations where the median hourly pay is less than £6.50 (sales and customer services, and elementary occupations). Relatedly, there is a clear inverse relationship between the gender pay gap and female-dominated professions. Consistent with increased female representation being associated with shrinking gender pay gaps cross-sectionally, if not always over time.

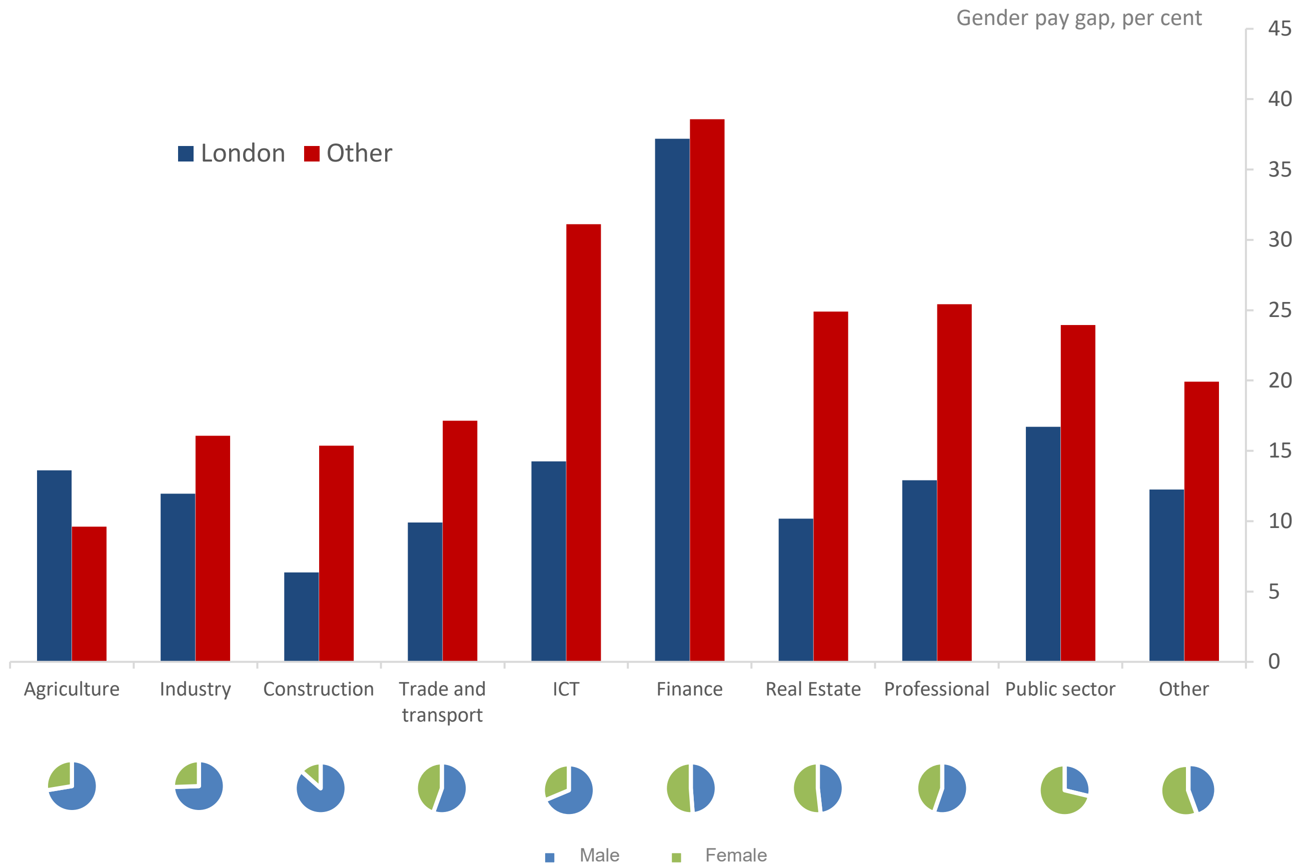
Chart 10: Median gender pay gap by occupation, sample average



Source: ONS Labour Force Survey and Bank of England calculations.
Note: A positive gender pay gap in this chart indicates that women earn less than men.

Finally, if we look at unconditional gender pay gaps by sector (**Chart 11**), gaps are broadly-based across sectors. The largest gaps are in the finance sector, both in London and the rest of the UK. These average close to 40%. This is materially larger than the next-worst sector, ICT, which averages around 30%. The evolution of the gender pay gap in finance suggests it has fallen only modestly, from over 45% in the mid-1990s to around 38% in 2018.

Chart 11: Median gender pay gap by sector, sample average

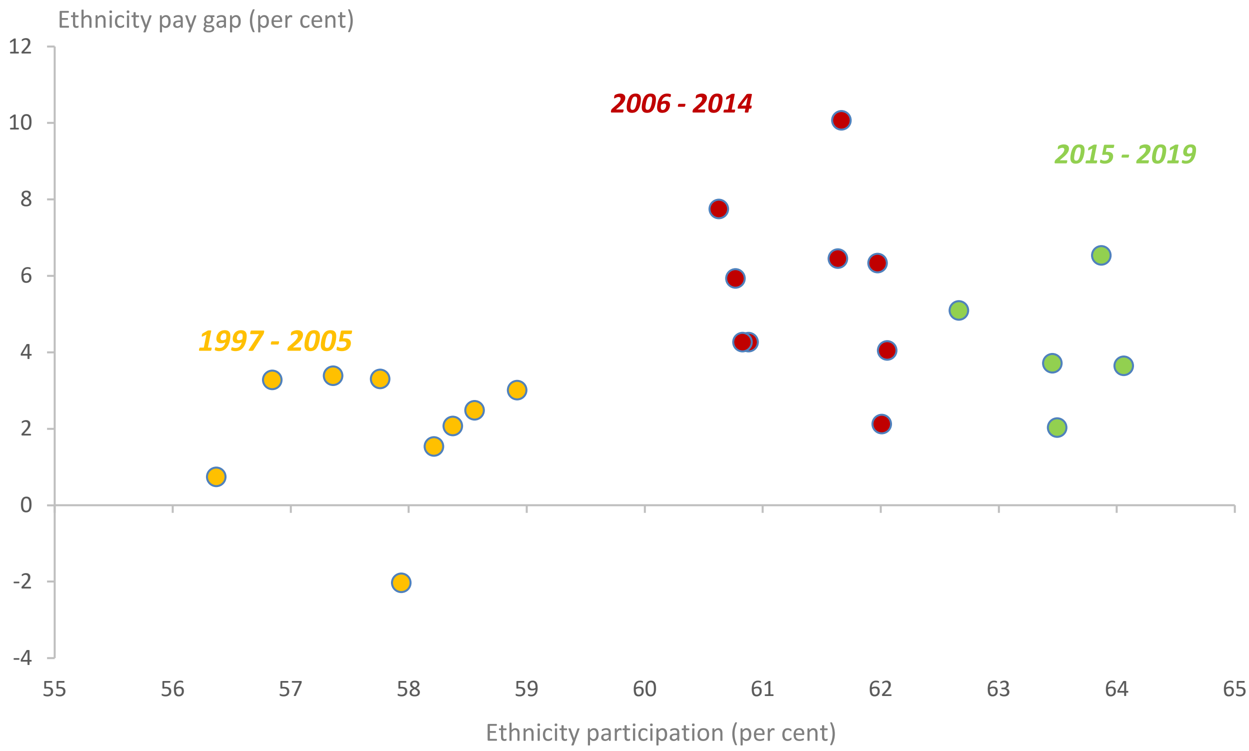


Source: ONS Labour Force Survey and Bank of England calculations.
Note: A positive gender pay gap in this chart indicates that women earn less than men.

The unconditional ethnicity pay gap exhibits a rather different pattern than the gender pay gap. This gap has been materially lower, averaging around 4% over the sample. As the gender gap fell sharply in the decade to 2005, the ethnicity pay gap was broadly stable at around 2% (yellow dots in **Chart 11**). The ethnicity pay gap then began increasing steadily between 2006 and 2014 (red dots), averaging 6% over the period. Recently, it has begun to fall (green dots), reaching just under 4% in 2018.

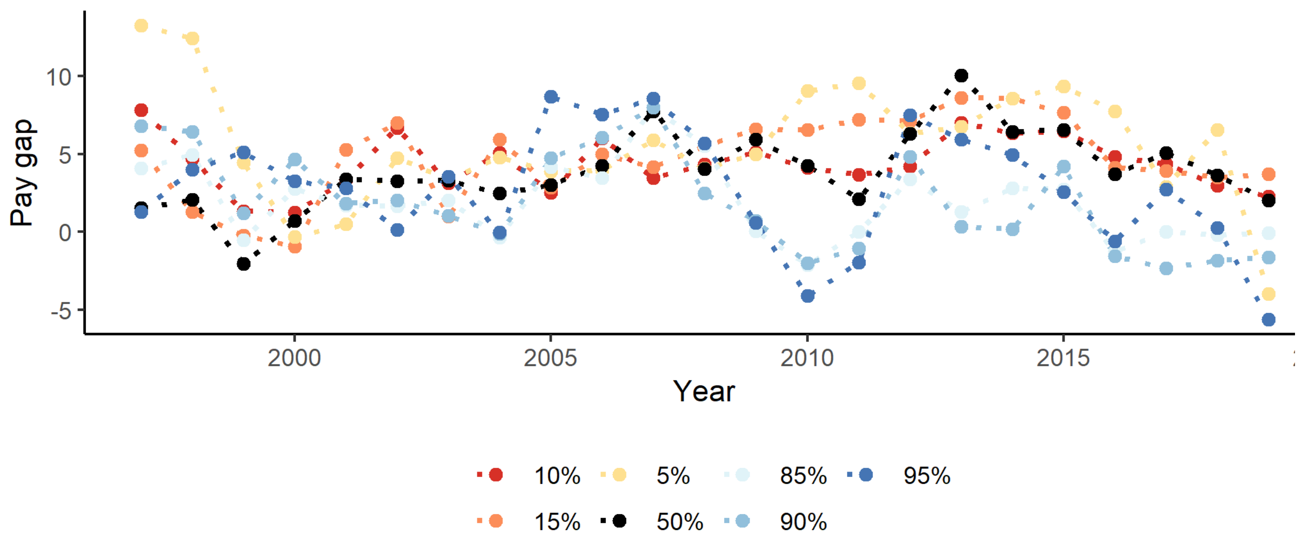
Chart 12 shows that higher ethnic minority participation in the workplace has only been associated with lower pay gaps very recently. This recent drop in the ethnicity pay gap seems to be driven predominantly by the upper end of the wage distribution (**Chart 13**). It is worth noting that the wage distribution of the ethnicity pay gap is quite different to the gender pay gap. The overall volatility of the series is considerably higher.Up until the mid-2000s there is a considerable degree of co-movement between the upper and the lower ends of the wage distribution, with the upper end of the distribution falling somewhat more from that point onwards.

Chart 12: Ethnic minority participation and unconditional pay gaps



Source: ONS Labour Force Survey and Bank of England calculations.
Note: A positive ethnicity pay gap in this chart indicates that ethnic minorities earn less than their white counterparts, whereas a negative ethnicity pay gap indicates that ethnic minorities earn more than their white counterparts.

Chart 13: Unconditional ethnicity pay gap by percentiles



Source: ONS Labour Force Survey and Bank of England calculations.
Note: A positive ethnicity pay gap in this chart indicates that ethnic minorities earn less than their white counterparts, whereas a negative ethnicity pay gap indicates that ethnic minorities earn more than their white counterparts.

Looked at by qualification, white workers earn more than ethnic minorities for most levels of qualifications. The exception are those with "other" or no qualifications living outside London. Perhaps surprisingly given the significant share of ethnic minorities in the workforce, ethnicity pay gaps are larger in London than outside London, for all qualifications (**Chart 14**). These gaps are larger for those with higher levels of qualification, such as a degree. This presents a second puzzle in the unconditional pay gap data.

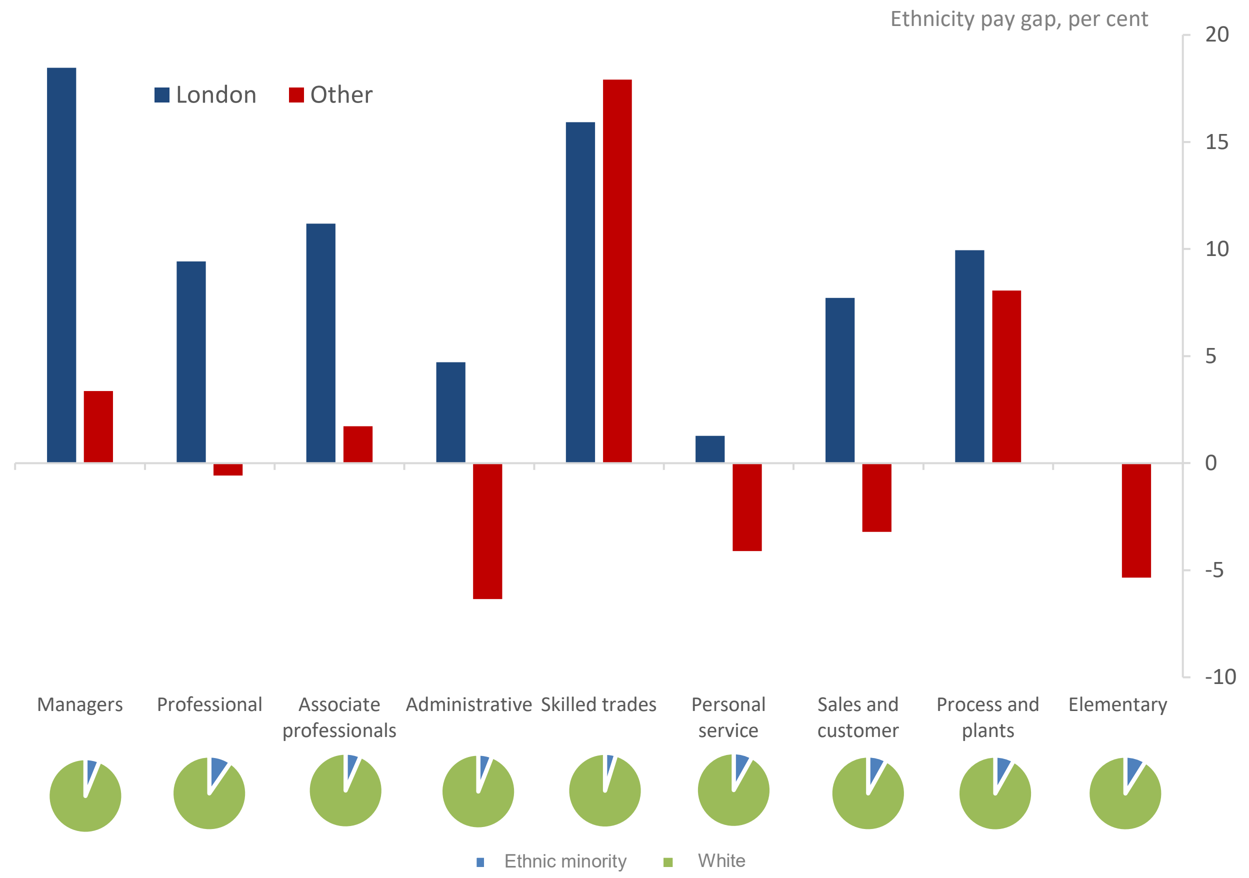
Recent data do not change this picture. In the latest calendar year (2018), ethnicity pay gaps are positive across all qualifications, averaging 8%. They remain larger in London than elsewhere, with the highest ethnicity pay gaps in degree and A-level qualification categories. Unconditional ethnicity pay gaps are still consistently smaller than unconditional gender pay gaps.

Chart 14: Median ethnicity pay gap by qualification, sample average

Source: ONS Labour Force Survey and Bank of England calculations.
Note: A positive ethnicity pay gap in this chart indicates that ethnic minorities earn less than their white counterparts, whereas a negative ethnicity pay gap indicates that ethnic minorities earn more than their white counterparts.

Ethnicity pay gaps differ significantly by occupation and sector. They are largest in managerial, professional and skilled occupations and lowest, or even negative, in elementary, personal service and sales and customer occupations (**Chart 15**). This is the mirror-image of gender, where pay gaps were largest among the lowest-paid occupations. By sector, pay gaps are largest in the professional and finance sectors (**Chart 16**). In other words, ethnicity pay gaps are largest among the highest-paid.

Chart 15: Median ethnicity pay gap by occupation, sample average



Source: ONS Labour Force Survey and Bank of England calculations.
Note: A positive ethnicity pay gap in this chart indicates that ethnic minorities earn less than their white counterparts, whereas a negative ethnicity pay gap indicates that ethnic minorities earn more than their white counterparts.

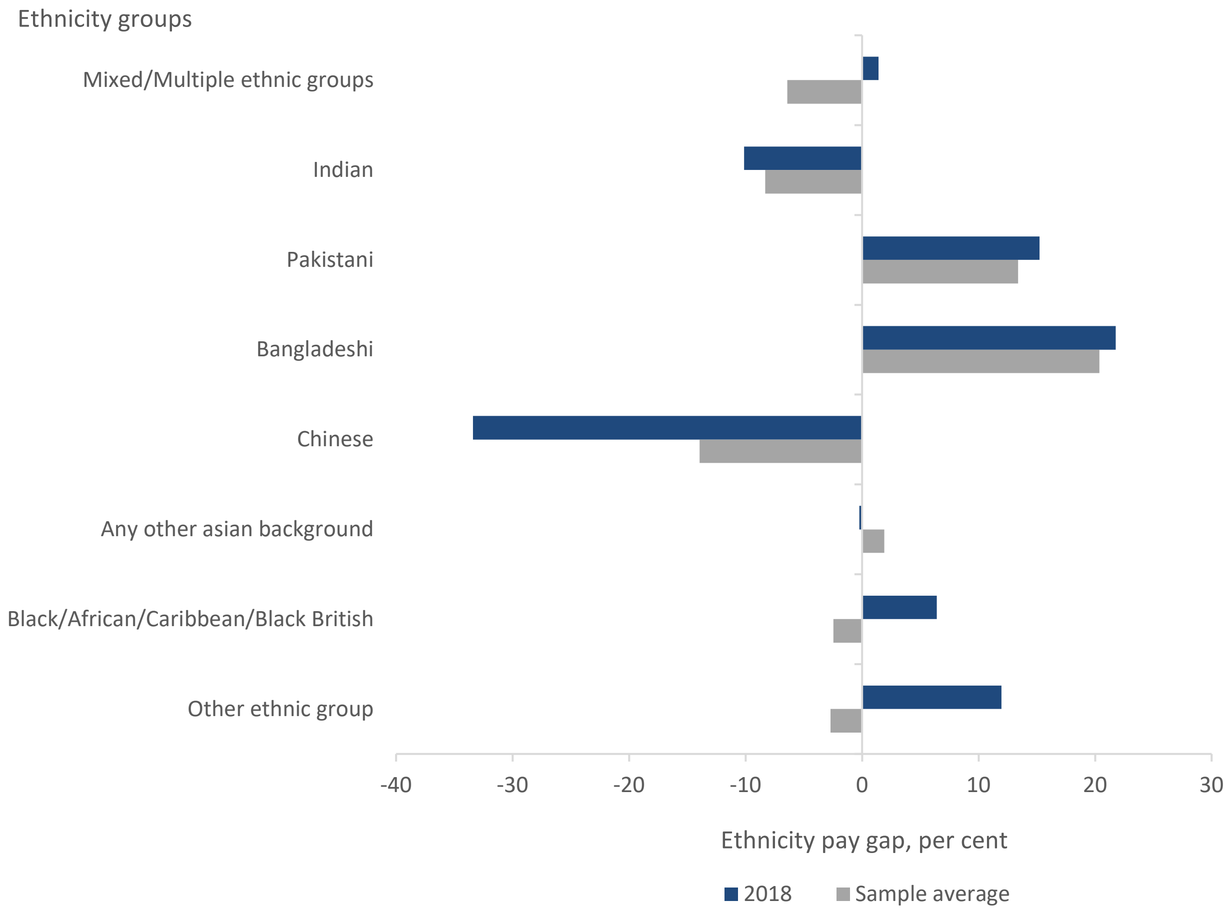
Chart 16: Median ethnicity pay gap by sector, sample average

Source: ONS Labour Force Survey and Bank of England calculations.
Note: A positive ethnicity pay gap in this chart indicates that ethnic minorities earn less than their white counterparts, whereas a negative ethnicity pay gap indicates that ethnic minorities earn more than their white counterparts.

If we look at ethnic minority workers at a more granular level, some interesting cohort effects emerge. There is a very wide dispersion of pay among different ethnic minority cohorts, with some having negative and others positive pay gaps compared with their white counterparts (**Chart 17**). Median hourly pay is highest for those of Chinese ethnicity, at just over £11, or around 15% higher than for whites. There are also negative pay gaps, though smaller ones, for workers from a mixed/multiple ethnic and Indian background.

At the other end of the spectrum, there are significantly positive pay gaps for other ethnic minority cohorts, including black and Afro-Caribbean workers. The largest pay gaps are for workers from a Pakistani and Bangladeshi background, which average 13% and 20% respectively (**Chart 17**). These large pay gap differences between different ethnic minority cohorts beg the question of whether it is useful to think about a single "ethnicity pay gap".

Chart 17: Granular ethnicity pay gaps

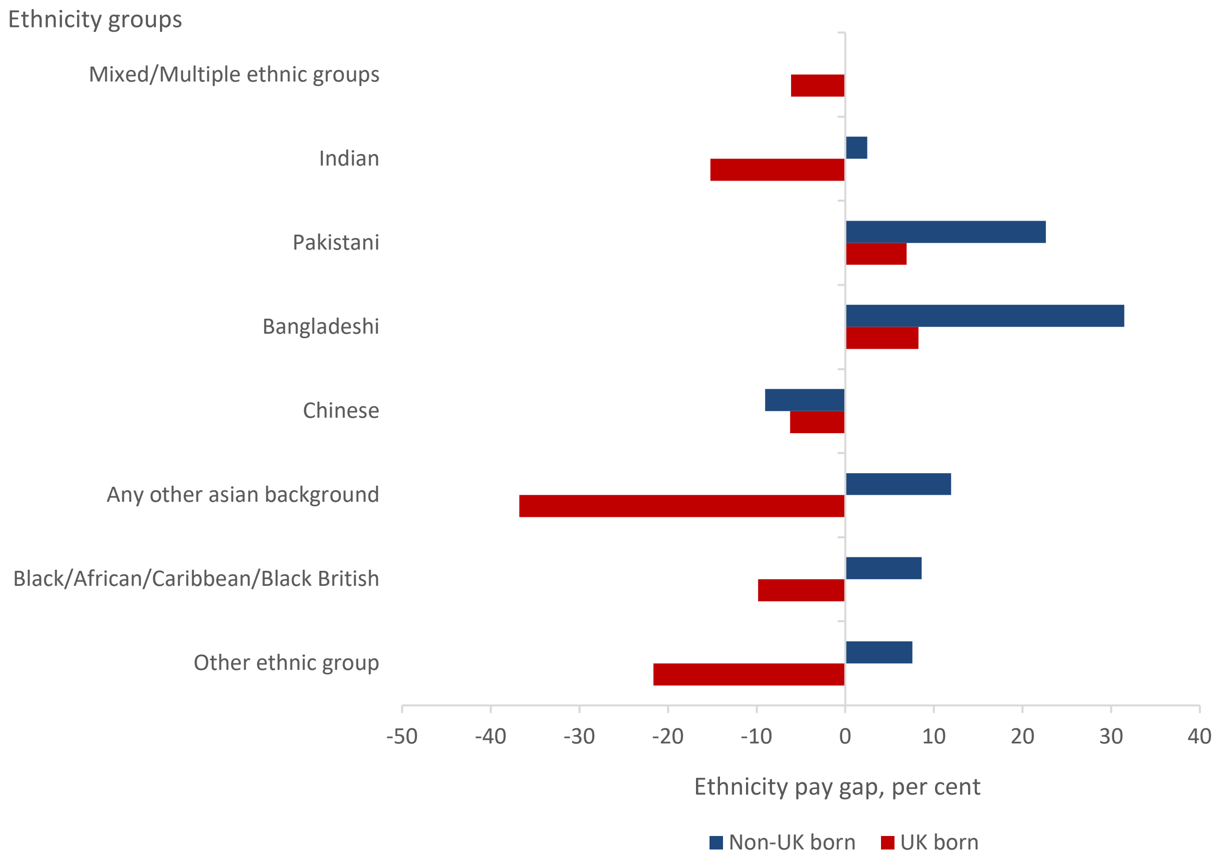


Source: ONS Labour Force Survey and Bank of England calculations.
Note: A positive ethnicity pay gap in this chart indicates that ethnic minorities earn less than their white counterparts, whereas a negative ethnicity pay gap indicates that ethnic minorities earn more than their white counterparts.

Whether an ethnic minority individual is born in the UK or not also plays an important role in their pay. **Chart 18** shows that ethnic minorities born in the UK (apart from those from Bangladeshi and Pakistani backgrounds) earn more than UK-born white people. Educational attainment is part of the explanation here. Although ethnic minorities born in the UK are a small part of our sample (2%), they are almost twice as likely to have a degree relative to white UK-born workers (40% versus 21%).

In stark contrast, most ethnic minorities born outside the UK earn considerably less than white people born outside the UK. This in part reflects compositional effects, as a higher proportion of non-UK born ethnic minorities have no qualifications compared to their white counterparts.

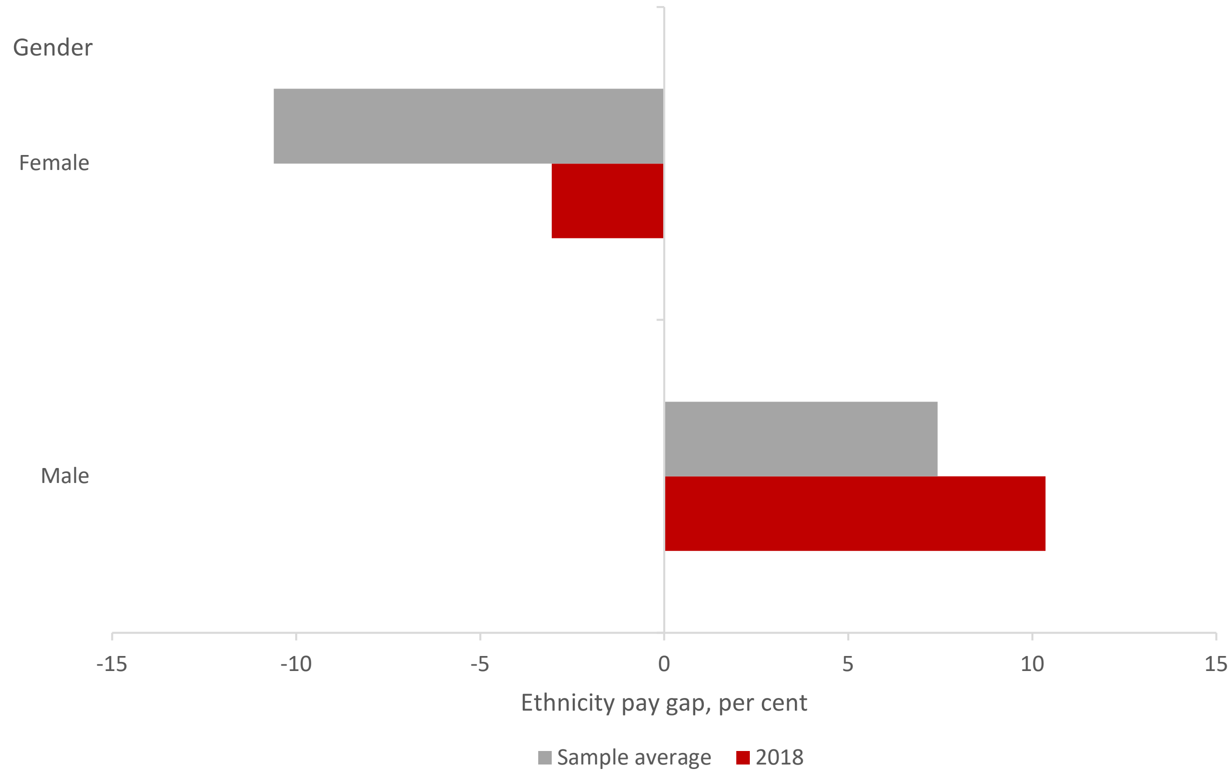
Chart 18: Granular ethnicity gaps by country of origin, sample average



Source: ONS Labour Force Survey and Bank of England calculations.
Note: A positive ethnicity pay gap in this chart indicates that ethnic minorities earn less than their white counterparts, whereas a negative ethnicity pay gap indicates that ethnic minorities earn more than their white counterparts.

On average, ethnic minority women earn more than white women, whereas ethnic minority men earn less than white men (**Chart 19**). This is also true in the latest data. Unconditionally, there is a clear and well-defined pay gap for females. Indeed, the largest gap observed in the data is between white males and females. It was around 29% in 1997 but has decreased over the last two decades to just under 20%. There is also a clear and well-defined pay gap for ethnicity but, somewhat surprisingly, no clear, well-defined pay gap for ethnic minority females. This is a third puzzle in the unconditional pay data.

Chart 19: Ethnicity pay gaps by gender



Source: ONS Labour Force Survey and Bank of England calculations.
Note: A positive pay gap in this chart indicates that ethnic minorities of this gender earn less than their white counterparts of this gender, whereas a negative pay gap indicates that ethnic minorities of this gender earn more than their white counterparts of this gender.

Section 4: Explaining Pay Gaps

In this section, we explore the factors contributing to gender and ethnicity pay gaps. Accounting for individual and job characteristics helps us to estimate *conditional* gender and ethnicity pay gaps. Can pay gaps be explained by characteristics of the individuals (such as their level of education or location) or the jobs they are doing (such as the sector or occupation)? How much of the pay gap remains "unexplained" once these characteristics are accounted for? As well as providing a greater understanding of the drivers of pay gaps, this approach helps resolve some of the puzzles otherwise apparent in the unconditional pay gap data.

Before discussing the estimates for conditional pay gaps and the marginal impact of individual and environmental factors in more detail, we analyse the share of the conditional pay gap that is 'accounted for' and 'unaccounted for'. We also identify what proportion of the 'accounted for' component the individual and environmental factors make up. One way of doing so is by using the Oaxaca-Blinder decomposition. This decomposes the gap between the wages of two groups into two parts. The first captures the share of the gap explained by the different compositional characteristics of the two groups. The second captures the sensitivity of pay to those characteristics, something which is not typically observable.

Suppose *y* is our variable of interest, in this case wages. We have two groups, say male and female. We assume *y* is explained by a vector of determinants, *x*, according to the following model:

$$(1) \quad y_i = \begin{cases} \beta^{female} x_i + \varepsilon_i^{female} \; if\; female \\ \beta^{male} x_i + \varepsilon_i^{male} \; if\; male \end{cases}$$

where the vectors of the β parameters include intercepts. To keep things simple, assume there is a single factor – education – and that males benefit more, wage-wise, than females from a given level of education. In other words, at each educational level (*x*), the level of wages (*y*) are higher for males than females. Assume, again for simplicity, that males also have higher levels of educational attainment than females. This means that, for compositional reasons, we would also expect males to earn more than females.

The gap between male and female wages, y^{male} and y^{female}, is

$$(2) \quad y^{male} - y^{female} = \beta^{male} x^{male} - \beta^{female} x^{female}$$

where x^{male} and x^{female} are vectors of explanatory variables evaluated at their means for males and females, respectively. The "twofold" Oaxaca-Blinder decomposition[10] allows us to split up the overall gap into the part that is attributable to (i) differences in *x*'s (the so-called "accounted for" component capturing compositional differences) and (ii) differences in the β's (the "unaccounted for" component reflecting the greater impact of a given factor on males versus females). In other words, the wage gap between the two groups can be expressed as:

$$(3) \quad y^{male} - y^{female} = \Delta x \beta^{female} + \Delta \beta x^{male}$$

$$\text{where} \quad \Delta x = x^{male} - x^{female} \text{ and } \Delta\beta = \beta^{male} - \beta^{female}$$

In this way, we can split the gender pay gap into a part that can be accounted for by females having different characteristics (*x*'s) than males, and a part resulting from females being treated differentially to males given those characteristics (β's). This expression can be further rewritten as (4), which compares the regressions coefficients to their hypothetical value in a world of no labour market discrimination. The β^*, β^{male} and β^{female} represent vectors of coefficients from a pooled regression of all individuals in both male and female groups as well as individual group-wise regressions, respectively.

$$(4) \; y^{male} - y^{female} = \Delta x \beta^* + x^{male}(\beta^{male} - \beta^*) + x^{female}(\beta^* - \beta^{female})$$

$$\text{where} \quad \Delta x = x^{male} - x^{female} \text{ and}$$

$$\beta^* = vector\ of\ non - discriminatory\ coefficients\ from\ pooled\ regression$$

We use an extensive list of factors or characteristics, *x*, to help explain pay gaps. Some of these relate to the characteristics of the individual worker – for example, their number of years in employment, their tenure in post, where they live, their age and their educational qualifications. Other factors relate to the nature of

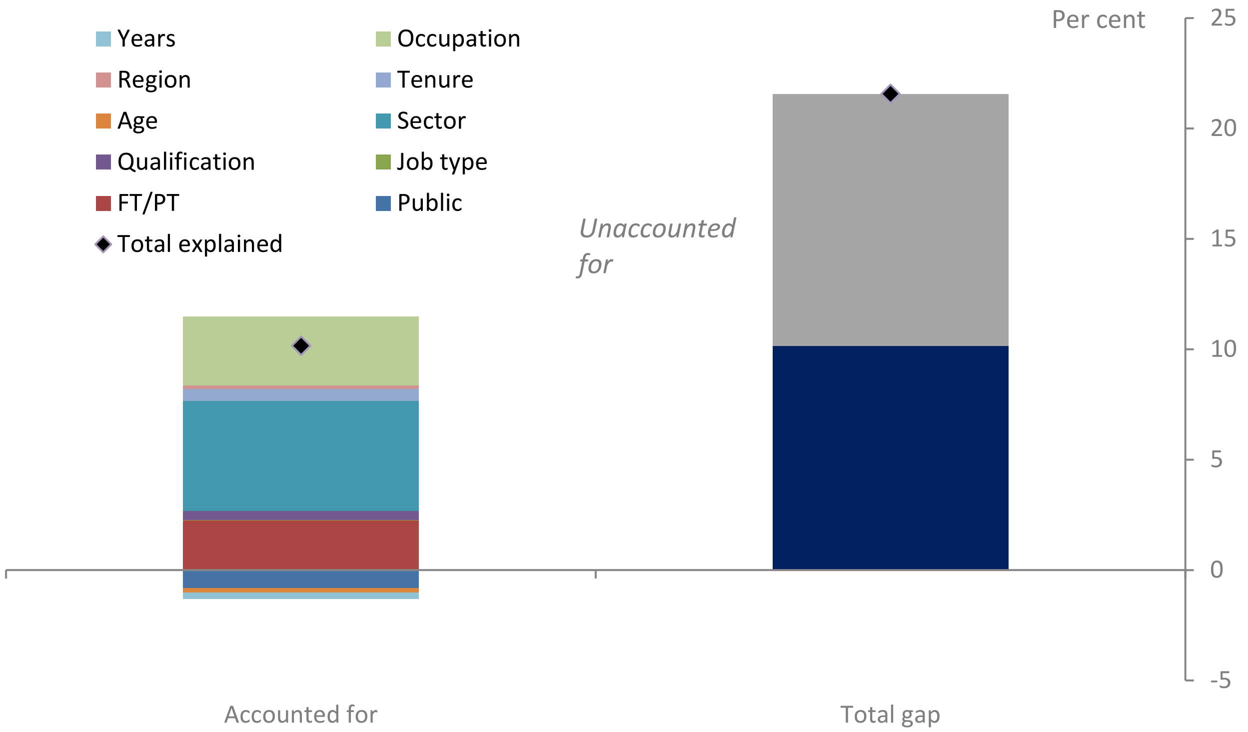
[10] It is important to note that in "twofold" decomposition the "unaccounted for" part will also capture all potential effects of differences in unobserved variables.

the job itself – whether it is full or part-time, the occupation, sector and job-type. Both factors, individual and job-specific, are likely to be important in explaining pay.

Chart 20 shows the Oaxaca-Blinder decomposition of the gender pay gap over the sample, when the average gender pay gap in the UK was close to 22%. From the decomposition, around half of that gap can be accounted for by compositional effects, arising from the different characteristics of either the worker or the job they are carrying out. That leaves around 11 percentage points of the pay gap unaccounted for by these factors. In other words, around half of the gender pay gap is difficult to justify on fundamental grounds, consistent at least with some significant degree of gender pay "bias".

Of those factors explaining the gender pay gap, the most important relate to the characteristics of the *job* rather than the *individual*. Occupation, sector, and the full/part-time nature of work are the most important factors accounting for the gender pay gap (Mumford and Smith (2009)). It is difficult to know how much these reflect personal choice (workers' preference for a certain sector or way of working) rather than legacy environmental factors (such as the preponderance of males in certain professions or sectors).

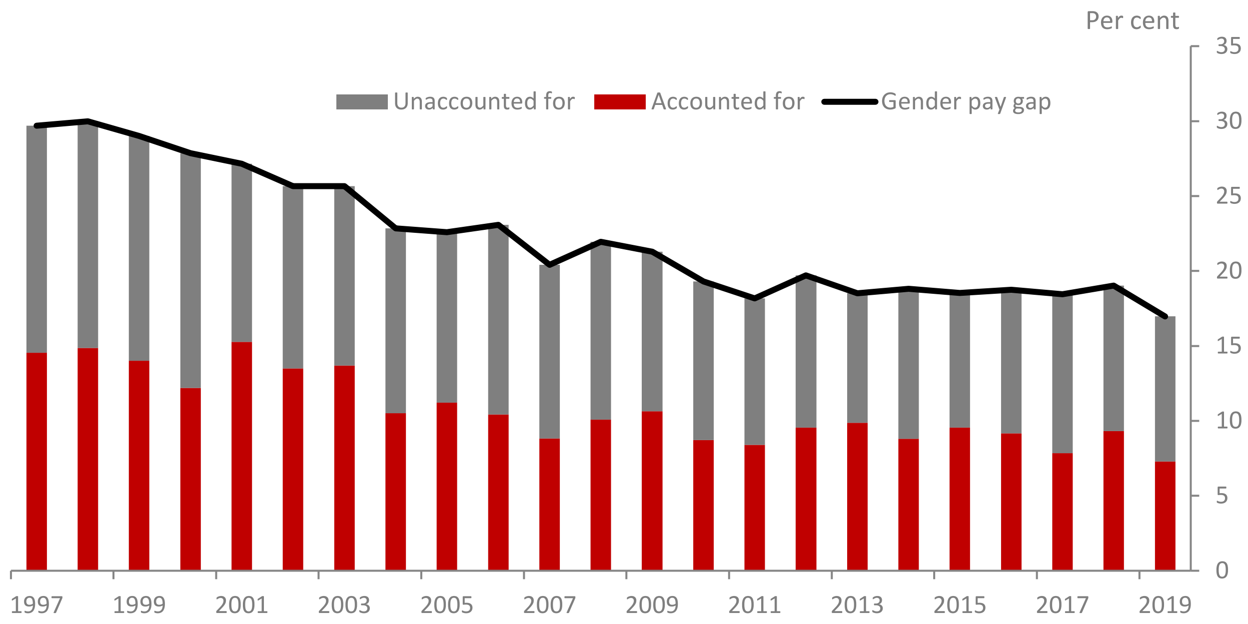
Chart 20: Oaxaca-Blinder decomposition of gender pay gap, sample average



Source: ONS Labour Force Survey and Bank of England calculations.
Note: A positive gender pay gap in this chart indicates that women earn less than men, whereas a negative gender pay gap indicates that women earn more than men. 'Years' refer to time-fixed effects, 'Job type' captures if the job is temporary or permanent.

Looked at over time, the halving of the gender pay gap since the mid-90s has been driven roughly equally by accounted and unaccounted for components (**Chart 21**). The main factor causing the shrinkage in the explained component is qualifications. While at the start of the sample the qualification component was adding to the gender pay gap, by the end it was dragging. This reflects the significant increase in relative educational attainment by females over the period. The unexplained – or "gender pay bias" – component has shrunk somewhat, though remains significant at just under 10% at the end of the period.

Chart 21: Gender pay gap Oaxaca-Blinder decomposition time series



Source: ONS Labour Force Survey and Bank of England calculations.
Note: A positive gender pay gap in this chart indicates that women earn less than men.

Looked at regionally, although the unconditional gender pay gap is relatively stable over the sample in London, once we allow for compositional effects the picture is more promising. The unexplained ("pay bias") component of pay has fallen over time in London, reaching 5.5% by the end of the sample. Outside London, the gender pay gap has also been on a downward trend, driven by both explained and unexplained factors.

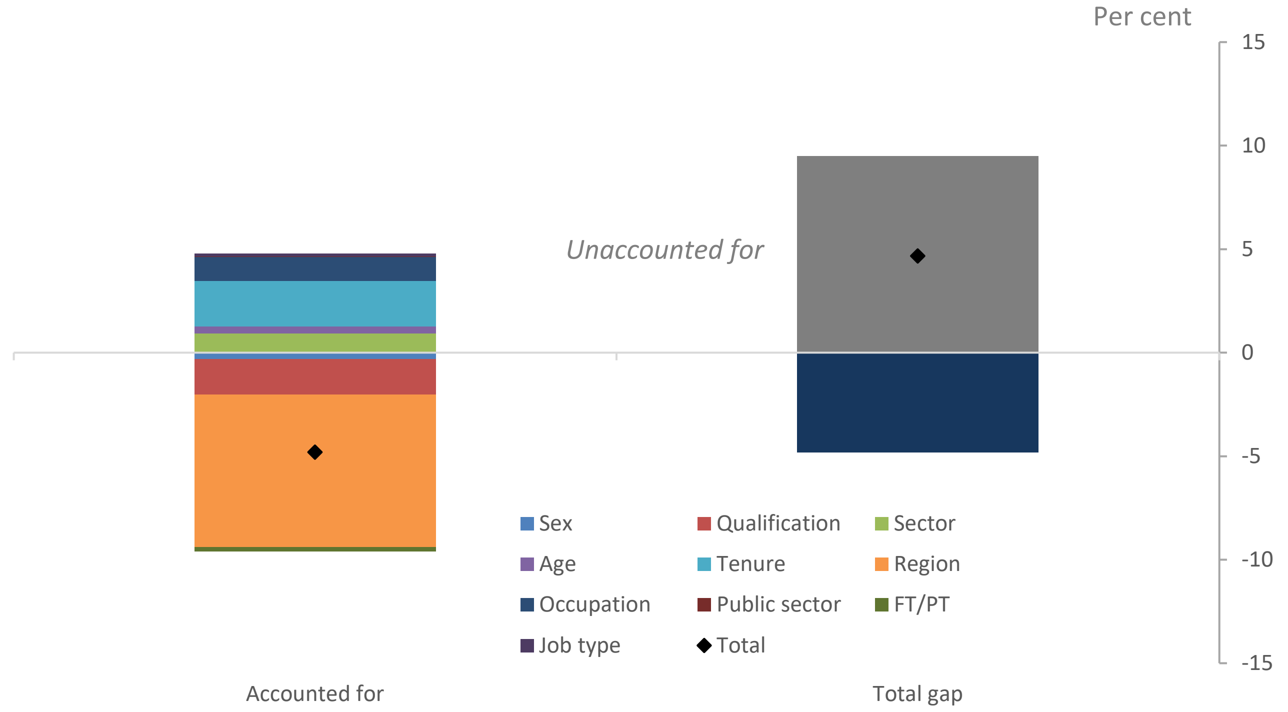
Next we implement the same methodology for the ethnicity pay gaps.[11] **Chart 22** shows the Oaxaca-Blinder decomposition of the ethnicity pay gap over the full sample. The ethnicity pay gap averages a relatively modest 5% over the sample, smaller than for gender. This is no longer the case once we account for compositional effects. These point to *higher*, rather than lower pay, for ethnic minorities. Specifically, ethnic minority workers tend to be employed in regions where wages are higher (40% of ethnic minorities work in London) and tend to have higher qualifications than their white counterparts.

Once these compositional effects are accounted for, the unexplained ("pay bias") ethnicity pay gap is as large as for females. It averages just under 10 percentage points over the sample. This demonstrates one of the perils of interpreting raw, unconditional, pay gap data too literally. Replicating this analysis for people

[11] The share of the ethnic minority population has been increasing over time in our sample from approximately 4% in 1994 to 10% in 2019. This means the median observation for the white group occurs a lot earlier than for the ethnic minority group. As a result, when we run a pooled Oaxaca-Blinder decomposition, more weight is placed on later observations, where the ethnic minority population is larger leading to a negative ethnicity pay gap. This is at odds with time-series results which take into account the relative shares of the two groups in each year. To ensure that the results are comparable with the gender pay gap, we aggregated the results from the time series regressions using the share of the two groups in each year as weights.

born in the UK reduces by half the size of the pay bias. Conversely, for people born outside the UK from ethnic minority backgrounds we estimate a significantly larger pay bias, at around 12 percentage points.

Chart 22: Ethnicity pay gap Oaxaca-Blinder decomposition, sample average

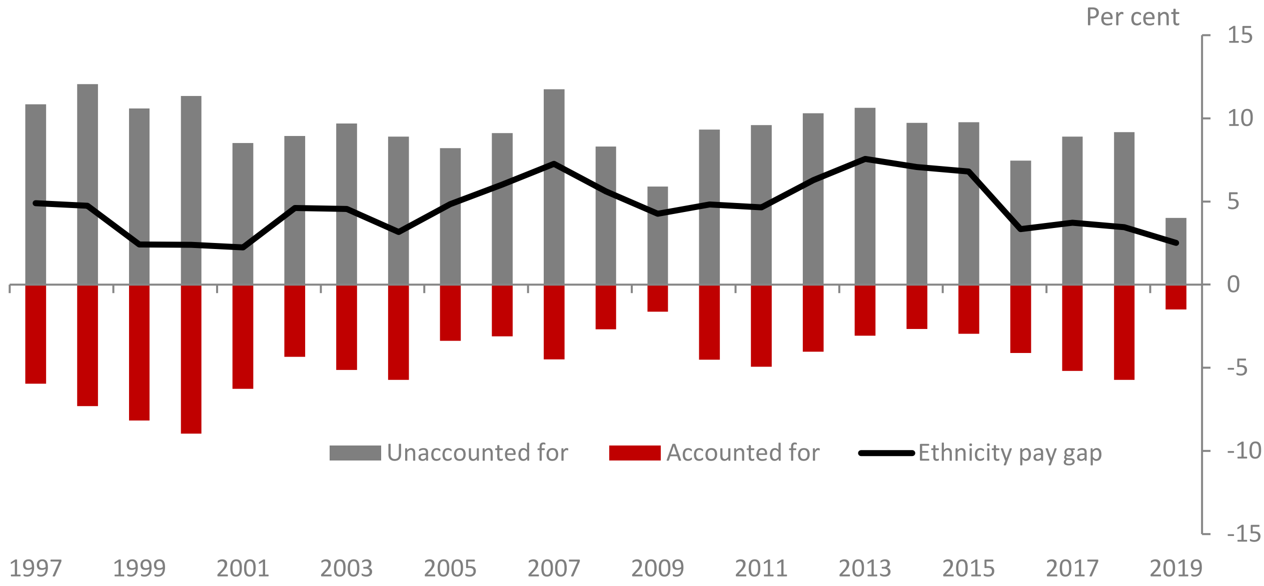


Source: ONS Labour Force Survey and Bank of England calculations.
Note: A positive ethnicity pay gap in this chart indicates that ethnic minorities earn less than their white counterparts, whereas a negative ethnicity pay gap indicates that ethnic minorities earn more than their white counterparts. 'Job type' captures if the job is temporary or permanent.

Looking over time (**Chart 23**), the unconditional ethnicity pay gap was broadly stable from the mid-1990s until 2015, since when it has declined. That decline can to a large extent be explained by the rise in the relative educational performance of ethnic minorities which, by the end of the sample, is subtracting 2 percentage points from the pay gap.

By contrast, the unexplained ethnicity pay gap has been largely unchanged over the sample. Not only is the unexplained ("pay bias") part of the ethnicity pay gap as large as for gender; it appears also to have been more persistent and has shown fewer signs of falling over time. The ethnicity pay gap problem in the UK is every bit as acute as the gender pay gap problem, contrary to the message from the raw pay gap data.

Chart 23: Ethnicity pay gap Oaxaca-Blinder decomposition time series



Source: ONS Labour Force Survey and Bank of England calculations.
Note: A positive ethnicity pay gap in this chart indicates that ethnic minorities earn less than their white counterparts, whereas a negative ethnicity pay gap indicates that ethnic minorities earn more than their white counterparts.

The decomposition also helps explain the otherwise puzzling finding of a larger ethnicity pay gap in London than elsewhere in the UK. That larger gap appears largely to reflect compositional effects. Once these are accounted for, the unexplained ethnicity pay gap in London, at 13 percentage points, is similar to the sample average, at just under 10 percentage points, and is about as persistent.

We now explore the coefficients of conditional pay gaps and its determinants using regression techniques. In our baseline regressions, we use the approach of Goldin (2014) to estimate gender and ethnicity pay gaps. Given the rich set of controls in our dataset, this offers robust estimates of conditional gender and ethnicity pay gaps. It also provides useful insights into the factors, individual and job-specific, most important for driving headline pay gaps.

Following Goldin (2014), the specification of our earnings function is:

$$(5)\ \ln(pay) = \propto + \beta * Female + \mu * Controls + \varepsilon$$

$$\text{Where } Female = \begin{cases} 1 \ \ if \text{ female} \\ 0 \ \ if \text{ male} \end{cases}$$

We regress the natural log of average gross hourly pay on a binary female coefficient and a set of controls, wider than the ones used in Goldin (2014). The set of controls comprises both individual and job-specific characteristics. It includes: age, female-age group interactions, usual hours worked, public or private sector, full time or part time, contract type, whether born in the UK, has a child under 2, female and child under 2 interaction, occupation, female and occupation interaction, educational qualifications, tenure, region of home and sector (**Annex Table 1A**).[12]

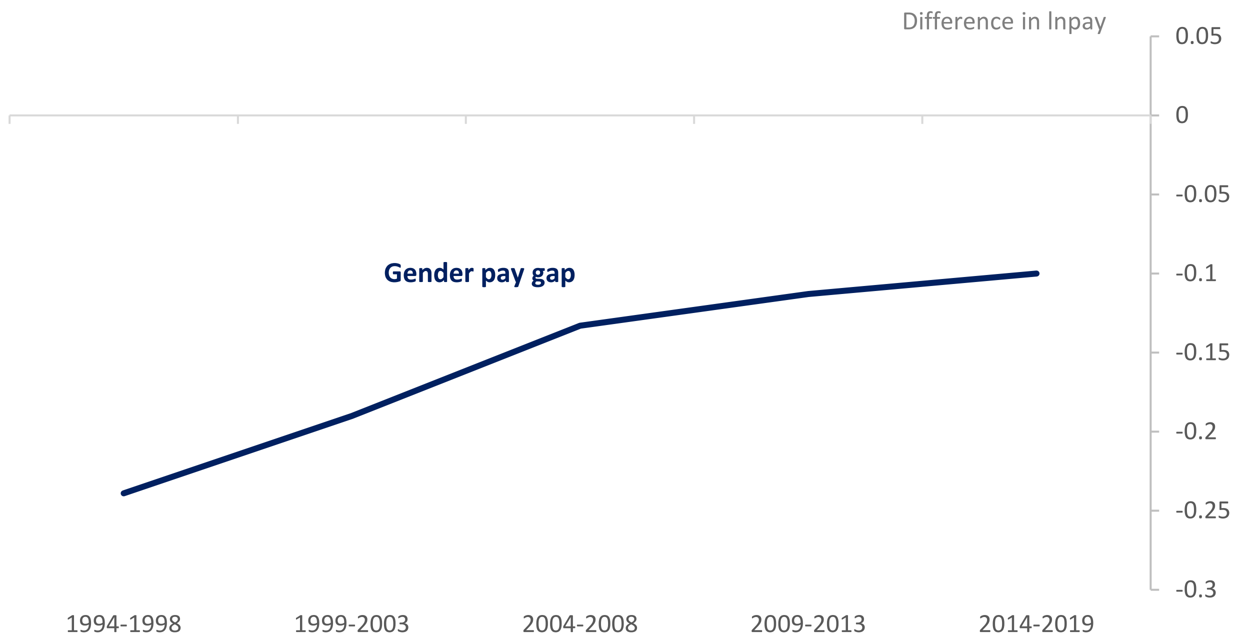
Once we take account of these factors, **Table 2** suggests that there was, on average, a conditional gender pay gap of just under 15% between 1994 and 2019.[13] This gender pay gap is highly statistically significant. To understand how it has changed over time, we split the sample into five periods (1994-1998, 1999-2003, 2004-2008, 2009-2013, 2014-2019) and re-estimate (5). As **Chart 24** shows, the gender pay gap has fallen over time, though it remains around 10% and statistically significant even at the end of the sample.

Table 2: Gender pay gap for specification (5)

	Coefficient	Pay gap, per cent	Number of observations for females
Female	-0.159*** (-11.17)	15%	291,859
Observations	537,177		

Source: ONS Labour Force Survey and Bank of England calculations.
Note: Coefficients are recalculated into percentages as per Palmquist (1980) due to log-linear specification. A negative pay gap in this chart indicates that women earn less than men.

Chart 24: Conditional gender wage gap under specification (5)

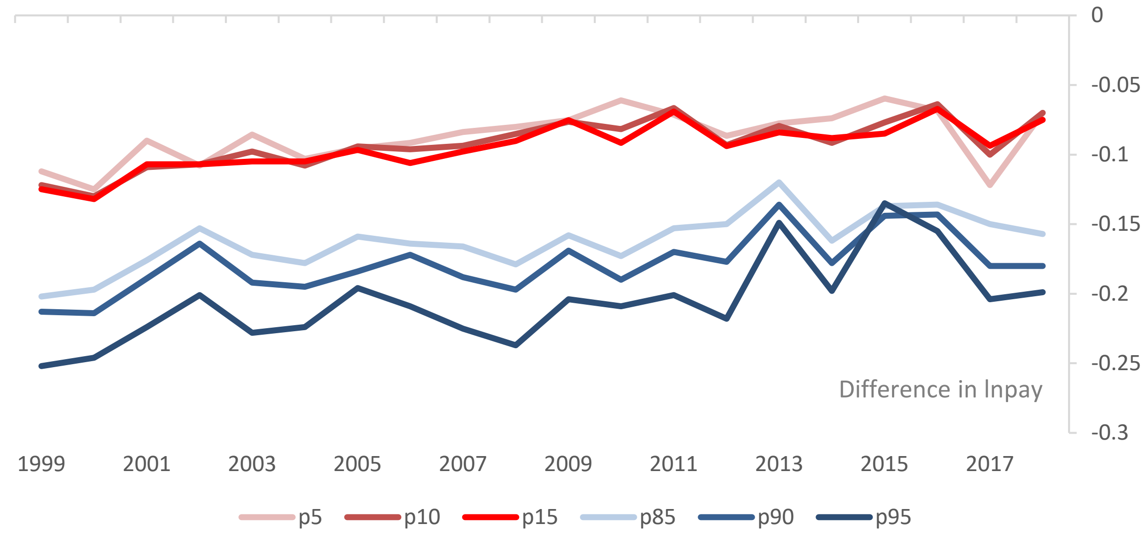


Source: ONS Labour Force Survey and Bank of England calculations.
Note: A negative gender pay gap in this chart indicates that women earn less than men.

[12] The regressions assume the effect of the controls on pay is homogenous between different groups. If we run a Chow test on this restriction, it fails in our sample. This would be a useful area for future research.
[13] Coefficients are recalculated into percentages as per Palmquist (1980) due to log-linear specification.

To test whether these changes are influenced by movements at different ends of the wage distribution, we ran quantile regression versions of specification (5) for the upper and the lower percentiles of the distribution for each year of the sample (**Chart 25**).[14] This shows a statistically significant reduction in the gender pay gap over time at both the upper and the lower ends of the distribution. The reduction was larger for percentiles at the lower end of the distribution at around 40% compared to around 22%, 15% and 21% for the 85th, 90th and 95th percentiles, respectively. However, pay gaps at the upper percentiles are larger than pay gaps at the lower percentiles. This is in line with our findings from the unconditional gender pay gap and similar studies (e.g. Arulampalam et al. (2007)).

Chart 25: Conditional gender wage gap under specification (5) by percentile



Source: ONS Labour Force Survey and Bank of England calculations.
Note: A negative gender pay gap in this chart indicates that women earn less than men.

We can replicate this regression for ethnicity with the same set of controls, except that the occupation, age groups, and children under 2 variables now interact with the ethnic minority variable.

$$(6)\ \ln(pay) = \propto + \beta * Ethnic\ minority + \mu * Controls + \varepsilon$$

$$\text{Where } Ethnic\ minority = \begin{cases} 1\ \ if \text{ person does not belong to white ethnic group} \\ 0\ \ if \text{ person belongs to white ethnic group} \end{cases}$$

With this specification, the conditional gap for ethnic minorities averages around 11% and is again significant at the 1% level. Looked at over time, **Chart 26** shows that this gap was quite volatile in the early part of the sample, although the coefficients are also insignificant for this period. Since 2009, the ethnicity pay gap has remained in double digits for most of the period and has been statistically significant.[15]

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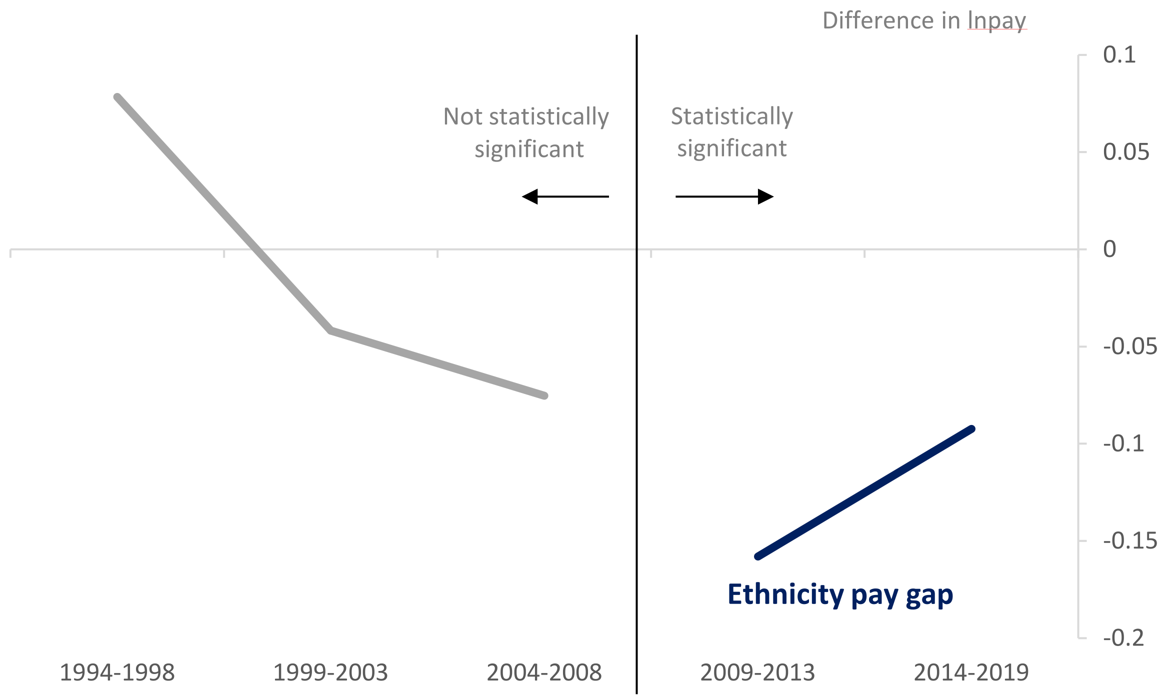
[14] The controls are the same as those used for specification (5) although we did not incorporate gender-age interaction groups due to computational constraints.
[15] This may in part because of the rising proportion of ethnic minorities in the sample population.

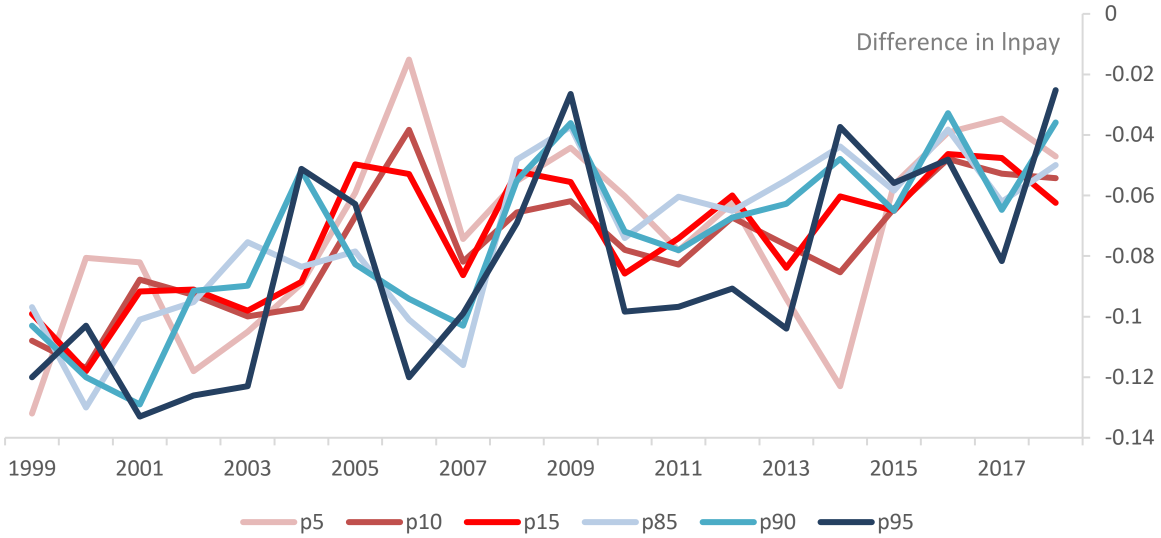
Chart 26: Conditional ethnicity wage gap under specification (6)



Source: ONS Labour Force Survey and Bank of England calculations.
Note: A negative ethnicity pay gap in this chart indicates that ethnic minorities earn less than their white counterparts, whereas a positive ethnicity pay gap indicates that ethnic minorities earn more than their white counterparts.

Chart 27 presents the conditional ethnicity pay gap across different percentiles of the wage distribution. The chart shows an overall reduction in the ethnicity pay gap over time at both the upper and the lower ends of the wage distribution, with the majority of coefficients being statistically significant at both ends. However, the ethnicity pay gap is much more volatile over time, compared to the gender pay gap for the same percentiles, and the decrease is of similar magnitude at both ends of the distribution. This is in line with our findings from the unconditional ethnicity pay gap.

Chart 27: Conditional ethnicity wage gap under specification (6) by percentile



Source: ONS Labour Force Survey and Bank of England calculations.
Note: A negative ethnicity pay gap in this chart indicates that ethnic minorities earn less than their white counterparts, whereas a positive ethnicity pay gap indicates that ethnic minorities earn more than their white counterparts.

The raw, unconditional pay data suggests that wage patterns may vary significantly across different ethnic minority groups, with some pay gaps negative and others positive. To see whether these effects hold true having accounted for compositional effects, we can run (7) with separate binary variables for each ethnicity group *i* relative to a white control group, namely: mixed/multiple ethnic groups, Indian, Pakistani, Bangladeshi, Chinese, other Asian background, Black/African/Caribbean/Black British and "Other".

$$(7)\ \ln(pay) = \propto + \beta * Ethnic\ minority_i + \mu * Controls + \varepsilon$$

$$\text{Where } Ethnic\ minority_i = \begin{cases} 1 & if \text{ person does belongs to ethnic group } i \\ 0 & if \text{ person belongs to white ethnic group} \end{cases}$$

From **Table 3**, the mixed ethnic group does not have a statistically significant pay gap. All other ethnic groups do have a significant and negative pay gap, varying from -6% and -7% for Indians and Chinese through to 20% and 13%, respectively, for workers from a Bangladeshi and Pakistani ethnic background. In other words, once we account for compositional effects, a more consistent pattern of negative ethnicity pay gaps emerges, although the size of the gap varies significantly across different ethnic minority groups.

Table 3: Conditional granular ethnicity pay gaps for specification (7)

Ethnicity	Coefficient (compared to coefficient for White)	Pay gap, per cent	Number of observations for ethnic minority groups
Mixed ethnic	0.0186 (-0.82)	2%	3,022
Indian	-0.0774*** (-10.29)	-7%	10,480
Pakistani	-0.144*** (-13.19)	-13%	3,521
Bangladeshi	-0.228*** (-12.98)	-20%	1,235
Chinese	-0.0617*** (-3.35)	-6%	1,797
Any other Asian background	-0.139*** (-11.90)	-13%	3,893
Black/African/Caribbean/Black British	-0.135*** (-17.04)	-13%	10,222
Other ethnic group	-0.0824*** (-7.34)	-8%	4,623
Observations	251,064		

Source: ONS Labour Force Survey and Bank of England calculations.
Note: Coefficients are recalculated into percentages as per Palmquist (1980) due to log-linear specification. A negative pay gap in this table indicates that ethnic minorities earn less than their white counterparts, whereas a positive pay gap indicates that ethnic minorities earn more than their white counterparts.

We can extend these specifications by considering interaction effects between gender and ethnicity. This is achieved by adding two dummy variables to the original specification (5):

$$(8)\ \ln(pay) = \propto + \beta * Female + \rho * \text{Ethnic}\, minority + \sigma * (Female * \text{Ethnic}\, minority) + \mu * Controls + \varepsilon$$

$$\text{Where } Ethnic\ minority = \begin{cases} 1\ \ if \text{ person does not belong to white ethnic group} \\ 0\ \ if \text{ person belongs to white ethnic group} \end{cases}$$

As shown in **Table 4**, we find that the conditional gender wage gap (for white women) remains around 15%. For female ethnic minorities this becomes larger at around 18%, suggesting an additional “pay bias”. This resolves another puzzle in the unconditional pay data. By contrast, ethnic minority men suffer no such additional bias. Indeed, at around -10 percentage points, their pay gap is smaller than for white women.

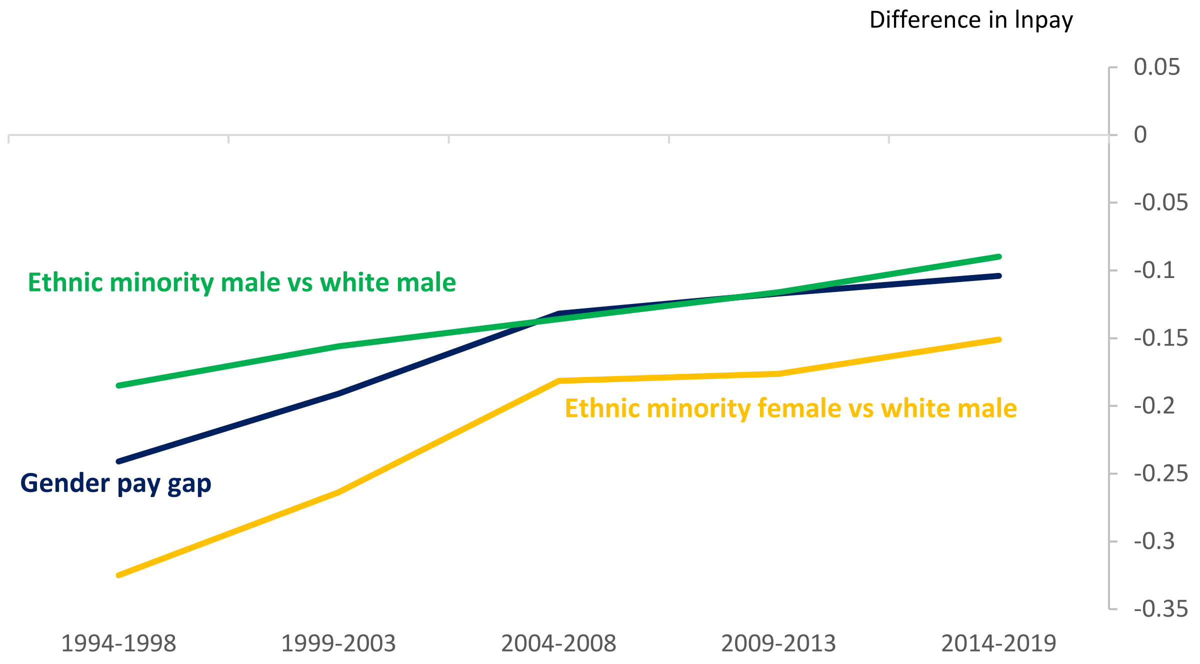
Table 4: Conditional gender pay gap for specification (5) and (8)

	Specifications				
	(5)		(8)		
	Coefficient	Pay gap, per cent	Coefficient	Pay gap, per cent	Number of observations per group
Female	-0.159*** (-11.17)	-15%	-0.163*** (-11.30)	-15%	291,859
Ethnic minority			-0.102*** (-23.01)	-10%	38,793
Female*Ethnic minority			0.0719*** (-13.57)	7%	
Observations	537,177		524,612		

Source: ONS Labour Force Survey and Bank of England calculations.
Note: Coefficients are recalculated into percentages as per Palmquist (1980) due to log-linear specification. In order to calculate the pay gap for female ethnic minorities, we have added up the coefficients of the female, ethnic minority, and the female-ethnic minority interaction dummies, as all of these dummies take the value 1 for a female ethnic minority.

If we run these regressions over time, the same broad pattern emerges. White men earn more than any of the other three categories (ethnic minority males and females and white females), although all of these pay gaps have shrunk somewhat over the past 25 years (**Chart 28).** Pay gaps for ethnic minority males have tended to be a little smaller, but have also fallen less rapidly. Pay gaps for ethnic minority women, while halving over the period, remain strikingly high.

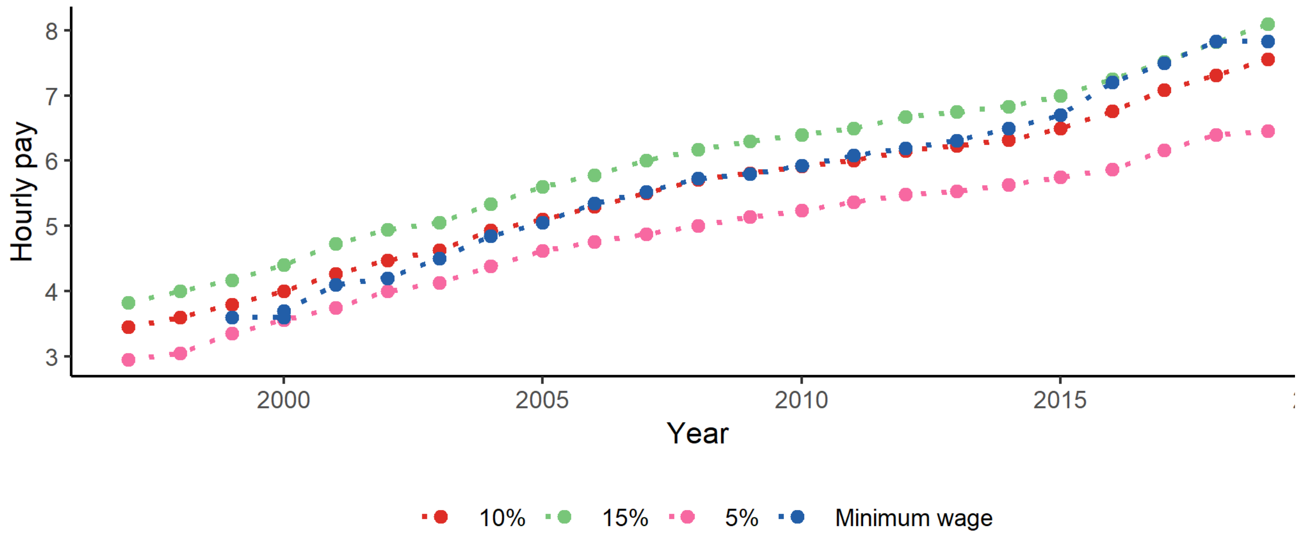
Chart 28: Conditional gender and ethnicity pay gaps under specification (8)



Source: ONS Labour Force Survey and Bank of England calculations.
Note: A negative pay gap in this chart indicates that the sub-group earns less than white men.

We previously found that the gender pay gap showed a larger reduction at the lower end of the distribution. One possible reason for this could be the introduction of, and subsequent increases in, the minimum wage. **Chart 29** shows the change in the hourly pay for the 5th, 10th and 15th percentiles alongside the change in the minimum wage. It shows that the minimum wage was below the 5th percentile until 2006, after which it followed very closely the 10th percentile until 2014 when it increased above the 10th percentile.

Chart 29: Change in hourly pay by percentile against change in minimum wage



Source: ONS Labour Force Survey and Bank of England calculations.

To test if increases in the minimum wage affected the gender pay gap, we ran quantile regressions for the 5th, 10th and 15th percentiles as per specification (9).

$$(9)\ \ln(pay) = \propto + \beta * Female + \rho * Minimum\ wage + \sigma * (Female * Minimum\ wage) + \mu * Controls + \varepsilon$$

We use the same set of controls as in our other quantile regressions including a minimum wage time series variable[16]. As shown in Table 5, we find that a £1 increase in the minimum wage leads to a statistically significant decrease in the gender pay gap by around 1% at the 5th, 10th and 15th percentiles. This finding is in line with those in other empirical studies (e.g. Dex et al. (2000)). Further work could explore this relationship with alternative specifications, alternative datasets and look at follow-up questions such as the effect of small and large changes in the minimum wage.

[16] We construct the minimum wage time series variable using the 'Main Rate' which applies to workers in our dataset aged 25 and over.

Table 5: Conditional gender pay gap for specification (9) by percentile

	Percentile					
	5		10		15	
	Coefficient	Effect, per cent	Coefficient	Effect, per cent	Coefficient	Effect, per cent
Female	-0.154*** (-18.29)	-14%	-0.154*** (-19.95)	-14%	-0.147*** (-26.25)	-14%
Minimum wage	0.110*** (-93.28)	12%	0.112*** (-127.99)	12%	0.113*** (-194.39)	12%
Female*Minimum wage	0.012*** (-8.58)	1%	0.011*** (-8.43)	1%	0.009*** (-8.8)	1%
Observations	485,210		485,210		485,210	

Source: ONS Labour Force Survey and Bank of England calculations.
Note: Coefficients are recalculated into percentages as per Palmquist (1980) due to log-linear specification.

Just because a pay gap can be explained by a set of individual and work-specific characteristics does not mean it is necessarily either reasonable or justifiable. Differences in these characteristics may themselves suggest inequalities or biases that need rectifying. It is interesting to examine what our regression results tell us about the relative importance of various factors in determining pay gaps. To assess this, we ran separate regressions for white men, white women, ethnic minority men and ethnic minority women as the effect of various factors on pay is not homogenous for these groups. Results are summarised in **Table A2** in the Annex. Some key findings include:

(a) *Education*. The "penalty" for having no qualification, compared to having a degree, is on average 39%. That penalty exists irrespective of gender or ethnicity. The penalty is not equal across these groupings, however. This penalty is highest for white women, at 41%, and lowest for ethnic minorities at 33%. The story is slightly different when we compare degrees with "other" qualifications. For ethnic minorities, where university degrees from abroad often end up in this category, the penalty is a lot smaller, at around 24%, compared with non-ethnic minorities.

(b) *Age*. Compared to the earnings of the 25-29 age group, each subsequent age group earns more up to around the mid-50s, when the earnings 'premium' flattens out a bit. For example, those aged 45-49 earn a pay premium, on average, of around 19% compared with those aged 25-29. This pay premium is notably larger for white men than women or ethnic minorities. Men aged 45-49 earn an "extra" wage premium of around 10% compared with the other sub-groups.

(c) *Part-time and non-permanent work*. Part-time work, compared with full-time employment, reduces earnings across all four sub-groups, on average by 16%. This discount is larger for white men (22%) than for ethnic minorities and white women (10%). If employment is not permanent, this also reduces earnings across the sub-groups, with white men again being affected the most (10% reduction in pay).

(d) *Children under 2*. Viewed on its own, having a child under 2 appears to have a positive effect on the earnings of both white men and women, of 6% and 1% respectively. For ethnic minority men, the effect is not statistically significant while for ethnic minority women earnings are reduced by 1%. The results are more interesting if we interact having a child under 2 with a variable capturing full or part-time employment. While for white men, the effect on earnings is still positive, for women the effect of having a child under 2 is only positive for women working part-time. For women working full-time, having a child under the 2 *reduces* earnings by around 6%. This suggests women in full-time jobs experience a 'maternity penalty', whereas men and women in part-time employment do not. Of course, in our sample we are only observing wages for women that are in employment and the results could be subject to sample selection bias. We are not using Heckman (1979) correction in our analysis and it should be noted that the results could be affected by women withdrawing from the labour force when they have a child under 2.

(e) *Financial sector*. Compared to earnings in the benchmark sector (agriculture), most sectors have higher pay. The sector with the highest relative pay is finance, with a 46% premium relative to the benchmark. This premium is notably higher for men than women (58% versus 32%), although it is highest for ethnic minority men (76%). These are large pay gaps, bearing in mind these estimates take account of differences in the individual characteristics of the workers, such as age and educational achievement.

(f) *Born in the UK*. Being born in the UK, on average, leads to slightly lower earnings than not. However, this average masks sharply opposing trends among whites and ethnic minorities. Being born in the UK and white reduces earnings by around 7% compared with whites born outside the UK. This largely reflects the effects of those with "other qualifications", and the fact that white people born outside the UK tend to be more educated. By contrast, ethnic minorities born in the UK boosts earnings by around 7% relative to non-UK born ethnic minorities. UK-born ethnic minorities tend to be more educated and earn more across all the types of qualifications, compared with non-UK born ethnic minorities.

(g) *London*. Compared to the benchmark (the North), the region in which people live and work plays a relatively very small role in determining their pay, with one exception – London and the South East. A job there boosts earnings, relative to the North, by 21% and 12% respectively. This effect is present across all four sub-groups. The 'London effect' is if anything more pronounced among white women, who earn 26% more.

Section 5: Conclusion

Let us conclude by summarising some of our main findings and then setting out some of the potential next steps, policy-wise, that flow from this analysis.

First, the good news is that, once we control for various job and individual-specific factors, there is clear evidence of progress having been made in shrinking gender and ethnicity pay gaps in the UK over the past quarter-century or so. Based on the results from the Oaxaca-Blinder decomposition, the mean gaps have shrunk by around half for females, and by a little less than that for ethnic minorities. These gaps have shrunk not only at the mean, but also at the lower and upper ends of the pay distributions. The introduction of minimum wage legislation appears to have contributed significantly to a shrinking of the gender pay gap among lower wage workers.

Second, the gender and ethnicity pay gaps remain large even once various compositional effects are taken into account, at around 10 percentage points. Pay gaps have not only been large but persistent, strikingly so among ethnic minorities, even once we make allowance for differences in skill and job attributes. Furthermore, gender pay gaps at the upper end of the pay distribution are much larger than the pay gaps at the lower end of the distribution. This suggests, despite progress, much remains to be done.

Third, even where we can “explain” pay gaps using various fundamental factors, this should not be taken to imply these gaps are necessarily justifiable. For example, consistent and large education and skills differences between cohorts could themselves be taken as evidence of a policy failure. So too might a preponderance of certain types in certain sectors or occupations.

Fourth, consistent with that, our results suggest that existing pay biases can be amplified and exaggerated by the effects of age, the nature of the employment contract, educational qualifications and having children under the age of 2. On average, these too tend to further the pay disadvantage for women and ethnic minorities.

In terms of policy implications, a number of important government initiatives are already underway, among central banks and more widely. The Bank of England began publishing its gender pay gaps in 2017 and has chosen voluntarily to publish its ethnicity pay gap too since 2018. In 2019, the Bank’s median gender pay gap was 23% and the median ethnicity pay gap was just under 7%, reflecting lower representation of both groups at senior levels. Published pay gaps have been a useful prompt for further action by the Bank.

The Bank is committed to closing these pay gaps, including by setting stretching targets for representation, in general and at senior levels. Good progress is being made. The share of BAME and female staff below senior management in the Bank currently stands at 19% and 46%, respectively, compared to targets of 20%

and 50%. At senior management, BAME and female representation is 5% and 31%, compared to targets of 13% and 35%.[17] A wide array of initiatives are underway to ensure the Bank meets these targets.

Other central banks have also made a push towards improving their staff diversity, although few publish pay gaps. The ECB's Executive Board introduced gender targets in 2013 in order to double the share of women in management by 2019. As of the end of 2018, 29% of management positions were held by women compared with a target of 35% for the end of 2019. For the most senior management roles the share was 22% against a target of 28% for the end of 2019. The ECB announced additional measures last year. The Fed announced a Diversity and Inclusion Strategic Plan for 2016-19, aimed at fostering diversity in the organisation. In order to foster transparency and accountability, they report the composition of their employees by diversity statistics annually.

Looking beyond central banks, the analysis presented here suggests some clear directions of travel. First, our results suggest minimum wage legislation has had a positive impact in reducing the gender pay gap among lower-paid female workers, with each £1 increase on average shrinking the pay gap by 1%. This suggests that, at the time minimum wage levels are being decided, pay inequality factors should be weighed in the decisions, alongside its likely impact on average pay and employment.

Second, at present gender pay gap reporting in the UK only covers companies with more than 250 employees. In practice, this means it covers only around 40% of the UK working population in the private sector.[18] To tackle the pay gap comprehensively, this suggests there is a strong case for extending the pay reporting regime to smaller companies – say, those with 30 or more staff.

Third, there is currently no compulsory system of company reporting on the ethnicity pay gap in the UK, though the government has consulted on doing so. The ethnicity pay gap is at least as large as for females, and if anything has been more persistent. In our opinion, there are therefore strong grounds for extending compulsory reporting to ethnicity as well as gender. This analysis also emphasises the importance of looking at labour market outcomes for *different* ethnic minority groups, rather than necessarily treating ethnic minorities as a single group.

Fourth, at present only a handful of countries internationally require companies to publish gender and ethnicity pay gaps. There is a strong case for reporting diversity pay gaps, on an internationally-harmonised basis, to allow cross-country as well as cross-company comparison. Given their expertise on labour market issues, this might be something on which the OECD and ILO could lead. The international central banking community could also help lead by example.

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[17] Carney (2019a) discusses diversity and inclusion in the Bank. Carney (2019b) notes that the Bank's gender pay gap is lower than for most companies in the financial sector.
[18] https://www.gov.uk/government/publications/business-population-estimates-2019/business-population-estimates-for-the-uk-and-regions-2019-statistical-release-html

The benefits of internationally-harmonised disclosures, as an incentive device for action, have recently been demonstrated in the case of climate change disclosures. Today, financial firms with around $34 trillion assets under management have committed to harmonised reporting using the Task-Force on Climate-related Financial Disclosures (TCFD) template.[19] This has encouraged wider scrutiny of, and actions to mitigate, the risks to companies' profits and balance sheets posed by climate change. Pay gap disclosure could have similarly behavioural effect on companies.

Fifth, there is also a strong case for improving the sets of data available publicly to monitor progress towards equality of pay and opportunity in the workplace. One example of useful additional data would be to expand the longitudinal data tracking individuals from school into employment, perhaps using administrative data or new surveys. This would help to understand the key determinants, and obstacles, to career and pay progression.

Sixth and finally, published pay gap data are imperfect and can sometimes give a misleading impression of diversity patterns. We have demonstrated how raw pay gap data can sometimes give rise to puzzles. We have also demonstrated, however, that a careful consideration of various compositional factors can resolve these puzzles and provide a clearer picture of underlying patterns. There is no reason why companies could not use these techniques when interpreting their own results.

Others have argued that publishing pay gap data may discourage companies from investing in a pipeline of diverse talent for the future, as hiring younger and lower-paid workers could actually show up as a worsening pay gap in the near-term, even if it bears fruit longer-term. These are legitimate concerns. But they are far from being knock-down arguments when it comes to publishing pay gap data.

Published pay gaps are a starting point for corporate and national accountability and explanation, not an end-point. No single metric can perfectly summarise all dimensions of diversity. But publication of a single metric can, and has, served as the catalyst for an explanation and action, at the company and national levels. For example, it prompts companies to justify their misses and to explain how and over what horizon they expect their pay gap and diversity targets to be hit.

There is an analogy here with inflation-targeting using monetary policy. The single target does not wholly or perfectly summarise all dimensions of the economy. But having the target serves as a catalyst for explanation and action – an explanation for misses and an action plan for returning inflation to target. That improves policy accountability and societal outcomes. The same could be true of companies when it comes to diversity policies and outcomes.

[19] TCFD (2019).

Annex

Table A1: Variables used

Variable	Calculation/Description
Age groups	'AGEGROUPS'
Children under 2	‘FDPCH2’ Number of dependent children in family aged under 2
Education	A combination of 'HIQUAPD', 'HIQUALD', 'HIQUAL4D', 'HIQUAL5D', 'HIQUAL8D', 'HIQUL11D', and 'HIQUL15D' to create 6 classes of highest qualification attained
Ethnicity	A combination of ‘ETHUKEUL’, ‘ETHCEN15’, ‘ETHCEN’ to create 9 classes of ethnicity as these change across time
Full-time / Part-time	‘FTPT’ Whether working full or part-time
Gender	‘SEX’ Sex of respondent
Job Type (Permanent or Temporary)	‘JOBTYP’
Occupation	Occupation (main job). Calculated through a combination of ‘SOC2KM’, ‘SC102KM’, SC2KMMJ’, ‘SOC10M’ and ‘SOCMAIN’ to create 10 classes of occupations as these change across time
Pay	Log of average gross hourly pay in main job (‘HOURPAY’)
Public sector or private sector	‘PUBLICR’ Whether working in the public or private sector
Region	Region of usual residence ‘URESMC’
Sector	A combination of Sector (SIC2007) ‘IND07’ and industry section (main job) ‘IND07M’ as these change across time
Tenure	Length of time continuously employed ‘EMPLEN’
UK-born	A combination of varying country of origin and

	country of birth variables: 'CRYOX', 'CRYOX7', 'CRYO', 'CRYO7' and 'CRY01'
Usual hours worked	Log of total usual hours in main job (including overtime) 'TTUSHR'
Wave	'THISWV' Wave to which the data refers to

Table A2: Separate group regression results[20]

	White male	**White female**	**Ethnic minority male**	**Ethnic minority female**
Constant	**3.615*** **	**2.810**	**2.873**	**3.012**
Age groups				
30-34	0.110***	0.081***	0.114***	0.078***
35-39	0.179***	0.111***	0.130***	0.109***
40-44	0.221***	0.119***	0.164***	0.143***
45-49	0.233***	0.132***	0.178***	0.134***
50-54	0.226***	0.132***	0.195***	0.159***
55-59	0.202***	0.128***	0.160***	0.145***
60-64	0.168***	0.136***	0.143***	0.165***
65-69	0.172***	0.103***	0.163***	0.147***
70+	*0.000*	0.076***	*0.037*	0.161*
Log hours worked	-0.203***	-0.059***	-0.111***	-0.122***
Public sector	-0.041***	0.018***	*0.014*	0.040***
Full-time/part-time	-0.252***	-0.106***	-0.167***	-0.101***
Job type	-0.103***	-0.087***	-0.083***	*-0.021*
UK-born	-0.077***	-0.058***	0.066***	0.080***
Have children under 2	0.054***	0.013***	*0.003*	*-0.011*
Occupation				
Professional	0.014***	0.081***	0.128***	0.099***
Associate professional	-0.093***	-0.091***	-0.081***	-0.098***
Administrative	-0.410***	-0.305***	-0.360***	-0.313***
Skilled trades	-0.351***	-0.425***	-0.332***	-0.411***
Personal service	-0.482***	-0.413***	-0.495***	-0.412***
Sales and customer	-0.412***	-0.392***	-0.426***	-0.462***
Process and plants	-0.447***	-0.491***	-0.381***	-0.514***
Elementary	-0.523***	-0.468***	-0.445***	-0.487***

[20] Raw regression coefficients are reported in this table. In the main body, these are recalculated into percentages as per Palmquist (1980). For example, a coefficient of (-0.41) equals to a 33% decrease in hourly pay.

Education				
Higher educ	-0.175***	-0.211***	-0.182***	-0.189***
GCE A Level or equiv	-0.263***	-0.259***	-0.196***	-0.185***
GCSE grades A-C or equiv	-0.278***	-0.341***	-0.235***	-0.264***
Other qualifications	-0.377***	-0.444***	-0.277***	-0.280***
No qualification	-0.470***	-0.531***	-0.397***	-0.397***
Don't know	-0.346***	-0.351***	-0.279***	-0.271***
Tenure				
3 months but less than 6	0.019**	*0.005*	*0.036*	*0.006*
6 months but less than 12	*0.004*	*0.006*	*0.008*	*0.015*
1 year but less than 2	0.032***	0.024***	*0.028*	0.031*
2 years but less than 5	0.064***	0.062***	0.065***	0.077***
5 years but less than 10	0.113***	0.112***	0.093***	0.115***
10 years but less than 20	0.159***	0.175***	0.160***	0.162***
20 years or more	0.206***	0.266***	0.251***	0.211***
Region				
Yorks & Humber	*0.007*	0.013***	*-0.028*	*0.029*
East Midlands	0.025***	0.025***	*0.014*	*0.012*
East Anglia	0.042***	0.037***	0.093***	0.066**
London	0.199***	0.229***	0.113***	0.142***
South East	0.127***	0.098***	0.137***	0.108***
South West	0.011***	*0.005*	*0.058*	*0.044*
West Midlands	0.020***	0.025***	*-0.004*	*0.001*
North West	0.013***	0.021***	*-0.017*	*-0.011*
Wales	-0.024***	*0.005*	*-0.021*	*0.025*
Scotland	0.026***	0.034***	*-0.036*	*0.033*
Northern Ireland	-0.038***	0.019***	*-0.032*	*-0.001*
Industry				
Mining and quarrying	0.424***	0.418***	0.478**	*0.239*
Manufacturing	0.206***	0.152***	*0.194*	*-0.081*
Electricity, gas, steam and air conditioning supply	0.387***	0.330***	0.435**	*0.126*
Water supply, sewerage and waste management	0.239***	0.193***	*0.239*	*-0.121*
Construction	0.251***	0.208***	*0.294*	*-0.044*
Wholesale and retail trade	0.113***	*0.004*	*0.135*	-0.194**
Transport and storage	0.234***	0.193***	*0.298*	*0.009*
Accommodation and food service activities	*0.008*	*-0.010*	*0.041*	-0.221**
ICT	0.323***	0.258***	0.387*	*0.109*

Financial and insurance activities	0.450***	0.275***	0.563***	*0.156*
Real estate activities	0.232***	0.164***	*0.227*	*0.018*
Professional services	0.288***	0.232***	*0.354*	*0.051*
Administrative and support service activities	0.153***	0.143***	*0.200*	*-0.088*
Public administration	0.241***	0.152***	*0.264*	*-0.079*
Education	0.134***	*0.026*	*0.171*	-0.190**
Human health and social work activities	0.132***	0.067***	*0.264*	*-0.140*
Arts, entertainment and recreation	0.048***	*-0.011*	*0.224*	-0.190**
Other service activities	*0.002*	*0.019*	*0.103*	*-0.108*
Activities of households as employers	-0.096***	-0.046*	*0.172*	*-0.224*
Activities of extraterritorial organisations and bodies	0.400***	0.334***	0.385*	*-0.016*

Notes: For all groups, the log of hourly pay growth is regressed on full set of explanatory variables. ***, **, * refer to 1%, 5% and 10% statistical significance levels.

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