Dissertation

On the Determinants and Evolution of the Ethnicity Wage Gap

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DECLARATIONS:

1. This dissertation is my own work and, with the exception of quotations (which are clearly marked and referenced), is written in my own words.
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Abstract

This paper uses Labour Force Survey data to study the ethnicity pay gap from 1997 to 2019, pooling 23 years of data to create one of the largest analyses of the UK Labour Market. Blinder–Oaxaca decompositions show that ethnic minority males face statistically significant levels of unexplained negative wage differences. Conversely, ethnic minority women earn a higher wage than White women, due to favourable characteristics, and sometimes despite unexplained negative wage pressure. Both male and female Asian workers, in particular, have evidence of direct pay discrimination. All minorities of both sexes have higher levels of education, yet men cluster into lower-paid positions, while women into higher paid ones (compared to their White counterparts). Direct pay discrimination has been stationary, if not fallen, over time. However, unexplained wage gaps seemed to widen immediately following the financial crisis, although volatility prevents reliable conclusions from being made.

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Chapter 1

Introduction and Theory

1.1 Introduction

Racial wage discrimination became illegal in the UK in 1965 (GOV.UK, 1965) with the Race Relations Act, in light of increased immigration after WWII. The law was later strengthened in 1968 and 1976 (Sooben, 1990). Yet despite criticism of the legislation in the wake of the Brixton riots of 1981 (Solomos, 2003), the inadequacy of labour market protections for ethnic minorities was not addressed until 2010 through the Equality Act (Brown, 2018). With little recent research into ethnicity pay gaps, unlike gender pay gaps (Metcalf, 2009), and even less research into how they have changed over time, this paper seeks to address this. Recent criticism of economic models by Spriggs (2020), in response to global anti-racism protests, has shown the need for a more objective approach to discrimination research.

Ethnicity pay gaps are just one, among many, expressions of discrimination in modern economies. Pay gaps are where ethnic minorities are paid different amounts (often less) than native workers and can occur in three main ways. Either employees have different characteristics (economically justifying their different wage), employers directly pay minorities a lower wage for the same job, or workers cluster into lower-paying industries. All three can foster an element of discrimination, and are interlinked. If a job applicant has less education or labour market experience, an employer is legally entitled to pay a lower wage. However, minorities may have less education, for example, because they are not willing to train to work in industries that are perceived to be racist. Over time, this leads to occupational clustering, where minorities are over-represented in some industries and under-represented in others. Consequently, pay gaps emerge and are often persistent, with many underlying factors at play, making policy solutions complex — even though direct pay discrimination is illegal in the UK.

In the next section, we explore economic models and theories which attempt to characterise aspects of the labour market, along with the literature surrounding ethnicity pay gaps in the UK. Chapter 2.1 outlines the details of data collection along with descriptive analysis, which provides the backdrop for decompositions and analysis of endowments. The Blinder-Oaxaca decomposition technique is then outlined and implemented in Chapter 3, with a detailed discussion of the results. To conclude, Chapter 4 discusses the limitations of the analysis along with areas for future research and finished by concluding with the main findings of this paper. Appendices can be found in Chapter 5.

1.2 Theory

Economic discrimination can manifest itself in three ways. The first is individual discrimination, where agents directly treat minorities unfavourably — be it female, minority ethnic, or other forms of minorities. For example, a firm may choose to employ a White worker over a minority worker when they are equal in every other way. The second form is institutional discrimination, where institutions and practices within the economy work against specific groups at a “nonconscious level” (López, 2000, p. 1814), even if individuals themselves do not. Thirdly, there is structural discrimination, which refers to the ongoing perpetuation of disparities in opportunity and outcome (Lawrence et al., 2004). There are several economic models which serve to shed light on the mechanisms at work within these discriminatory practices, which will now be explored.

1.2.1 Taste Models

Taste models pioneered by Becker (1957) and Arrow (1973) assert that employers have a preference for White workers. Therefore, they only employ minorities at a lower wage rate to compensate themselves for receiving a lower utility, paying a price to avoid employing minorities. Even if direct wage discrimination does not occur, firms that are prejudiced may only offer minorities jobs in lower-paying occupations. Therefore, ethnic minorities are forced into earning lower wages, either through being paid lower wages for the same job or only being offered lower occupation jobs (Coate and Loury, 1993).

With perfectly competitive markets, firms have a profit incentive to offer minorities a 'fair' wage, attracting talented minorities. That is, non-prejudiced firms pay minorities the same wage as their counterparts until prejudiced employers are forced to exit the market. Discrimination may therefore only exist in practice if firms can collude to allow prejudice to exist long-term, especially if institutions permit this collusion (Lundberg and Startz, 1998b). Alternatively, if customers are prejudiced and value the output of minorities less, this will lead to a material difference in Marginal Revenue Product (MRP)[1], meaning economic incentives exist for firms to offer them lower wages.

1.2.2 Statistical Discrimination and Signalling Models

Statistical discrimination is different to taste-based discrimination, in that it is not a result of direct prejudice. Instead, it occurs in the presence of asymmetric information. If employers cannot easily determine the productivity of workers, they may have an irrational perception that minorities are less productive than White workers (Phelps, 1972; Lundberg and Startz, 1998b). Consequently, firms will only offer minorities a lower wage, regardless of their true productivity, causing ethnic minorities to be trapped in a low wage equilibrium (Barr, 2012). A key aspect of this model is that minorities are unable to 'signal' to employers their true productivity, and as such the employer is forced to make assumptions. Although, these assumptions can be based upon (discriminatory)

[1] MRP is the additional revenue from employing an extra worker, due to the output they produce. It falls because prejudiced customers reduce the revenue of the firm, not the productivity of the minority.

stereotypes and biases.

Statistical models of discrimination built upon the work of Arrow (1973) show that average differences between minorities and Whites can occur endogenously. These extend beyond the work of Phelps (1972), which assumes that discrimination occurs as a result of a combination of imperfect information and exogenous differences between Whites and minorities. We can go so far as to say that minorities' outcomes can be a result of endogenous interactions alone: that is, the assumptions made by employers in the presence of asymmetric information is enough to cause minorities to be trapped in a low wage equilibrium.

1.2.3 Entrenchment

Group differences can become entrenched as minorities make investment decisions regarding their education. If minorities expect to earn a lower wage, their returns to education, and therefore incentives to invest in education, are lower than is economically efficient. This is a self-fulfilling prophecy; incentives cause minorities to have less education than their White counterparts, and the expectations of the prejudiced employers are realised when they would not have been otherwise (Fang and Moro, 2010). This can lead to comparative advantage in certain job types, further entrenching occupational segregation (Altonji and Blank, 1999). The theory, therefore, predicts that ethnic minorities will earn less than White British men because of this endogeneity of investment in education. Therefore, statistical discrimination explains why discrimination can persist even in the presence of perfectly competitive markets (Lundberg and Startz, 1998b).

Occupational clustering and segregation can also be caused by differences in preferences (Thaler and Rosen, 1976). For example, if the preferences of White men are such that they are willing to work in recycling centres when other ethnicities are much less willing to, the scarcity of labour supply will command a higher wage (Altonji and Blank, 1999). Aggregating these micro-economic factors leads to occupational clustering which can become entrenched over time.

1.2.4 Other Causes of Wage Determination

Aside from discrimination, multiple sociological factors affect the wages of workers.[2] Family structures can vary by ethnicity, and women may under-invest in education if they expect to spend less time in the labour market. This can lead to the depreciation of skills and productivity, hampering wages. Additionally, certain ethnicities may invest in higher education more than others, increasing productivity and labour market remunerations (Becker, 1957). Further, those who are married may command a higher wage, as productive workers may be more attractive in the marriage market, and can take advantage of the division of labour within the household (Nakosteen and Zimmer, 1987; Bardasi and Taylor, 2005).[3]

Practical considerations can also affect wages; those living in specific regions (such as London) may naturally earn a higher wage to compensate for increased living costs. Additionally, part-time workers may be willing to work for a lower wage if it is supplementing alternative forms of income. Economy-wide wages have also increased as a result of increasing consumer prices for the entirety of the post-war period (World-Bank, 2020). All of the above factors will be considered in our model where possible. Additional factors such as motivation and ambition also determine wages, but cannot be measured easily and are also probably endogenous (similar to the discussion in Section 1.2.2).

1.3 Literature

In the UK, outcomes for non-White workers are very heterogeneous. Individuals of Bangladeshi ethnicity typically receive the lowest pay, with Chinese, Indian, and mixed-race workers receiving a higher median annual pay than White British employees (ONS, 2018). Research often finds vastly different outcomes even within ethnic groups (Heath and Cheung, 2006). Black African and Caribbean men face larger pay gaps than Black mixed-race workers, with a similar picture for women. Additionally, Pakistani and Banglade-

[2] Other factors include difficulties in integrating into society, which can lead to alienation, possibly due to past experiences of discrimination (Berthoud, 2000), hampering labour market outcomes.

[3] Additional effects of marriage on the labour market are explored by Ahituv and Lerman (2005).

shi men have some of the largest pay gaps.

Many techniques focus on the pay gap at the average wage. However, ethnicity pay gaps vary depending on the position in the wage distribution, and across time. Amadxarif et al. (2020) find that over the last 25 years ethnicity pay gaps have fallen by 50% over the whole distribution, and attribute the effect at the lower end to minimum wage policy. GOV.UK (2008) also found that the pay gap has been falling at the lower end of the distribution due to the minimum wage. However, there has been little research into the trend over time. Whilst raw (unconditional) ethnicity pay gaps have fallen from 30% to 20% from the mid-1990s to 2018 (Amadxarif et al., 2020, p. 11), there has been little evidence of a fall towards the end of the sample, particularly for women (Metcalf, 2009; Blackaby et al., 2005).

1.3.1 Gender

Outcomes also vary by gender, albeit with women of every ethnicity subject to the gender pay gap. Longhi and Brynin (2003) found that the ethnicity pay gap is larger for men than for women, such that ethnic minority women have a smaller pay gap (relative to White women) than for ethnic minority men (relative to White men). However, Metcalf (2009) even found that female ethnic minorities seem to outperform White women, although all women are subject to the gender pay gap (Heath and Cheung, 2006).

1.3.2 Components of the Wage Gap

There are many reasons why ethnic minorities are paid different wages to White workers and, as such, the literature often distinguishes 'explained' and 'unexplained' components of the pay gap. The 'explained' component refers to the differences in characteristics (education, experience, marital status, etc.), whereas the 'unexplained' portion is any part of the wage gap which cannot be explained by the model used. It is important to note that the 'explained' wage gap can encompass an element of endogenous discrimination. Additionally, the 'unexplained' portion is not necessarily entirely due to discrimination, especially if the model is not perfect; the level of discrimination is difficult to measure precisely. Instead, it can be seen as an upper bound on the level of direct pay discrimination. The literature points to the pay gap comprising of a mix of unexplained components and differences in characteristics. However, the majority of research is consistent with a not-insignificant level of discrimination (Metcalf, 2009), particularly for Black employees, with 49% of the earnings gap left unexplained (calculated from Blackaby et al. (2005, p. 374)).

The distinction between the 'explained' and 'unexplained' components implies a subtle distinction between direct labour market discrimination and previous discrimination faced by parents and grandparents (Lundberg and Startz, 1998a). The former is included in the 'unexplained' wage gap. However, historical discrimination can affect education and occupation decisions, as minorities that believe they will experience discrimination in a particular occupation will be more likely to avoid it. Therefore, it is included within the 'unexplained' component. These pre-labour market experiences can have a lasting effect on future earnings (Altonji and Blank, 1999; Hedman et al., 2019; Berthoud, 2000).

1.3.3 The Explained Wage Gap

Ethnic minorities may receive higher or lower wages than White British workers for several reasons. The wage equation proposed by Mincer (1958) outlines how education and experience are key determinants of wages. The positive pay gap for Chinese workers is often attributed to a relative drive for educations (Leslie and Drinkwatr, 1999; Berthoud, 2000), and all minorities tend to have higher levels of education, levelling wages (Longhi and Platt, 2008). The literature also focuses on the importance of occupational clustering, where, over time, minorities become over-represented in certain occupations and under-represented in others. Whilst clustering often negatively impacts wages, Chinese and Indian workers earn a wage premium thanks to occupational clustering (Brynin and Güveli, 2012). As noted in Sections 1.2.2 and 1.3.2, occupational clustering can be indicative of statistical and structural racism, despite being encompassed within the 'explained' portion of the wage gap.

Aside from traditional determinants of wages, several variables have been used in the literature. Ethnic wage gaps vary depending on whether the individual is born in the UK or not (Brynin and Güveli, 2012; ONS, 2018; Shields and Price, 1998); the pay gap for Black/African/Caribbean widens from 7.7% to 15.3% for those born overseas (ONS, 2018), potentially due to the unwillingness of employees to recognise the equivalence of foreign qualifications. Even the region within the UK is an important factor, with the largest pay gap between White and non-White workers being in London at 21.7% (ONS, 2018). Therefore, complex factors are at play; those working in London can expect to earn a higher wage compared to the rest of the population, but minorities are at a relative disadvantage.

1.3.4 Employment

Disadvantages extend beyond pay itself, with many minorities more likely to be unemployed (Heath and Cheung, 2006). Additionally, the unemployment rates of ethnic minorities tend to increase faster in a recession than White British individuals (Jones, 1993). Consequently, even if pay gaps were to be non-existent, outcomes would not be equitable. Unemployment may also further worsen minorities' integration into the labour market and wider society. Overall, ethnic inequalities are manifested in a variety of ways and, even though this paper focuses on pay gaps, other labour market disparities exist.

1.3.5 Policy

Various policies have been implemented to curtail the ethnicity pay gap. Well designed policies bring both equity and efficiency gains, a Pareto Improvement[4] (Lundberg and Startz, 1998b), and significant gains to GDP (GOV.UK, 2017). The largest UK firms engage in pay reporting, which is seen as a "starting point" and not an "end-point" (Amadxarif et al., 2020, p. 39). However, research has shown how many such initiatives, along with Equal Opportunities Policies, often have "little or no impact" (Noon and Hoque, 2001, p. 113). Additionally, with the vast majority of research pointing to dif-

[4] A Pareto Improvement is where one agent within an economy can be made better off without adversely affecting others (Varian, 2006).

ferences in endowments among workers, pay reporting policies place excessive emphasis on the prejudice of companies rather than addressing past policy failures. Given that occupational segregation is a complex and endogenously-driven phenomenon, it requires specific policy interventions to ensure (educational and other) outcomes are more equitable. The nature of the policy recommendations, therefore, depends on whether the pay gaps are due to direct pay discrimination or specific differences in endowments.

Chapter 2

Dataset and Initial Analysis

2.1 Data Source

In order to conduct a rigorous analysis of the UK labour market, a large sample size is required. Initially, the British Cohort Study 1970 was preferred (BCS, 1970), but the sample of ethnic minority groups was insufficient. Additionally, wage data within the BCS is limited, causing the overall sample from ethnic minorities with wage data to be very small. Consequently, the Labour Force Survey (LFS) is the main source of data for subsequent analysis (ONS, 2020f).

The LFS was initially a bi-annual survey of UK households, first conducted in 1973. In 1984 it became an annual survey, and since 1992 it has been conducted quarterly. The LFS is the largest of its kind in the UK and used for official UK statistics regarding both employment and unemployment (ONS, 2020c). It covers approximately 40,000 households and 100,000 individuals in each quarter, with each household being interviewed for 5 waves (quarters). The period covered will be 1997 through to 2019, inclusive. Reliable earnings data, not subject to attrition bias, is only available from 1997 (ONS, 2020d) and, at the time of writing, only three-quarters of the 2020 data are available, resulting in a reduced sample size. Only those in wave 1 have been kept to remove attrition bias and because changes in wages from wave 1 to 5 are expected to be minimal (which would generate serial correlation from clustering).

There are several drawbacks to using the LFS. Firstly, it does not include past labour market experience, meaning that detailed analysis of periods out of the labour market cannot be conducted. Secondly, 2001-Q1 is a corrupted file on the UK Data Service, and so is excluded from the analysis, consistent with Longhi et al. (2009). Finally, there is a high proportion of proxy responses, which can bias the likelihood of reporting certain qualities (Clarke and Tate, 1999; Davies and Jones, 2005). However, the effect on this paper's conclusions is believed to be minimal. Despite these drawbacks, the LFS is the richest data source of its kind, with a large sample size and the ability to conduct analysis across time.

To enrich the dataset, regional unemployment data was pooled from ONS (2021) with data regarding British attitudes coming from the Understanding Society (US) survey, which was available in waves 1, 3 and 6 (US, 2020). This was merged with the LFS dataset and all forthcoming analysis uses this merged dataset unless otherwise stated. In total, 12 million observations are pooled which, when reduced to those who were employed in wave 1, reduces the sample to approximately 1 million. Keeping only observations with data for both hourly wages and each of the explanatory variables reduces the sample size to 515,980. This is comprised of 473,485 (93.44%) White workers, 9,430 who are Black (1.86%), 1,712 Chinese (0.34%), 18,891 who are Asian but not Chinese (3.73%), and 3,221 (0.64%) who are mixed-race. For the remainder of this paper, only these ethnic groupings will be considered, which are defined in Figure 2.1:

Ethnicity	**Definition**
White	White (*incl. British*)
Black	Black (*incl. British/Caribbean/African*)
Chinese	Chinese
Asian	Asian excl. Chinese (*incl. British/Indian/Pakistani/Bangladeshi*)
Mixed	mixed-race (*incl. Black Mixed*)

Figure 2.1: Ethnicity definitions used throughout this paper

2.1.1 Setup

The forthcoming analysis uses hourly wages to eliminate the differences in weekly hours worked and the income effect of increased hourly wages. This increases accuracy but loses 12.6% of the sample compared to weekly wages. Net wages are more likely to be accurately reported, but gross wages have been used to remove any effects of tax changes. Wages have also been deflated using the GDP deflator (ONS, 2020b) so that controlling for changes over time more accurately depicts any changes in the labour market which affect minorities in differential ways.

To approximate experience, 'age minus years of education' has been used. This is relatively accurate for men, who are less likely to take time out of the labour market or be employed part-time (Olsen and Walby, 2004). However, there is a scarring effect of prolonged non-full-time work (contributing to 52% of the simulated pay gap), which is likely to have biased my findings for women.[1] Any differences in continuous employment across ethnicities will therefore be encompassed within the 'unexplained' portion.

Numerous regional controls have been employed. The number of years living in the UK will be used to control for the differing outcomes seen with non-natives. This is simply the age for natives (49% of minorities in the sample), but for immigrants, it uses the year of arrival in Britain, combined with the age and year of interview. Thus there can be inaccuracies depending on the months of interview, arrival, and respondent's birthday. These issues are thought to be relatively insignificant and are the same as those faced by Berthoud (2000). Within the UK, all regions except Northern Ireland have been included, due to minorities clustering in London and the South East, with only 0.6% of the sample living in Northern Ireland. Additionally, the ethnicity question for Northern Ireland is not comparable with the rest of the UK (Longhi et al., 2009).

Due to the dataset covering 23 years, there are several challenges in consistently pooling the data. Most variables were relatively unchanged from 2001 onwards, notable exceptions include industry and occupation data, with industry data using an approximate conversion to the 1992 classification. Education data collected by the LFS has changed

[1] See further discussion by Walby and Olsen (2002).

over time, so we have condensed our controls into 4 categories: under 5 GCSEs at grade C, 5 GCSEs at grade C or above, 2 or more A-Levels (or equivalent), an undergraduate degree. Furthermore, a unique household identifier is only included in Stata datasets from 2001-Q3 onwards. Consequently, all analysis will be conducted without clustering, to keep 1997-2001 within the analysis. The effect of this on the reliability of our findings will be discussed in the 'limitations' section (Section 4.1).

2.2 Descriptive Analysis

2.2.1 Descriptive Statistics

Descriptive Statistics have been included in Table 5.1 of Appendix A. Given that the LFS is a large sample size, and we have pooled data from 23 years, it is expected to be representative of the wider UK population. 26% of the sample work part-time, 28% of the sample work in the public sector, and 52% of the sample is female. 71% of the sample are married, and the average gross hourly pay is £15.77 per hour, using 2018/19 prices. However, there is significant variation in these figures for each ethnic group considered, which the next section outlines.

2.2.2 Labour Market Outcomes

It is important to first understand the wider labour market conditions in the sample. Figure 2.2a depicts the unemployment rates for each ethnicity, with Whites being the least likely to be unemployed. Only Chinese workers had a lower unemployment rate at times over the sample period. Note that Black and mixed-race workers had the highest unemployment rates over the entirety of the sample, although all minorities saw unemployment rates fall over the sample period.

One of the reasons for the relatively low Chinese unemployment rate is the high proportion of inactive workers. Figure 2.2b shows that 37.4% of the Chinese sample were inactive on average over the sample period. This may be due to workers becoming discouraged, or cultural norms, given that the female inactivity rate was 42.1% compared

(a) Unemployment rate over time **(b)** Labour market status (average of sample)

Figure 2.2: Labour market characteristics, by ethnicity

to 31.9% for men. Additionally, 10.5% were self-employed, the highest of any ethnic grouping, possibly explaining the low unemployment rate.

The heterogeneity between Chinese and Asian (excl. Chinese) labour market participants is important to note. Both have similar labour market characteristics, but the reasons for these are starkly different. Chinese workers are much less likely to have 2 or more children (17.0% compared to 32.7%). Additionally, Asian women have stubbornly high inactivity rates in the 30-39 age bracket relative to 16-21, with the ratio of the two falling to just 0.65, compared to 0.45-0.55 for most other ethnicities. This, combined with the greater number of children, on average, is evidence of heterogeneity in labour market histories for women (possibly due to discouragement during teenage years and early twenties). Consequently, the effect of the number of children on wages will be contained in the 'explained' part of the analysis, with any behaviours in response to this which differ by ethnicity will bias the 'unexplained' portion upwards.

Furthermore, Figure 2.2b shows that Black and mixed-race workers both had some of the lowest inactivity rates, yet high unemployment rates. This may be due to a willingness to work, but difficulty in obtaining employment. It is also notable how both groups had the lowest self-employment rates among the sample. Consequently, the following analysis is likely to have underestimated the pay gap, given that the LFS contains no self-employed wage data, which is typically lower than median wages (GOV.UK, 2016).

2.2.3 Raw Wages

An initial view of median hourly wages reveals vast disparities. Figure 2.3 contains the pay gap at specific percentiles, showing it is much bigger at the higher end of the distribution. Black, male workers particularly struggle to reach high paying jobs, with Black females facing similar challenges, but to a lesser extent. The lowest 10% of Black females earn £0.69 more per hour than White females. Across the board, the distribution is much more even for women, with White females earning one of the lowest hourly wages. Significant heterogeneity exists within ethnic groups, particularly for Chinese workers. Whilst decomposition analysis at different points of the distribution is beyond the scope of this paper, several observations can be made from Figure 2.3. We can see that the lowest 10% of Chinese male workers are significantly disadvantaged, earning just £6.13 per hour, yet the highest 10% earn more than any other ethnic grouping. The converse is true for Black females, who have much less variation in earnings compared to other women. Note that this table corroborates the existing literature regarding gender pay gaps, with women earning less than men at each percentile.

Figure 2.3: Median gross hourly pay (£) percentiles by gender, using 2018/19 prices

Male						Female					
Percent	10	25	50	75	90	Percent	10	25	50	75	90
White	6.92	9.30	13.52	20.60	30.86	White	5.90	7.48	10.39	15.88	23.20
Black	6.77	8.47	11.76	17.32	25.43	Black	6.59	8.23	11.51	16.53	22.55
Chinese	6.13	8.15	14.76	22.58	33.66	Chinese	5.85	7.58	11.97	18.72	27.26
Asian	6.21	7.80	11.64	19.46	30.02	Asian	6.08	7.60	10.68	16.44	24.24
Mixed	6.38	8.47	12.86	20.34	32.13	Mixed	6.05	7.88	11.36	17.07	25.19
All	6.87	9.20	13.41	20.51	30.76	All	5.91	7.49	10.43	15.94	23.24

Even though similar proportions of the working population work full-time relative to part-time for each minority (24-27%), the earnings profiles in Figure 2.4 reveal important features of the labour market. Among full-time earners, women earn a higher hourly wage in the 16-17 age bracket, and similar amounts until the age of 40. However, beyond the age of 40, the reversal in earnings is much more pronounced than for males. This could be due to the reintroduction of mothers into the labour market who accept a lower wage, skewing the median wage downwards. Interestingly, this effect is less pronounced among part-time workers, even when expressed in proportions. This could be because part-time workers, the majority of whom are women, are less likely to receive pay rises and are more concentrated near the minimum wage (Dias et al., 2018; ONS, 2016).

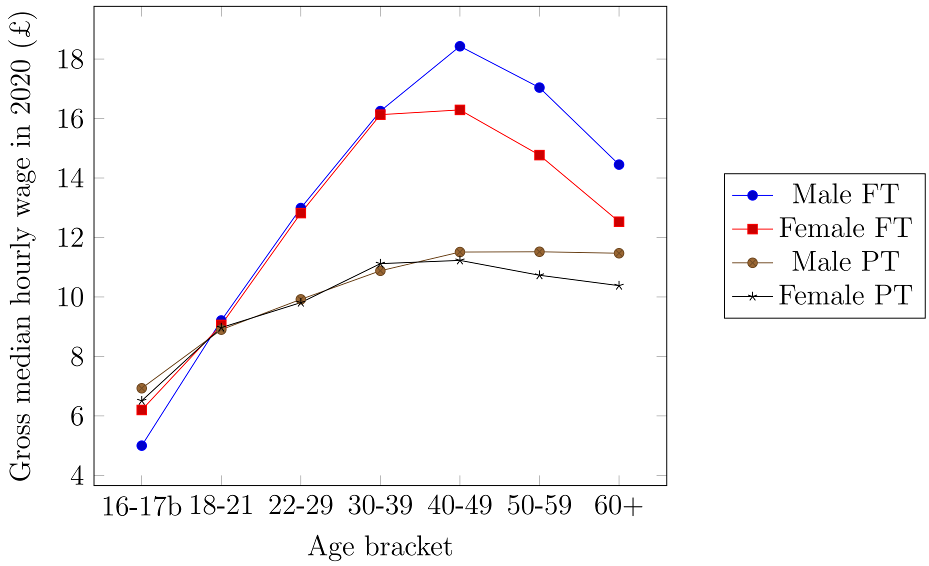


Figure 2.4: The set of earnings profiles in 2020, derived from ONS (2020a). For additional analysis including education, see Mincer (1975)

Significant changes in wages have occurred over time. Figure 2.5 shows how median hourly wages have been increasing for each ethnic group, with the difference between each line giving the relative pay gap.[2] Asian workers have consistently been paid less than Whites, with those who are Black initially earning the same as those who are White, but earning less after the financial crisis of 2008. Both the Asian and Black pay gap has narrowed in the last three years. Chinese workers have earned more than Whites, relatively consistently, but have accelerated in earnings growth since the financial crisis, with a dip in recent years. Finally, mixed-race workers have earned similar amounts to White employees, with some periods above and some periods below the median White wage. The trends post-financial crisis have been increasingly heterogeneous, which may be due

[2] The Chinese and mixed-race time series are significantly more volatile, which is likely due to the smaller sample size noted in Section 2.1 Median wages minimise the effect of outliers from year to year.

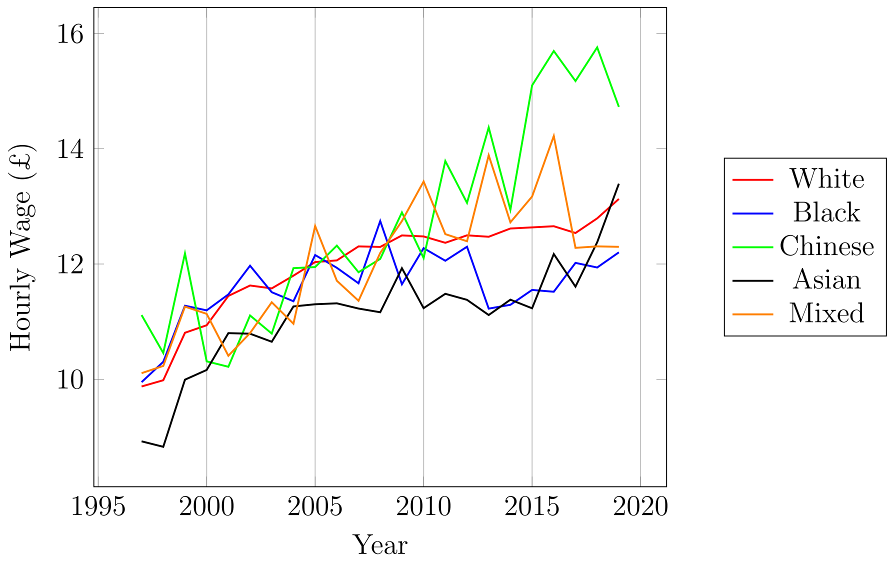


Figure 2.5: Median wages over time for each ethnicity, 2018/19 prices

to a combination of increased migration (ONS, 2020e) and a reduction in unemployment rates, particularly for minorities (Figure 2.2). Exploring why these earnings differentials exist is the subject of the preceding chapters; it may be due to different characteristics, or outright pay discrimination.

Chapter 3

Decomposition Analysis

3.1 Methodology

3.1.1 Model

To begin the decomposition analysis, a wage equation will be built upon Mincer (1958). Traditional explanatory variables have been used, along with the following variables of interest: disability (binary), part-time (binary), industry (1-digit SIC) and occupation (2-digit SOC), region of UK, public sector employment (binary), and a binary variable for whether the employee works for a firm with under 25 employees. The regional unemployment rate has also been included as it may affect the ability of workers to negotiate higher wages (Bell et al., 2000) and, secondly, it will help to mitigate the effects of any missing variables which are not time-invariant. Existing literature has explored the theoretical and econometric impact of public sector employment and the firm size (Longhi et al., 2009; Longhi and Brynin, 2003); public firms may be vectors of institutional discrimination, whereas large firms (e.g. FTSE 100 listed) may be under greater pressure to publish pay gaps and not discriminate.

Due to the presence of heteroscedasticity in a linear-linear model, the log of hourly wages is preferred. Whilst taking the natural logarithm of the dependent variable significantly reduces the test statistic, a Breusch-Pagan test for heteroscedasticity gives a p-value of 0.000. Consequently, heteroscedasticity-robust standard errors are used throughout.

3.1.2 Blinder-Oaxaca Decompositions

There are two reasons why wages may differ in the labour market. On the one hand, different individuals have different characteristics (or 'endowments'). If one can successfully control for every factor relevant to determining wages, any remaining gap can be attributed to 'unexplained' factors, which are often termed 'coefficients' (Blinder, 1973). This refers to the coefficients of the multiple linear regression model, which we assume differs between the two groups (e.g. White and Black).

To analyse the level of the pay gap which can be attributed to 'explained' and 'unexplained' factors, we need to take into account the different endowments possessed by the two groups. In a simple linear regression model, the wage gap (D) can be expressed as (O'Donnell et al., 2008):

$$D = [\bar{x_w} - \bar{x_b}]\beta_b + [\beta_w - \beta_b]\bar{x_b} \tag{3.1}$$

We can attribute the first portion to the changes in the endowments (the 'explained' part) and the second portion to the 'unexplained' part (the coefficients and the interaction with endowments):

$$D = [Explained] + [Unexplained] \tag{3.2}$$

3.2 Decomposition Results

The results of the two-fold Blinder-Oaxaca decomposition in Equation 3.1 can be computed using Ben Jann's Stata Oaxaca-st0001 package (Jann, 2008). The full results are included in Appendix C in Tables 5.3 and 5.8, with a summary of the output included below.

Both tables show the mean log hourly wage for the two comparison groups. The pay gap between the two groups can be extracted intuitively, with negative numbers implying a negative contribution to earnings. 'Non-Whites' is a combined analysis of all ethnic groups, with the other decompositions providing a breakdown of the gap between White workers and the four other ethnic groupings.

3.2.1 Males

The first decomposition (non-White) in Table 3.1 has a raw gap in log hourly wages of -0.0983, meaning there is a statistically significant wage gap favouring Whites, among men. However, it is important to consider how much of this gap is present when we make like-for-like comparisons. Table 3.2 shows that a quarter of this gap can be 'explained' by differences in characteristics (endowments), with a significant proportion (77.1%) left 'unexplained' by the model. This can be thought of as direct pay discrimination, but only if the regression model fully captures all wage-determining characteristics. It was noted in Section 2.1.1 that this caveat is more applicable to women than men, however, any factors which disproportionately cause minority ethnic men to earn a lower wage relative to White men will be part of this 'unexplained' component.

Table 3.1: Oaxaca Decompositions for Males

	(1) Non-white	(2) Black	(3) Chinese	(4) Asian	(5) Mixed
group_1	2.575***	2.543***	2.690***	2.565***	2.678***
	(536.37)	(297.25)	(108.60)	(410.28)	(159.23)
group_2	2.673***	2.673***	2.673***	2.673***	2.673***
	(2065.67)	(2065.67)	(2065.67)	(2065.67)	(2065.67)
difference	-0.0983***	-0.130***	0.0167	-0.108***	0.00510
	(-19.77)	(-15.00)	(0.67)	(-16.96)	(0.30)
explained	-0.0225***	-0.0318***	0.0603***	-0.0189***	0.00528
	(-5.41)	(-4.61)	(3.43)	(-3.67)	(0.42)
unexplained	-0.0758***	-0.0980***	-0.0436*	-0.0894***	-0.000185
	(-17.82)	(-13.03)	(-2.56)	(-17.26)	(-0.02)
N	244605	231904	228532	238270	229185

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We can isolate the 'explained' and 'unexplained' portions of the wage gap for each ethnic grouping. Table 3.1 shows that the wage gap for Black and Asian males is statistically significant and negative. Table 3.2 shows that 75.5% of the Black wage gap (and slightly more of the Asian wage gap) is 'unexplained' by characteristics. A large part of this is likely to be direct pay discrimination, although some may be due to issues discussed in Section 4.1.

We can see that Chinese and mixed-race wages are not statistically different from

Table 3.2: Oaxaca Decompositions for Males (proportions)

	Non-white	Black	Chinese	Asian	Mixed
overall	-	-		-	
explained	22.9***	24.5***	360.4***	17.4***	N/A
unexplained	77.1***	75.5***	-260.4*	82.6***	N/A

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the wages of White workers. Chinese males have characteristics that are associated with higher wages, but this is suppressed by 'unexplained' factors. Whilst Figure 3.2 has large percentages for Chinese workers, the level of pay discrimination is minimal because the raw pay gap is statistically insignificant (see Figure 3.1). For mixed-race males, both the raw pay gap and the 'explained' and "explained" components are not statistically different from zero.

3.2.2 Females

The results are very different for female workers. Turning to Table 3.3, we can see that non-White females earn more than White females (with a 0.0571 log hourly wage gap). The largest wage gap is for Chinese females at 0.105, with women of each ethnic minority earning more than White women. Table 3.4 shows that, for Black and Asian women, the positive wage gap is despite some 'unexplained' downward pressure on their wage, with their endowments commanding an even larger positive wage gap. Asian women, in particular, have strong evidence of pay discrimination, much more than could be due to factors explored in Section 4.1. In contrast, neither the Chinese nor mixed-race female wage gap is due to pay discrimination, with 'unexplained' components being statistically insignificant at the 5% significance level. Note that whilst ethnic minority females earn more than White females, all ethnicities are subject to the gender wage gap (see Section 1.3 and Section 2.2.3).

Table 3.3: Oaxaca Decompositions for Females

	(1) Non-white	(2) Black	(3) Chinese	(4) Asian	(5) Mixed
group_1	2.488***	2.495***	2.536***	2.470***	2.528***
	(564.12)	(349.10)	(114.95)	(391.94)	(188.61)
group_2	2.431***	2.431***	2.431***	2.431***	2.431***
	(2112.02)	(2112.02)	(2112.02)	(2112.02)	(2112.02)
difference	0.0571***	0.0638***	0.105***	0.0389***	0.0972***
	(12.54)	(8.82)	(4.77)	(6.08)	(7.22)
explained	0.0897***	0.0929***	0.122***	0.0905***	0.0966***
	(23.92)	(15.49)	(8.36)	(18.32)	(9.81)
unexplained	-0.0325***	-0.0291***	-0.0169	-0.0516***	0.000591
	(-8.47)	(-4.79)	(-1.03)	(-10.16)	(0.06)
N	262134	251011	246665	254106	247521

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.4: Oaxaca Decompositions for Females (proportions)

	Non-white	Black	Chinese	Asian	Mixed
overall	+	+	+	+	+
explained	156.9***	145.6***	116.0***	232.4***	99.4***
unexplained	-56.9***	-45.6***	-16.0	-132.4***	0.6

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.3 Explained Differences

3.3.1 Males

Given that wage differentials can largely be explained, especially for women, discussing the factors contributing to these is beneficial. This section includes a caveat that any 'explained' parts of the wage gap can also be vectors of discrimination. For example, occupational clustering may occur because minorities perceive an industry to be particularly racist.

Graphing the detailed decomposition results in Tables 5.3 and 5.8 from Appendix C gives Figures 3.1 and 3.2, respectively. These stacked bar charts show any positive contributions to wages above the zero-line, and any negative contributions to wages below. The net effect of these (positive – negative) is the total shown by the black scatter mark, corresponding to the total pay gaps outlined in Tables 3.3. Both the unexplained and the explained contributions to wages, along with their magnitudes and relative sizes, can therefore be easily compared.

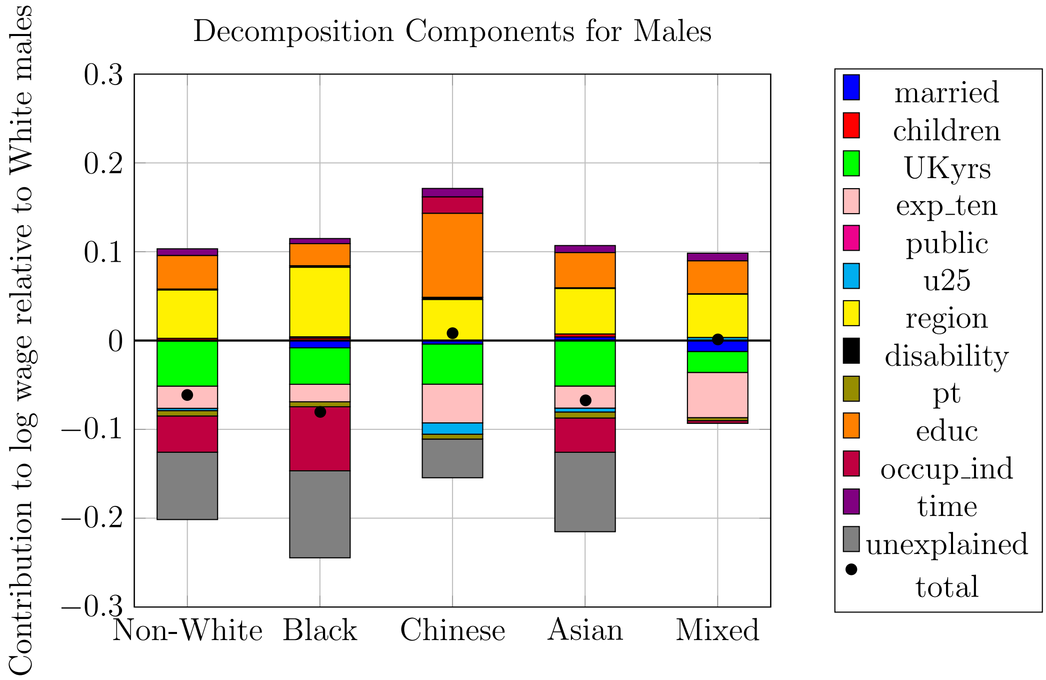


Figure 3.1: The portion of the log wage gap which is attributed to various factors, for males, by ethnic group

It was detailed above that Black and Asian males typically receive a lower wage in part due to differences in endowments. Figure 3.1 shows this is mainly due to them working in lower-paid occupations/industries, along with the fact that they have been working in the UK for less than their White counterparts, and experience large unexplained components. For Chinese and mixed-race males, mean wages are not statistically different to the wages of White males. They are buoyed down by less labour market experience and tenure with their current firm; this could be due to an increased tendency to switch jobs more frequently compared to White males. Interestingly, higher levels of education and working regions associated with higher pay combine to make the overall wage gap negligible. Across all ethnicities, males had higher levels of education than their White counterparts, and occupational clustering was important in some cases. Appendix B shows that ethnic minority males are more likely to work in education, health, and finance than White males, and less likely to work in agriculture, energy, and manufacturing. However, Black and Asian minorities are less likely to be managers or work in skilled trades, and instead typically work in care, leisure, and elementary occupations.

As noted previously, these 'explained' components can themselves be a result of (statistical and structural) discrimination, as detailed in Section 1.2.2. Occupational clustering could be due to a belief that some higher-paying occupations are 'more racist' or more likely to discriminate; lower levels of experience/tenure for mixed-race workers could be due to workers quitting due to an experience of discrimination, for example. Further, fewer years in the UK could mean that English language fluency is poorer, but it could affect wages through discrimination if the individual lacks a 'British accent'. Whilst this is not likely to affect all workers, it could mean that labour market discrimination is present, on top of the direct pay discrimination experienced by Black and Asian males.

3.3.2 Females

We have already noted that the picture is starkly different for women. Chinese, Asian, and mixed-race women tend to have higher wages because they work in higher-paying occupations than White women (hotels/restaurants, education and health — see Appendix B), and have higher levels of education, as seen in Figure 3.2. Black women, on the other hand, tend to have higher wages because they work in regions that are associated with higher pay, which itself could be a product of structural discrimination causing regional clustering. Although, this positive wage differential is attenuated somewhat by an unexplained component. All minorities have wages depressed by varying numbers of years in the UK, consistent with the literature regarding differing labour market outcomes for native and non-native workers (Section 2.1.1). Note that differences in marital status and the number of children do not explain a significant portion of the wage gap. This increases the reliability of the female analysis, as differing labour market histories do not seem to be affecting the pay of different ethnicities in a significant way. Thus, the concerns of Section 2.2.2 regarding the bias of the 'unexplained' portion of the wage gap are likely to be minimal, if anything (especially because the 'unexplained' component is not statistically significant for most ethnic groups considered).

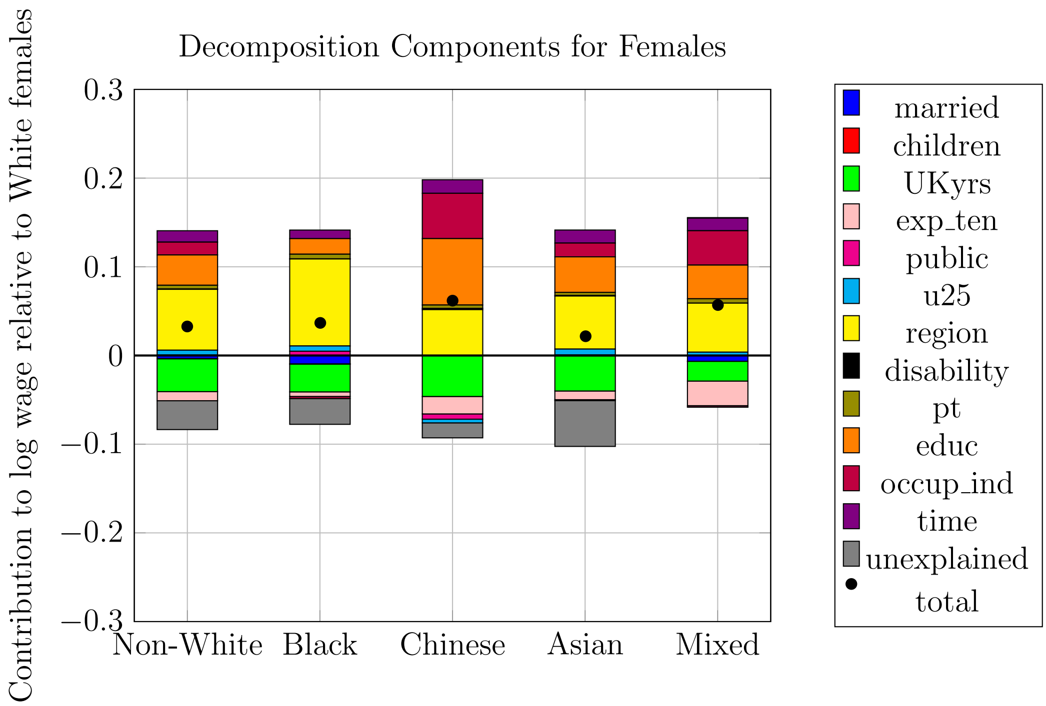


Figure 3.2: The portion of the log wage gap which is attributed to various factors, for females, by ethnic group

3.4 Trends

The literature surrounding ethnicity pay gaps rarely explores the trends. The large sample considered in this paper allows for a detailed analysis of how pay gaps have changed over time. Raw pay trends were already discussed in Section 2.2.3, but it would be beneficial to explore how much of this has historically been due to 'unexplained' factors, which is likely to be due to pay discrimination, at least in part. Blinder-Oaxaca decompositions have been conducted for each year of the sample, where sample size allows, by ethnicity and gender.

Figure 3.3 shows that, for Black and Asian males, the 'unexplained' component has been relatively stationary, with some improvement over the sample. A slight deterioration appeared to take place across all three ethnicities from 2008 to 2012, with an improvement through to 2019, indicating discrimination may be a contributing factor. However, due to this being a highly granular analysis, it is difficult to say with certainty. Mixed-race workers seem to have experienced an erosion in their largely positive 'unexplained' component of the wage gap from 2016 to 2019.

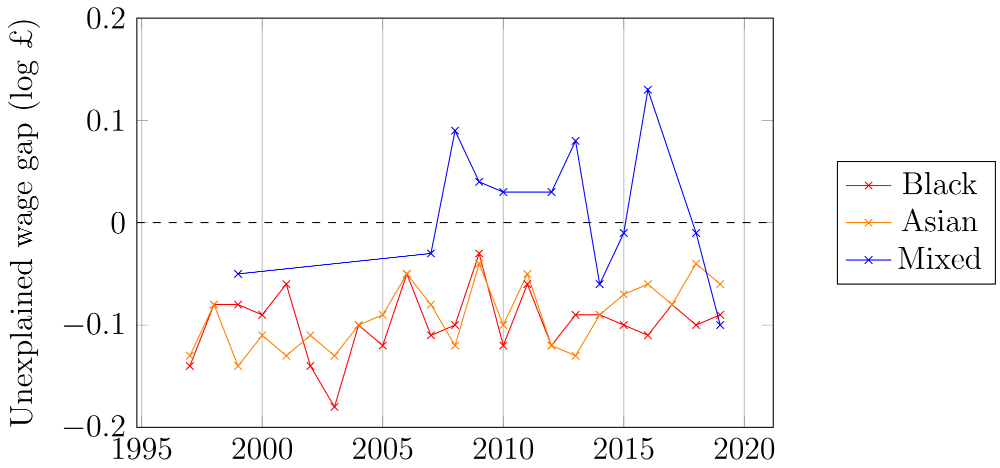


Figure 3.3: The portion of the male wage gap which is unexplained, over time

When the 'unexplained' female wage gap is considered, a different picture emerges. Figure 3.4 is consistent with the findings in Section 3.2.2, with only Asian females experiencing a persistent negative unexplained wage gap. Similar to males, all ethnic groupings seemed to experience increasingly negative 'unexplained' wage gaps in the wake of the financial crisis, from 2008 to 2011, with a partial recovery since. This indicates that ethnic minorities faced increased discrimination as the economy suffered. Additionally, mixed-race females also experienced an increasingly negative 'unexplained' wage gap from 2016 to 2019. This may indicate increased discrimination, but may also take into account factors that have affected mixed-race workers more than other ethnicities (which seems relatively unlikely).

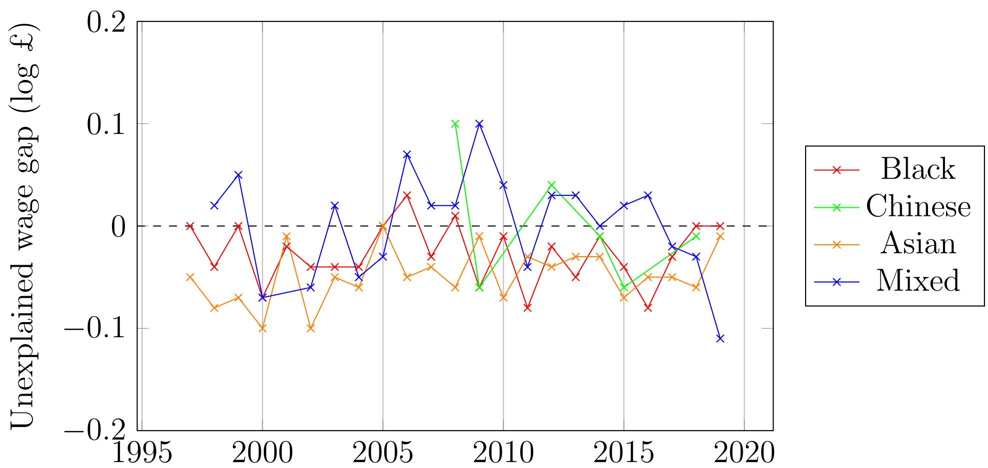


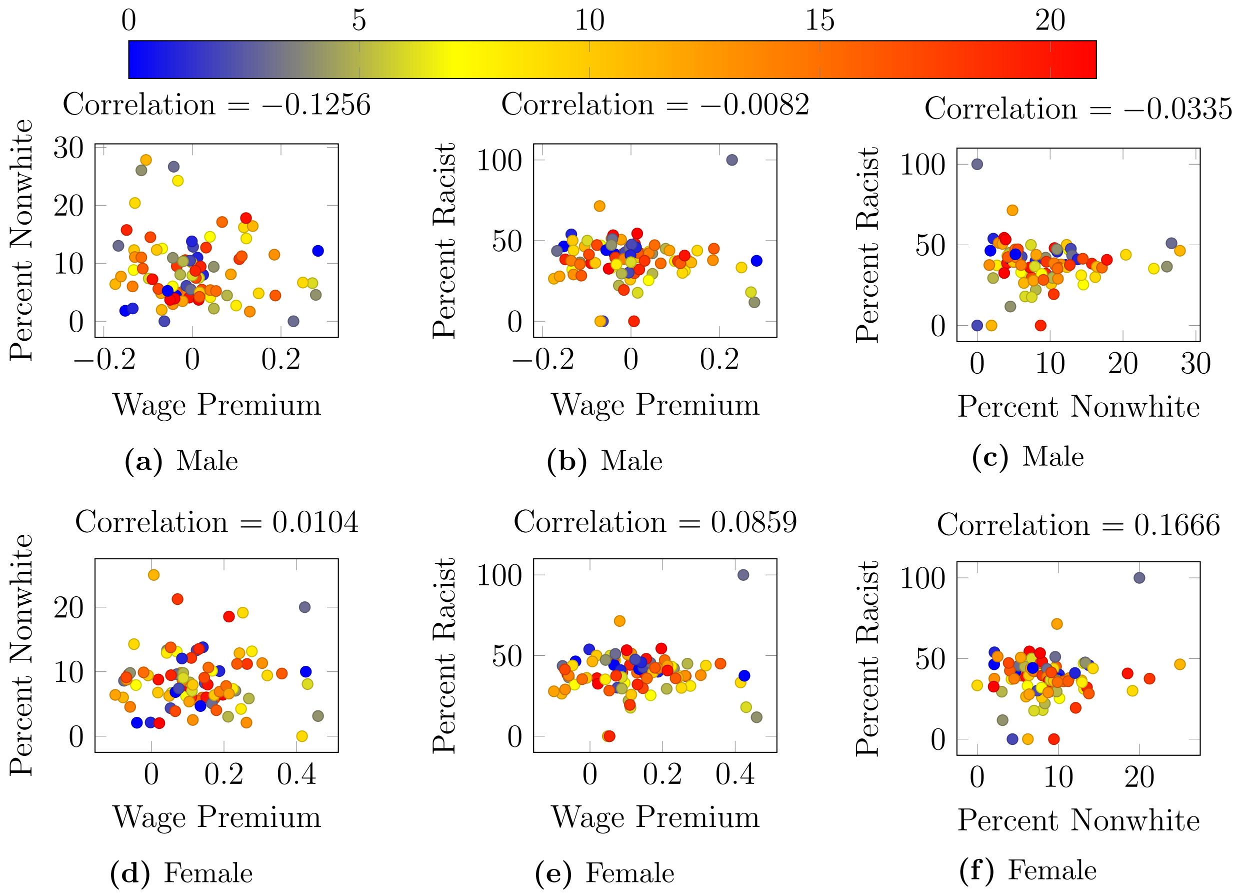
Figure 3.4: The portion of the female wage gap which is unexplained, over time

3.5 Endogeneity

We have seen that occupational clustering occurs affects most ethnic groupings, putting downwards pressure on the pay of males (but not females). Therefore, it would be beneficial to observe whether minorities are either avoiding, or being excluded from, the highest paying jobs.

Occupational clustering may be due to differences in preferences, as explored in Section 1.2.2; if minorities prefer not to work in particular industries, we would expect to see a relatively higher wage premium for minorities working in such industries. However, observing Figures 3.5a and 3.5d for males and females, respectively, there is very little correlation (if any) between the percentage of non-White workers and the wage premium in each industry. This implies preferences are not causing occupational clustering.

Figure 3.5: Cross-correlations of indicators, coloured by industry group



(a) Male **(b)** Male **(c)** Male

(d) Female **(e)** Female **(f)** Female

An alternative factor causing clustering may be perceptions. If workers believe that an industry is particularly 'racist', they may avoid it even if this leads to lower remuneration (which may explain the negative effect of clustering on the wages of males seen in

Section 3.2.1). Minorities may also choose to avoid such industries which have historically undervalued, or currently undervalue, the productivity of minorities. However, this is not seen in Figures 3.5b and 3.5e, with no correlation between racist attitudes and the wage premium; those working in 'racist' industries do not seem to experience a larger (negative) wage premium. Furthermore, there is no significant correlation between racist attitudes and the proportion of non-White workers in each industry (Figures 3.5c and 3.5f), meaning that minorities do not seem to be avoiding 'racist' industries.

Two factors can explain this. Firstly, the survey of 'British-ness' attitudes from the Understanding Society dataset (US, 2020) could be a poor indicator of racist attitudes. Levels of reported racist incidents are available but suffer from a poor sample size. Thus, analysis using a more accurate proxy may yield alternative results. Secondly, the data uses industry, rather than occupation, data due to the incompatibility of 1992 and 2007 occupational codes. Finally, since Figures 3.1 and 3.2 outlined that education was a positive factor influencing the wages of all minorities, both male and female, it could be that male minorities have high levels of education yet employers undervalue their productivity.

Therefore, the dataset provides no clear indication of why occupational clustering occurs. Given the importance of occupational clustering in determining wages, as discussed in Section 3.3, future research into this will provide valuable insights into how policy can address the pay gap, particularly for males.

Chapter 4

Limitations and Concluding Remarks

4.1 Limitations

As with all research, there are some limitations to the analysis. Firstly, household identification data was only included in the Labour Force Survey from 2001. All analysis up until this point has not used clustered standard errors, to prevent the loss of 1997-2001 data. Allowing for clusters of households does not affect the statistical significance of any variables, with standard errors only rising slightly, as can be seen from Tables 5.9, 5.10, 5.11, and 5.12 in Appendix D. The statistical significance of the decompositions (both the explained and unexplained portions) is not affected. This is likely due to the very large sample size used in this paper. Therefore, it is reasonable to conclude that the non-clustered analysis on the LFS data thus far is still reliable.

Secondly, a large proportion of Chinese workers (and some other ethnic minorities) had "other qualifications" as their highest NVQ level. As such, to prevent the loss of the minority sample, any ethnicity selecting this was coded to NVQ level 2. This mainly affects the analysis of Asian workers, but only in a minimal way. Under 15% of Asian workers reported "other qualifications", with even less for other minorities.

Finally, decompositions are subject to a lack of labour market history data (Sections 2.1.1 and 2.2.2). However, only a very minimal amount of the (female) ethnicity wage gap can be attributed to the number of children, meaning that the findings of this paper are likely to be reliable (see Section 3.3.2). Although, analysis using panel data would increase the reliability of findings, as labour market histories could be taken into account.

4.2 Future Research

The discontinuity of variables makes it very difficult to analyse earlier years, in the 1992-1994 region and prior. More effort needs to be put into making data consistent, converting variables into the same format. 2-digit 1992 SIC codes were used along with 1-digit SOC codes because the changes in occupation codes at this level of data were too substantial to be used. Work to make LFS data more consistent will assist future researchers.

This paper corroborated the existing literature regarding the importance of occupational clustering in explaining wage gaps, despite minorities having higher levels of education than their White counterparts. We found that clustering appears to be neither a result of preferences nor racist attitudes. Consequently, given the large impact of clustering on wages, and the differing outcomes between men and women, further research into the dynamics of occupational clustering would likely prove fruitful.

Finally, this paper has not directly considered the experiences between minorities (the Black vs Chinese experience), nor the heterogeneous experiences within minorities, particularly at either end of the income distribution. Whilst raw median pay disparities were detailed in Section 2.2.3, decomposing the wage gap at different parts of the distribution will be important in more accurately determining which policies can be used to improve labour market outcomes, and help evaluate the impact of recent policy.

4.3 Conclusions

This paper has contributed to the literature by pooling a large, clean dataset with a large number of ethnic minorities, spanning 23 years. The analysis has shown that pay gaps are large and persistent over time. Decompositions corroborate the existing literature, showing that labour market outcomes are starkly different for male and female ethnic minorities. The majority of the female wage gap is explained and not unexplained, indicating that differing labour market histories have been accounted for by the number of children and that the results are reliable. Consequently, this paper has given a unique insight into the evolution of the wage gap over time, not just for men, but also for women.

Pay discrimination is most common among Black and Asian workers of both genders. Chinese and mixed-race workers have little (if any) evidence of pay discrimination, with males having no statistically significant pay gap compared to White males, and females having a positive wage gap thanks to higher levels of education and occupational clustering. The 'unexplained' pay gap is largest for men, with women facing less, if any, evidence of direct pay discrimination. However, all women are subject to the gender pay gap.

Numerous characteristics have a large influence on the pay of ethnic minorities. All minorities have higher levels of education relative to their White counterparts. However, occupational clustering negatively impacts the wages of men, but positively influences female wages. Regardless of the direction of the impact on wages, clustering is possible evidence for discrimination, as minorities tend to avoid particular occupations and favour others. Given that ethnic minority males have higher levels of education yet cluster in lower-paid occupations, future research needs to explore the endogeneity of education and occupational decision making. Other 'explained' components may also be vectors of structural discrimination, and more research into these is required.

The 'unexplained' pay gap can be thought of as an upper bound on the level of pay discrimination in the labour market. 'Unexplained' pay gaps are largest for men, but there is also evidence of direct pay discrimination against Black and Asian women. No clear trends can be observed in the 'unexplained' component of the pay gap. There appears to have been a slight improvement since 2011/2012, but this is from an increase in the 'unexplained' pay gap in the wake of the financial crisis, indicating that discrimination increased during this period, and has subsequently fallen.

Discrimination extends beyond pay gaps, with minorities being more likely to be unemployed or inactive. Well designed policies that address significant disparities experienced by ethnic minorities can lead to a Pareto Improvement, bringing both equity and efficiency gains (Lundberg and Startz, 1998b). Future policy will need to focus on reducing the barriers preventing ethnic minority males into highly paid occupations, likely caused by structural racism. Discrimination is certainly not absent from the UK labour market, and policy must continue to dismantle the entrenched effects of structural discrimination.

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Chapter 5

Appendices

5.1 Appendix A

Descriptive statistics for the variables included in the dataset are below in Table 5.1.

Table 5.1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
year	2007.3	6.7	1997	2019	506739
quarter	2.55	1.1	1	4	506739
children	0.64	0.94	0	10	506739
industry	42.38	12.75	1	60	506739
SIC1D	6.16	2	1	9	506739
married	0.71	0.45	0	1	506739
region	6.92	3.23	1	12	506739
pt	0.24	0.42	0	1	506739
white	0.93	0.25	0	1	506739
nonwhite	0.07	0.25	0	1	506739
black	0.02	0.14	0	1	506739
asian	0.04	0.19	0	1	506739
chinese	0	0.06	0	1	506739
mixed	0.01	0.08	0	1	506739
ethnic	0.16	0.67	0	4	506739
disability	0.13	0.34	0	1	506739
emplen	11.97	8.43	0.13	20	506739
exper	22.55	12.54	0	72	506739
u25	0.32	0.47	0	1	506739
public	0.28	0.45	0	1	506739
educ	1.3	1.14	0	3	506739
female	0.52	0.5	0	1	506739
hhid	2218769836.04	1423823252.46	120025	4201935956	391354
occup	4.44	2.58	1	9	506739
time	27528.76	11026.56	11997	42019	506739
UKyrs	38.18	13.96	0	65	506739
paygh	15.77	18.07	1	4310.39	506739
attitudes	37.65	5.5	27.41	47.16	506739
regional_u	5.79	1.86	2.45	13.11	506739
lwage	2.55	0.61	0	8.37	506739
exper2	665.81	600.7	0	5184	506739

5.2 Appendix B

Table 5.2 contains the number of individuals working in each 2-digit SIC code, by ethnic group. Note that there are some industries with 0 or very few minorities, despite a large number of white individuals. Typically these SIC codes correspond to the A:B or C:E sections 1-digit SIC codes, as outlined in Tables 5.3 and 5.4.

Table 5.2: 2-Digit SIC codes by ethnicity

	White	Black	Chinese	Asian	Mixed	Total
01:Agriculture,hunting,etc	3583	12	1	16	6	3618
02:Forestry,logging etc	216	2	0	1	0	219
05:Fishing,fish farms,hatcheries etc	99	0	0	0	0	99
10:Coal,lignite mining,peat extraction	201	1	0	0	0	202
11:Oil,gas extractn etc (not surveying)	1240	14	5	30	6	1295
12:Uranium,thorium ore mining	8	0	0	0	0	8
13:Mining of metal ores	34	0	0	1	1	36
14:Other mining,quarrying	469	6	0	8	0	483
15:Food,beverage manufacture	8105	108	12	447	49	8721
16:Tobacco products manufacture	100	1	0	2	1	104
17:Textile manufacture	1795	15	3	167	7	1987
18:Clothing,fur manufacture	1048	19	4	169	6	1246
19:Leather,leather goods manufacture	326	4	0	12	1	343
20:Wood,straw,cork,wood prods(not furn)	1322	9	2	7	2	1342
21:Pulp,paper,paper prods manufacture	1762	10	3	53	3	1831
22:Printing,publishing,recorded media	5978	75	15	118	44	6230
23:Coke,petrol prods,nuclear fuel man	856	4	1	13	5	879
24:Chemicals,chemical products man	5594	50	14	202	30	5890
25:Rubber,plastic products manufacture	3832	36	3	122	19	4012
26:Other non-metallic products man	2342	10	1	35	4	2392
27:Basic metals manufacture	2190	9	4	58	5	2266
28:Fabric-metal prod (not mach,eqt) man	5739	45	4	127	23	5938
29:Mach,eqt manufacture	7838	88	16	222	25	8189
30:Office mach,computer manufacture	1677	23	4	53	17	1774
31:Elec mach,eqt manufacture	3243	30	7	105	15	3400
32:Radio,TV,communication eqt man	1762	12	8	66	3	1851
33:Medical,precision,optical eqt man	2778	27	15	76	7	2903
34:Motor veh,trailer,etc manufacture	4529	69	8	199	22	4827
35:Other transport eqt manufacture	4466	27	5	78	21	4597
36:Furniture etc manufacture	3091	32	3	109	20	3255
37:Recycling	294	2	0	6	1	303
40:Elec,gas,steam etc supply	3009	26	6	85	16	3142
41:Water collection,purif.,supply etc	1352	6	5	28	1	1392
45:Construction	24031	229	30	383	94	24767
50:Sales of motor vehs,parts,fuel etc	8096	78	12	252	30	8468
51:Wsale,commiss. trade (fee,contract)	13263	130	49	587	83	14112

52:Retail trade (not motor veh) repairs	44410	722	138	2200	320	47790
55:Hotels,restaurants	17891	389	339	1427	183	20229
60:Transport by land,pipeline	9273	235	15	374	50	9947
61:Water transport	626	6	3	11	2	648
62:Air transport	997	23	2	86	16	1124
63:Aux transport activ.,travel agents	9491	186	27	460	60	10224
64:Post,telecommunications	10168	260	27	601	76	11132
65:Financl intermed(not insur.,pensn.)	11915	177	55	634	90	12871
66:Insurance,pensions (not Social Sec)	3324	55	10	99	19	3507
67:Other financial (not insur.,pensn.)	7040	97	34	272	44	7487
70:Real estate activities	7135	218	13	217	61	7644
71:Personal,hhld,mach,eqt rental(no op)	2070	23	3	58	4	2158
72:Computer,related activities	8868	148	65	757	91	9929
73:Research,development	2145	18	16	80	10	2269
74:Other business activities	33996	937	165	1524	319	36941
75:Public admin,defence,social security	37670	799	56	1107	245	39877
80:educ	49285	737	179	1304	360	51865
85:Health,social work	67019	2794	241	3318	502	73874
90:Sanitation,sewage,refuse disposal etc	2472	25	4	20	9	2530
91:Activ. of membership organisations	4226	105	18	108	32	4489
92:Recreational,cultural,sporting activ	11566	176	35	185	103	12065
93:Other service activities	4317	60	16	139	45	4577
95:Private hhlds with employed persons	927	15	1	47	6	996
99:Extra-territorial organisations etc	386	16	10	26	7	445
Total	473485	9430	1712	18891	3221	506739

Table 5.3: 1-Digit SIC codes by ethnicity for males (proportions)

	White	Black	Chinese	Asian	Mixed	Total
A-B: Agriculture & fishing	1.2	0.3	0.1	0.1	0.2	1.1
C,E: Energy & water	2.1	0.9	1.6	1.0	1.2	2.0
D: Manufacturing	22.2	12.3	9.1	16.3	14.8	21.7
F: Construction	8.7	4.2	3.0	3.0	5.2	8.3
G-H: Distribution, hotels & restaurants	15.7	16.2	33.0	27.0	20.0	16.2
I: Transport & communication	9.5	13.1	5.1	10.7	8.9	9.6
J-K: Banking, finance & insurance etc	17.3	21.3	22.3	20.8	20.9	17.6
L-N: Public admin, educ & health	18.6	27.1	21.9	18.9	22.6	18.8
O-Q: Other services	4.7	4.8	3.9	2.4	6.3	4.6
Total	100.0	100.0	100.0	100.0	100.0	100.0

Table 5.4: 1-Digit SIC codes by ethnicity for females (proportions)

	White	Black	Chinese	Asian	Mixed	Total
A-B: Agriculture & fishing	0.5	0.1	0.0	0.1	0.2	0.4
C,E: Energy & water	0.6	0.3	0.4	0.6	0.4	0.6
D: Manufacturing	8.2	3.7	6.6	8.8	6.7	8.1
F: Construction	1.7	1.1	0.7	0.8	1.1	1.7
G-H: Distribution, hotels & restaurants	19.5	12.3	30.1	19.5	18.4	19.4
I: Transport & communication	3.6	3.1	3.7	4.9	4.3	3.6
J-K: Banking, finance & insurance etc	15.1	15.0	20.1	17.4	19.0	15.2
L-N: Public admin, educ & health	45.4	60.6	32.6	44.7	43.7	45.6
O-Q: Other services	5.4	3.8	5.7	3.3	6.3	5.3
Total	100.0	100.0	100.0	100.0	100.0	100.0

Table 5.5: Occupation by ethnicity for males (proportions)

	White	Black	Chinese	Asian	Mixed	Total
Managers, Directors & Senior Officials	18.4	9.1	14.9	12.2	14.4	18.0
Professional	16.2	16.8	35.2	22.2	21.0	16.6
Associate Professional & Technical	14.0	13.4	12.5	11.2	17.3	13.9
Administrative & Secretarial	6.0	7.3	5.7	6.9	5.6	6.0
Skilled Trades	14.7	8.9	13.6	9.4	11.5	14.3
Caring, Leisure & Other Service	3.7	9.4	3.9	4.3	4.8	3.8
Sales & Customer Service	4.4	5.4	4.5	8.3	6.7	4.6
Process, Plant & Machine	12.7	10.3	2.2	11.4	8.4	12.5
Elementary	10.0	19.4	7.4	14.1	10.1	10.3
Total	100.0	100.0	100.0	100.0	100.0	100.0

Table 5.6: Occupation by ethnicity for females (proportions)

	White	Black	Chinese	Asian	Mixed	Total
Managers, Directors & Senior Officials	9.9	6.3	9.6	5.9	9.2	9.7
Professional	14.4	16.7	23.8	20.4	19.6	14.7
Associate Professional & Technical	13.7	16.1	16.9	13.8	17.1	13.8
Administrative & Secretarial	22.5	16.8	14.9	17.9	18.6	22.2
Skilled Trades	1.7	1.3	2.5	1.6	1.4	1.7
Caring, Leisure & Other Service	14.6	22.8	8.7	13.3	13.2	14.7
Sales & Customer Service	10.7	7.7	10.8	11.9	11.2	10.7
Process, Plant & Machine	2.5	1.4	1.0	4.5	1.8	2.5
Elementary	9.9	10.9	11.9	10.8	7.9	9.9
Total	100.0	100.0	100.0	100.0	100.0	100.0

5.3 Appendix C

The following tables contain Stata output from numerous Blinder-Oaxaca Decompositions. Tables 5.3 and 5.8 contain the detailed output of summary tables 3.1 and 3.3, respectively.

Table 5.7: Oaxaca Decompositions for Males

	(1) Non-white	(2) Black	(3) Chinese	(4) Asian	(5) Mixed
overall					
group_1	2.575***	2.543***	2.690***	2.565***	2.678***
	(536.37)	(297.25)	(108.60)	(410.28)	(159.23)
group_2	2.673***	2.673***	2.673***	2.673***	2.673***
	(2065.67)	(2065.67)	(2065.67)	(2065.67)	(2065.67)
difference	-0.0983***	-0.130***	0.0167	-0.108***	0.00510
	(-19.77)	(-15.00)	(0.67)	(-16.96)	(0.30)
explained	-0.0225***	-0.0318***	0.0603***	-0.0189***	0.00528
	(-5.41)	(-4.61)	(3.43)	(-3.67)	(0.42)
unexplained	-0.0758***	-0.0980***	-0.0436*	-0.0894***	-0.000185
	(-17.82)	(-13.03)	(-2.56)	(-17.26)	(-0.02)
explained					
married	-0.000748*	-0.00817***	-0.00393**	0.00394***	-0.0123***
	(-2.34)	(-11.46)	(-2.59)	(10.13)	(-10.03)
children	0.00235***	0.00260***	0.000185	0.00332***	0.000190
	(6.47)	(7.38)	(0.51)	(7.03)	(0.71)
UKyrs	-0.0506***	-0.0411***	-0.0452***	-0.0512***	-0.0236***
	(-20.36)	(-15.18)	(-13.17)	(-18.00)	(-12.35)
exp_ten	-0.0250***	-0.0197***	-0.0436***	-0.0249***	-0.0509***
	(-20.22)	(-9.28)	(-8.20)	(-16.54)	(-12.16)
public	-6.12e-08	0.0000988	0.0000228	-0.000147	0.0000252
	(-0.00)	(0.60)	(0.36)	(-1.74)	(0.28)
u25	-0.00260***	0.00145	-0.0127***	-0.00422***	0.00311
	(-4.58)	(1.36)	(-4.82)	(-5.90)	(1.74)
region	0.0545***	0.0783***	0.0459***	0.0513***	0.0488***
	(42.59)	(35.97)	(11.91)	(36.29)	(17.68)
disability	0.00104***	0.00178***	0.00246***	0.000719***	0.000389
	(7.68)	(7.45)	(5.13)	(4.39)	(0.94)
pt	-0.00605***	-0.00559***	-0.00550***	-0.00678***	-0.00339***
	(-15.34)	(-10.26)	(-5.13)	(-14.43)	(-4.74)

educ	0.0378***	0.0248***	0.0946***	0.0397***	0.0372***
	(32.23)	(11.52)	(18.31)	(26.86)	(10.28)
occup_ind	-0.0408***	-0.0721***	0.0185	-0.0386***	-0.00286
	(-18.70)	(-19.24)	(1.88)	(-13.91)	(-0.43)
time	0.00759***	0.00577***	0.00956***	0.00798***	0.00864***
	(16.98)	(8.42)	(7.02)	(15.73)	(8.20)
unexplained					
married	-0.0148*	-0.00965	-0.0515	-0.0153	-0.0134
	(-2.14)	(-0.85)	(-1.77)	(-1.55)	(-0.74)
children	-0.0242***	-0.0182**	0.00703	-0.0272***	-0.0133
	(-7.22)	(-2.97)	(0.59)	(-6.02)	(-1.46)
UKyrs	0.0514***	0.0455**	0.000971	0.0499***	0.0206
	(5.65)	(3.09)	(0.03)	(4.89)	(0.59)
exp_ten	-0.151***	-0.202***	-0.0699	-0.155***	0.0235
	(-12.74)	(-9.30)	(-1.43)	(-10.05)	(0.66)
public	0.0130***	0.0138*	0.0139	0.0152***	-0.00348
	(4.77)	(2.50)	(0.80)	(4.64)	(-0.35)
u25	-0.00539	0.00898	0.0128	-0.00872*	-0.00000708
	(-1.96)	(1.92)	(0.75)	(-2.39)	(-0.00)
region	-0.0301	-0.0695	0.114	-0.0226	-0.0600
	(-0.90)	(-1.03)	(0.72)	(-0.53)	(-0.56)
disability	0.000287	0.00568*	0.0150**	-0.00189	0.000558
	(0.22)	(2.35)	(2.84)	(-1.19)	(0.11)
pt	0.00446**	0.00576*	0.0208**	0.00482*	-0.000590
	(2.88)	(2.04)	(2.77)	(2.34)	(-0.14)
educ	-0.000439	-0.00311	-0.0103	0.0000163	0.00699
	(-0.17)	(-0.66)	(-0.52)	(0.00)	(1.27)
occup_ind	0.0488**	0.0518*	0.0685	0.0406*	0.000303
	(3.26)	(2.48)	(1.44)	(2.01)	(0.01)
time	-0.000875	-0.00120	-0.00525	-0.00167	0.0106
	(-0.55)	(-0.39)	(-0.46)	(-0.74)	(1.58)
_cons	0.0334	0.0739	-0.159	0.0328	0.0281
	(0.86)	(0.99)	(-0.88)	(0.67)	(0.24)
N	244605	231904	228532	238270	229185

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5.8: Oaxaca Decompositions for Females

	(1) Non-white	(2) Black	(3) Chinese	(4) Asian	(5) Mixed
overall					
group_1	2.488***	2.495***	2.536***	2.470***	2.528***
	(564.12)	(349.10)	(114.95)	(391.94)	(188.61)
group_2	2.431***	2.431***	2.431***	2.431***	2.431***
	(2112.02)	(2112.02)	(2112.02)	(2112.02)	(2112.02)
difference	0.0571***	0.0638***	0.105***	0.0389***	0.0972***
	(12.54)	(8.82)	(4.77)	(6.08)	(7.22)
explained	0.0897***	0.0929***	0.122***	0.0905***	0.0966***
	(23.92)	(15.49)	(8.36)	(18.32)	(9.81)
unexplained	-0.0325***	-0.0291***	-0.0169	-0.0516***	0.000591
	(-8.47)	(-4.79)	(-1.03)	(-10.16)	(0.06)
explained					
married	-0.00341***	-0.00939***	-0.0000912	0.000581**	-0.00648***
	(-15.37)	(-17.30)	(-0.17)	(3.24)	(-12.07)
children	-0.000350	-0.000393	0.0000759	-0.000337	-0.0000590
	(-1.59)	(-1.22)	(0.87)	(-1.42)	(-1.00)
UKyrs	-0.0370***	-0.0312***	-0.0461***	-0.0397***	-0.0223***
	(-17.71)	(-14.66)	(-13.75)	(-15.98)	(-13.08)
exp_ten	-0.0103***	-0.00514***	-0.0197***	-0.00980***	-0.0278***
	(-10.62)	(-3.82)	(-6.07)	(-7.41)	(-10.99)
public	0.000497	0.00479***	-0.00595***	-0.00111**	-0.00140
	(1.82)	(9.37)	(-5.68)	(-2.96)	(-1.79)
u25	0.00550***	0.00597***	-0.00413**	0.00666***	0.00376***
	(15.10)	(9.88)	(-2.74)	(13.53)	(3.63)
region	0.0686***	0.0981***	0.0516***	0.0598***	0.0553***
	(51.87)	(45.83)	(14.96)	(39.67)	(21.09)
disability	0.000386***	0.000180	0.00144***	0.000550***	-0.000316
	(5.32)	(1.66)	(5.72)	(5.50)	(-1.60)
pt	0.00422***	0.00522***	0.00380***	0.00359***	0.00495***
	(16.44)	(13.06)	(4.45)	(11.45)	(7.90)
educ	0.0342***	0.0175***	0.0749***	0.0400***	0.0380***
	(32.59)	(10.44)	(17.37)	(27.76)	(13.02)
occup_ind	0.0145***	-0.00238	0.0511***	0.0156***	0.0387***
	(7.00)	(-0.71)	(5.54)	(5.37)	(6.57)
time	0.0128***	0.00966***	0.0153***	0.0147***	0.0142***

	(24.59)	(11.74)	(8.80)	(22.06)	(11.28)
unexplained					
married	0.000840	-0.00124	0.0143	0.00954	0.00496
	(0.19)	(-0.25)	(0.54)	(1.22)	(0.49)
children	-0.00363	-0.000656	0.0220	-0.00744	-0.00645
	(-1.18)	(-0.13)	(1.71)	(-1.67)	(-0.80)
UKyrs	0.0380***	0.0217	0.0368	0.0430***	0.0441
	(4.05)	(1.56)	(1.20)	(3.68)	(1.49)
exp_ten	-0.0794***	-0.117***	-0.0367	-0.0714***	-0.0244
	(-6.90)	(-5.83)	(-0.83)	(-4.41)	(-0.80)
public	-0.000353	-0.00350	-0.0163	0.00736	-0.0116
	(-0.09)	(-0.53)	(-0.97)	(1.37)	(-1.14)
u25	0.00203	0.00884*	0.00720	-0.00107	0.00600
	(0.85)	(2.37)	(0.45)	(-0.33)	(0.81)
region	-0.0171	0.0401	0.273	-0.0784	-0.0697
	(-0.50)	(0.66)	(1.69)	(-1.67)	(-0.69)
disability	0.000996	0.000628	0.00335	0.00215	-0.00294
	(0.75)	(0.28)	(0.53)	(1.20)	(-0.70)
pt	0.00715*	0.00621	0.0155	0.00907*	0.00550
	(2.57)	(1.42)	(1.14)	(2.33)	(0.72)
educ	0.00322	0.00140	0.0258	0.00541	-0.00147
	(1.47)	(0.33)	(1.13)	(1.82)	(-0.29)
occup_ind	0.0558***	0.0660**	0.132*	0.0477***	0.0109
	(5.00)	(3.01)	(2.29)	(3.36)	(0.46)
time	-0.00192	0.00189	0.00677	-0.00306	-0.0146**
	(-1.26)	(0.71)	(0.81)	(-1.32)	(-2.82)
_cons	-0.0381	-0.0533	-0.500**	-0.0145	0.0602
	(-1.02)	(-0.81)	(-2.85)	(-0.29)	(0.55)
N	262134	251011	246665	254106	247521

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.4 Appendix D

A comparison of clustered and non-clustered standard errors has been conducted on the available data, from 2002 through to 2019 inclusive. See discussion in Section 4.1.

Table 5.9: Non-clustered Oaxaca Decompositions for Males (2002-2019)

	(1) Non-white	(2) Black	(3) Chinese	(4) Asian	(5) Mixed
overall					
group_1	2.601***	2.559***	2.725***	2.592***	2.713***
	(499.27)	(269.40)	(105.58)	(384.69)	(149.79)
group_2	2.712***	2.712***	2.712***	2.712***	2.712***
	(1792.23)	(1792.23)	(1792.23)	(1792.23)	(1792.23)
difference	-0.110***	-0.152***	0.0138	-0.119***	0.00111
	(-20.36)	(-15.84)	(0.53)	(-17.27)	(0.06)
explained	-0.0396***	-0.0548***	0.0508**	-0.0350***	-0.00881
	(-8.76)	(-7.08)	(2.78)	(-6.30)	(-0.65)
unexplained	-0.0709***	-0.0977***	-0.0370*	-0.0843***	0.00992
	(-15.24)	(-11.64)	(-2.06)	(-15.02)	(0.78)
N	181111	170333	167648	175863	168189

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5.10: Clustered Oaxaca Decompositions for Males (2002-2019)

	(1) Non-white	(2) Black	(3) Chinese	(4) Asian	(5) Mixed
overall					
group_1	2.601***	2.559***	2.725***	2.592***	2.713***
	(487.37)	(267.23)	(103.54)	(372.79)	(148.22)
group_2	2.712***	2.712***	2.712***	2.712***	2.712***
	(1768.57)	(1768.57)	(1768.57)	(1768.57)	(1768.57)
difference	-0.110***	-0.152***	0.0138	-0.119***	0.00111
	(-19.90)	(-15.72)	(0.52)	(-16.75)	(0.06)
explained	-0.0396***	-0.0548***	0.0508**	-0.0350***	-0.00881
	(-8.49)	(-6.96)	(2.68)	(-6.04)	(-0.64)
unexplained	-0.0709***	-0.0977***	-0.0370*	-0.0843***	0.00992
	(-15.08)	(-11.57)	(-2.05)	(-14.83)	(0.78)
N	181111	170333	167648	175863	168189

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5.11: Non-clustered Oaxaca Decompositions for Females (2002-2019)

	(1) Non-white	(2) Black	(3) Chinese	(4) Asian	(5) Mixed
overall					
group_1	2.516***	2.524***	2.563***	2.500***	2.546***
	(525.27)	(319.88)	(107.87)	(368.76)	(175.64)
group_2	2.485***	2.485***	2.485***	2.485***	2.485***
	(1890.69)	(1890.69)	(1890.69)	(1890.69)	(1890.69)
difference	0.0311***	0.0386***	0.0779**	0.0148*	0.0614***
	(6.27)	(4.82)	(3.27)	(2.15)	(4.21)
explained	0.0608***	0.0677***	0.0912***	0.0612***	0.0595***
	(15.14)	(10.34)	(5.95)	(11.69)	(5.66)
unexplained	-0.0297***	-0.0291***	-0.0134	-0.0463***	0.00185
	(-7.07)	(-4.32)	(-0.74)	(-8.40)	(0.18)
N	197458	187939	184408	190769	185142

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5.12: Clustered Oaxaca Decompositions for Females (2002-2019)

	(1) Non-white	(2) Black	(3) Chinese	(4) Asian	(5) Mixed
overall					
group_1	2.516***	2.524***	2.563***	2.500***	2.546***
	(518.90)	(317.43)	(107.19)	(363.37)	(175.01)
group_2	2.485***	2.485***	2.485***	2.485***	2.485***
	(1868.58)	(1868.58)	(1868.58)	(1868.58)	(1868.58)
difference	0.0311***	0.0386***	0.0779**	0.0148*	0.0614***
	(6.19)	(4.79)	(3.25)	(2.12)	(4.20)
explained	0.0608***	0.0677***	0.0912***	0.0612***	0.0595***
	(14.86)	(10.22)	(5.86)	(11.40)	(5.60)
unexplained	-0.0297***	-0.0291***	-0.0134	-0.0463***	0.00185
	(-7.04)	(-4.30)	(-0.74)	(-8.36)	(0.18)
N	197458	187939	184408	190769	185142

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Acronyms

BCS British Cohort Study.

LFS Labour Force Survey.

MRP Marginal Revenue Product.

UK United Kingdom.

US Understanding Society.