LUND UNIVERSITY
School of Economics and Management

Master's Programme in Economic Growth, Population, and Development

Mind the Gap!

Pay, Gender, and Ethnicity in the United Kingdom

by

Hannah Leadbetter

ha2521le-s@student.lu.se

Despite many years of progress towards closing the gender pay gap and achieving racial equality, women from ethnic minority groups in the United Kingdom earn less compared to their male counterparts and to the population average. The extent of channelling into certain areas of occupation and employment are a prominent feature of the employment of minority groups in the UK and is a key mechanism investigated in this study. This study therefore uses micro-level data from the Annual Population Survey 2018 in a linear regression to explain the extent to which occupational segregation explains the adjusted pay gap. In this way, accounting for observable factors that contribute to pay penalties pertains to a discussion of double disadvantage. The aim of this study therefore is to measure the pay differentials faced by ethnic minority groups, and whether a double disadvantage occurs for women of ethnic minority backgrounds. The study finds that while occupational segregation explains some of the pay differential, albeit varying in degree by each ethnic minority group, much is left unexplained. Thus, the mechanisms behind the gender ethnicity pay gap align with occupational segregation, but so too with unexplained factors, where discrimination and disadvantage play a role. Additionally, the study finds that relative to white male pay, ethnic minority men face a greater pay disadvantage relative to their female counterparts, and thus according to this study, ethnic minority women face no double disadvantage.

Key words… Pay gaps, gender, ethnicity, occupational segregation, double disadvantage.

EKHS22
Master's Thesis (15 credits ECTS)
June 2020
Supervisor: Faustine Perrin
Examiner: Kristin Ranestad
Word Count: 16,950

Acknowledgements

I would like to thank my thesis supervisor Faustine Perrin for her invaluable support and advice during this learning process. I also thank the UK Data Service and the Office for National Statistics for providing the Annual Population Survey for 2018 data used. I additionally thank my wonderful friends, Amalie Østhassel, Anne Grootenhuis, and Victor Flick with whom support, advice, and love, has always been available as we write our theses together.

Table of Contents

List of Tables

List of Figures

1 Introduction

1.1 Research Problem

On Friday 7th June of 1968, 187 female employees walked out of work at Ford Dagenham, East London. Their justification: unequal pay. Compared to that of men rated at the same skill grade, the women were not paid the same. Not only did the Dagenham machinists by striking show the essential nature of their labour in production, but their demand for equal pay shed light on the persistence of lower pay for women's work. Yet, five decades later, despite the Equal Pay Act of 1970 and the Sex Discrimination Act of 1975, a gender pay gap persists in the United Kingdom. Following the Equality Act of 2010, employers with over 250 staff must disclose their pay for male and female employees. Recent results of this reporting show that 8 in 10 employers pay men more than women (Gender Pay Gap Service, 2020). Indeed, the latest figures for 2019 calculate that among full-time employees, the gender pay gap stands at 9%, down by 0.6% since 2012 (ONS, 2019). For all employees, the gap is 17% (ONS, 2019). Hence, the pay gap stubbornly remains.

Yet, employment for women in the UK since the time of the Dagenham Strike has changed markedly. The expansion of education and the rise in strength of the Union Movement has supported the increase in labour force participation from 53% to 71% between 1971 and 2019 (ONS, 2019). Women are pursuing education to higher levels, delaying marriage, and having fewer children (Olsen et al, 2014). Likewise the movement away from industry and towards the service sector creates many opportunities for women to work and see rewards to their education. Despite economic downturn and a long-lasting recession in the previous decade, the strength of job performance pertains in the economy, where there are high employment rates. For 2016-17 the unemployment rate stood at 3% where 79% of 22-64 year olds were in work (Henehan & Rose, 2018). As such, employment prospects for women are better today than ever before.

While progress occurs and these factors all contribute to bettering employment outcomes for women in the UK, what remains is a persistent pay gap. The gender pay gap being the average percentage difference in earnings between working men and women (Olsen et al, 2014). Women have increased their labour force participation, surpassed men in their level of educational attainment, and fought for protective governmental legislation. Now other explanations must be sought to explain the 'sticky' gap. New research shifts focus towards encompassing racial inequality and double disadvantage as drivers of the gender pay gap (Breach & Li, 2017; Nandi & Platt, 2010; Moosa, 2008; Henehan & Rose, 2018). This is because different pay gaps are found for women of different ethnic groups, and so understanding whether women from ethnic minority groups have double disadvantage; lower pay relative to the white majority population but so too to their male counterparts, is important.

Additionally, the composition of the population of the UK is changing over time, where the annual number of long-term migrants arriving trebled from 211,000 to 631,000 between 1960 and 2015 (ONS, 2015). Immigration in past decades has incorporated half a million commonwealth nationals, from the Windrush generation of the Caribbean, to inflows from India, Sri Lanka, and Pakistan, all providing labour in the post-war years (Blackwell, 2003). Asylum seeking from Yugoslavia and the Nigerian and Kenyan Asian crises followed in the decades after. Integration with the wider European Union and the free movement of labour increased the proportion of immigrants living in the United Kingdom following the 1998 Immigration Act (Henehan & Rose, 2018). Thus, this debate must account for Britain's changing demographics, lack of homogeneity, where its black, Asian, and minority ethnic (hereafter, BAME) population has many compositional differences which have varied over time. As such, the United Kingdom is chosen for this study because of its persistent pay gap and because of its changing ethnic minority composition, where addressing if several reinforcing pay gaps exist in the UK is vital.

Ethnic minorities therefore face a number of differences which both influence and push them into certain directions regarding employment, and as a result affect their earnings. Of key importance to evaluate is the adjusted and non-adjusted pay gaps; where certain groups of people earn less because they work fewer hours, have lower skills, or have taken time out of the labour force. The implications of these observational differences on employment are varied, and are the result of multiple factors which all play a role. Indeed, gender pay gaps highlight differences *between* women in the UK too. By accounting for the work of women from BAME backgrounds, pay gaps between women, and between women and men of the same ethnic background, emerge. Accounting for differences and using adjusted pay gaps can therefore distinguish the impact of observable and unobservable characteristics on pay outcomes, which this study addresses. Clarity is provided in understanding determinants of gender ethnic pay differentials, and thus provides an explanation as to why the gender pay gap persists in the United Kingdom.

Understanding, explaining, and closing the differences in earnings for men and women across BAME groups is important. Firstly, differences in pay are problematic because when individuals are earning less, they contribute less to their pensions, risking greater exposure to poverty in later life. As most children live with their mothers, when women earn less, the risk of children growing up in poverty is more likely. Understanding the mechanisms of pay differentials also explains the effect ethnicity may have in its potential to act as a driver, and is thus important from both a social justice and an economic perspective. If, as the insightful McGregor-Smith Review (2017) indicates, Britain has 'a fundamental structural and historical bias that favours certain individuals'[1], knowing what these biases are, who they do not favour,

[1] McGregor-Smith Review (2017). 'In the UK today, there is a structural, historical bias that favours certain individuals. This does not just stand in the way of ethnic minorities, but women, those with disabilities and others'. The McGregor-Smith Review is an indepedent review conducted by Baroness McGregor-Smith and it considers the multiple issues that effect black and minority ethnic groups in the workplace. It sets out recommendations for employers in both public and private sectors in order to better diversity within the respective organisations. The report argues that the favouring of a certain set of individuals in the history of the UK is the reuslt of bias which operates at every stage in a person's career, and even before it commences. The review explains this trend by focusing on bias which is found in networks, in recruitment, and in the workforce itself. They explain that this fundamental structure of bias is inherent through racism, which they argue belongs more to the past than to the present, and of unconscious bias, which is more insidious because it is harder to identy and recitfy.

and their extent, is imperative in reducing the gender ethnicity pay gap and ‘levelling the playing field’ (Blackaby et al, 2002). The problem of unconscious or conscious bias will continue to occur against those from a different ethnic minority and for women as a whole, unless policy and legislation targeting these issues are not created and enforced.

As ethnic minority women stand at the intersection between race and gender, they may face a double disadvantage for pay, and thus, without understanding the drivers of pay gaps, the talents of BAME women are not maximised. Indeed, the UK economy loses out on a £24bn boost every year because the productive resources of BAME women are underutilised; 1.3% of GDP (McGregor-Smith Review, 2017). Closing the gender ethnicity pay gap is important for increasing productivity in the economy, providing additional national income, fuelling long-run economic growth, and fulfilling economic potential. Earnings differentials for the BAME community and for ethnic minority women imply that there is a clear failure of social and economic integration in British society (Brynin & Güveli, 2012). Hence, understanding the compounding effects of gender and ethnicity is crucial for targeting areas of improvement in legislation and policy, in order to create equal pay and an equal nation.

1.2 Aim and Scope

The aim of this study is to explore female BAME pay as a component of the overall gender pay gap, and as an explanatory mechanism behind the persistent gender pay gap. The study investigates the association between occupational segregation and BAME groups using quantitative methods. It considers whether BAME women face a double disadvantage; if they are paid less because they are female and belong to an ethnic minority group. As such, this study contributes to the overall debate of what remains in upholding the stubborn gender pay gap in the United Kingdom.

This study aims to capture the complexities within the gender pay gap, and to contribute to explaining different types and measurements of pay gaps. This study utilises the Annual Population Survey data from 2018. This is the most recent set of micro-level data which captures individual characteristics of the population of the UK. An Ordinary Least Squares regression uses this data to measure predictors of earnings. Accounting for demographic characteristics and occupational controls, the study measures observational differences between those aged 16-64, and thus discovers to what extent certain factors explain pay differentials, and how these differentials compare between men, women, and across BAME groups. Thus, the study provides clarity as to the relationship between gender and ethnicity in accounting for pay differences. Hence, the study shows how much of the gender ethnicity pay gap is explained by occupational differences, but also gives an oversight of the unexplainable aspects to differences in gender and ethnicity too.

This study asks;

To what extent does occupational segregation explain the gender ethnicity pay gap?

This research question is followed by hypotheses which examine these relationships further;

1. H_0 – There is no gendered difference in pay
   H_1 – Women earn less than men

2. H_0 – Ethnic minorities face no difference in pay
   H_1 – Ethnic minorities earn less than the white ethnic group

3. H_0 – Occupational segregation is not associated with pay
   H_1 – Occupational segregation is associated with pay

4. H_0 – Being an ethnic minority woman is not associated with a double disadvantage in pay
   H_1 – Being an ethnic minority woman is associated with a double disadvantage in pay

The study is as a consequence, the only source of research which uses the most recent data from the Annual Population Survey. It is an original study which pools together the previous literature which on one hand considers the gender pay gap, and on the other, pay differences for ethnic minority groups. Likewise, few studies go into thorough detail regarding the number of ethnic minority groups, where this study uses nine ethnic groups, other studies assume homogeneity when combining BAME groups together in their analysis. This study contributes to the ongoing research into what factors remain in keeping the gender pay gap stubbornly present, where few authors have approached this topic from the angle of the intersection of BAME women who stand at a point between race and gender. The study contributes clarity on the mechanisms behind earnings differentials in order to combat social and economic inequality for those belonging to ethnic minority groups. As a result, while progress has combatted both racial and gendered inequality, the study indicates that plenty more progress must be made so as to tackle occupational segregation and discrimination so that equality is achieved in the United Kingdom.

1.3 Outline of the Thesis

The study is organised as follows; the following chapter explains the previous literature surrounding the topic; the theoretical background and literature review. Chapter 3 focuses on the data in use, which is described in detail and its limitations discussed. Chapter 4 provides the empirical methods of analysis, explaining the Ordinary Least Squares model, and the variables used. Chapter 5 presents the results and the analysis, where Chapter 6 gives discussion. Chapter 7 closes the study with a conclusion.

2 Previous Literature

2.1 Theoretical Background

2.1.1 Productivity

Typically, gender pay gap studies search for the drivers of pay differences and the key components that determine earnings. Productivity measurements and productivity related differences are crucial in these calculations, and thus, human capital accrual provides an initial explanation of the gender pay gap. In their influential study on human capital endowments, Mincer and Polachek (1974) calculated that earnings were the function of educational attainment and years of work experience, where the skill premium is produced with every additional year. There exists a strong positive correlation between earnings and schooling therefore, where higher qualifications, skill levels, and considerable labour market experience produce greater labour market success (Polachek, 2007).

As such, human capital differences act as a mechanism for differences in pay. Indeed, the abating of the gender pay gap since the 1980s was argued to be chiefly due to the effect of an increase in female labour force participation and the greater accumulation of education and work experience (O'Reilly, 2015; Olsen et al, 2014; Joshi et al, 2007; Blau & Kahn, 2016). Over time, the human capital accrual by women has increased rapidly, where women have increased their commitment to work and have also increased their labour market qualifications (Blau & Kahn, 2016). Women have caught up with men in terms of human capital endowments, and in some instances overtaken them (Blau & Kahn, 2016).

However, human capital is also composed of years of work experience accrued. The allocation of time and production between market and nonmarket activities forms a considerable determinant of comparative advantage and earning powers within a family unit (Mincer & Polachek, 1974). As Blau and Kahn (2016) illustrate, the gender pay gap in the United States in 1981 reveals that while the male advantage in education was the foundation for the gender pay gap however, the higher rates of male work experience dramatically increased the gap further (Blau & Kahn, 2016). The amount of time spent in full-time employment is associated with higher wages, where wages grow at 2.6% for every additional year accrued (Olsen & Walby, 2004). Conversely, for every year of part-time work, wages fall (Olsen & Walby, 2004). The male lead in years of work experience accounts for a significant component of the gender pay gap, making this a critical measurement. Therefore, work experience, particularly years of full-time work experience, is essential in increasing earnings for women.

2.1.2 Channelling and Segregation

However, another factor which explains the persistence of the gender pay gap is that of part-time employment for women, which is highly segregated. Career interruptions and part-time work are other measurements of work experience where human capital approaches to accounting for the gender pay gap remain relevant. The specialisation and gender-based division of labour in the household means that the attachment of women to the labour force is a topic long discussed throughout the gender pay gap debate (Mincer & Polachek, 1974; Becker, 1985). Mincer and Polachek (1974) argue that specialisation between married couples acts as a deterrent for women to work, as the perceived benefits to specialisation of labour for women in the household outweighs the perceived opportunity costs of leaving the labour force. Because women bear the burden of childcare more than their partners, the most optimal result for couples is to prioritise the male career and earning capacity. The result of which is that many women have career breaks and prioritise family responsibilities, so they take up part-time work in order to split their commitments, and opt out of firm specific training because of anticipating interruptions.

Subsequently, gendered differences in work experience with special reference to career interruptions result in penalties on income, and the persistence of a gendered pay gap. Olsen and Walby (2004) find that interruptions to paid employment because of family commitments like that of having children, reduces potential future wage. Typically, the ‘motherhood’ penalty means after a birth of a child, a woman chooses to either leave the labour force altogether, or to self-select into a more ‘family-friendly’ job (Blau & Kahn, 2016; Anderson et al, 2003). Women seek compensating differentials in part-time work, accepting lower pay in order to ‘buy’ better working conditions, or the flexibility in order to provide unpaid care work in the home (Olsen et al, 2014). However, they face penalties for shorter working hours, less experience, and interruptions, which are strongly related to career-family trade-offs and combine to reduce overall earning potentials. For every year that is spent interrupted, future earnings fall by 0.8% and time is taken away from accruing full-time work experience years (Olsen & Walby, 2004). Women in Britain who work part-time face an hourly earnings reduction of 22% compared to full-time women, where this difference has increased over time (Manning & Petrongolo, 2008). Interruptions to careers create a long-term scarring effect on wages therefore, where care provision interrupts the acquisition of human capital. Hence, channelling into part-time work acts as a mechanism of the gender pay gap and there is a double negative effect on wages as women take time away from work to care for family and so fall behind in career progression and accrual of full-time work experience (Olsen & Walby, 2004).

This effect is exacerbated further on a woman’s wage when she takes time out from a highly male dominated occupation (Swaffield, 2007). Besides this, part-time work is less protected, and less likely to be unionised or be permanent (Olsen et al, 2014). When calculating the gender pay gap and including part-time hourly earnings, the gap has not reduced since the 1970s and the gender pay gap widens to 40% between female hourly part-time pay, and male full-time pay (Olsen & Walby, 2004). The compounding effect of part-time work therefore, is a significant negative influence on earnings which account for an ever increasing component of the gender pay gap.

Nonetheless, it is not only the accrual factor that is important in accumulating human capital, but so too the type of human capital that acts as a mechanism behind the gender pay gap. Selection into types of education and work make occupational segregation an important component of the gender pay gap. Occupational segregation is the result of different groups of people working in seperate occupations (Blackwell, 2003). Blackwell (2003) believes that segregation is the outcome of the exclusion, denial of entry or driving out, of some groups in certain employment areas, which helps to support stereotypes (Blackwell, 2003). Occupational segregation is the result of multiple factors; either some occupations are closed to certain groups because of discrimination and, or, the inability to convince employers of sufficient qualifications, and voluntary clustering or sorting into occupations via networks which pay enough for the worker (Brynin & Güveli, 2012).

By considering choice variables taken from recent graduates, Chevalier (2007) studies how that channelling takes place, where men and women self-select into certain paths and specialisations. In the UK men specialise in subjects such as science and engineering, tend to work in the more male-dominated private sector, and take more career-oriented choices (Chevalier, 2007). Conversely, women opt for specialisation in languages, education, and the arts, work for smaller firms, and make choices based on the expectation that they will take career breaks (Chevalier, 2007). Despite the degree to which segregation has declined since the 1970s, gendered differences in occupations remain important today as women tend to cluster into administrative and service support occupations, as well as in nursing and teaching (Blau & Kahn, 2016). Women are funnelled into low-value jobs where explanatory factors are reflected in the division of unpaid labour in the home and the resultant working time schedules (O'Reilly et al, 2015). Indeed, when women work in 'typically female' employment, they earn less than men working in the same industry by comparison (Olsen et al, 2014). As such, women and men are channelled into different occupations which each have their respective differences in pay, and it is this which molds the gender pay gap (Manning & Petrongolo, 2008).

Additionally, the public sector is a large employer of female labour. Of the working population in the UK, 17% of women versus 8% of men are employed by the public sector, which is due to more flexible working conditions, protected maternity leave, and robust safeguards against discrimination (Olsen et al, 2014). While the public sector offers lower pay than the private sector, it has a compressed pay scale which means pay differences between men and women are less, and so has a smaller gender pay gap. Pay relative to external employers remains lower by comparison however. The effect of occupational segregation and channelling into certain areas, whether public sector, part-time, or as reflective of the gendered specialisation of labour, segregation has a significant impact on the gender pay gap.

Furthermore, it is not only occupational segregation which acts as a mechanism behind the gender pay gap, but so too vertical segregation within sectors. Vertical segregation and its persistence is highly gendered, for example, headteachers are male, teachers are female, doctors are male, and nurses are female (Blackburn et al, 2002). While women form half of all managers in fortune 500 companies, they only account for 14% of executive officers and 4% of CEOs (Blau & Kahn, 2016). Indeed, global trends indicate that at lower levels of pay, earnings differences are narrow, but these differences widen as the pay scale risis (ILO, 2015). Therefore, while men and women are working in a variety of different occupations, the genders tend to be employed at different levels on the overall hierarchy. As such, vertical segregation impacts and explains the persistence of the gender pay gap.

2.1.3 The Unexplained

Nonetheless, other theory focuses on endowments that discuss unobservable differences in occupational and human capital factors. These mechanisms help retain the gender pay gap as they are the result of ‘unexplained’ factors between men and women. The first of these unexplained factors relate to the psychological attributes and noncognitive skills of men and women, where gendered differences in competitiveness, risk aversion, and assertiveness appear. By conducting tournaments, Booth (2009) studies attitudes towards competitive behaviour and finds that attitudes differ between men and women, starting from a young age. Depending on the environment, competition and risk-taking behaviour is dampened or exacerbated, where boys express competitive behaviour with ease, yet girls become more shy (Booth, 2009). Differences in competitiveness, confidence, and attitudes towards competition therefore, mean fewer women enter and win in competitions (Niederle & Vesterlund, 2011). As higher paying levels of employment exist in a male dominated environment, the result of these behavioural tendencies therefore favour typically male qualities like assertiveness, risk-taking, and antagonism.

Secondly, individual choices help retain the gender pay gap. Career expectations and corresponding behaviour are highly influential in the decision-making process, and thus account for the unexplainable component of the pay gap (Chevalier, 2007). Here, choices impact career decisions. After three years of completing a degree, a pay gap of 13% emerges between male and female postgraduates due to different choices being made at university and in careers (Chevalier, 2007). Attitudes and choices towards childbearing expectations form a main driver in the gender pay gap where for women with strong preferences towards childrearing, the knock-on effect is that before a fertility decision is made, job search is reduced and they have less intensive job searching behaviour (Chevalier, 2007).

As such, those who possess traditional views towards childrearing lower their expectations and aspirations and are less likely to be in a well matched job (Chevalier, 2007). Additionally, some women may intend to remain in a poorly matched job hoping that their employer will compensate them by accommodating their career when childbearing occurs, and so staying with the employer becomes an investment into certain job conditions for the future; another aspect of compensating differentials (Chevalier, 2007). Yet, a good job match correlates with higher wages, and therefore, when these fertility-based decisions are made early in the career, earnings are forgone (Chevalier, 2007). Choices surrounding childbearing preferences therefore effect wage, and help clarify the unexplainable component of the gender pay gap. Hence, Blau and Kahn (2016) find that gendered psychological differences between men and women account for up to 28% of the gender pay gap. As such, delving into the unexplained factors that contribute to pay differentials exposes newer informative factors, thus accounting for the pay gap’s persistence.

Finally, the unexplained portion of the gender pay gap surrounds the impact of discrimination on female earnings. While discrimination exists in a variety of direct and indirect ways, as discriminatory attitudes have become less socially acceptable, discrimination shifts to a more subtle and unconscious form (Olsen & Walby, 2004; Blau & Kahn, 2016). The 'credentialization' of women throughout the 20th century fostered integration into the labour force and overcame the 'pollution' of women working in exclusively male-held occupations (Goldin, 2002). Yet, discrimination remains an important component of the gender pay gap as it operates at a more subtle level. Indeed, statistical discrimination provides a barrier to women, and is a source of discriminatory pay difference. Employers who incorrectly perceive that women are more likely to quit their jobs compared to men, provide less firm specific training or they assign women to dead-end jobs (Blau & Kahn, 2016). When not being provided the motivation or incentive to remain in that job, women therefore respond to this employee behaviour by exhibiting the expected response; to leave, creating high female turnover (Blau & Kahn, 2016).

An outcome of discrimination is such that because of the gender related expectations placed on women, women avoid attaining firm-specific training and opt instead for transferable general training. According to Blau & Kahn (2016) rewards reaped from firm specific training occur when an employee stays in employment for a long period of time and so the investment is rewarded in the long-run, but women avoid jobs that require this level of training. The knock-on effect of this is the anticipation of behaviour that employers and employees may assume regarding women's labour, acting as a deterrent for training and promoting women altogether, regardless of marital status or the presence of children. Some employers express statistical discrimination and avoid hiring women who would require them to invest in employer specific training (Swaffield, 2007). Subsequently, Swaffield (2007) investigates pay differences between women with and without children and finds that women without children are better paid than women with children, but still paid less than male counterparts, indicating that there is an expectation placed on women that they will intend to reduce their labour supply even before childbearing has happened. Indeed, direct discrimination, preferences, motivations of women, and factors associated with being female, account for 38% of the gender pay gap (Olsen & Walby, 2003).

In summary, the persistence of the gender pay gap suggests that discrimination takes place at many levels and provides feedback to other variables such as education, segregation, and channelling which combined all contribute to earnings differentials. Discrimination alongside other factors mentioned; human capital, gendered segregation into occupations and part-time work, and psycological differences, all add to the explanation as to the factors which maintain the gender pay gap in the United Kingdom.

2.2 Literature Review

2.2.1 Background

The implications of the history of migration into the UK is that each ethnic minority group comprises of different demographic characteristics relative to the native population, and between BAME groups too. Ethnic minorities now account for 15% of the overall population of 66 million people (Henehan & Rose, 2018). Ethnic minorities have lower age profiles relative to the white population, with a larger proportion born outside of the country, and are spatially distributed differently across regions (Henehan & Rose, 2018). More BAME individuals live in London and the South East which have higher average pay, and ethnic minorities have higher levels of educational attainment relative to the white population (Henehan & Rose, 2018).

Progress has been made with regards to observational differences for BAME groups living in the United Kingdom, as between 1996 and 2016, employment rates for black, Pakistani, and Bangladeshi men increased by over a quarter, and over a half for Pakistani and Bangladeshi women (Henehan & Rose, 2018). Additionally, between 2007 and 2017 there was an increase of 28% in Pakistani and Bangladeshi women and 24% for black men and women obtaining university degrees (Henehan & Rose, 2018). Yet, disparities remain in the UK where Pakistanis, Bangladeshis, and black Africans have higher unemployment rates, belong to lower occupational classes, and earn less relative to the majority of the population (Brynin & Güveli, 2012). Additionally, even when participating in the labour force, occupational segregation and discrimination keep many BAME men and women in low-paid work. As such, compositional differences between the majority population and ethnic minorities are important. Indeed, economic activity differs across groups and between men and women of the same group. Time factors also allow for better established and integrated ethnic minority groups relative to others. Thus, there are implications in the national labour market which must be explored.

2.2.2 Gendered Ethnicity Pay Gap Studies

Gender and BAME pay are established subjects for researchers in the United Kingdom. This literature review considers how other scholars have attempted to explain why and how pay differences occur for ethnic minority women, ethnic minority groups generally, and the role of occupational segregation in this debate. Considering differences in pay gaps by gender for each BAME group, Platt (2006) and Nandi and Platt (2010) explain pay differences, where Dale et al, (2006), Holdsworth and Dale (1997), O’Higgins (2015) and Botcherby (2006) seek explanations as to why this is the case. Focusing on ethnicity and gendered pay differences, Nandi and Platt (2010) use British data from the Family Resources Survey and Households Below Average Income data from 2003 to 2008, to measure inequality and poverty ratios using a Gini coefficient method. Their results show that women from all ethnic groups face lower incomes compared to men of the same ethnic group, where the largest gap exists for Bangladeshi and Pakistani women, and the smallest for black Caribbean and Chinese women

(Nandi & Platt, 2010). Indian and white British women have high household incomes, but relatively moderate personal incomes, where black African and black Caribbean women have high personal income but low household income, yet Pakistani and Bangladeshi women have both low personal income and low household income (Nandi & Platt, 2010). As such, their approach in answering to what extent a gender and ethnicity pay difference affects the gender pay gap concludes that it is due to the income inequalities between men and women within ethnic minority groups, but that this level differs by BAME group and that double disadvantage is present for BAME women.

Platt (2006) considers concepts of inequality and poverty, and compares average hourly full- and part-time earnings by ethnic group and gender from the UK using the Quarterly Labour Force Survey from 2001-2005. Her results show that the gaps for men and women stand at £12.45 and £10.28 for Indian, £9.32 and £8.31 for Pakistani, but £10.34 and £10.50 for black Caribbean groups. The average pay gap for ethnic minority women compared to the white average stands at -13%, whereas for men this is at -5%, nearly a third of the size of the gap (Platt, 2006). Her explanations for these pay gaps are such that the substantial variance in qualifications, economic activity, time of immigration into the country, familiaral networks, discrimination, and segregation by gender into 'feminised' occupations all play a role (Platt, 2006). Additionally, when earnings increase along the income distribution, the pay gap for white British, Indian, black Caribbean, and black African women widens further as income rises (Platt, 2006). Her results show that women in ethnic minority groups face a double disadvantage against their wage, where men from the same ethnic minority background do not face the same economic outcomes.

Studies by Dale, Lindley, and Dex (2006) and Holdsworth and Dale (1997) investigate pay differences for BAME women based on economic activity, and thus seek explanations as to why the gender pay gap persists. Dale et al (2006) take data from the Labour Force Survey across 1992-2003 and implement a life-course approach following a multivariate Logit method. Holdsworth and Dale (1997) use the 1991 census and the 1981-1991 ONS Longitudinal Study to create Logit models for each BAME group. Both studies seek to measure likelihood of participation in economic activity for women across ethnic minority groups, and for different life stages. Black, African, or Caribbean women have higher labour force participation rates across the life-course compared to white women, and they stay in work even when they have children (Dale et al, 2006). Indeed, ethnic minority women who are married and with children tend to work in full-time employment more than married white women with children, despite not having any easier access to affordable childcare (Holdsworth & Dale, 1997).

However, they find that Pakistani and Bangladeshi women have the lowest attachment to the labour force[2] of all the BAME groups (Holdsworth & Dale, 1997). By scrutinizing which mechanisms effect labour force participation, the motherhood penalty, and gendered divisions of labour in the household, their study indicates how economic activity plays a role in predicting earnings potentials, and therefore the degree to which women's pay differs from

[2] Dale, Lindley, & Dex (2006). A caveat appears when accounting for single women aged 18-34 and with higher levels of educational attainment as they are just as likely to be active economically relative to the average population (Dale et al, 2006).

men's[3]. Additionally, their study finds that the outcome of cultural expectations of women, the necessity to earn, and selection into work, differs in degree across BAME groups, and so the effect on pay is not homogenous.

Other areas of study which seek to explain why ethnic minority women face pay differentials include O'Higgins' (2015) nonparametric matching analysis of the Roma community of Central and Eastern Europe in 2011. O'Higgins (2015) decomposes the role of educational attainment, occupational segregation, discrimination, and other factors in determining the mechanisms behind the gender ethnicity pay gap between Roma and non-Roma communities. By investigating the double disadvantage faced by women of the Roma community, he contends that ascribed differences in educational attainment do not fully explain why women from the Roma minority group not only face lower market outcomes compared to the majority ethnic group, but also men of the Roma community too (O'Higgins, 2015). This therefore suggests that women of the Roma community face not only lower pay compared to the non-Roma community but so too their male Roma counterparts, and hence there is a double disadvantage. Thus, occupational differences explain some of the gender ethnicity pay gap, but discrimination and unobservables also play an important role in answering this question.

Furthermore, double disadvantage for migrant and British born BAME women is investigated by Botcherby (2006). Her study conducts surveys which interview BAME and white British women in 2005, and interviews ask questions along the key themes of employment participation, progression, and pay. The study finds that gendered ethnicity pay differences are explained by over qualification and job mismatch. When finding employment appropriate to skill attributes, job seekers lower their expectations and accept more poorly matched and poorly paid work rather than being unemployed with no income at all. Half of the ethnic minority women report that finding a job is difficult, compared to 3 in 10 white British women, highlighting persistent employment disadvantage in access to jobs for women belonging to BAME groups (Botcherby, 2006). Thus in terms of qualifications, women from ethnic minorities find it 3-4 times more likely to take a job which they are under qualified for compared to white women, equating for 1 in 5 ethnic minority women employed in a job below their potential because they could not find employment suited to their level of qualification (Botcherby, 2006). As such, over qualification and mismatch contributes to the channelling of ethnic minority women into lower paid and lower skilled work. Hence, mismatch contributes to occupational segregation which explains why women from ethnic minority groups face a pay differential, and thus accounts for the continuation of the gender pay gap.

The combination of mismatch, over qualification, gendered division of labour, and lower economic activity all contribute in explaining the factors behind the gender ethnicity pay gap. Indeed, the discussion of double disadvantage also brings forth the role of occupational

[3] Dale, Lindley, & Dex (2006), Dale (1997). Likewise, both studies investigate partner's employment and economic activity, where a male partner is employed there is a positive effect for black and white women, but there is no change in likelihood for being economically active when a Pakistani or Bangladeshi woman has an employed partner (Dale et al, 2006). For Indian women there is a much more traditional association that exists between economic activity, marriage and childbearing, but where educational attainment equals that of white women (Dale et al, 2006). However, over the life course, ethnic minority women face higher levels of unemployment compared to white women, which is not fully explained by differences in human capital accumulation, but Holdsworth and Dale (1997) find it is instead the result of discrimination.

segregation in accounting for the gender ethnicity pay gap. In this case, previous research by Blackwell (2003) and Brynin and Güveli (2012) are discussed. Blackwell (2003) takes 1991 census data and conducts a Gini index of values based on pay of BAME groups relative to the white average and between each BAME group. Their study considers occupational segregation; the tendency for different groups of people to work in seperate occupations, as the main mechanism which explains pay differences. The results show that white men and women have relatively less gendered occupational segregation compared to other groups which are heavily concentrated into a few occupations and face crowding (Blackwell, 2003). Their results show the differences between part- and full-time work on ethnic segregation, where the former is found to be more gender segregated and less likely to be in prestigious occupations (Blackwell, 2003). Yet Blackwell (2003) notes that patterns of occupational advantage and disadvantage are complex, where gender and ethnicity do not always combine to form a double disadvantage for working minority women. As such, there is a level of contradiction surrounding the double disadvantage of women from BAME backgrounds.

2.2.3 Ethnicity and Occupational Segregation Studies

Similarly, Brynin and Güveli (2012) use Labour Force Survey data from 1993 to 2008 to investigate double disadvantage, pay differentials, and occupational segregation in the ethnicity pay gap. They use a two-step Ordinary Least Squares model in calculating the ethnicity pay gap and test for changes over time, comparing the mean pay of ethnic minority groups against the white group average. They find that ethnic minorities are overrepresented in low paid work, which is more likely to be temporary, casual, and insecure (Brynin & Güveli, 2012). Additionally, most minority ethnic groups have either lower representation in managerial levels compared to that of people from a white ethnic background, or that there is higher representation in the routine class, which is especially so for those of Pakistani or Bangladeshi backgrounds (Brynin & Güveli, 2012). As such, the ethnic pay gap varies by the ethnicity group itself, but exists largely as a result of occupational segregation by ethnicity (Brynin & Güveli, 2012). However, their results indicate that there is no double disadvantage for BAME women as they are paid equally as low wages as their male counterparts (Brynin & Güveli, 2012).

Brynin and Güveli's (2012) study therefore considers discrimination that results in occupational segregation where ethnic minority groups not only work in low paid occupations, but also because they have limited integration. They suggest ethnic minority pay gaps are the result of sorting and from self-selection, where minorities cluster into low paid occupations (Brynin & Güveli, 2012). They find that nearly half of Caribbean and African immigrants work in the health sector in the UK (Brynin & Güveli, 2012). Their results imply both a failure of social and economic integration, where occupational segregation is a reflection of the allocation of peoples into positions because of both voluntary and involuntary practice (Brynin & Güveli, 2012). Ethnic minority groups face different trajectories and assimilation into society, where first generation migrants and subsequent generations face stratification and different economic outcomes compared to the native average (Zhou, 1997). Because of segmented assimilation, differences between groups persist because of different backgrounds and experiences shaping the assimilation process (Brynin & Güveli, 2012; Zhou, 1997). As such, segmented assimilation and persistent segregation contribute to keeping ethnic minority pay lower relative to the white average.

Other studies also seek to explain the persistence of the ethnicity pay gap. Clark and Drinkwater (2007) use UK Labour Force Survey data from 2002-2005 to measure occupational segregation. In their study they control for adjusted pay gaps which account for occupational differences using Ordinary Least Squares regressions. They find that while occupational segregation does occur, it is not the pay gaps between occupations that are significant in affecting earnings outcomes, but the differences in pay within the same occupations that are causing differentials (Clark & Drinkwater, 2007). Likewise, Longhi, Nicoletti, and Platt (2009) also use Labour Force Survey Data from 2002 to 2008 and uncover the mechanisms of the pay gap using an Oaxaca-Blinder decomposition method. They find that a large portion of pay differentials at the bottom of the pay scale are explained by personal and job characteristics, but the unexplained component increases as the income distribution rises (Longhi et al, 2009). Despite the presence of ethnic minorities at the top of the pay scale with equitable education, skills, and experience, there are factors which are still affecting pay to a greater extent than those working at routine levels.

In summation, this review has captured the results of other studies which seek to explain not only ethnic minority differentials, but so too gendered ethnic minority differentials. Comprehending the different experiences that ethnic minority women have relative to their male counterparts, and relative to the white population uncovers many mechanisms at play as to why pay differences exist. Studies investigate a variety of mechanisms that explain pay gaps; ranging from differences in labour force participation and the gendered expectations of women in the household. Likewise, these expectations contribute to channelling into certain occupations, and to the unobserved factors of discrimination and differences in assimilating into society, which are all factors which account for the gender ethnic pay gap. Of importance to note is the debate regarding whether BAME women face double disadvantage. Where Nandi and Platt (2010), Platt (2006), O'Higgins (2015) and Botcherby (2006) agree that ethnic minority women earn less than men of the same ethnic minority group and less than the white male average. However, Brynin and Güveli (2012), Clark and Drinkwater (2007), Longhi et al (2009), and for some minority groups, Blackwell (2003) disagree, and argue that both women and men from ethnic minority groups are paid equally less than the white average.

3 Data

The Annual Population Survey (hereafter, APS) is a major data source which provides reliable and comprehensive estimates of changing characteristics of the population of the United Kingdom. The APS began in 2004 and comprises information from households and individuals, across all regions of Great Britain and Northern Ireland. The APS is a continuous survey, comprised of the Labour Force Survey, (hereafter, LFS), and associated survey boosts from Scotland, Wales and Northern Ireland (UK Data Service, 2018). The combination of the LFS into the APS allows for key topics surrounding employment, training, education, health, and ethnicity to be measured (UK Data Service, 2018). The data collection is carried out quarterly, where each quarter relates to a single year and approximately 170,000 households and 360,000 individuals have their data captured (UK Data Service, 2018).

Collection of the data for Great Britain is conducted by the Office for National Statistics, and the Northern Ireland Statistics and Research Agency for Northern Ireland respectively (ONS, 2018). The APS, and the LFS which contributes to it, is funded by the government; the Department for Education and Skills and the Department for Work and Pensions (ONS, 2018). Access to the data however, is granted by the UK Data Service. The aim of the APS is to gather nationally representative information about households and individuals across the United Kingdom of Great Britain and Northern Ireland in order to asses long term trends and identify appropriate areas of policy response. Consequently, it is a critical source of information and a vital tool to monitor and promote equal opportunities across the workplace and society (ONS, 2018). As such, the APS is a robust resource of labour market and macroeconomic information (ONS, 2018).

3.1 Annual Population Survey 2018

The Annual Population Survey from 2018 is the most recent and accessible data available. The APS gathers data from the Labour Force Survey, which commenced collection in January 2018 until December of the same year, and took place via successive calendar quarterly waves thereby ensuring an even number of surveys took place throughout the year. Figure 3.1 below replicates the structure of the APS through the year of 2018, and the waves of data collection used.

	Jan - March 2018	April - June 2018	July - Sept 2018	Oct - Dec 2018
LFS Cohort 1	Wave 5			
LFS Cohort 2	Wave 4	Wave 5		
LFS Cohort 3	Wave 3	Wave 4	Wave 5	
LFS Cohort 4	Wave 2	Wave 3	Wave 4	Wave 5
LFS Cohort 5	Wave 1	Wave 2	Wave 3	Wave 4
LFS Cohort 6		Wave 1	Wave 2	Wave 3
LFS Cohort 7			Wave 1	Wave 2
LFS Cohort 8				Wave 1

Figure 3.1 APS Dataset: January - December 2018 (ONS, 2018)

As seen in Figure 3.1, while the data is a repeated cross sectional study, the survey has a panel element, in that individuals were interviewed over a number of waves, although different questions forming separate sections of the survey were asked in each wave (UK Data Service, 2018). For consecutive yearly surveys however, these individuals are dropped and replaced each year, therefore it is not a longitudinal study (UK Data Service, 2018). The units of observation in the data are at the micro-level, where 284,104 random cases are recorded (UK Data Service, 2018). The method of data collection is via either face-to-face interview for the initial wave, and then via telephone interview. The population sample consists of persons resident in private households as well as young people living away from their parental homes (UK Data Service, 2018).

The APS questionnaire and survey are comprehensive in nature, where individuals are asked questions ranging from demographic features to economic activity. Firstly, information is gathered on household and individual characteristics, specifically gender, marital status, nationality, ethnicity, and religion (ONS, 2018). It gathers information about economic activity, earnings, occupation and industry, type of employment, unemployment, and if individuals have second jobs (ONS, 2018). Certain variables such as that of unemployment and occupational industry follow definitions provided by the International Labour Organisation, and thus it upholds international standards of definition of employment and unemployment (ONS, 2018).

Other aspects of the survey consider travel to work, sickness, benefit entitlement, education, and health and personal well-being (ONS, 2018). Of critical importance to this study is that of the demographic and economic information of individuals, how they work, what they earn, and the factors associated with this. Therefore, the APS and the LFS within it, form comprehensive and in-depth research across a large set of individuals in the United Kingdom. The result of which is that it provides a thorough, detailed, and accurate insight into the lives of citizens of the UK, and the demographic characteristics of the population as a whole. It is a highly integrated source of information regarding labour market activities, thus making it the most reliable source of data available.

Indeed, the use of the APS is the most appropriate when considering women and their earnings, as well as accounting for differences in economic activity for ethnic minority groups. By capturing information on human capital factors, type of employment, and pay, much is revealed regarding decomposition of the gender pay gap. Further accurate information is given about the lives of the many ethnic minority groups in the UK, their nationalities, human capital, and the occupations individuals are employed in. As such, this data is not only reliable but the most appropriate source of information that is used to understand and explain differences in earnings among different ethnic groups within the labour force.

Limitations of the Annual Population Survey are that while it incorporates the majority of information taken from the Labour Force Survey, it only uses core variables where non-core variables are not captured (ONS, 2018). This means that some variables such as household size, the number of children in a household, and respective ages of children, are not accounted for, this limits testing when the models factor in why individuals withdraw from the labour market. Not included are tenure and years of work experience, and information about partners and spouses such as if they are unemployed or working, and their type of work. Additionally, the APS does not obtain any measurement of unpaid work, which is another feature heavily associated with female labour. However, as this variable is by nature complicated and hard to define, it would be ambitious to accurately measure and capture this variable on a scale as large as that found in the APS.

While the survey also takes information regarding weekly and yearly earnings, these are only given as banded estimates, not in a continuous format, and are provided as expected earnings for the course of a year. For a measurement of earnings in a continuous form, the main variable that captures earnings are hourly, derived from the variables Gross Weekly Pay and Hours Worked. The ONS (2018) however, use hourly pay for their study and decomposition of the gender pay gap, and while it is accepted that hourly pay does not include overtime pay or bonuses, they argue it is the best measure of calculating pay differences. As such, this study uses hourly earnings to measure raw and adjusted pay gaps.

Furthermore, while in the UK most nationalities of the world are found, the APS does not provide detailed information and coding for all nationalities or ethnic minority groups. Instead, nationalities are associated with continents, and ethnic groups are merged to form nine groups in all; white, mixed/multiple, Indian, Pakistani, Bangladeshi, Chinese, other Asian, black/African/Caribbean/black British, and other. As a result, the ethnic group variable does not capture separate groups for those who are white but from outside the UK or the Irish traveller community. Those who are of mixed ethnicity form one composite group. Homogeneity is assumed for the black/African/Caribbean/black British group where this may not be the case. However, while these limitations are considered when interpreting results, an increase in the number of ethnic groups would decrease observations belonging to each and therefore reduce likelihood of statistical significance, resulting in poorer estimates. As such, the nine ethnic groups are maintained for this study.

In order to provide as accurate estimates as possible, the study reduces the size of the data set in order to increase robustness of results. Firstly, as this study focuses on those who are of an economically active age, i.e., pay differences are not appropriate for children or those who are retired, the data is reduced so as to only include those of working age, 16 to 64. While full-time education is mandatory until age 18, children can work from age 16, and so any child under this bracket is inactive (ONS, 2018). As of 2010 legislation, the retirement age for women was brought in line to that of retirement age for men, increasing from 60 to 65 between 2010 and 2020 (ONS, 2018). Therefore, the study considers all those of working age to be between 16 and 64 years of age, removing 165,132 observations from the study.

The dependent variable in this study is that of pay, so to calculate any differences in earnings, those who have stated they are employed yet have not disclosed any information regarding income are removed; 43,325 observations. Likewise, those with extreme values in their hourly pay, more than £80 or less than £1 an hour, are removed in order to reduce bias and remove negative log values. Fewer than 100 observations were dropped in this instance. Observations who claim to be employed but do not declare their occupational class are also dropped. However, for all other variables, observations which ‘do not apply’ or ‘does not know’ are the response given, separate categories are provided so as to minimise loss of important observations. Subsequently, the final data set encompasses 121,568 individuals, of which 78,587 are in employment and have declared their hourly pay.

3.2 Descriptive Statistics

As this study investigates the extent to which occupational segregation explains the gender ethnic pay gap, crucial areas of data encompass determinants of economic activity, human capital accumulation, and occupational differences. The variables that are associated with these components and how they differ between different ethnic minority groups are of key importance to this study. This section compares and contrasts the statistics and data for these key variables, and between men and women.

3.2.1 Population Overview

Picturing the demographic characteristics of the United Kingdom as a whole, the first area to consider is the proportions of different ethnic groups in their size relative to the population. Figure 3.2 below indicates the proportion of each ethnic group as a total of the dataset, the composition of each ethnic group by economic activity, and the educational average of each gender. As seen in Figure 3.2, 88% of the dataset fall under the white ethnic group, where the second largest ethnic group is black/African/Caribbean/black British at 2.6%.

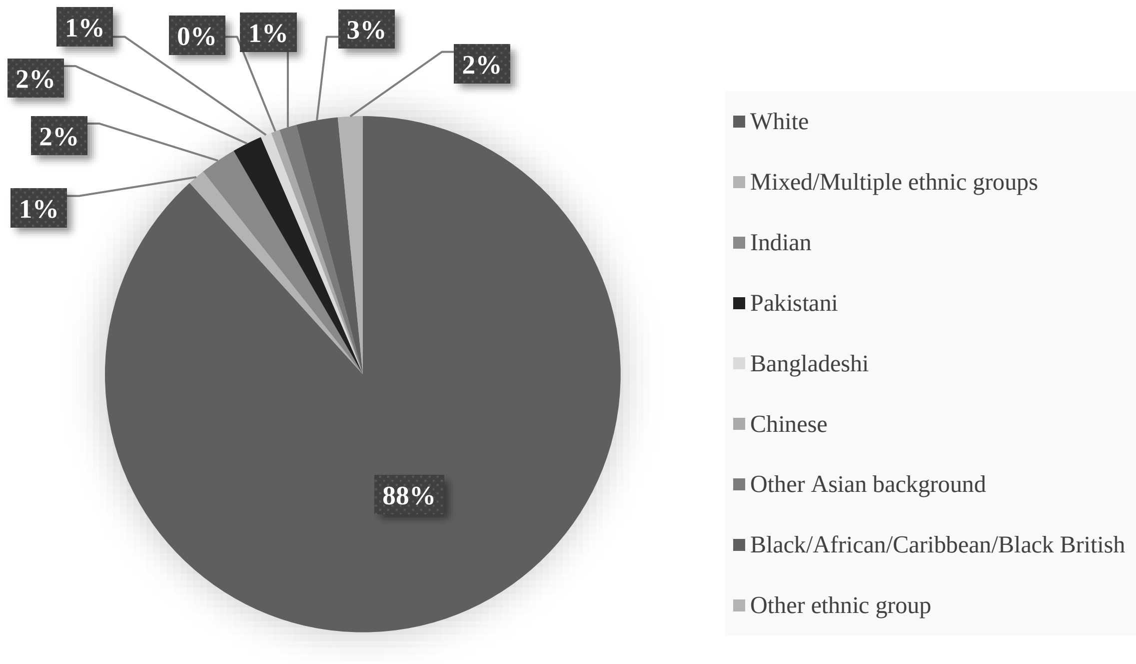

Figure 3.2 Ethnic Groups in the United Kingdom, % (APS, 2018)

Economic Activity

As earnings differences are a considerable aspect to this study, it is important to note who earns, and who does not. Figures 3.3 and 3.4 below compare differences between economic activity and labour force participation. Takeaway observations from these descriptions are that on the whole, more than half of all men by group are economically active, whereas women have lower levels of employment, and higher rates of being inactive. Across all ethnic groups, men are in employment more than women from the same ethnic group. Women from Bangladeshi and Pakistani groups have the lowest levels of economic activity, at 22% and 27% respectively. The smallest unemployment rate is for white men and women, at 5% and 3%, where Chinese, 5% and 4%, and Indian, 5% for both men and women, are not far behind. However, those with the highest unemployment rates are black and mixed ethnicity males, at 9% and 8%, nearly double the rate compared to white men. Black and Bangladeshi women have rates of unemployment at 7%. Thus, variations are seen in economic activity between men and women, and across groups.

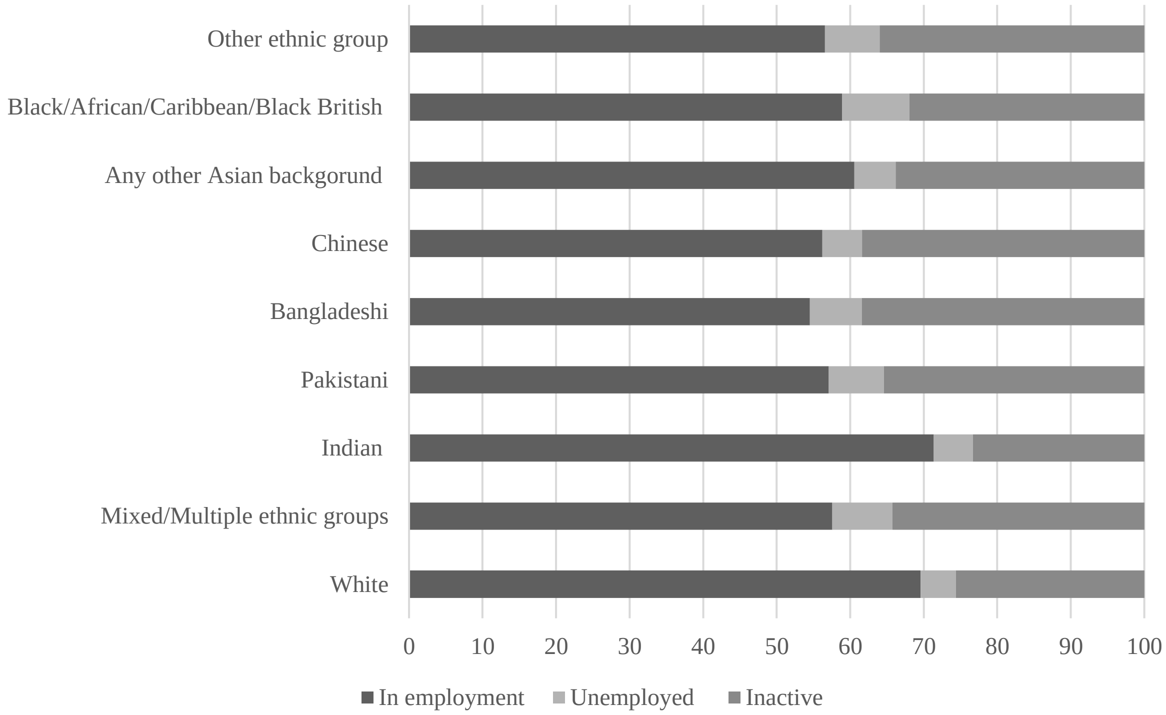

Figure 3.3 Economic Activity by Ethnic Groups for Men, % (APS, 2018)

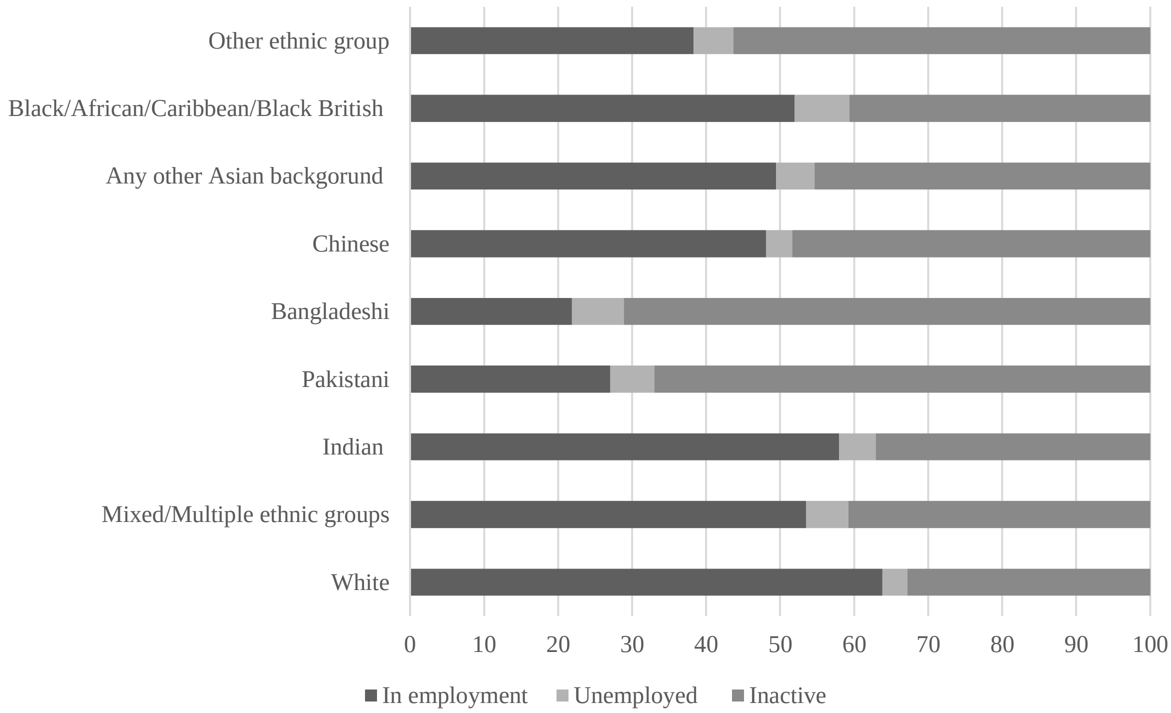

Figure 3.4 Economic Activity by Ethnic Groups for Women, % (APS, 2018)

Education

Differences in human capital and education are crucial factors in pay gap calculations. Figure 3.5 below indicates the highest level of qualification that men and women have. A higher proportion of women are educated to higher or degree level compared to men, at 29% and 10% compared to the male 27% and 8%. Women finish secondary school with a greater number of GCSE pass grades, but a greater proportion of men complete A level education. A greater proportion of men have no qualifications compared to women, at 10% of men and 9% of women.

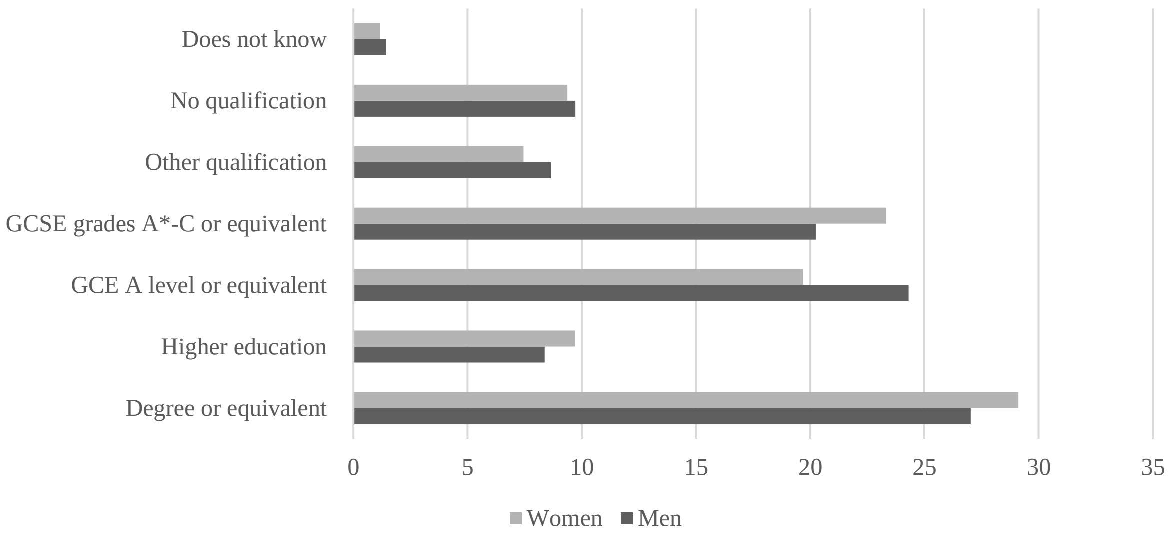

Figure 3.5 Educational Attainment by Gender, % (APS, 2018)

3.2.2 The Sample

The group of those within the dataset which declare they are in employment and provide their earnings details sum 78,587 individuals. The following descriptions provide an overview of occupational characteristics by ethnic group. Table 3.1 provides an overview of mean and median average hourly pay for men and women, across ethnic groups. This table gives an indication of the raw pay gaps between groups, where the difference between the genders is presented. For internal raw gaps within most ethnic groups, men earn more per hour than women, and the highest paid for both genders are the Chinese. Those who face the lowest pay are Bangladeshi males and Pakistani females. The largest pay gap between men and women of the same ethnic group is Indian men and women with a mean difference of £4.78, and median difference at £3.65. The Bangladeshi group sees a negative pay gap for men, who earn a -£0.71 mean difference less than women. Additionally, average male pay across groups is more stratified relative to female pay. Between the men, there is a difference of £7.91 between Chinese and Bangladeshi men, whereas women's pay is relatively less stratified, with a difference of £4.97 between Chinese and Pakistani women.

Table 3.1 Raw Hourly Pay for Men and Women Across Ethnic Groups, in Pound Sterling, £

	Men		Women		Raw Gap	
	Mean	Median	Mean	Median	Mean Diff.	Med. Diff.
All	16.26	13.20	13.24	10.88	3.02	2.32
White	16.33	13.35	13.24	10.87	3.09	2.48
Mixed/Multiple	15.94	12.66	13.44	11.16	2.50	1.50
Indian	19.32	15.68	14.54	12.03	4.78	3.65
Pakistani	13.69	10.58	11.07	9.20	2.62	1.38
Bangladeshi	11.41	8.97	12.12	9.83	-0.71	-0.86
Chinese	18.73	16.62	16.04	13.89	2.69	2.73
Other Asian	15.59	11.84	12.99	10.32	2.60	1.52
Black	13.56	11.00	12.62	10.77	0.94	0.23
Other Ethnic Group	14.99	11.22	13.07	9.95	1.92	1.27

Industry

Figures 3.6 and 3.7 below provide a summary of the proportions of which ethnic groups work in each sector. It gives an indication of which employers are the largest per men and women and across the ethnic groupings. The largest five employment industries account for a greater proportion of women than they do the largest five for men, where men are employed in other industries to a greater extent than women. An obvious takeaway of note is that the largest employer of men and women of all ethnic groups are those of public administration, education, and health and social work. However, the extent of employment is larger for women, pertaining to approximately 50% of all women by ethnic group on average, who are employed by this industry compared to 20-30% of men. The retail, accommodation and food service employers also compose a large employer for women across all ethnic groups, varying between 13% to 25%. For the same industry for men, while retail, accommodation and food service comprises a large employer, the proportion varies to a greater degree than it does women, from 17% to 50% per group. Likewise, the financial, insurance, real estate, and academic industries have a greater proportion of men employed across all ethnic groups, apart from the other ethnicity group.

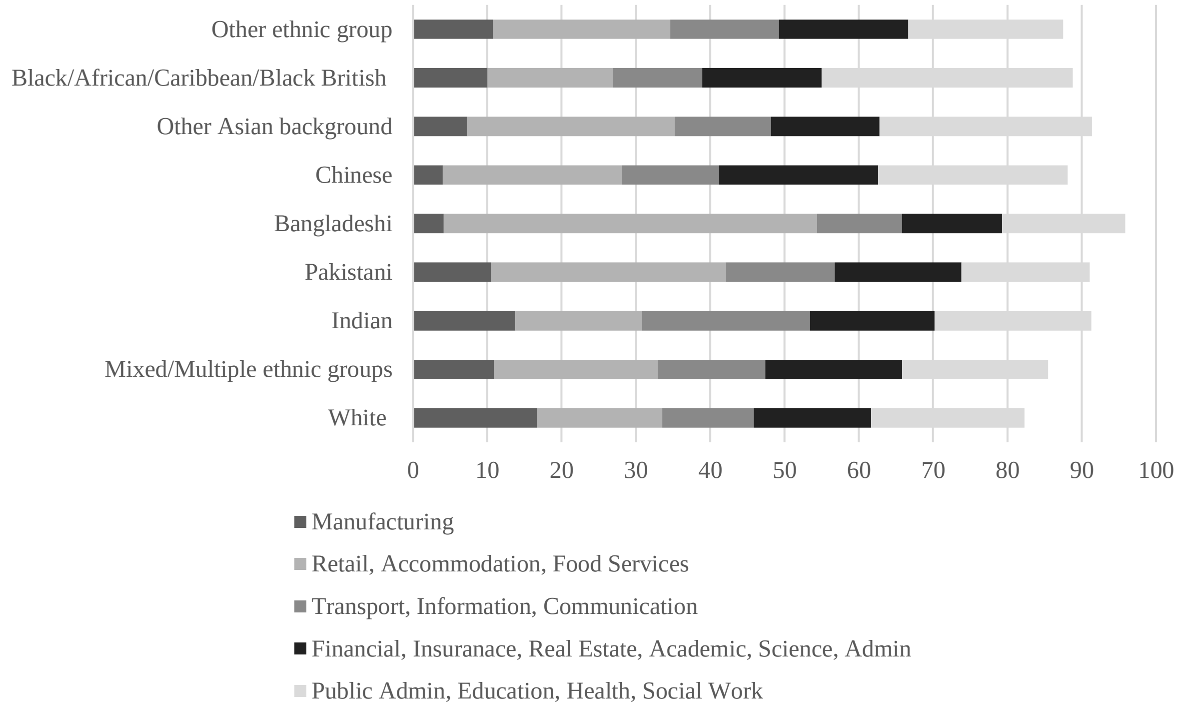

Figure 3.6 Top 5 Indsutry Employers by Ethnic Group for Men, % (APS, 2018)

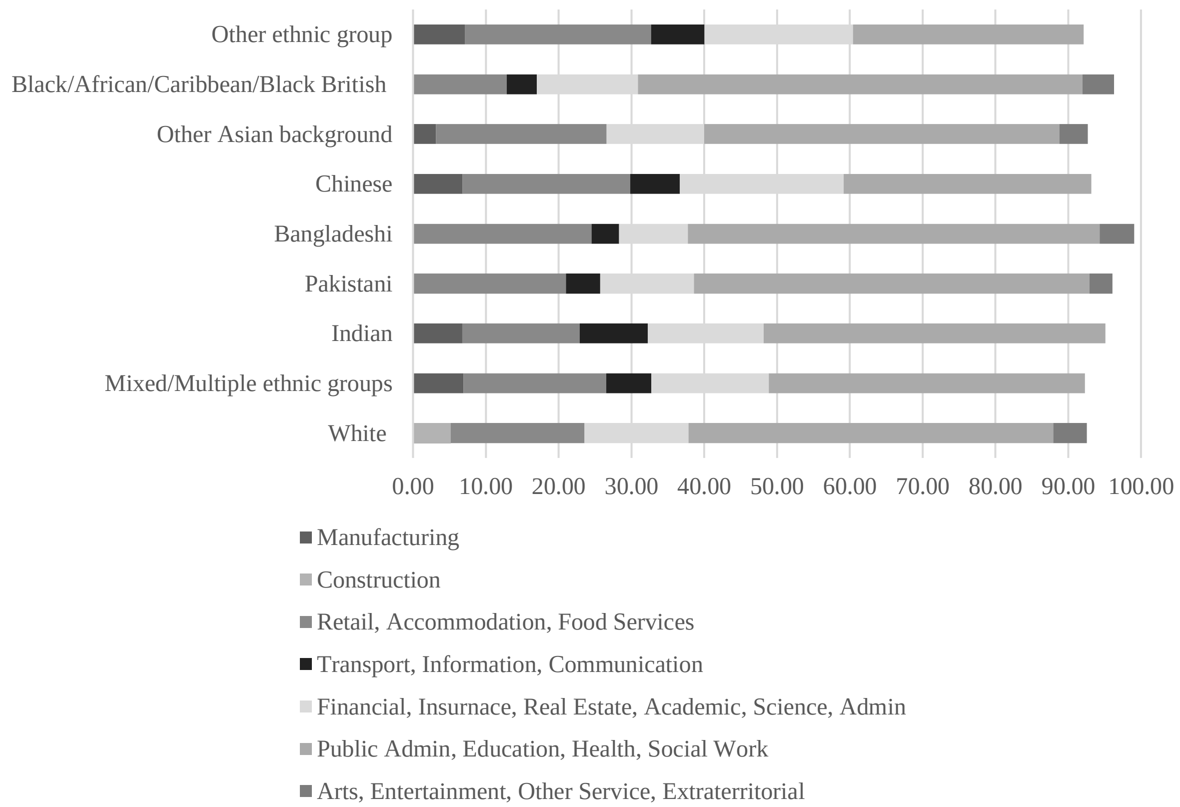

Figure 3.7 Top 5 Industry Employers by Ethnic Group for Women, % (APS, 2018)

Occupational Class

Occupational class describes those who are employed at the professional and highly skilled level, to intermediate skilled roles, and those who are low skilled working in routine jobs. The Occupational group provides a proportion of which men, women and ethnic minority groups are represented at different levels of occupational class. It is clear that the percentages of each ethnic group differ, where two-thirds of Chinese men are employed in the highest occupational class, compared to 30% of Bangladeshi men. Likewise, 59% of Chinese women are in this class and 35% of Pakistani women are too. A greater proportion of women compared to men work at the low-skilled occupational level and across all the ethnic groups.

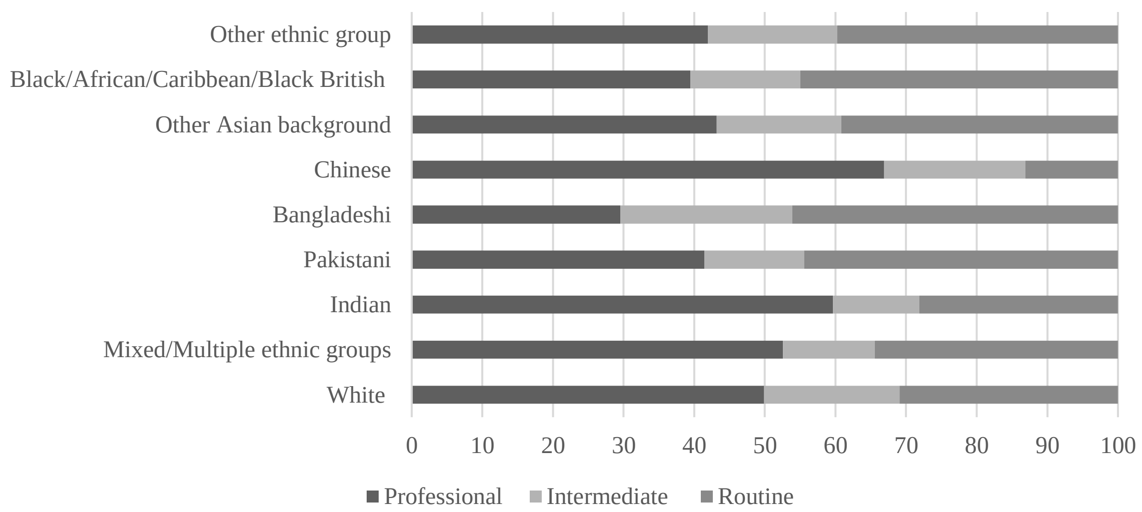

Figure 3.8 Occupational Class by Ethnic Group for Men, % (APS, 2018)

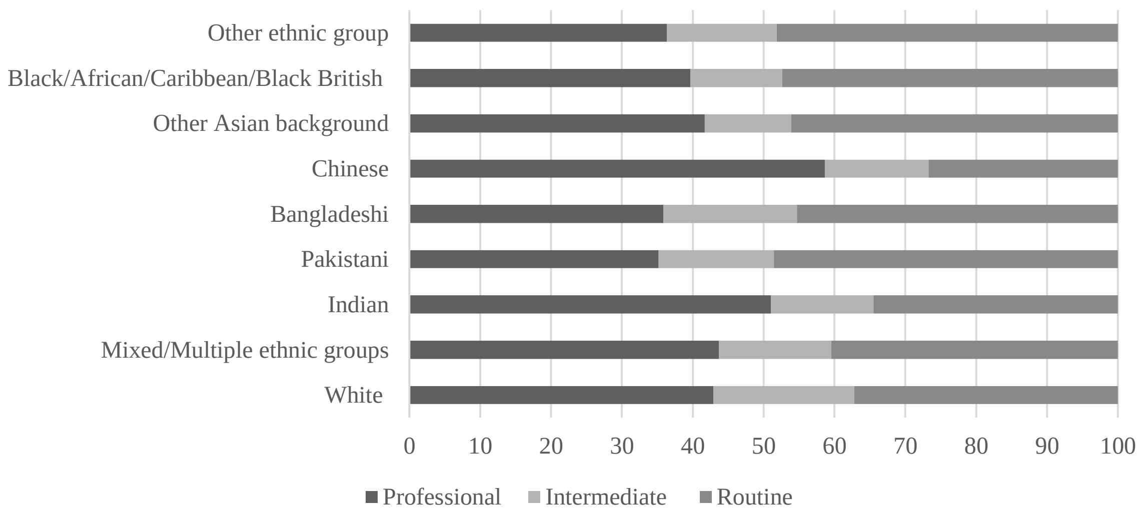

Figure 3.9 Occupational Class by Ethnic Group for Women, % (APS, 2010)

Considering occupational differences between ethnic groups and the men and women belonging to each, is of critical importance in this study. Using the descriptive statistics of those employed, the study begins to disentangle the differences between ethnic groups and occupational segregation. It is clear from the descriptive statistics alone that differences emerge; by pay, economic activity status, educational attainment, employment by sector, and occupational class. These factors are therefore all important when questioning the explanatory components of the gender ethnic pay gap, and the role of occupational segregation within this.

4 Empirical Method

4.1 Methodology

To understand which factors explain the gender ethnicity pay gap, the study aims to explain hourly pay based on a variety of components, and the degree to which occupational segregation accounts. The study uses a quantitative method and implements the cross-sectional data taken from the APS 2018 to uncover the association between occupational segregation and pay differences for BAME women. The study provides a snapshot in time from 2018 to describe the structure of the labour market at the micro-level and the state of the gender ethnicity pay gap. This study conducts this via the use of computer software STATA. In seeking associations between earnings and individual characteristics, an Ordinary Least Squares (hereafter, OLS) regression is applied using a log-linear multiple regression model to answer the research question.

Using OLS regression modelling techniques, testing predictors of hourly pay are conducted by holding for demographic characteristics and for occupation related factors. By using the same treatment across all BAME groups relative to the white group, the size of raw and adjusted pay gaps are given. Raw gaps being present prior to the addition of occupational controls, which when added give the adjusted pay penalty. The relationships between these factors account for occupational segregation, and to what extent occupational segregation explains pay differentials. The study provides a measurement of determinants of earnings for not only those belonging to ethnic minority groups, but what extent women from BAME groups face a double disadvantage in terms of economic and pay penalty outcomes relative to the white group average. As such, the regression separates men and women by gender and by ethnic group in order to compare each respective group to the relative white male or female average. Therefore, the analysis contributes a clear breakdown of pay gaps for ethnic minorities and the men and women among them. By understanding the differences in pay between groups therefore, the study contributes to explaining why a gendered ethnicity pay gap contributes to the overall gender pay gap persistence in the United Kingdom.

The OLS model is chosen in this study because it provides a clear breakdown of what factors, the independent variables, impact and explain pay, the dependent variable. In this way, multiple variables are controlled for and factored into the regression. Not only are the relationships between the independent and dependent variables made clear, but they show the magnitude and extent to which relationships hold. Categorical variables are useful tools to show how some observations face different outcomes on the dependent variable relative to the most common group, which in this case is highly apt for testing ethnic minority groups relative to the white group. The OLS also provides an indication of how well the independent variables explain the dependent; the goodness of fit of the model. Likewise how much statistical significance each variable has indicates the extent to which the results are reliable. This means that the OLS model and the explanatory variables within it are compared with regard to magnitude and statistical significance, where some variables provide different relationships with bigger impacts relative to others.

The OLS model allows for controlling of the compositional characteristics, where the remainding gap after factoring in controls indicates what is left unexplained by the observed characteristics, showing the effect of omitted factors. As such, the model shows the extent to which observed and unobserved factors make in explaining the dependent variable, where the size of each is important when discussing the gender ethnicity pay gap.

Indeed, the OLS regression technique is the best model for this study which is clarified by other studies who wish to measure the gender pay gap, and the ethnicity pay gap. Olsen and Walby (2004), Olsen et al (2014), and Swaffield (2007) all use OLS modelling techniques to investigate which components explain the gender pay gap. Brynin and Güveli (2012), Clark and Drinkwater (2007), and Henehan and Rose (2018) also use OLS modelling when measuring the impact of occupational segregation on the BAME pay gap. As such, this is an appropriate method of use for this study because it provides a variety of ways to manipulate and compare results, which other authors have maximised.

4.2 The Model

Therefore, this study comprises a model which measures and accounts for the mechanisms associated with earnings. These models are separated by gender, so that comparisons for each ethnic minority group are made relative to white pay. By using a number of models, comparisons are made between magnitudes of variable results, indicating which additional variable explains the raw and adjusted pay gaps.

When using the log of hourly pay, the regression takes a log-linear form, meaning the logarithmic function of the dependent variable, hourly pay, is equal to a linear combination of the parameters of the model (Gujarati & Porter, 2010; 133). By using a log-linear form of regression, the coefficients for each result measure elasticity, where a one unit increase in an independent variable, X_i estimates a percentage change in the dependent variable (Gujarati & Porter, 2010; 133-4). Even if the independent variables are not linear themselves; they are categorical or dummy, a percentage change remains.

As such, each model indicates the addition of important variables which explain the raw pay and create the adjusted pay gap, for ethnic minority groups for men and for women. With each addition, the difference is compared so as to measure impact on the pay gap. Likewise, when running regressions for the three occupational classes and by gender, the final regression equation with all demographic, human capital, and occupational variables incorporated.

The study tests the relationship between the log of hourly pay as the dependent variable, and the independent explanatory variables. The OLS model estimates the value of hourly pay given the values of the independent values, where a one unit increase in the independent variable predicts a corresponding increase in the dependent variable (Gujarati & Porter, 2010; 22). β_0 is the intercept in the equation, the ε_i is the residuals, $\beta_5 X_{Region}$ is a vector for regional dummy variables, and $\beta_7 X_{IndustrySector}$ signifies the dummies of the industry sector.

The OLS multiple regression model where the logarithmic form of Y_i is the dependent variable hourly pay, is as follows;

$$log\ Y_i = \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_n X_{ni} + \varepsilon_i$$

Figure 4.1. The Log-Linear Model (Gujarati & Porter, 2010: 133)

Following the method of Clark and Drinkwater (2007) who control for a number of variables, pay differentials are presented without any human capital or occupational controls, where these are added in across testing. In this way, the OLS model predicts the log hourly pay controlling for demographic characteristics, education, and occupational factors. By using the categorical variable of ethnic groups where white is the baseline, pay is presented as relative to the white group, where the size of raw and adjusted pay gaps are given. As such, the OLS shows how much occupational segregation explains the pay gap and any pay differentials.

The OLS equations are as follows, where the same equation is repeated for the male and female observations separately;

$$log\ Y_i = \beta_0 + \beta_1 Age_i + \beta_2 AgeSquared_i + \beta_3 EthnicGroup_i + \beta_4 MaritalStatus_i + \beta_5 X_{Region} + \varepsilon_i$$

When accounting for human capital controls, educational attainment is added to the equation in order to see the effect this has on the adjusted pay gap;

$$log\ Y_i = \beta_0 + \beta_1 Age_i + \beta_2 AgeSquared_i + \beta_3 EthnicGroup_i + \beta_4 MaritalStatus_i + \beta_5 X_{Region} + \beta_6 EducationalAttainment_i + \varepsilon_i$$

When controlling for occupational controls, and thereby accounting for occupational segregation, industry sector, managerial status, and whether employment is in a permanent, part-time, or public sector job, is added;

$$\log Y_i = \beta_0 + \beta_1 Age_i + \beta_2 AgeSquared_i + \beta_3 EthnicGroup_i + \beta_4 MaritalStatus_i + \beta_5 X_{Region} + \beta_6 EducationalAttainment_i + \beta_7 X_{IndustrySector} + \beta_8 ManagerialStatus_i + \beta_9 PartTime_i + \beta_{10} Permanent_i + \beta_{11} PublicSector_i + \varepsilon_i$$

4.3 Empirical Strategy

As this study outlines the multiple factors that are associated with earnings, and also differences in earnings between specified groups, there are a number of influences on pay and thus a number of variables used to explain the dependent, hourly pay, variable. The dependent variable of the log of hourly pay is regressed against independent variables which capture these characteristics at the micro-level, and form several variables to explain the dependent variable, which are explained below.

4.3.1 Dependent Variable

Log of Hourly Pay

Continuous: 0 - 4.48.

Because this study investigates pay gaps and which components explain them, the dependent variable of use for this study is hourly pay; Pound Sterling per hour. Because the relationship between the determinants of earnings and hourly pay are non-linear, but exponential, the variable of hourly pay provided by the APS data (UK Data Service, 2018) is transformed into a logarithmic form. Because incomes are distributed asymmetrically, they are skew; a positive skew exists whereby a greater quantity of individuals have incomes at lower levels of the pay distribution, but the right tail of the distribution is longer due to a smaller quantity of higher incomes along the distribution. In this instance, the mean of average hourly income is considerably higher than the median income, but introducing a transformed dependent variable accounts for this.

Likewise, the relationship between the determinants of earnings and hourly pay are in fact non-linear, but exponential. Indeed, while age increases the potential for earnings to a degree, its effects flatten out. Moreover, increases in pay pose different effects at different levels of income because money is multiplicative. Thus, a logarithm of hourly pay is used as the dependent variable to account for a percentage change in income, rather than an absolute increase in income by the Pound Sterling. As such, where hourly pay as the dependent variable appears as Y_i , when transformed it is described as $\log Y_i$. As mentioned in the previous chapter, only those observations who declare their economic activity status as 'employed' and have disclosed their hourly pay, which is between £1 and £80 only, are included in testing. Thus, there are 78,587 men and women captured in this variable.

4.3.2 Independent Variables

Ethnic Group

Categorical: White, Mixed/Multiple Ethnicity, Indian, Pakistani, Bangladeshi, Chinese, Other Asian, Black/African/Caribbean/Black British, Other.

The ethnic group that individuals identify as are important as different groups experience different employment outcomes, as well as different rates of economic activity in the first instance. While some ethnic groups work in certain professions because of targeted immigration policy, they may face concentration into both low and high levels of occupational class (Blackwell, 2003; Brynin & Güveli, 2012). Those belonging to a BAME groups but are second generation also equate to different employment outcomes, and so it is not only migrant groups which are important to consider but all those in BAME groups (Blackaby et al, 2002). Using ethnic minority groups as categorical variables instead of a number of dummy variables means the white group is the base level, so percentage differences in outcomes on pay are compared across groups relative to white pay. No changes are made in creating this variable as all observations declare the ethnic group they belong to.

Gender

Dummy: Not-female, Female.

Gender as a binary dummy variable is of paramount importance in this study which investigates pay gaps. Being female means an expected lower pay relative to male observations. Due to differences in human capital accrual and specialisation within the household (Mincer & Polachek, 1974), the motherhood penalty (Anderson et al, 2003), participation in part-time work (Olsen et al, 2014), employment based on 'feminsed' roles (Blau & Kahn, 2016; Manning & Petrongolo, 2008) and discrimination (Goldin, 2002; Swaffield, 2007), women are likely to have a pay penalty. The magnitude of this penalty is likely to differ by group dependending on the level of human capital, the breadth of cultural expectations placed on women, and the amount of discrimination received. No changes are made to this variable.

Industry of Employment

Multiple Dummies: Agriculture/Forestry/Fishing, Energy/Water, Manufacturing, Construction, Distribution/Hotels/Restaurants, Transport/Communication, Banking/Finance, Administration/Education/Health, Other Services, Does not know.

The industry of employment variable provides 10 categories of industry that observations work in. The categories are transformed into dummy variables for each industry sector, and any individual that does not declare their industry are made into the new, does not know, variable. Otherwise, the classification of each industry sector is as provided by the APS data and explained in the User Guide (ONS, 2018). As occupational segregation is a key explanatory factor in this study, industry of work is a part of this, where gender and BAME group expect to find clustering into low paid industries (Blackwell, 2003; Brynin & Güveli, 2012). 65% and 53% of Bangladeshi and Chinese men work in just five occupations, mainly catering, and 39% of Black women work in the health and social care sector (Blackwell, 2003; Rose & Henehan, 2018). Industry of occupation has clear links to gender, ethnicity, and pay outcomes therefore.

Managerial status

Categorical: Manager, Foreman/Supervisor, Not Manager/Supervisor, Does not know, Did not answer.

Vertical segregation is an important factor when considering gendered differences and outcomes on pay (Blackburn et al, 2002). While men and women work across industries, within these industries, each gender is employed at different levels in the heirarchy, and so controlling for this is important when explaining pay differentials. Those who are neither a manager nor supervisor expect to earn less, where those who are at rudimentary level are the base level for this category. This variable is altered little from the original data, only those who did not respond are put into the new category did not answer.

Part-time

Dummy: Not part-time, Part-time.

Part-time employment is highly gendered in the UK and faces lower hourly pay compared to full-time work (Olsen et al, 2014). Part-time work pays less because it less likely to be protected by unions, and so factoring part-time work into occupational controls is important because of gender and because of outcomes on pay. No change has been made from the APS 2018 dataset other than reclassifying the variable from categorical to dummy.

Permanent Employment

Dummy: Not permanent, Permanent.

Whether work is permanant or not is an important occupational factor, where ethnic minorities are more likely to be in non-permanant roles, although this differs between BAME groups (Henehan & Rose, 2018). Likewise, women too are less likely to be in permanent positions (Olsen & Walby, 2004). Work that is not permanent is therefore operating with a fixed-contract, is casual, or are working on behalf of an agency. Permanent employment is therefore rewarded with higher earnings and thus factored into the model. Like the part-time variable, the permanent employment variable is transformed from category to dummy but no other changes are made from the original APS 2018 dataset.

Public sector

Dummy: Not public sector, Public sector.

Working in the public sector is highly gendered and receives lower average pay (Olsen et al, 2014). While the public sector has greater union protection and protection against discrimination, it has a compressed pay scale, and so while there is a smaller pay gap between individuals working in the public sector, there is an external pay differnce compared to other employers. For use in this study, the variable was transformed from a categorical variable to a dummy variable instead where there were no missing observations.

Occupational class

Multiple Dummies: Professional, Intermediate, Routine/Semi-Routine.

The final step in modelling in this study comprises an additional comparison of pay within occupations, according to the method of Rose and Henehan (2018) and Clark and Drinkwater (2007). The data set is split by gender and by occupational class so as to make comparisons for each. Occupational class is derived from the APS 2018 categorical variable of Major Occupation Group which comprises nine classifications. Following Clark & Drinkwater's (2007) method, Occupational Class for this study is combined into three occupational groups, Professional, Intermediate, and Routine/Semi-Routine, which then each form three dummy variables so as to separate the dataset into three sub datasets of observations. Undeclared statuses are dropped. The classification of the occupational groups are as follows;

Major Occupation Group Classification	Occupational Class
Managers, Directors, and Senior Officials Professional Occupations Associate Professional and Technical Occupations	Professional
Administrative and Secretarial Occuppations Skilled Trades Occupations	Intermediate
Caring, Leisure, and Other Service Occupations Sales and Customer Service Occupations Process, Plant, and Machine Operatives Elementary Occupations	Routine/Semi-Routine

Figure 4.2 Classification of Occupational Groups According to Clark and Drinkwater (2007)

4.3.3 Control Variables

Age, Age^2

Continuous: 16 - 64, 256 - 4096.

Age and Age squared are important control variables when accounting for wage. As earnings increase with age, albeit at a decreasing rate of marginal returns, age to a degree captures years of work experience which is an important aspect of the earnings function (Mincer & Polachek, 1974). While the age variable is provided in the APS 2018 data, Age squared is a new transformation of this variable. Indeed as mentioned in the Data chapter, as this study is relevant only to those of working age, all observations less than 16 years of age or 65 years and over are removed.

Region

Multiple Dummies: North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East, South West, Wales, Scotland, Northern Ireland.

Average pay varies across regions where London and the South East have the highest incomes. Every observation declared their region in the APS 2018, and so no changes are made to this variable other than transforming the 11 categories into 11 individual dummy variables.

Marital Status

Categorical: Single/Never Married, Married/Living with Spouse, Married/Separated from Spouse, Divorced, Widowed, Currently/Previously in Civil Partnership.

Gender and marital status are crucial determinants of calculating pay gaps. Specialisation within the household acts as a deterrent and barrier for women (Mincer & Polacheck, 1974; Blackwell, 2003). Likewise traditional associations exist between marriage and childbearing to a degree for some ethnic groups and less so for others (Dale et al, 2006). The marital status variable is unchanged from what is provided by the APS 2018 dataset, and every observant declared their marital status.

Educational attainment

Categorical: Degree, Higher education, A-Level, GSCE, Other qualifications, No qualification, Does not know, Did not answer.

Educational attainment is a crucial human capital factor which effects earnings potentials. With an increase in education, earnings expect to rise. Little transformation of the variable takes place, where only those who have not declared their educational attainment have a new category of did not answer so as to make sure these observations are not missing and omitted from testing.

4.4 Robustness Checks

Regarding robustness, the study understands that an important component of the gender and ethnicity pay gap debate surrounds differences in economic inactivity. Those individuals for whom the OLS applies because they have provided their hourly pay, are non-randomly selected because they have made a choice to be in the labour force. In this instance, the reservation wage offered by employers does not meet the reservation wage of individuals, who therefore choose to provide their labour at home rather than the labour force (StataCorp, 2013). Therefore, there are some variables which strongly effect the chances of this to occur, and where the reservation wage is met. The result of which is that any regression only using the non-random selection of data where a choice is made to self-select into employment, has omitted variable bias (Heckman, 1979). A solution to account for this is a two-step Heckman correction. In order to measure the impact of non-random selection, the study creates two further OLS models with and without a Heckman correction to test the impact of omitted variable bias.

The main model presented above does not incorporate a Heckman correction because its primary focus is on incorporating occupational controls and to break down the observations who are employed in occupational classes. Using the whole data sample would produce spurious results. However, the issue of non-random selection and omitted variable bias are born in mind when interpreting results. The OLS model is tested for normality of residuals which are plotted in two ways; for normal distribution and in a linear model (Gujarati & Porter, 2010: 77-8). Heteroskedasticity is tested using a Breusch-Pagan test, and skewness is accounted for using the Jarque-Bera method (Gujarati & Porter, 2010; 78). Multicollinearity between variables is measured in addition.

5 Empirical Analysis

5.1 Results

As this study seeks to explain the gender ethnicity pay gaps, testing and results are presented relative to the white ethnic group, so that a comparison is made. While the OLS provides coefficient results for each independent variable, further interpretation is applied so that a percentage difference is given. The Halvorsen Palmquist (1980) transformation[4] of coefficient results are provided in the main results, where a wage differential is calculated according to the method of Clark and Drinkwater (2007). The transformation is as follows where D_i^* represents the wage differential faced by the ethnic minority groups;

$$D_i^* = [\exp(\hat{\gamma}_j) - 1] \times 100$$

Figure 5.1 Halvorsen & Palmquist Transformation Formula (Clark & Drinkwater, 2007)

The earnings differential relative to the white ethnic group is calculated in percentage form using this method. As such, results below are given in percentage forms. Tables 5.1 and 5.2 provide the main results for the final model of this study. Table 5.1 contains the estimates of modelling of earnings for men, where table 5.2 provides similar estimates for women. These results are given in percentage terms, relative to the earning of the white ethnic group. The first three tests carried out control for personal characteristics, adding in human capital, and finally occupational controls, in order to establish how much influence occupational segregation has on earnings.

Controls for the first test include age, age squared, marital status, and region of the UK, where earnings relative to white pay are mostly negative for all ethnic minority groups, except for Chinese men and women although this has no statistical significance. In order to answer the study's research question as to what extent occupational segregation accounts for the gender ethnic pay gap, both of these tables provide answers. As theory pertains, occupational segregation is an explanatory variable of earnings and therefore a factor in the gender ethnicity

[4] Halvorsen & Palmquist (1980). The authors investigate the interpretations of coefficients when logarithmic dependent variables are in use in regressions. They criticise the assumption that the coefficient result multiplied by 100 equals the percentage effect that the explanatory variable has on the dependent variable.

pay gap. Indeed, as tables 3.6 and 3.7 confirm in the descriptive statistics, ethnic minority groups are clustered into certain occupations to higher degrees than the white population. Therefore, the tests are presented without human capital or occupational controls, then they are added across tests. Thus, this detects the influence that occupation has in accounting for earnings, and how much of the raw pay gap it explains. In considering occupational pay differences further, this study uses the final three tests in this model to pool individuals by occupational class of Professional, Intermediate, and Routine/Semi-Routine to investigate differences in pay within occupational classes.

5.1.1 Pay Differential for Men

Table 5.1 Male BAME Percentage Differences in Pay Relative to White Male Pay

	No Occupational Controls	Including Human Capital Controls	Including Occupational Controls	Professional	Internediate	Routine/Semi-Routine
Ethnic Group *(Base as White)*						
Mixed/Multiple ethnic groups	-2.95	-5.83***	-2.83	-1.45	2.10	-4.63
Indian	-0.95	-5.65**	-2.17	2.01	0.43	-0.713***
Pakistani	-21.42***	-21.65***	-15.63***	-10.33***	-13.84***	-10.42***
Bangladeshi	-40.13***	-37.56***	-27.46***	-30.37***	-22.89***	-12.01***
Chinese	1.84	-7.56**	-0.41	-2.17	-7.02	0.61
Any other Asian background	-21.49***	-21.73***	-14.27***	-6.63*	-14.36***	-11.22***
Black/African/Caribbean/Black British	-23.66***	-23.66***	-17.63***	-14.96***	-10.42***	-8.80***
Other Ethnic Group	-22.82***	-19.02***	-12.45***	-9.97***	-10.42***	-6.99***
Observations	37,003	37,003	37,003	18,366	6,960	11,677

No Occupational or Human Capital controls: Age, Age squared, Marital status, Region
Human capital controls: Educational Attainment
Occupational controls: Industry Sector, Managerial Status, Permanent job, Part-time, and Public Sector.
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As initial raw pay gaps stand, where only demographic variables are used to explain the pay gap, all BAME ethnic minority males apart from Chinese men face a raw disadvantage relative to white males. The largest in magnitude is for Bangladeshi men at -40% followed by black at just below -24%, other at -23%, Pakistani and other Asian at -21%, and -3% and -1% for mixed ethnicity and Indian men. Conversely, Chinese men have a positive raw pay gap relative to white men, at just shy of 2%. Statistical significance at the 1% level is only observed for Pakistani, Bangladeshi, other Asian, black, and other Asian groups where all others have no statistical significance.

Using educational attainment as a proxy for human capital explains a small amount of the earnings gap for men, where Bangladeshi and other ethnicity see a decrease in the gap falling to -38% and -19%. However, educational differences increase the pay gap for mixed and Indian men at -6%, and Chinese men at -8%, relative to the white male average. Accounting for educational attainment has mixed outcomes in explaining the pay differential for BAME groups therefore.

Adding occupational controls of industry sector, managerial status, and whether employment is permanent, part-time, or in the public sector reduces the earnings difference across all ethnic groups for males. After adding occupational variables, males who face the highest pay gap are the Bangladeshi, followed by black, Pakistani, other Asian, and other ethnicity at -27%, -18%, -16%, -14% and -12% respectively. Mixed, Indian, and Chinese males face the lowest adjusted pay gaps, at -3% and -2%, where Chinese men, the difference reaches close to zero at -0.4%, although this is not statistically significant. When observing how much of an effect occupational controls have on the adjusted pay gap, they explain a difference of approximately 3% for mixed/multiple and Indian men, and 6% for Pakistani, Chinese, black, and other groups. The largest differences are found for other Asian backgrounds at nearly 7% pay difference, and Bangladeshi males whose earning differential falls by 10%. Overall however, after controlling for both human capital and occupational factors, men of Pakistani, Bangladeshi, other Asian, black, and other, all face pay gaps of at least -12%, where Bangladeshi men face the highest gap of -27%, albeit only 5 of these groups have statistical significance of any level. Therefore, occupational factors do explain differences in pay relative to the white males, but they vary according to ethnic groups.

The results show earnings disadvantages for each ethnic minority group relative to the pay of white average across different occupational classes. Of the BAME males relative to white male pay, the only groups who have a pay advantage are Indian men at professional level at 2%, mixed ethnicity and Indian men in intermediate positions at 2% and 0.4%, and Chinese men at routine level at 0.6%, although no statistical significance is observed. Indeed, Pakistani, Bangladeshi, other Asian, black, and other ethnic groups all face earnings disadvantages across all occupational groups relative to the white male pay in each group. Disadvantage is highest for Bangladeshi and black men at the highest occupational class, at -30% and -15% respectively. Bangladeshi and other Asian men face the highest earnings difference at intermediate level occupations at just under -23% and -14%. Relatively speaking, the smallest earnings differences are at the routine level at -12% or less.

5.1.2 Pay Differential For Women

Table 5.2 Female BAME Percentage Differences in Pay Relative to White Female Pay

	No Occupational Controls	Including Human Capital Controls	Including Occupational Controls	Professional	Intermediate	Routine/Semi-Routine
Ethnic Group *(Base as White)*						
Mixed/Multiple ethnic groups	0.53	-0.41	-0.45	1.32	1.33	0.70
Indian	-2.41	-5.78***	-4.16***	-0.72	-1.29	-5.10***
Pakistani	-18.13***	-18.45***	-13.41***	-12.37***	-9.10**	-7.50***
Bangladeshi	-19.27***	-15.63**	-10.51***	-9.52	-0.44	-7.61*
Chinese	8.61**	-1.43	1.91	-0.20	1.92	4.24
Any other Asian background	-14.27***	-13.67***	-9.15***	-9.97***	-1.05	-3.73
Black/African/Caribbean/Black British	-13.32***	-12.37***	-9.14***	-10.42***	-10.95***	-0.26
Other Ethnic Group	-13.76***	-11.57***	-8.19***	-8.63***	-10.24**	-1.22
Observations	41,584	41,584	41,584	17,856	8,050	15,678

No Occupational or Human Capital controls: Age, Age squared, Marital status, Region
Human capital controls: Educational Attainment
Occupational controls: Industry Sector, Managerial, Permanent job, Part-time, Public Sector.
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Raw pay gaps across BAME groups for women are also varied, where mixed and Chinese groups have positive pay differences at 0.5% and 9%. The largest raw pay gaps are found for Bangladeshi women at -19%, followed by Pakistani women at -18%, other Asian and other ethnicity both with -14%, black at -13% and Indian at -2%. However no statistical significance is found for mixed or Indian women.

For women from BAME groups relative to white women, educational attainment reduces the pay gap slightly in most instances. Education explains less than 1% of pay differentials for Bangladeshi, other Asian, and other ethnicity, who all see a reduction in the raw pay gap. For mixed, Indian, and Pakistani women the differential worsens, going from 0.5% to -0.4%, -2.4% to -5.8%, -18.1% to -18.5% for each group. The worsened gap with the greatest change is for Chinese women the largest difference is found at -10% change, from 8.6% to -1.4%, although statistical significance is lost when educational attainment is accounted for.

Accounting for occupational controls reduces the earnings differences relative to white female pay, and reduces the adjusted pay gap for all BAME groups but the mixed ethnicity group. The adjusted gap is highest for Pakistani women at -13%, followed by Bangladeshi women at -11%, other Asian and black at -9%, other at -8%, Indian at -4%, and mixed at -0.5%. Chinese women are the only BAME group with a positive adjusted pay gap at just below 2% although there is no statistical significance found. The greatest reduction in the gap by factoring in occupational controls is for Pakistani, Bangladeshi, and other Asian women at 5%, and 3% and 2% for black and Indian women respectively. Yet, after controlling for human capital and occupational factors, Indian, Pakistani Bangladeshi, other Asian, black, and other ethnic groups have pay gaps ranging from -8% to -13%, where all have statistical significance at the 1% level.

For women, results provide earnings disadvantages across the occupational classes relative to the earnings of white women in each respective occupational grouping. Women from mixed or multiple ethnic groups consistently have an earnings advantage across all occupational groups, as well as Chinese women in intermediate and routine classes, however no statistical significance is observed for these results. The largest differences in pay are observed at the professional occupational class, where other, other Asian, Bangladeshi, black, and Pakistani women face pay gaps ranging from just under -9% to over -13%. At the intermediate occupational class black women face the largest pay disadvantage at nearly -11%, and other and Pakistani women face -10% and -9% disadvantages, whereas Indian and other Asian women face a -1% difference. Where the intermediate occupational class has both high and low values of pay differentials, at routine level there are consistent pay disadvantages between -1% and approximately -7.5% for all women bar Chinese and mixed ethnic groups. However, statistical significance is found only for Indian and Pakistani women at the 1% level, and Bangladeshi women at the 10% level.

5.2 Robustness Checks

In testing for robustness, the study corrects for omitted variable bias by using a two-step Heckman correction to indicate how economic activity is the result of selection by individuals, and thus, how this correction changes pay differentials for women and for ethnic minority groups, as shown in tables B.1 and B.2 in Appendix B. Between the uncorrected and the Heckman correction tables, they show that all women face a -11 to -15% pay disadvantage relative to male pay. Testing across both shows that while allowing for personal factors, human capital, and occupational characteristics, does explain and reduce the pay gap, there is an element of ‘stickiness’ where the gap does not close altogether and robustness checks confirm that a gender pay gap is present in the UK.

Likewise, ethnic minority groups receive lower pay relative to the white majority, where accounting for personal, human capital, and occupational characteristics explain only part of expected earnings. The Heckman Correction indicates that all ethnic minority groups face a pay disadvantage, as when ethnic minority group is accounted for in the selection equation portion of the linear regression, the pay disadvantage increases in magnitude across all ethnic groups. The robustness checks confirm that relative to the white ethnic group, ethnic minorities face a pay gap in the UK However, the magnitudes of each percentage differential changes between ethnic groups, where some groups face greater disadvantages relative to others.

Checks for residuals indicate improvement in goodness-of-fit for the model, although the R squared is initially low, it increases for both male and female observations as variables are added, indicating improvement in variable fit across modelling. For men, the R squared increases from 0.199 to 0.413, and for women, 0.131 to 0.398. R squared scores are lower when the observations are split into smaller datasets for occupational class, which is explained by a smaller quantity of observations belonging to each. Some multicollinearity is present between variables such as age and age squared and marital status, likewise for the age variables and educational attainment, and gender and part-time work, which is to be expceted. The collection of dummy variables for region and industry sector omit Northern Ireland and Does not Know because of multicollinearity but this is because they are in dummy form not categorical form so multicollinearity is not actually present. As all of these variables capture important components of earnings and differences between earnings by ethnic groups, they are not removed in the modelling.

6 Discussion and Implications

6.1 Discussion

The purpose of this study is to determine how much occupational segregation explains pay disadvantages for the gender ethnicity pay gap, and how these explanatory factors differ between ethnic minority groups in the United Kingdom. The study contributes insight from 2018 data to give clarity on the ‘sticky’ pay gap that the UK suffers, and the level of double disadvantage BAME women living in the UK face. By using the most appropriate method available, linear regressions account for differences in pay for women, for those belonging to ethnic minority groups, and for occupational factors. The model in this study directly answers the research question; to what extent occupational segregation accounts for the gender ethnicity pay gap. While it is clear that all BAME groups, apart from the Chinese men and women and mixed ethnicity women, face a pay differential relative to the white group, adding variables in the testing indicates how much the variable explains in the adjusted pay differentials. However, controlling for personal and demographic characteristics, human capital, and occupational related factors by ethnicity and by gender, pay penalties remain intact for BAME groups relative to the white group. Indeed, these penalties are in place but vary across groups. Of importance to this study are the controls which account for occupational segregation, and the extent of the component that explains the pay gap. In response to the questions and hypotheses, this study responds;

To what extent does occupational segregation explain the gender ethnicity pay gap?

Occupational segregation across all ethnic mimority groups respective of gender, reduces the raw pay gap, and thus explains part of the pay differences for BAME men and women. The effect that occupational controls; industry sector, managerial level, part-time work, and permenant and public sector employment, differs in magnitude by BAME group and between men and women belonging to each group. For instance, controlling for occupational segregation explains 10% of the pay differential of Bangladeshi men, but only 3% for mixed ethnicity and Indian men. For women, occupational factors explain 5% of the gap for Pakistani, Bangladeshi, and other Asian women, but only 2% for black women. Indeed, even when accounting for occupational segregation, pay differentials remain. The results of the study show that occupational segregation is an important component of the gender ethnicity pay gap, but it is not the *only* explanatory factor.

Regarding the study's hypotheses;

1. H_0 – There is no gendered difference in pay
   H_1 – Women earn less than men

This study rejects the null hypothesis because robustness checks in tables B.1 and B.2 of Appendix B confirm that there are gendered differences in pay, at -11% or -14% for uncorrected and Heckman corrected OLS estimators. Likewise across tests, OLS models in Appendix C the coefficient has a negative function.

2. H_0 – Ethnic minorities face no difference in pay
   H_1 – Ethnic minorities earn less than the white ethnic group

This study rejects the null hypothesis as ethnic minorities have different earnings relative to the white ethnic group. This pay differential differs by ethnic group, where some fare better than others. Differences are sometimes positive relative to the white average, where the Chinese group has a pay differential value that is above 0 but this does not always hold constant as confirmed by the robustness checks. Likewise, within occupational classes, in some instances, some ethnic groups; mixed, Indian, and Chinese, earn higher than the white average but this changes between men and women and across occupational classes.

3. H_0 – Occupational segregation is not associated with pay
   H_1 – Occupational segregation is associated with pay

This study rejects the null hypothesis as controlling for occupational segregation, measuring industry of occupation, managerial status, permanent, public sector, or part-time work, these all impact and explain pay differences. Occupational segregation therefore explains why some ethnic minority individuals earn less than the white average, although magnitudes differ across the ethnic groups and between men and women.

4. H_0 – Being an ethnic minority woman is not associated with a double disadvantage in pay
   H_1 – Being an ethnic minority woman is associated with a double disadvantage in pay

This study fails to reject the null hypothesis. Relative to white women, ethnic minority women are paid less apart from Chinese women even after controlling for human capital and occupational differences. The magnitude of each pay difference differs by BAME group, as visualised in Figure 6.1 below. Compared to the magnitudes of the male groups however, women face a smaller pay disadvantage by comparison. As such, women are paid less, but so are ethnic minority men, so the study fails to accept any case of double disadvantage for BAME women.

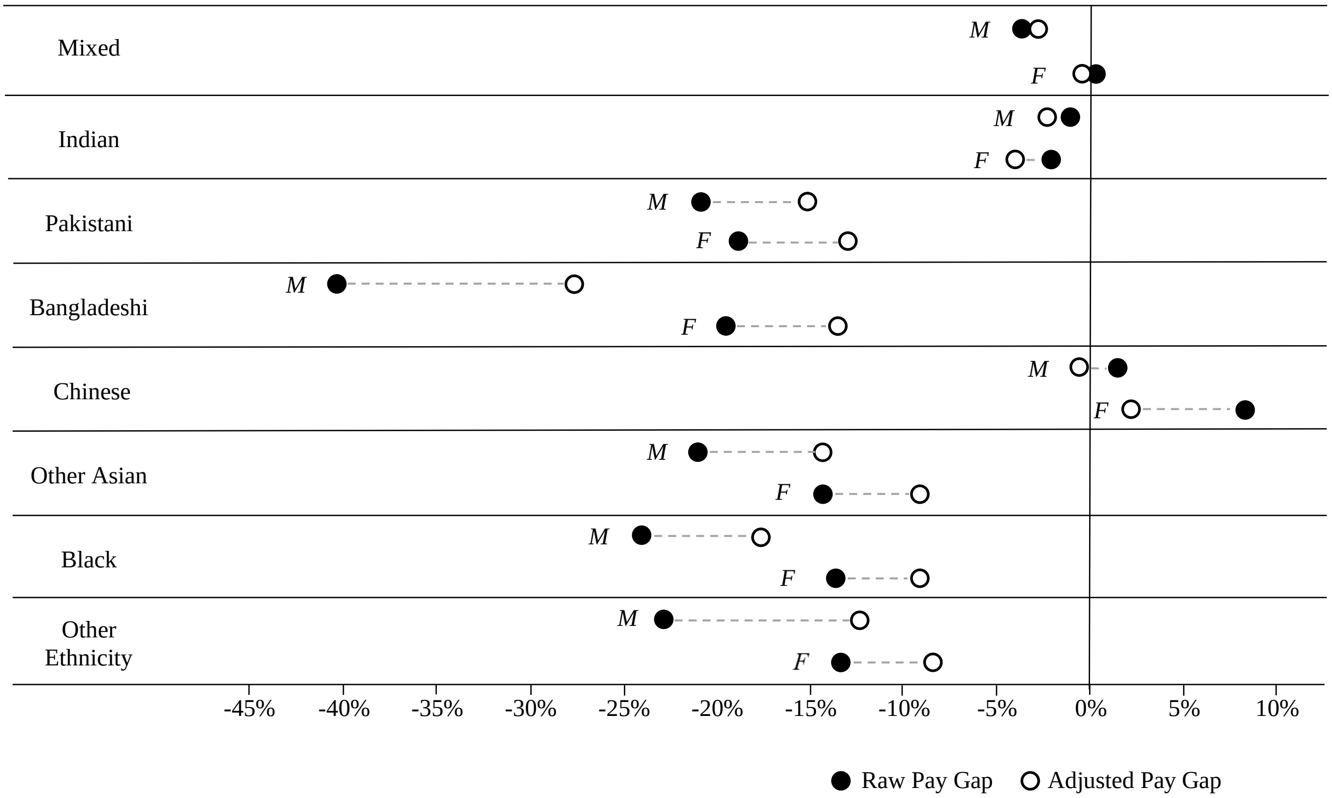

Figure 6.1 Raw and Adjusted Pay Gap Across BAME Groups and Gender

Figure 6.1 above indicates that most female BAME groups face a pay penalty relative to white women, where all but Chinese women earn less. The findings confirm previous research by Platt (2006) and Nandi and Platt (2010), that ethnic minority women face a pay differential relative to female white pay, and that on the whole, ethnic minority groups face large raw pay gaps relative to the white population, which support the results found by Rose and Henehan (2018). Apart from Chinese women, all BAME women face a pay gap relative to their white counterparts.

With regards to occupational segregation, the results align with previous studies by Brynin and Güveli (2012) that occupational factors play an important role in explaining ethnic minority pay gaps. Figure 6.1 above shows that by adding education and occupational factors, the raw pay gap reduces, although the relative change is different for certain groups. The biggest difference is for Bangladeshi men with a reduction of 13% and 11% for other ethnic background men. Education and occupational controls produce little change for the mixed ethnicity and

Indian men and women, indicating that this provides a small explanation as to their pay gap, yet their pay gap is relatively smaller in the first instance.

Regarding double discrimination and the gendered element to BAME pay, the study is in agreement with Brynin and Güveli (2012) who do not find double discrimination occuring. The results of this show that occupational segregation need not always have a negative effect on ethnic minority pay, where Chinese women face a positive pay differential after accounting for occupational controls. ‘Protected’ pay is evaluated by Brynin and Güveli (2012) too, hence in terms of Chinese women in this study, this element agrees with their research. Indeed, the study agrees too with Blackwell (2003) who finds that patterns of occupational advantage or disadvantage are complex, context specific, and differ according to ethnic minority group and between men and women.

Likewise, the results also support previous research by Elliot and Lindley (2007) who argue that occupational segregation and human capital factors only explain a portion of the wage differentials for ethnic minorities. Education poses a suprising result to the raw pay gaps, where for some BAME groups the raw gap reduces, but also widens for others. This is in line with Blau and Kahn’s (2016) O’Higgins’ (2015) and Joshi et al’s (2006) arguments to a degree in that educational attainment, while crucial in increasing potential earnings of the individuals, explains less of gender pay gap in comparison to other factors which overshadow human capital effects. In fact, higher levels of education in some instances equate to bigger pay gaps emerging, especially so for mixed, Indian, and Pakistani women, and Indian and Chinese men. This means that mismatch may play a role in keeping ethnic pay gaps open, an aspect that Botcherby (2006) and Bunglawala (2008) agree with. Additionally, it may suggest that qualifications and high level education received externally from the UK may account for less with employers (Brynin & Güveli, 2012).

However, another critical factor in explaining the gender ethnicity pay gap is that of discrimination. Indeed, the results of the study indicate that while education and occupational segregation explain part of the raw pay differentials, other factors contribute which keep the negative difference high in magnitude even after accounting for these factors. Likewise, pay penalties are actually greater for BAME men than for BAME women, where controlling for personal, educational, and occupational factors explain a greater amount than it does for males who are left with higher adjusted pay penalties. Indeed, by breaking down earnings predictions across ethnic groups, it appears that the higher up the occupational scale, greater ethnic pay differences emerge, where Pakistani and Bangladeshi men, and Pakistani and black women face the largest pay gaps. While occupational controls therefore explain some extent of pay differentials, it is *within* occupational differences that have influential outcomes on pay and on pay gaps, an outcome which Clark and Drinkwater (2007), Longhi et al (2009) and Rose and Henehan (2018) agree with.

The observed characteristics only explain some of the pay penalties for BAME individuals, leaving large unexplained components for some groups. This could firstly be due to legitimate variables that were omitted from the model, and secondly, due to discrimination and disadvantage. Adding a proxy variable for socioeconomic background, such as parental employment when a child, could measure disadvantage for instance, but this would be tricky to incorporate for first generation migrants and is not measured in the data. Secondly, the sizeable adjusted pay gap that remains despite controlling for observable characteristics implies discrimination plays a role in the pay gap, which agrees with the findings of Bunglawala (2008). Indeed, discrimination effects all components that explain earnings potentials, from the type of human capital accrued and the quality of a degree obtained, to how challenging a promotion is to gain and facing higher barriers to entry, to getting job interviews. Thus, discrimination operates in feedback loops and are pertinant results in this study, which agree with findings by Rose and Henehan (2018) who study ethnic discrimination and Blau and Kahn (2016) who consider gendered discrimination. As such, while occupational segregation explains some of the gender ethnicity pay gap, discrimination too plays an important role.

While the study investigates the extent to which occupational segregation explains the gender ethnicity pay gap, it is limited. Primarily, the P values across testing increase to 0.42, this means that the variables included in the study do not fully explain the factors associated with earnings, or the effect of feedback loops in disadvantage or discrimination which effects all components of the earnings predictor. As such, more testing could investigate these factors, where alternative methods are implemented. Likewise, the results suggest that the earnings differences are less about individuals selecting into areas of work which are segregated, but more about individuals being paid differently in the same occupational class. Understanding this therefore, means further study must examine discrimination as an explanatory factor, and how it has an effect. Indeed, the study does not test the pay differential of ethnic minority women against white male pay, where white women already face a pay gap. While there is less variation in BAME women's pay penalty, it must be born in mind that this figure may be larger relative to white men. The results provided are given the method used, where another method may indicate different results, and so further study may wish to query this.

6.2 Implications

This study implies that while differences in human capital factors explain a significant proportion of the gender pay gap in the past, there is now an element of O'Reilly et al's (2015) 'moving goalposts' because other factors now play a larger role in retaining the gender pay gap. Occupational segregation too is an important component of pay gaps, and thus channelling and self-selecting into certain areas of employment explains why some BAME groups are being paid less compared to others.

Additionally, the results of this study suggest that discrimination, disadvantage, and feedback loops play a role in explaining why ethnic minority groups including ethnic minority women have lower pay. Ethnicity is an important factor in explaining earnings differences, and why some groups face greater penalties to earnings than others. Indeed, the results indicate that discrimination is a pertinant issue in the United Kingdom, where even after controlling for observational differences large pay penalties remain. This implies that more active policymaking and affirmative action by educational and employment institutions must take place to target discrimination at all levels where discrimination can play a role.

As a consequence, this study contributes further analysis of the state of employment and earnings outcomes in the United Kingdom. This study bridges together previous research into the field of the gender pay gap, and the ethnicity pay gap, and sheds light on the intersection of BAME women in the gender ethnicity pay gap. In this way, the study contributes to this important ongoing social and economic debate and the mechanisms which explain earnings differentials.

7 Conclusion

The aim of this study was to evaluate the explanatory mechanisms that form female BAME pay, and investigate why ethnic minority women face a pay differential. Using quantitative methods, the study has assessed the impact that occupational segregation has in explaining pay gaps, and implies what other unexplained factors remain. Using micro-level Annual Population Survey data from 2018, and using linear regression modelling techniques, the study has controlled for predictors of earnings such as demographic characteristics, human capital, and occupational controls as per the theoretical background, for all those aged 16-64 living in the UK. Model testing detects how much influence each of these factors have on the BAME raw pay gap groups relative to the white population. Following this, the study has then shown the pay differences within occupational classes, and how the pay differential changes between ethnic groups across the genders.

The study has found that on average, women in the United Kingdom can expect a pay differential of between -10% to -14% relative to men, where ethnic minority groups also have a raw pay gap. Indeed, the study has found that there are many pay gaps in existence in the UK. The largest raw pay gaps are for Bangladeshi men and women at -40% and -19% respectively. Likewise, the study found that human capital and segregation into occupations, by industry sector, managerial status, part-time, public sector, or non-permanent work are all associated with pay outcomes, and this produces an adjusted pay penalty that differs in magnitude across all BAME groups. Most groups can expect lower earnings relative to white pay. Indeed, the issue of female double disadvantage has been addressed, and while most ethnic minority women earn less than white women, ethnic minority men also earn less than white men, and to a greater magnitude. Thus, female BAME double disadvantage is not confirmed, although further investigation of this may want to compare women from BAME groups' pay against white male pay. This study has found that controlling for occupational segregation explains why ethnic minorities earn less, but that unobserved factors play a role alongside this. As such, occupational segregation explains the gender ethnicity pay gap to a certain extent, but other factors also contribute to this gap. This study has found that discrimination and disadvantage may explain this. Indeed, the study accepts that bias and discrimination may be difficult to disentangle from all determinating factors of earnings.

As such, future research must investigate the issue of unobserved factors where discrimination and disadvantage operating at all levels in the employment process must be considered. Indeed, other research may consider progress over time of the gender ethnicity pay gap, and how much the adjusted pay gap differs when BAME women are compared relative to the white male group. Further areas of study should consider discrimination, aspiration, and psychological differences which play an important role in determining pay, pay within occupational classes, and why a pay difference increases for BAME individuals at higher levels of occupational class.

As such, this study has contributed to the overall debate as to what remains in upholding the ‘sticky’ gender pay gap in the United Kingdom. Only Chinese women are found to have a positive adjusted pay gap relative to white women, and thus, this study confirms that all other BAME women earn less than the white population. This therefore implies that there is an association between occupational mechanisms, discrimination, and lower BAME female pay. As such this study contributed in explaining what factors remain in keeping the gender pay gap ever-present in the UK, and has combined the intersection of BAME women who stand in the middle of race and gender in this discussion. The study has facilitated previous theory and literature throughout this process, and provides a novel and original study which pools together the topics of gender and ethnicity pay gaps. It has provided clarity as to the mechanisms which explain pay differentials for the variety of BAME groups that reside in the UK.

Consequently, the study indicates that despite progress in previous years, the United Kingdom must continue to tackle both gendered and racial inequality, where more effort is needed to reduce occupational segregation and discriminatory behaviour. Thus, combatting structural and historic bias is important to negate the negative social and economic outcomes as a result. By understanding the compounding effects of gender and ethnicity, workplace environments, legislation, and policy can be improved. In challenging these explanatory mechanisms and bettering legislation, the UK can expect to see a further reduction in the overall gender pay gap, and the achievement of equality sooner rather than later.

References

Anderson, D. J., Blinder, M., & Krause, K. (2003). The Motherhood Wage Penalty Revisited: Experience, Heterogeneity, Work Effort, and Work-Schedule Flexibility, *ILR Review*, vol. 56, no. 2, pp. 273-294

Becker, G. (1985). Human Capital, Effort and the Sexual Division of Labor, *Journal of Labor Economics*, vol. 3, no. 1, pp. 33-58

Blackaby, D. H., Leslie, D. G., Murphy, P. D., & O'Leary, N. C. (2002). White/Ethnic Minority Earnings and Employment Differentials in Britain: Evidence from the LFS, *Oxford Economic Papers*, vol. 54, no. 2, pp. 270-297

Blackburn, R. M., Browne, J., Brooks, B., & Jarman, J. (2002). Explaining gender segregation, *British Journal of Sociology*, vol. 53, no. 4, pp. 513-536

Blackwell, L. (2001). Occupational Sex Segregation and Part-time Work in Modern Britain, *Gender, Work and Organization*, vol. 8, no. 2, pp. 146-163

Blackwell, L. (2003). Gender and Ethnicity at Work: Occupational Segregation and Disadvantage in the 1991 British Census, *Sociology*, vol. 37, no. 4, pp. 713-731

Blau, F. D. & Kahn, L. M. (2016). The Gender Wage Gap: Extent, Trends, and Explanations, discussion paper, no. 9656, Institute for the Study of Labor

Booth, A. L. (2009). Gender and competition, *Labour Economics*, vol. 16, no. 6, pp. 599-606

Botcherby, S. (2006). Moving on up? Ethnic minority women and work: Pakistani, Bangladeshi and Black Caribbean women and employment survey: aspirations, experiences and choices, Equal Opportunities Commission Report [pdf] Available at: https://core.ac.uk/download/pdf/4162977.pdf [Accessed 15 January 2020]

Breach, A. & Li, Y. (2017). Gender Pay Gap by Ethnicity in Britain – Briefing [pdf] Available at: https://www.bl.uk/collection-items/fawsc-gender-pay-gap-by-ethnicity-in-britain-2017 [Accessed 15 January 2020]

Brynin, M. & Güveli, A. (2012). Understanding the ethnic pay gap in Britain, *Work, Employment and Society*, vol. 26, no. 4, pp. 574–587

Bunglawala, Z. (2008). Valuing Family, Valuing Work: British Muslim Women and the Labour Market, The Young Foundation Report [pdf] Available at: https://youngfound ation.org/wp-content/uploads/2013/01/Valuing-Family-Valuing-Work-British-Muslim-Women-and-the-Labour-Market-October-2008.pdf [Accessed 15 January 2020]

Bushway, S., Johnson, B. D., & Slocum, L. A. (2007). Is the Magic Still There? The Use of the Heckman Two-Step Correction for Selection Bias in Criminology, *J Quant Criminol*, vol. 23, pp. 151-178

Chevalier, A. (2007). Education, Occupation and Career Expectations: Determinants of the Gender Pay Gap for UK Graduates, *Oxford Bulletin of Economics and Statistics*, vol. 69, no. 6, pp. 819-842

Clark, K. & Drinkwater, S. (2007). Ethnic minorities in the labour market: Dynamics and diversity, Joseph Rowntree Foundation Report, Bristol: Policy Press

Dale, A., Lindley, J., & Dex, S. (2006). A Life-Course Perspective on Ethnic Differences in Women's Economic Activity in Britain, *European Sociological Review*, vol. 22, no. 4, pp. 459-476

Elliot, J. R. & Lindley, J. K. (2008). Immigrant wage differentials, ethnicity and occupational segregation, *Journal of the Royal Statistical Society*, vol. 171, no. 3, pp. 645-671

Gender Pay Gap Service (2020). Search and compare gender pay gap data, Available online: https://gender-pay-gap.service.gov.uk/ [Accessed 15 May 2020]

Goldin, C. (2002). A Pollution Theory of Discrimination: Male and Female Differences in Occupations and Earnings, working paper, no. 8985, National Bureau of Economic Research

Goldin, C. (2006). The Quiet Revolution that Transformed Women's Employment, Education, and Family, working paper, no. 11953, National Bureau of Economic Research

Gujarati, D. N. & Porter, D. C. (2010). Essentials of Econometrics, New York: McGraw Hill

Halvorsen, R. & Palmquist, R. (1980). The Interpretation of Dummy Variables in Semilogarithmic Equations, *The American Economic Review*, vol. 70, no. 3, pp. 474-475

Heckman, J. J. (1979). Selection Bias as a Specification Error, *Econometrica*, vol. 47, no. 1, pp. 153-161

Henehan, K. & Rose, H. (2018). Opportunities Knocked? Exploring pay penalties among the UK's ethnic minorities Report [pdf] https://www.resolutionfoundation.org/app/uploads /2018/07/Opportunities-Knocked.pdf [Accessed 15 May 2020]

Holdsworth, C. & Dale, A. (1997). Ethnic Differences in Women's Employment, *Work, Employment & Society*, vol. 11, no. 3, pp. 435-457

International Labour Organization (2015). Global Wage Report 2014/15, Available online: https://www.ilo.org/global/research/global-reports/global-wage-report/2014/lang--en/index.htm [Accessed 15 January 2020]

Joshi, H., Makepeace, G., & Dolton, P. (2006). More or Less Unequal? Evidence on the Pay of Men and Women from the British Birth Cohort Studies, Gender, Work & Organization, vol. 14, no. 1, pp. 37-55

Longhi, S., Nicoletti, C., & Platt, L. (2009). Decomposing pay gaps across the wage distribution: investigating inequalities of ethno-religious groups and disabled people, Institute for Social & Economic Research, working paper, no. 2009-31, University of Essex

Manning, A., & Petrongolo, B. (2008). The Part-Time Pay Penalty for Women in Britain, The Economic Journal, vol. 118, no. 526, pp. 28-51

McGregor-Smith Review (2017). Race in the workplace Report [pdf] Available online: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/594336/race-in-workplace-mcgregor-smith-review.pdf [Accessed 15 January 2020]

Mincer, J. & Polachek, S. (1974). Family Investments in Human Capital: Earnings of Women, in T. W. Schultz (eds), Economics of the Family: Marriage, Children, and Human Capital, National Bureau of Economic Research, pp. 397-431

Moosa, Z. (2008). Seeing Double: Race and gender in ethnic minority women's lives Report [pdf] https://www.academia.edu/2908433/Seeing_Double_Race_and_Gender_in_Ethnic_Minority_Women_s_Lives [Accessed 15 January 2020]

Mueller, G. & Plug, E. (2006). Estimating the Effect of Personality on Male and Female Earnings, *Industrial and Labor Relations Review*, vol. 60, no. 1, pp. 3-22

Nandi, A. & Platt, L. (2010). Ethnic minority women's poverty and economic well being, Government Equalities Office Report [pdf] Available online: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/85528/ethnic-minority-women_s-poverty.pdf [Accessed 15 January 2020]

Niederle, M. & Vesterlund, L. (2011). Gender and Competition, *The Annual Review of Economics*, vol. 3, pp. 601- 630

O'Higgins, N. (2015). Ethnicity and gender in the labour market in Central and South-Eastern Europe, *Cambridge Journal of Economics*, vol. 39, pp. 631-654

O'Reilly, J., Smith, M., Deakin, S., & Burchell, B. (2015). Equal Pay as a Moving Target: International perspectives on forty-years of addressing the gender pay gap, *Cambridge Journal of Economics*, vol. 39, no. 2, pp. 299-317

Office for National Statistics (2015). International migration: a recent history, Available online: https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/internationalmigration/articles/internationalmigrationarecenthistory/2015-01-15 [Accessed 10 May 2020]

Office for National Statistics (2018). Gender pay gap in the UK: 2018, Available online: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/bulletins/genderpaygapintheuk/2018 [Accessed 6 January 2020]

Office for National Statistics (2018). Labour Force Survey User Guide 2018, Available online: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentan demployeetypes/methodologies/labourforcesurveyuserguidance [Accessed 22 March 2020]

Office for National Statistics (2019). Gender pay gap in the UK: 2019, Available online: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/bulletins/genderpaygapintheuk/2019 [Accessed 10 May 2020]

Olsen, W. K., & Walby, S. (2004). Modelling Gender Pay Gaps, Manchester: Equal Opportunities Commission

Olsen, W., Gash, V., Vandecasteele, L., Heuvelman, H., & Walthery, P. (2014). The Gender Pay Gap in the UK Labour Market, in R. Giovanni (eds), *Gender Inequality in the Labour Market in the UK*, Oxford: Oxford University Press, pp. 52-75

Platt, L. (2006). Moving on up? Pay Gaps: The Positions of Ethnic Minority Women and Men, Equal Opportunities Commission Report [pdf] Available at: https://lucindaplatt.files.wordpress.com/2015/12/ethnic-minority-women-and-work.pdf [Accessed 15 January 2020]

Platt, L. (2011). Inequality within ethnic groups, Joseph Roundtree Foundation Report [pdf] Available at: https://www.jrf.org.uk/sites/default/files/jrf/migrated/files/inequality-ethnicity-poverty-full.pdf [Accessed 15 January 2020]

Polachek, S. W. (1981). Occupational Self-Selection: A Human Capital Approach to Sex Differences in Occupational Structure, *The Review of Economics and Statistics*, vol. 63, no. 1, pp. 60-69

Polachek, S. W. (2007). Earnings Over the Lifecycle: The Mincer Earnings Function and its Applications, discussion paper, no. 3181, Institute for the Study of Labor

StataCorp (2013). Heckman Selection Model, Available online: https://www.stata.com/manuals13/rheckman.pdf [Accessed 22 March 2020]

Swaffield, J. K. (2007). Estimates of the Impact of Labour Market Attachment and Attitudes on the Female Wage, The Manchester School, vol. 75, no. 3, pp. 349-371

UK Data Service (2018). Annual Population Survey 2018, Available online: https://beta.ukdataservice.ac.uk/datacatalogue/series/series?id=200002#!/abstract [Accessed 22 March 2020]

Zhou, M. (1997). Segmented Assimilation: Issues, Controversies, and Recent Research on the New Second Generation, *The International Migration Review*, vol. 31, no. 4, pp. 975-1008

Appendix A

Table A.1 Descriptive Statistics for Population Dataset, for Continuous Variables

Population

Continuous Variables

	Men & Women					
	Obs.	Missing	Min.	Max.	Mean	Std. Dev.
N	121,568					
Age	121,568	0	16	64	41.73	14.15
Age Squared	121,568	0	256	4096	1941.52	1161.40
	Men					
	Obs.	Missing	Min.	Max.	Mean	Std. Dev.
N	53,960					
Age	53,960	0	16	64	41.45	14.45
Age Squared	53,960	0	256	4096	1926.57	1177.8
	Women					
	Obs.	Missing	Min.	Max.	Mean	Std. Dev.
N	67,608					
Age	67,608	0	16	64	41.95	13.90
Age Squared	67,608	0	256	4096	1953.48	1148.61

Table A.2 Descriptive Statistics for Population Dataset, for Categorical Variables

Population

Categorical Variables

	Men & Women			**Men**			**Women**		
	Obs.	Missing	Percent	Obs.	Missing	Percent	Obs.	Missing	Percent
N	121,568			53,960			67,608		
Age Groups	121,568	0			0		67,608	0	
16-17	5,362		4.41%	2,733		5.06%	2,629		3.89%
18-19	4,265		3.51%	2,178		4.04%	2,087		3.09%
20-24	8,940		7.35%	4,312		7.99%	4,628		6.85%
25-29	10,146		8.35%	4,377		8.11%	5,769		8.53%
30-34	12,082		9.94%	4,967		9.20%	7,115		10.52%
35-39	12,888		10.60%	5,409		10.02%	7,479		11.06%
40-44	11,606		9.55%	5,044		9.35%	6,562		9.71%
45-49	13,097		10.77%	5,816		10.78%	7,281		10.77%
50-54	14,001		11.52%	6,157		11.41%	7,844		11.60%

55-59	14,332		11.79%	6,336		11.74%	7,996		11.83%
60-64	14,849		12.21%	6.631		12.29%	8,218		12.16%
Ethnic Group	121,568	0		53,960	0		67,608	0	
White	107,317		88.28%	48,062		89.07%	59,255		87.64%
Mixed/Multiple ethnic groups	1,328		1.09%	575		1.07%	753		1.11%
Indian	2,772		2.28%	1,222		2.26%	1,550		2.29%
Pakistani	2,291		1.88%	883		1.64%	1,408		2.08%
Bangladeshi	839		0.69%	354		0.66%	485		0.72%
Chinese	655		0.54%	258		0.48%	397		0.59%
Other Asian background	1,326		1.09%	497		0.92%	829		1.23%
Black/African/Caribbean/Black British	3,155		2.60%	1,287		2.39%	1,868		2.76%
Other ethnic group	1,885		1.55%	822		1.52%	1,063		1.57%
Marital Status	121,568	0		53,960	0		67,608	0	
Single, never married	48,730		40.08%	23,508		43.57%	25,222		37.31%
Married, living with spouse	57,579		47.36%	25,106		46.53%	32,473		48.03%
Married, separated from spouse	3,238		2.66%	1,186		2.20%	2,052		3.04%
Divorced	9,847		8.10%	3,550		6.58%	6,297		9.31%
Widowed	1,911		1.57%	486		0.90%	1,425		2.11%
Currently or previously in civil partnership	263		0.22%	124		0.23%	139		0.21%
Economic Activity	121,568	0		53,960	0		67,608	0	
In employment	78,587		64.64%	37,003		68.57%	41,584		61.51%
Unemployed	5,228		4.30%	2,732		5.06%	2,496		3.69%
Inactive	37,753		31.06%	14,225		26.36%	23,528		34.80%
Educational Attainment	121,568	0		53,960	0		67,608	0	
Degree or equivalent	34,265		28.19%	14,586		27.03%	19,679		29.11%
Higher education	11,087		9.12%	4,519		8.37%	6,568		9.71%
GCE A level or equivalent	26,438		21.75%	13,116		24.31%	13,322		19.70%
GCSE grades A*-C or equivalent	26,694		21.96%	10,925		20.25%	15,769		23.32%
Other qualification	9,707		7.98%	4,669		8.65%	5,038		7.45%
No qualification	11,578		9.52%	5,245		9.72%	6,333		9.37%
Does not know	1,541		1.27%	766		1.42%	775		1.15%
Did not answer	258		0.21%	134		0.25%	124		0.18%
Region	121,568	0		53,960	0		67,608	0	
North East	8,647		7.11%	3,887		7.20%	4,760		7.04%
North West	15,525		12.77%	6,888		12.77%	8,637		12.78%
Yorkshire	9,755		8.02%	4,339		8.04%	5,416		8.01%
East Midlands	6,137		5.05%	2,804		5.20%	3,333		4.93%
West Midlands	9,407		7.74%	4,156		7.70%	5,251		7.77%
East England	7,619		6.27%	3,290		6.10%	4,329		6.40%
Greater London	9,904		8.15%	4,271		7.92%	5,633		8.33%
South East	13,436		11.05%	6,058		11.23%	7,378		10.91%
South West	9,890		8.14%	4,376		8.11%	5,514		8.16%
Wales	12,865		10.58%	5,741		2.64%	1,890		2.80%
Scotland	15,074		12.40%	6,727		12.47%	8,343		12.34%
Northern Ireland	3,313		2.73%	1,423		10.64%	7,124		10.54%

Table A.3 Descriptive Statistics for Population Dataset, for Dummy Variables

Population

	Dummy Variables								
	Men & Women			**Men**			**Women**		
	Obs.	Missing	Percent	Obs.	Missing	Percent	Obs.	Missing	Percent
Sex	121,568	0		-	-		-	-	
Male	53,960		44.39%	-		-	-		-
Female	67,608		55.61%	-		-	-		-
Currently married	121,568	0		53,960	0		67,608	0	
Not currently married	60,751		49.97%	27,668		51.28%	33,083		48.93%
Currently married	60,817		50.03%	26,292		48.72%	34,525		51.07%

Table A.4 Descriptive Statistics for Sample Dataset, for Continuous Variables

Sample

	Continuous Variables					
	Men & Women					
	Obs.	Missing	Min.	Max.	Mean	Std. Dev.
N	78,587					
Age	78,587	0	16	64	42.04	12.31
Age squared	78,587	0	256	4096	1918.41	1026.70
Hourly pay	78,587	0	1	80	14.66	9.40
Log Hourly pay	78,587	0	0	4.38	2.53	0.55
	Men					
	Obs.	Missing	Min.	Max.	Mean	Std. Dev.
N	37,003					
Age	37,003	0	16	64	42.02	12.39
Age squared	37,003	0	256	4096	1919.42	1034.25
Hourly pay	37,003	0	1	80	16.26	10.46
Log Hourly pay	37,003	0	0	4.38	2.62	0.57
	Women					
	Obs.	Missing	Min.	Max.	Mean	Std. Dev.
N	41,584					
Age	41,584	0	16	64	42.05	12.23
Age squared	41,584	0	256	4096	1917.52	1019.93
Hourly pay	41,584	0	1	80	13.24	8.07
Log Hourly pay	41,584	0	0	4.38	2.44	0.51

Table A.5 Descriptive Statistics for Sample Dataset, for Categorical Variables

Sample

	Categorical Variables								
	Men & Women			**Men**			**Women**		
	Obs.	Missing	Percent	Obs.	Missing	Percent	Obs.	Missing	Percent
N	78,587			37,004			41,584		
Age Groups	78,587	0		37,003	0		41,584	0	
16-17	857		1.09%	400		1.08%	457		1.10%
18-19	1,462		1.86%	722		1.95%	740		1.78%
20-24	4,881		6.21%	2,389		6.46%	2,492		5.99%
25-29	7,513		9.56%	3,512		9.49%	4,001		9.62%
30-34	9,275		11.80%	4,320		11.67%	4,955		11.92%
35-39	9,902		12.60%	4,618		12.48%	5,284		12.71%
40-44	9,078		11.55%	4,294		11.60%	4,784		11.50%
45-49	10,185		12.96%	4,804		12.98%	5,381		12.94%
50-54	10,363		13.19%	4,779		12.92%	5,584		13.43%
55-59	9,064		11.53%	4,212		11.38%	4,852		11.67%
60-64	6,007		7.64%	2,953		7.98%	3,054		7.34%
Ethnic Group	78,587	0		37,004	0		41,584	0	
White	71,250		90.66%	33,434		90.35%	37,816		90.94%
Mixed/Multiple ethnic groups	734		0.93%	331		0.89%	403		0.97%
Indian	1,771		2.25%	872		2.36%	899		2.16%
Pakistani	885		1.13%	504		1.36%	381		0.92%
Bangladeshi	299		0.38%	193		0.52%	106		0.25%
Chinese	336		0.43%	145		0.39%	191		0.46%
Other Asian background	711		0.90%	301		0.81%	410		0.99%
Black/African/Caribbean/Black British	1,729		2.20%	758		2.05%	971		2.34%
Other ethnic group	872		1.11%	465		1.26%	407		0.98%
Marital Status	78,587	0		37,004	0		41,584	0	
Single, never married	27,913		35.52%	13,422		36.27%	14,491		34.85%
Married, living with spouse	41,123		52.33%	20,178		54.53%	20,945		50.37%
Married, separated from spouse	2,069		2.63%	807		2.18%	1,262		3.03%
Divorced	6,384		8.12%	2,273		6.14%	4,111		9.89%
Widowed	915		1.16%	235		0.64%	680		1.64%
Currently or previously in civil partnership	183		0.23%	88		0.24%	95		0.23%
Educational Attainment	78,587	0		37,004	0		41,584	0	
Degree or equivalent	27,419		34.89%	12,156		32.85%	15,263		36.70%
Higher education	8,118		10.33%	3,542		9.57%	4,576		11.00%
GCE A level or equivalent	17,594		22.39%	9,139		24.70%	8,455		20.33%
GCSE grades A*-C or equivalent	15,542		19.78%	6,828		18.45%	8,714		20.96%
Other qualification	5,462		6.95%	3,000		8.11%	2,462		5.92%

No qualification	3,581		4.56%	1,869		5.05%	1,712		4.12%
Does not know	781		0.99%	418		1.13%	363		0.87%
Did not answer	90		0.11%	51		0.14%	39		0.09%
Region	78,587	0		37,004	0		41,584	0	
North East	5,437		6.92%	2,528		6.83%	2,909		7.00%
North West	9,934		12.64%	4,647		12.56%	5,287		12.71%
Yorkshire	6,291		8.01%	2,976		8.04%	3,315		7.97%
East Midlands	3,993		5.08%	1,964		5.31%	2,029		4.88%
West Midlands	5,801		7.38%	2,741		7.41%	3,060		7.36%
East England	5,098		6.49%	2,376		6.42%	2,722		6.55%
Greater London	6,075		7.73%	2,903		7.85%	3,172		7.63%
South East	9,323		11.86%	4,498		12.16%	4,825		11.60%
South West	6,956		8.85%	2,238		8.75%	3,718		8.94%
Wales	8,123		10.34%	2,775		10.20%	4,348		10.46%
Scotland	9,710		12.36%	4,527		12.23%	5,183		12.46%
Northern Ireland	1,846		2.35%	830		2.24%	1,016		2.44%
Industry Sector	78,587	0		37,004	0		41,584	0	
Agriculture, forestry, fishing	389		0.49%	270		0.73%	119		0.29%
Energy & water	1,703		2.17%	1,350		3.65%	353		0.85%
Manufacturing	8,080		10.28%	5,945		16.07%	2,135		5.13%
Construction	3,734		4.75%	2,993		8.09%	741		1.78%
Distribution, hotels, restaurants	14,132		17.98%	6,487		17.53%	7,645		18.38%
Transport & communication	6,411		8.16%	4,674		12.63%	1,737		4.18%
Banking & finance	11,855		15.09%	5,873		15.87%	5,982		14.39%
Public admin, education, health	28,551		36.33%	7,751		20.95%	20,800		50.02%
Other services	3,415		4.35%	1,504		4.06%	1,911		4.60%
Does not know	317		0.40%	156		0.42%	161		0.39%
Managerial Status	78,587	0		37,004	0		41,584	0	
Manager	19,652		25.01%	10,909		29.48%	8,743		21.02%
Foreman or supervisor	8.742		11.12	4,283		11.57%	4,459		10.72%
Not manager or supervisor	50,126		63.78%	21,773		58.84%	28,353		68.18%
Does not know	16		0.02%	12		0.03%	4		0.01%
Did not answer	51		0.06%	26		0.07%	25		0.06%
Major Occupation Class	78,587	0		37,003	0		41,584	0	
Managerial, directors, senior staff	7,482		9.52%	4,591		12.41%	2,891		6.95%
Professional occupations	17,404		22.15%	7,812		21.11%	9,592		23.07%
Associate, professional, technical	11,336		14.42%	5,963		16.11%	5,373		12.92%
Administrative & secretarial	9,403		11.97%	2,008		5.43%	7,395		17.78%
Skilled trades	5,607		7.13%	4,952		13.38%	655		1.58%
Caring, leisure, other services	7,709		9.81%	1,258		3.40%	6,451		15.51%
Sales & customer services	6,374		8.11%	2,091		5.65%	4,283		10.30%
Process, plant, machine operatives	4,878		6.21%	4,212		11.38%	666		1.60%
Elementary occupations	8,394		10.68%	4,116		11.12%	4,278		10.29%

Table A.6 Descriptive Statistics for Sample Dataset, for Dummy Variables

Sample

Dummy Variables

	Men & Women			**Men**			**Women**		
	Obs.	Missing	Percent	Obs.	Missing	Percent	Obs.	Missing	Percent
N	78,587			37,003					
Occupation Class *(Generated from Major Occupation Class)*									
Professional/Not	78,587	0		37,003	0		41,584	0	
Not Professional	42,365		53.91%	18,637		50.37%	23,728		57.06%
Professional	36,222		46.09%	18,366		49.63%	17,856		42.94%
Intermediate	78,587	0		37,003	0		41,584	0	
Not intermediate	63,577		80.90%	30,043		81.19%	33,534		80.64%
Intermediate	15,010		19.10%	6,960		18.81%	8,050		19.36%
Routine/Semi-Routine	78,587	0		37,003	0		41,584	0	
Not Routine/Semi-Routine	51,232		65.19%	25,326		68.44%	25,906		62.30%
Routine/Semi-Routine	27,355		34.81%	11,677		31.56%	15,678		37.70%
Sex	78,587	0		-	-		41,584	-	
Male	37,003		47.09%	-		-	-		-
Female	41,584		52.91%	-		-	-		-
Currently married	78,587	0		37,003	0		41,584	0	
Not married	35,395		45.04%	16,018		43.29%	19,377		46.60%
Married	43,192		54.96%	20,985		56.71%	22,207		53.40%
Permanent Job	78,587	0		37,003	0		41,584	0	
Not permanent	3,822		4.86%	1,645		4.45%	2,177		5.24%
Permanent	74,765		95.14%	35,358		95.55%	39,407		94.76%
Part-time	78,587	0		37,003	0		41,584	0	
Not part-time	58,461		74.39	33,413		90.30%	25,048		60.23%
Part-time	20,126		25.61	3,590		9.70%	16,536		39.77%
Public Sector	78,587	0		37,003	0		41,584	0	
Not public sector	55,897		71.13%	29,796		80.52%	26,101		62.77%
Public sector	22,690		28.87%	7,207		19.48%	15,584		37.23%

Appendix B

7.1 Robustness Checks

The Heckman correction using a two-step method uses the sample dataste to make a Probit estimator which predicts the participation in employment using a selection equation, prior to forming a linear regression. Then, to estimate the behavioural functions of interest, the estimated values which have not selected into employment, are used as regressors in the linear equation (Heckman, 1979). The first step of the Heckman correction is the selection equation, the dichotomous dependent choice variable as a Probit, as follows;

$$Y_2 = \propto Z + \delta$$

Figure B.1 The Selection Equation (Bushway et al, 2007: 159)

In the selection equation, Y_2 is the dichotomous dependent variable of employed or not employed, and Z is the independent variable, where $\propto$ is the coefficient of Z, and δ is the normally distributed error term (Bushway et al, 2007). The regression equation accounts for the Probit as below;

$$Y_1 = B_0 + B_1 X + \sigma\rho_{\varepsilon\delta}\lambda(T - \propto Z) + \sigma'\varepsilon'$$

Figure B.2 The Regression Equation (Bushway et al, 2007: 159)

In this case Y_1 is observed when Y_2 is greater than the threshold, T, and is censored because $Y_2 \leq T$. However, regressing Y on X will bias results because of the presence of the sigma term which represents the omitted variable (Bushway et al, 2007). The two step model therefore retains the Probit selection equation where the predicted values are retained and used as estimates of $T - \propto Z$ (Bushway et al, 2007). From this, the inverse Mills ratio is estimated, and becomes a regressor in the OLS regression. As such, this study incorporates the two step

Heckman correction model in order to remove omitted variable bias from those observations who are not in employment in the UK labour force.

7.2 Robustness Results

Table B.1 Absolute & Percentage Differences in Pay for Men and Women

Variables	(1) Hourly Pay	(2) Hourly Pay	(3) Log Hourly Pay	(4) Log Hourly Pay	(5) Log Hourly Pay	(6) Log Hourly Pay
	£	£	%	%	%	%
Female	-£2.98***	-£2.98***	-18.13***	-14.96***	-11.93***	-10.68***
Ethnic Group *(Base as White British)*						
Mixed/Multiple ethnic groups		-£0.27	-2.91*	-2.65	-1.88	-1.50
Indian		-£0.16	-5.83***	-5.81***	-5.80***	-3.33***
Pakistani		-£3.3***	-20,15***	-18.45***	-17.39***	-14.70***
Bangladeshi		-£6.23***	-30.02***	-25.99***	-24.42***	-21.65***
Chinese		£0.66	-4.36*	-3.4	-2.56	0.73
Any other Asian background		-£2.93***	-17.3***	-15.13***	-14.62***	-11.57***
Black/African/Caribbean/Black British		-£3.49***	-17.55***	-16.56***	-15-55***	-12.98***
Other Ethnic Group		-£3.12***	-15.55***	-14.44***	-13.41***	-10.51***
Industry Sector (Does not know omitted due to collinearity)						
Agriculture, forestry, fishing				-20.15***	-18.95***	-19.75***
Energy & water				19.24***	19.84***	21.05***
Manufacturing				9.89***	10.96***	12.41***
Construction				10.74***	11.4***	10.32***
Distribution, hotels, restaurants				-12.01***	-8.63***	-10.33***
Transport & communication				12.98***	14.34***	15.84***
Banking & finance				13.77***	15.60***	14.45***
Public admin, education, health				-0.83	-3.86	-3.82
Other services				-7.57***	-5.96**	-8.42***
Managerial status *(Base as not manager or supervisor)*						
Manager						37.16***
Foreman or supervisor						9.20***
R-squared	0.105	0.146	0.326	0.354	0.367	0.418
Observations	78,587	78,587	78,587	78,587	78,587	78,587

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The first OLS model provides a preliminary regression that calculates earnings differentials between the genders and between ethnic groupings, prior to carrying out the Heckman correction. As seen Table B.1 hourly pay is regressed for all those in employment aged 16-64.The results in this table are given in percentage forms as they have been calculated using the Halvorsen Palmquist transformation, and do not show the control variables age, age squared, marital status, region, educational attainment, or whether employment is permanent part time, or in the public sector. These control variables are added throughout testing. For the results all testing, see table C.1 in Appendix C.

There are seven tests, where the first two use hourly pay in its absolute form as the dependent variable. Subsequent tests use the logarithmic form of the hourly pay. The R squared improves across testing as the dependent variable is transformed and variables are added, beginning with a value of 0.105 for test 1, received to 0.418 for test 6. This means that the goodness-of-fit for the regression, giving the 'proportion or percentage of the total variation in the dependent variable Y explained by the single explanatory variable X' (Gujarati & Porter, 2010: 102).

This initial OLS regression takes account of the gender and the ethnic group pay gaps. The results indicate that women face a pay gap relative to men, which consistently functions at 1% level of statistical significance. Where early tests indicate a raw pay gap of just below £3 per hour, test seven indicates -11% pay gap relative to male pay. With the inclusion of more variables this figure reduces, but does not reach zero.

Likewise, as this study considers differences in pay for ethnic minority groups, this model regression shows that not only do ethnic groups face different earnings relative to white earnings, but that these differences vary for each group. Relative to white earnings, Bangladeshis face the largest earnings difference, with a gap of -22% at 1% level of statistical significance. Yet, Chinese workers see an improvement relative to white pay, with an increase of 0.73% in hourly earnings, although this is not statistically significant and changes from negative to positive across testing.

With regard to the component of occupational segregation, a preliminary insight into different pay in different sectors is observed. The dummy variables for industry show that relative to other industries, agriculture, forestry and fishing, face the largest negative impact on pay, at -20%, and is statistically significant at the 1% level. Conversely, energy and water industries have the largest positive impact on pay, at 21% at a 1% level of statistical significance.

Indeed, occupational variables also include statuses of responsibility, where supervisors and managers indicate progress at work. The results in Table B.1 indicate that supervisors and managers receive higher hourly earnings relative to those who are at menial level, at 37% and 9% increases, both at the 1% level of statistical significance. This first model therefore begins to explore the variety of explanatory factors that account for earnings, and the degree to which there are differences in pay, increasing the robustness of the main results of the study.

Table B.2 Heckman Correction Percentage Differences in Pay for Men and Women

Variables	(1) Log Hourly Pay	(2) Log Hourly Pay	(3) Log Hourly Pay	(4) Log Hourly Pay
	%	%	%	%
Female	-14.02***	-14.1***	-14.02***	-14.79***
Ethnic Group *(Base as White British)*				
Mixed/Multiple ethnic groups	-1.52	-1.52	-1.55	-5.81***
Indian	-3.44***	-3.48***	-3.46***	-7.62***
Pakistani	-14.79***	-14.62***	-14.62***	-26.8***
Bangladeshi	-21.73***	-21.49***	-21.49***	-33.63***
Chinese	0.72	0.76	0.74	-9.24***
Any other Asian background	-11.57***	-11.49***	-11.49***	-18.54***
Black/African/Caribbean/Black British	-12.98***	-12.98***	-13.06***	-18.29***
Other Ethnic Group	-10.60***	-10.42***	-10.42***	-20.71***
Industry Sector *(Does not know omitted due to collinearity)*				
Agriculture, forestry, fishing	-19.75***	-19.75***	-19.75***	-19.75***
Energy & water	21.05***	21.05***	20.92***	20.92***
Manufacturing	12.41***	12.41***	12.30***	12.30***
Construction	10.27***	10.25***	10.23***	10.24***
Distribution, hotels, restaurants	-10,42***	-10,42***	-10,42***	-10,52***
Transport & communication	15.72***	15.72***	15.60***	15.60***
Banking & finance	14.34***	14.34***	14.23***	14.23***
Public admin, education, health	-3.86	-3.93	-3.95	-3.99
Other services	-8.53***	-8.62***	-8.63***	-8.67***
Managerial status *(Base as not manager or supervisor)*				
Manager	37.03***	36.89***	36.89***	36.89***
Foreman or supervisor	9.20***	9.22***	9.22***	9.23***
Lambda	0.287***	0.294***	0.283***	0.367***
Observations	121,568	121,568	121,568	121,568

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The second model in the robustness checks incorporates the Heckman correction in order to account for those who are opting out of employment, and using this variable as an explanatory variable within the linear regression itself. In doing so, all of those observations of working age, 16-64 are included, seen in Table B.3 above. This model uses the same variables found in the linear regression taken from test 6 in the previous model, and shows building up of the selection equation. As testing progresses, more variables are added into the selection, Probit, equation. For full coefficient results for all variables in use, see table C.2 of Appendix C.

Of importance in the Heckman correction is the Lambda, or the inverse Mills ratio, which increases in value as more variables are added into the selection, or Probit, equation. The Lambda then exists as an explanatory variable in the linear regression (Heckman, 1979). As Lambda is consistently statistically significant at the 1% level, this means that the selection probability term does play a role in the unconditional expectation, and thus, selection is non-random. Results are presented once more as percentage differences, and comparisons are made against the previous OLS indicating the impact of the Heckman correction on the linear regression. Firstly, the gender pay gap after the correction, at -15%, is statistically significant at the 1% level. This means that the addition of the Heckman correction corrects for omitted variable bias and measures the selection into employment as a choice, is an outcome of characteristics, and therefore impacts pay gaps.

As seen in Table A.2 of the descriptive statistics, there are differences between ethnic groups in the proportions of men and women who are in employed, unemployed, or inactive in the labour market. With the additional Heckman correction, these differences are accounted for in the OLS regression, where ethnic minority group is added into the selection equation in test 4. The percentage earnings differences relative to the white group indicates that all ethnic minority groups face a negative pay difference, ranging from -5.8% for mixed/multiple groups, to -33.64% for the Bangladeshi group, where all results are statistically significant at the 1% level.

Appendix C

Table C.1 OLS Hourly Pay Differnces for Men and Women

Variables	(1) Hourly Pay	(2) Hourly Pay	(3) Log Hourly Pay	(4) Log Hourly Pay	(5) Log Hourly Pay	(6) Log Hourly Pay
Age	1.018***	0.998***	0.0633***	0.0574***	0.0517***	0.0438***
	(0.0186)	(0.0182)	(0.000951)	(0.000939)	(0.000943)	(0.000910)
Age Squared	-0.0112***	-0.0109***	-0.000658***	-0.000594***	-0.000530***	-0.000449***
	(0.000218)	(0.000214)	(1.12e-05)	(1.10e-05)	(1.11e-05)	(1.07e-05)
Female	-2.979***	-2.983***	-0.200***	-0.162***	-0.127***	-0.113***
	(0.0638)	(0.0625)	(0.00323)	(0.00340)	(0.00354)	(0.00340)
Marital Status *(Base as Married and Living with spouse)*						
Single, never married	-2.167***	-2.279***	-0.0930***	-0.0899***	-0.0949***	-0.0708***
	(0.0817)	(0.0805)	(0.00416)	(0.00407)	(0.00404)	(0.00388)
Married, seperated from spouse	-2.347***	-2.161***	-0.0828***	-0.0791***	-0.0816***	-0.0669***
	(0.201)	(0.196)	(0.0101)	(0.00991)	(0.00981)	(0.00941)
Divorced	-2.073***	-2.009***	-0.0666***	-0.0628***	-0.0717***	-0.0579***
	(0.121)	(0.119)	(0.00613)	(0.00600)	(0.00595)	(0.00571)
Widowed	-2.605***	-2.512***	-0.112***	-0.107***	-0.107***	-0.0838***
	(0.300)	(0.294)	(0.0151)	(0.0148)	(0.0147)	(0.0141)
Currently or previously in civil partnership	0.937	0.278	-0.0621*	-0.0451	-0.0522	-0.0397
	(0.659)	(0.644)	(0.0332)	(0.0325)	(0.0322)	(0.0309)
Ethnic Group *(Base as White British)*						
Mixed/Multiple ethnic groups		-0.271	-0.0295*	-0.0262	-0.0189	-0.0151
		(0.324)	(0.0167)	(0.0164)	(0.0162)	(0.0155)
Indian		-0.159	-0.0601***	-0.0599***	-0.0598***	-0.0339***
		(0.213)	(0.0110)	(0.0108)	(0.0107)	(0.0102)
Pakistani		-3.303***	-0.225***	-0.204***	-0.191***	-0.159***
		(0.296)	(0.0153)	(0.0150)	(0.0148)	(0.0142)
Bangladeshi		-6.230***	-0.357***	-0.301***	-0.280***	-0.244***
		(0.507)	(0.0261)	(0.0256)	(0.0254)	(0.0243)
Chinese		0.656	-0.0446*	-0.0346	-0.0259	0.00726
		(0.476)	(0.0246)	(0.0241)	(0.0238)	(0.0229)
Any other Asian background		-2.927***	-0.190***	-0.164***	-0.158***	-0.123***
		(0.330)	(0.0170)	(0.0167)	(0.0165)	(0.0158)
Black/African/Caribbean/Black British		-3.487***	-0.193***	-0.181***	-0.169***	-0.139***
		(0.215)	(0.0111)	(0.0109)	(0.0108)	(0.0103)
Other Ethnic Group		-3.120***	-0.169***	-0.156***	-0.144***	-0.111***
		(0.298)	(0.0154)	(0.0151)	(0.0150)	(0.0143)
Region *(Northern Ireland omitted due to collinearity)*						
North East		0.198	0.0177	0.0132	0.0171	0.0168
		(0.234)	(0.0121)	(0.0121)	(0.0120)	(0.0115)
North West		0.868***	0.0412***	0.0340***	0.0341***	0.0276**
		(0.221)	(0.0114)	(0.0115)	(0.0114)	(0.0109)
Yorkshire		0.506**	0.0252**	0.0206*	0.0257**	0.0166
		(0.230)	(0.0119)	(0.0120)	(0.0118)	(0.0113)
East Midlands		0.578**	0.0214*	0.0179	0.0218*	0.0120
		(0.245)	(0.0126)	(0.0127)	(0.0126)	(0.0120)
West Midlands		1.081***	0.0561***	0.0478***	0.0503***	0.0413***
		(0.233)	(0.0120)	(0.0121)	(0.0119)	(0.0115)
East England		2.613***	0.138***	0.127***	0.130***	0.112***
		(0.236)	(0.0122)	(0.0123)	(0.0121)	(0.0116)
Greater London		7.035***	0.284***	0.265***	0.266***	0.238***
		(0.234)	(0.0121)	(0.0122)	(0.0121)	(0.0116)
South East		3.848***	0.157***	0.146***	0.152***	0.131***
		(0.222)	(0.0115)	(0.0115)	(0.0114)	(0.0110)
South West		1.286***	0.0383***	0.0353***	0.0429***	0.0241**

		(0.228)	(0.0118)	(0.0118)	(0.0117)	(0.0112)
Wales		0.507**	0.00975	0.00977	0.0116	-0.000242
		(0.224)	(0.0116)	(0.0116)	(0.0115)	(0.0111)
Scotland		1.444***	0.0624***	0.0594***	0.0611***	0.0616***
		(0.221)	(0.0114)	(0.0115)	(0.0114)	(0.0109)
Northern Ireland		-	-	-	-	-
Educational Attainment *(Base as degree or equivalent)*						
Higher education			-0.245***	-0.239***	-0.229***	-0.201***
			(0.00574)	(0.00563)	(0.00558)	(0.00537)
GCE A level or equivalent			-0.351***	-0.342***	-0.330***	-0.282***
			(0.00444)	(0.00441)	(0.00438)	(0.00424)
GCSE grades A*-C or equivalent			-0.458***	-0.440***	-0.422***	-0.358***
			(0.00461)	(0.00463)	(0.00462)	(0.00449)
Other qualification			-0.550***	-0.533***	-0.516***	-0.430***
			(0.00672)	(0.00671)	(0.00666)	(0.00647)
No qualification			-0.627***	-0.603***	-0.579***	-0.485***
			(0.00811)	(0.00807)	(0.00802)	(0.00777)
Does not know			-0.460***	-0.447***	-0.440***	-0.376***
			(0.0163)	(0.0160)	(0.0158)	(0.0152)
Does not apply			-0.442***	-0.431***	-0.424***	-0.351***
			(0.0473)	(0.0464)	(0.0459)	(0.0440)
Industry Sector *(Does not know omitted due to collinearity)*						
Agriculture, forestry, fishing				-0.225***	-0.210***	-0.220***
				(0.0338)	(0.0335)	(0.0321)
Energy & water				0.176***	0.181***	0.191***
				(0.0276)	(0.0274)	(0.0262)
Manufacturing				0.0943***	0.104***	0.117***
				(0.0260)	(0.0257)	(0.0247)
Construction				0.102***	0.108***	0.0982***
				(0.0265)	(0.0263)	(0.0252)
Distribution, hotels, restaurants				-0.128***	-0.0902***	-0.109***
				(0.0258)	(0.0255)	(0.0245)
Transport & communication				0.122***	0.134***	0.147***
				(0.0261)	(0.0259)	(0.0248)
Banking & finance				0.129***	0.145***	0.135***
				(0.0258)	(0.0256)	(0.0245)
Public admin, education, health				-0.00837	-0.0394	-0.0389
				(0.0256)	(0.0254)	(0.0244)
Other services				-0.0787***	-0.0615**	-0.0880***
				(0.0266)	(0.0263)	(0.0252)
Does not know				-	-	-
Permanent job					0.102***	0.0672***
					(0.00737)	(0.00709)
Part-time					-0.125***	-0.0699***
					(0.00395)	(0.00385)
Public sector					0.0882***	0.101***
					(0.00474)	(0.00454)
Managerial status *(Base as not manager or supervisor)*						
Manager						0.316***
						(0.00381)
Foreman or supervisor						0.0880***
						(0.00489)
Does not apply						-0.436***
						(0.104)
No answer given						0.0194
						(0.0584)
Constant	-4.101***	-5.241***	1.485***	1.568***	1.562***	1.621***
	(0.391)	(0.432)	(0.0228)	(0.0321)	(0.0321)	(0.0308)
Observations	78,587	78,587	78,587	78,587	78,587	78,587
R-squared	0.105	0.146	0.326	0.354	0.367	0.418

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.2 Two Step Heckman Correction Pay Differences for Men and Women

	(1)		(2)		(3)		(4)	
Variables	Log Hourly Pay	Probit	Log Hourly Pay	Probit	Log Hourly Pay	Probit	Log Hourly Pay	Probit
Age	0.0762***	0.204***	0.0744***	0.192***	0.0732***	0.193***	0.0816***	0.193***
	(0.00676)	(0.00182)	(0.00418)	(0.00190)	(0.00406)	(0.00190)	(0.00370)	(0.00191)
	-	-	-	-	-	-	-	-
Age Squared	0.000846***	0.00252***	0.000820***	0.00235***	0.000806***	0.00236***	0.000913***	0.00239***
	(8.28e-05)	(2.18e-05)	(5.07e-05)	(2.27e-05)	(4.93e-05)	(2.27e-05)	(4.52e-05)	(2.29e-05)
Female	-0.151***	-0.269***	-0.152***	-0.285***	-0.151***	-0.285***	-0.160***	-0.279***
	(0.00853)	(0.00787)	(0.00630)	(0.00807)	(0.00615)	(0.00809)	(0.00574)	(0.00813)
Marital Status *(Base as Married and Living with spouse)*								
Single, never married	-0.0948***		-0.0850***		-0.0841***		-0.0956***	
	(0.00641)		(0.00449)		(0.00443)		(0.00478)	
Married, seperated from spouse	-0.0666***		-0.0659***		-0.0660***		-0.0657***	
	(0.00948)		(0.00945)		(0.00944)		(0.00946)	
Divorced	-0.0853***		-0.0757***		-0.0745***		-0.0878***	
	(0.00810)		(0.00626)		(0.00621)		(0.00648)	
Widowed	-0.116***		-0.106***		-0.105***		-0.122***	
	(0.0153)		(0.0140)		(0.0140)		(0.0139)	
Currently or previously in civil partnership	-0.0650**		-0.0554*		-0.0542*		-0.0662**	
	(0.0313)		(0.0312)		(0.0311)		(0.0313)	
Currently married		0.188***		0.126***		0.124***		0.173***
		(0.00874)		(0.00898)		(0.00900)		(0.00916)
Ethnic Group *(Base as White British)*								
Mixed/Multiple ethnic groups	-0.0153		-0.0153		-0.0156		-0.0599***	0.653***
	(0.0155)		(0.0155)		(0.0155)		(0.0173)	(0.0317)
Indian	-0.0350***		-0.0354***		-0.0352***		-0.0793***	0.402***
	(0.0103)		(0.0103)		(0.0103)		(0.0120)	(0.0487)
Pakistani	-0.160***		-0.158***		-0.158***		-0.312***	0.383***
	(0.0143)		(0.0143)		(0.0143)		(0.0208)	(0.0407)
Bangladeshi	-0.245***		-0.242***		-0.242***		-0.410***	-0.162***
	(0.0246)		(0.0245)		(0.0244)		(0.0298)	(0.0425)
Chinese	0.00719		0.00762		0.00742		-0.0969***	-0.222***
	(0.0230)		(0.0231)		(0.0230)		(0.0264)	(0.0573)
Any other Asian background	-0.123***		-0.122***		-0.122***		-0.205***	0.0623
	(0.0159)		(0.0159)		(0.0159)		(0.0187)	(0.0608)
Black/African/Caribbean/Black British	-0.139***		-0.139***		-0.140***		-0.202***	0.185***
	(0.0104)		(0.0104)		(0.0103)		(0.0127)	(0.0481)
Other Ethnic Group	-0.112***		-0.110***		-0.110***		-0.232***	0.298***
	(0.0145)		(0.0144)		(0.0144)		(0.0190)	(0.0392)
Region *(Northern Ireland omitted due to collinearity)*								
North East	0.0171		0.0168		0.0422***	0.183***	0.0528***	0.204***
	(0.0115)		(0.0115)		(0.0126)	(0.0279)	(0.0129)	(0.0280)
North West	0.0281***		0.0280**		0.0544***	0.191***	0.0721***	0.251***
	(0.0109)		(0.0109)		(0.0120)	(0.0262)	(0.0125)	(0.0263)
Yorkshire	0.0172		0.0169		0.0456***	0.208***	0.0614***	0.252***
	(0.0114)		(0.0113)		(0.0125)	(0.0275)	(0.0130)	(0.0276)
East Midlands	0.0125		0.0126		0.0413***	0.209***	0.0592***	0.267***
	(0.0120)		(0.0120)		(0.0132)	(0.0295)	(0.0138)	(0.0297)
West Midlands	0.0418***		0.0419***		0.0626***	0.149***	0.0807***	0.220***
	(0.0115)		(0.0114)		(0.0124)	(0.0276)	(0.0129)	(0.0278)
East England	0.112***		0.112***		0.146***	0.248***	0.165***	0.302***
	(0.0116)		(0.0116)		(0.0130)	(0.0286)	(0.0135)	(0.0288)
Greater London	0.238***		0.238***		0.237***	-0.0128	0.267***	0.168***
	(0.0116)		(0.0116)		(0.0121)	(0.0275)	(0.0128)	(0.0281)
South East	0.131***		0.130***		0.165***	0.258***	0.184***	0.312***
	(0.0110)		(0.0110)		(0.0124)	(0.0267)	(0.0129)	(0.0268)
South West	0.0241**		0.0239**		0.0661***	0.316***	0.0812***	0.335***
	(0.0112)		(0.0112)		(0.0131)	(0.0277)	(0.0133)	(0.0278)
Wales	0.000183		4.47e-05		0.0220*	0.158***	0.0301**	0.168***
	(0.0111)		(0.0110)		(0.0120)	(0.0266)	(0.0123)	(0.0267)
Scotland	0.0618***		0.0617***		0.0861***	0.176***	0.0950***	0.187***
	(0.0109)		(0.0109)		(0.0119)	(0.0262)	(0.0122)	(0.0263)
Northern Ireland	-		-		-	-	-	-

Educational Attainment *(Base as degree or equivalent)*								
Higher education	-0.201***		-0.216***	-0.127***	-0.216***	-0.134***	-0.222***	-0.150***
	(0.00537)		(0.00606)	(0.0156)	(0.00606)	(0.0157)	(0.00628)	(0.0158)
GCE A level or equivalent	-0.282***		-0.310***	-0.232***	-0.310***	-0.244***	-0.322***	-0.264***
	(0.00424)		(0.00586)	(0.0117)	(0.00590)	(0.0118)	(0.00599)	(0.0119)
GCSE grades A*-C or equivalent	-0.359***		-0.414***	-0.410***	-0.413***	-0.423***	-0.432***	-0.445***
	(0.00450)		(0.00881)	(0.0116)	(0.00878)	(0.0117)	(0.00854)	(0.0118)
Other qualification	-0.431***		-0.516***	-0.611***	-0.514***	-0.617***	-0.530***	-0.579***
	(0.00647)		(0.0133)	(0.0155)	(0.0131)	(0.0155)	(0.0117)	(0.0157)
No qualification	-0.486***		-0.676***	-1.141***	-0.668***	-1.141***	-0.715***	-1.114***
	(0.00773)		(0.0266)	(0.0151)	(0.0258)	(0.0152)	(0.0231)	(0.0153)
Does not know	-0.377***		-0.480***	-0.722***	-0.477***	-0.731***	-0.507***	-0.744***
	(0.0152)		(0.0211)	(0.0343)	(0.0209)	(0.0344)	(0.0204)	(0.0347)
Does not apply	-0.350***		-0.476***	-0.835***	-0.471***	-0.837***	-0.511***	-0.860***
	(0.0440)		(0.0482)	(0.0889)	(0.0480)	(0.0887)	(0.0482)	(0.0886)
Industry Sector *(Does not know omitted due to collinearity)*								
Agriculture, forestry, fishing	-0.220***		-0.220***		-0.220***		-0.220***	
	(0.0322)		(0.0321)		(0.0319)		(0.0318)	
Energy & water	0.191***		0.191***		0.190***		0.190***	
	(0.0263)		(0.0263)		(0.0261)		(0.0260)	
Manufacturing	0.117***		0.116***		0.116***		0.116***	
	(0.0247)		(0.0247)		(0.0245)		(0.0244)	
Construction	0.0978***		0.0976***		0.0974***		0.0975***	
	(0.0252)		(0.0252)		(0.0250)		(0.0249)	
Distribution, hotels, restaurants	-0.110***		-0.110***		-0.110***		-0.111***	
	(0.0245)		(0.0245)		(0.0243)		(0.0242)	
Transport & communication	0.146***		0.146***		0.145***		0.145***	
	(0.0248)		(0.0248)		(0.0246)		(0.0245)	
Banking & finance	0.134***		0.133***		0.133***		0.133***	
	(0.0245)		(0.0245)		(0.0244)		(0.0242)	
Public admin, education, health	-0.0394		-0.0401		-0.0403*		-0.0406*	
	(0.0244)		(0.0244)		(0.0242)		(0.0241)	
Other services	-0.0892***		-0.0901***		-0.0902***		-0.0907***	
	(0.0252)		(0.0252)		(0.0250)		(0.0249)	
Does now know	-		-		-		-	
Permanent job	0.0685***		0.0680***		0.0679***		0.0681***	
	(0.00701)		(0.00702)		(0.00702)		(0.00696)	
Part-time	-0.0711***		-0.0718***		-0.0718***		-0.0727***	
	(0.00383)		(0.00383)		(0.00383)		(0.00381)	
Public sector	0.101***		0.101***		0.101***		0.101***	
	(0.00453)		(0.00454)		(0.00454)		(0.00454)	
Managerial Status *(Base as not manager or supervisor)*								
Manager	0.315***		0.314***		0.314***		0.314***	
	(0.00383)		(0.00385)		(0.00385)		(0.00387)	
Foreman or supervisor	0.0880***		0.0882***		0.0882***		0.0883***	
	(0.00490)		(0.00490)		(0.00490)		(0.00491)	
Does not apply	-0.441***		-0.446***		-0.448***		-0.453***	
	(0.100)		(0.0995)		(0.0998)		(0.0964)	
No answer given	0.0204		0.0214		0.0211		0.0222	
	(0.0587)		(0.0587)		(0.0587)		(0.0586)	
Constant *(Log Hourly Pay)*	0.908***		0.970***		0.972***		0.798***	
	(0.151)		(0.0922)		(0.0927)		(0.0838)	
Constant *(Probit Function)*	-3.162***		-2.625***		-2.803***		-3.426***	
	(0.0337)		(0.0369)		(0.0439)		(0.0544)	
Lambda		0.287***		0.294***		0.283***		0.367***
		(0.0592)		(0.0390)		(0.0378)		(0.0343)
Observations	121,568	121,568	121,568	121,568	121,568	121,568	121,568	121,568

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.3 Hourly Pay Differences for Men

Variables	(1) Hourly Pay	(6) Hourly Pay	(2) Hourly Pay	(3) Hourly Pay	(4) Hourly Pay	(5) Hourly Pay
Age	0.0855***	0.0724***	0.0487***	0.0644***	0.0521***	0.0354***
	(0.00153)	(0.00142)	(0.00140)	(0.00250)	(0.00250)	(0.00178)
Age Squared	-0.000936***	-0.000761***	-0.000503***	-0.000650***	-0.000533***	-0.000377***
	(1.79e-05)	(1.66e-05)	(1.64e-05)	(2.86e-05)	(2.94e-05)	(2.11e-05)
Marital Status *(Base as Married and Living with spouse)*						
Single, never married	-0.170***	-0.138***	-0.0983***	-0.112***	-0.0330***	-0.0600***
	(0.00684)	(0.00628)	(0.00590)	(0.00901)	(0.0111)	(0.00850)
Married, seperated from spouse	-0.111***	-0.0671***	-0.0486***	-0.0412*	0.00408	-0.0247
	(0.0182)	(0.0167)	(0.0156)	(0.0244)	(0.0316)	(0.0207)
Divorced	-0.135***	-0.0833***	-0.0630***	-0.0451***	-0.0548***	-0.0250*
	(0.0113)	(0.0104)	(0.00971)	(0.0155)	(0.0186)	(0.0129)
Widowed	-0.103***	-0.0854***	-0.0458	-0.0462	0.0482	-0.0252
	(0.0334)	(0.0306)	(0.0286)	(0.0475)	(0.0553)	(0.0362)
Currently or previously in civil partnership	-0.0786	-0.142***	-0.0907*	-0.0748	-0.122	0.00660
	(0.0541)	(0.0496)	(0.0464)	(0.0655)	(0.114)	(0.0661)
Region *(Northern Ireland omitted due to collinearity)*						
North East	0.0358*	0.0571***	0.0534***	0.0434	0.0651**	0.0175
	(0.0203)	(0.0186)	(0.0178)	(0.0290)	(0.0306)	(0.0246)
North West	0.0582***	0.0666***	0.0524***	0.0591**	0.0367	-0.00799
	(0.0191)	(0.0175)	(0.0168)	(0.0272)	(0.0293)	(0.0234)
Yorkshire	0.0433**	0.0578***	0.0450**	0.0335	0.0310	0.0149
	(0.0199)	(0.0182)	(0.0175)	(0.0283)	(0.0304)	(0.0243)
East Midlands	0.0436**	0.0582***	0.0402**	0.0414	0.0418	-0.0245
	(0.0210)	(0.0193)	(0.0184)	(0.0297)	(0.0326)	(0.0255)
West Midlands	0.0732***	0.0946***	0.0707***	0.0855***	0.0377	-0.0109
	(0.0201)	(0.0184)	(0.0177)	(0.0284)	(0.0309)	(0.0247)
East England	0.182***	0.196***	0.162***	0.163***	0.143***	0.0623**
	(0.0204)	(0.0187)	(0.0180)	(0.0285)	(0.0320)	(0.0255)
Greater London	0.407***	0.328***	0.275***	0.301***	0.202***	0.135***
	(0.0202)	(0.0185)	(0.0178)	(0.0278)	(0.0327)	(0.0260)
South East	0.255***	0.222***	0.189***	0.193***	0.113***	0.0698***
	(0.0192)	(0.0176)	(0.0169)	(0.0269)	(0.0299)	(0.0242)
South West	0.110***	0.0938***	0.0683***	0.0735***	0.0419	0.00285
	(0.0197)	(0.0181)	(0.0174)	(0.0277)	(0.0305)	(0.0246)
Wales	0.0260	0.0299*	0.0187	0.0140	0.00365	-0.0134
	(0.0194)	(0.0178)	(0.0171)	(0.0276)	(0.0296)	(0.0238)
Scotland	0.0975***	0.0821***	0.0764***	0.0990***	0.0595**	0.0201
	(0.0191)	(0.0175)	(0.0169)	(0.0272)	(0.0291)	(0.0235)
Northern Ireland	-	-	-	-	-	-
Educational Attainment *(Base as degree or equivalent)*						
Higher education		-0.206***	-0.177***	-0.162***	-0.0604***	-0.0107
		(0.00895)	(0.00846)	(0.0114)	(0.0179)	(0.0161)
GCE A level or equivalent		-0.318***	-0.259***	-0.211***	-0.106***	-0.0365***
		(0.00659)	(0.00640)	(0.00941)	(0.0137)	(0.0121)
GCSE grades A*-C or equivalent		-0.440***	-0.353***	-0.284***	-0.229***	-0.0802***
		(0.00717)	(0.00701)	(0.0114)	(0.0152)	(0.0120)
Other qualification		-0.552***	-0.440***	-0.331***	-0.270***	-0.121***
		(0.00955)	(0.00930)	(0.0213)	(0.0193)	(0.0131)
No qualification		-0.630***	-0.499***	-0.433***	-0.310***	-0.168***
		(0.0117)	(0.0113)	(0.0304)	(0.0227)	(0.0144)
Does not know		-0.450***	-0.372***	-0.219***	-0.245***	-0.114***
		(0.0231)	(0.0218)	(0.0438)	(0.0375)	(0.0267)
Does not apply		-0.423***	-0.359***	-0.101	-0.191**	-0.122*
		(0.0651)	(0.0609)	(0.146)	(0.0862)	(0.0734)
Industry Sector *(Does not know omitted due to collinearity)*						
Agriculture, forestry, fishing			-0.242***	-0.302***	-0.279***	-0.0950*
			(0.0445)	(0.0810)	(0.0783)	(0.0577)
Energy & water			0.168***	0.190***	0.230***	0.149***
			(0.0378)	(0.0601)	(0.0678)	(0.0522)
Manufacturing			0.103***	0.107*	0.0668	0.128**
			(0.0364)	(0.0579)	(0.0648)	(0.0504)
Construction			0.0707*	0.0540	0.0108	0.155***
			(0.0368)	(0.0586)	(0.0650)	(0.0517)
Distribution, hotels, restaurants			-0.117***	-0.0851	-0.178***	-0.0257

			(0.0364)	(0.0581)	(0.0650)	(0.0502)
Transport & communication			0.125***	0.174***	0.114*	0.146***
			(0.0365)	(0.0579)	(0.0663)	(0.0504)
Banking & finance			0.111***	0.148**	-0.00506	0.00921
			(0.0363)	(0.0575)	(0.0653)	(0.0507)
Public admin, education, health			-0.0226	-0.0129	-0.0912	-0.0297
			(0.0365)	(0.0576)	(0.0659)	(0.0510)
Other services			-0.0915**	-0.111*	-0.110	-0.0320
			(0.0376)	(0.0592)	(0.0675)	(0.0527)
Does now know			-	-	-	-
Part-time			-0.102***	-0.0215	-0.100***	-0.0915***
			(0.00836)	(0.0169)	(0.0184)	(0.00934)
Permanent job			0.0719***	0.0731***	0.108***	0.0642***
			(0.0114)	(0.0196)	(0.0241)	(0.0135)
Public sector			0.0708***	0.0270**	0.0582***	0.0655***
			(0.00816)	(0.0116)	(0.0172)	(0.0130)
Managerial status *(Base as not manager or supervisor)*						
Manager			0.314***	0.182***	0.186***	0.246***
			(0.00554)	(0.00765)	(0.0126)	(0.0140)
Foreman or supervisor			0.0911***	0.0422***	0.0976***	0.104***
			(0.00734)	(0.0122)	(0.0120)	(0.0103)
Does not apply			-0.387***	-0.252	-0.395**	-0.529***
			(0.126)	(0.267)	(0.182)	(0.157)
No answer given			-0.0890	-0.134	-0.105	-0.0438
			(0.0852)	(0.139)	(0.181)	(0.105)
Ethnic Group *(Base as White British)*						
Mixed/Multiple ethnic groups	-0.0299	-0.0601**	-0.0287	-0.0146	0.0208	-0.0474
	(0.0281)	(0.0257)	(0.0241)	(0.0353)	(0.0551)	(0.0330)
Indian	-0.00958	-0.0582***	-0.0219	0.0199	0.00412	-0.0740***
	(0.0177)	(0.0163)	(0.0152)	(0.0211)	(0.0358)	(0.0231)
Pakistani	-0.241***	-0.244***	-0.170***	-0.109***	-0.149***	-0.110***
	(0.0229)	(0.0210)	(0.0197)	(0.0324)	(0.0437)	(0.0240)
Bangladeshi	-0.513***	-0.471***	-0.321***	-0.362***	-0.260***	-0.128***
	(0.0368)	(0.0338)	(0.0317)	(0.0616)	(0.0539)	(0.0378)
Chinese	0.0182	-0.0786**	-0.00406	-0.0219	-0.0728	0.00611
	(0.0422)	(0.0387)	(0.0362)	(0.0472)	(0.0676)	(0.0801)
Any other Asian background	-0.242***	-0.245***	-0.154***	-0.0686*	-0.155***	-0.119***
	(0.0295)	(0.0270)	(0.0253)	(0.0408)	(0.0505)	(0.0328)
Black/African/Caribbean/Black British	-0.270***	-0.270***	-0.194***	-0.162***	-0.110***	-0.0921***
	(0.0188)	(0.0173)	(0.0162)	(0.0272)	(0.0342)	(0.0199)
Other Ethnic Group	-0.259***	-0.211***	-0.133***	-0.105***	-0.110***	-0.0725***
	(0.0238)	(0.0219)	(0.0205)	(0.0335)	(0.0406)	(0.0263)
Constant	0.798***	1.269***	1.508***	1.244***	1.288***	1.479***
	(0.0366)	(0.0343)	(0.0467)	(0.0790)	(0.0837)	(0.0625)
Observations	37,003	37,003	37,003	18,366	6,960	11,677
R-squared	0.199	0.328	0.413	0.268	0.325	0.249

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.4 Hourly Pay Differences for Women

Variables	(1) Hourly Pay	(6) Hourly Pay	(2) Hourly Pay	(3) Hourly Pay	(4) Hourly Pay	(5) Hourly Pay
Age	0.0749***	0.0547***	0.0384***	0.0540***	0.0404***	0.0273***
	(0.00139)	(0.00127)	(0.00120)	(0.00229)	(0.00253)	(0.00141)
Age Squared	0.000838***	0.000562***	0.000388***	0.000540***	0.000409***	0.000281***
	(1.63e-05)	(1.50e-05)	(1.41e-05)	(2.66e-05)	(2.91e-05)	(1.69e-05)
Marital Status *(Base as Married and Living with spouse)*						
Single, never married	-0.0813***	-0.0510***	-0.0429***	-0.0482***	-0.0312***	-0.00462
	(0.00609)	(0.00549)	(0.00512)	(0.00783)	(0.0107)	(0.00710)
Married, seperated from spouse	-0.144***	-0.0859***	-0.0733***	-0.0516***	-0.0476*	-0.0488***
	(0.0139)	(0.0125)	(0.0116)	(0.0194)	(0.0245)	(0.0144)
Divorced	-0.0847***	-0.0479***	-0.0473***	-0.0565***	-0.0268**	-0.0168*
	(0.00828)	(0.00746)	(0.00694)	(0.0112)	(0.0136)	(0.00924)
Widowed	-0.143***	-0.114***	-0.0924***	-0.0975***	-0.0634**	-0.0182
	(0.0189)	(0.0170)	(0.0158)	(0.0302)	(0.0297)	(0.0187)
Currently or previously in civil partnership	0.0477	0.0173	0.0141	0.0310	-0.0509	-0.0397
	(0.0492)	(0.0443)	(0.0410)	(0.0558)	(0.0926)	(0.0647)
Region *(Northern Ireland omitted due to collinearity)*						
North East	-0.0342*	-0.0133	-0.0116	-0.0196	-0.0395	-0.00374
	(0.0174)	(0.0157)	(0.0149)	(0.0247)	(0.0291)	(0.0195)
North West	0.0185	0.0231	0.00970	-0.000720	-0.0116	0.00931
	(0.0164)	(0.0148)	(0.0141)	(0.0231)	(0.0271)	(0.0186)
Yorkshire	-0.0130	0.000711	-0.00500	-0.00802	-0.0242	-0.00373
	(0.0172)	(0.0155)	(0.0147)	(0.0242)	(0.0287)	(0.0192)
East Midlands	-0.0168	-0.00493	-0.00746	-0.00479	0.00675	-0.0380*
	(0.0184)	(0.0166)	(0.0157)	(0.0257)	(0.0312)	(0.0206)
West Midlands	0.0150	0.0260*	0.0182	0.00736	-0.00996	0.00249
	(0.0174)	(0.0156)	(0.0149)	(0.0242)	(0.0290)	(0.0197)
East England	0.0787***	0.0897***	0.0719***	0.0693***	0.0832***	0.0126
	(0.0176)	(0.0159)	(0.0151)	(0.0245)	(0.0290)	(0.0202)
Greater London	0.325***	0.247***	0.208***	0.220***	0.229***	0.0958***
	(0.0175)	(0.0158)	(0.0150)	(0.0238)	(0.0297)	(0.0209)
South East	0.123***	0.102***	0.0823***	0.0871***	0.0799***	0.0205
	(0.0166)	(0.0149)	(0.0142)	(0.0231)	(0.0274)	(0.0190)
South West	0.00268	-0.00495	-0.0103	-0.00778	-0.0397	-0.0255
	(0.0170)	(0.0153)	(0.0145)	(0.0237)	(0.0281)	(0.0193)
Wales	-0.000195	-0.00394	-0.0133	-0.0337	-0.0220	-0.00479
	(0.0167)	(0.0150)	(0.0143)	(0.0234)	(0.0277)	(0.0189)
Scotland	0.0656***	0.0491***	0.0519***	0.0431*	0.0365	0.0492***
	(0.0164)	(0.0148)	(0.0141)	(0.0230)	(0.0273)	(0.0186)
Northern Ireland	-	-	-	-	-	-
Educational Attainment *(Base as degree or equivalent)*						
Higher education		-0.274***	-0.219***	-0.176***	-0.111***	-0.0431***
		(0.00737)	(0.00686)	(0.00979)	(0.0151)	(0.0112)
GCE A level or equivalent		-0.384***	-0.306***	-0.249***	-0.121***	-0.0624***
		(0.00596)	(0.00566)	(0.00999)	(0.0116)	(0.00891)
GCSE grades A*-C or equivalent		-0.470***	-0.361***	-0.312***	-0.158***	-0.108***
		(0.00596)	(0.00582)	(0.0113)	(0.0118)	(0.00887)
Other qualification		-0.540***	-0.412***	-0.287***	-0.214***	-0.130***
		(0.00947)	(0.00904)	(0.0229)	(0.0190)	(0.0111)
No qualification		-0.616***	-0.462***	-0.401***	-0.270***	-0.151***
		(0.0112)	(0.0107)	(0.0358)	(0.0258)	(0.0120)
Does not know		-0.466***	-0.375***	-0.334***	-0.156***	-0.130***
		(0.0229)	(0.0213)	(0.0408)	(0.0406)	(0.0257)
Does not apply		-0.449***	-0.324***	-0.341**	0.0459	-0.123*
		(0.0691)	(0.0640)	(0.155)	(0.108)	(0.0722)
Industry Sector *(Does not know omitted due to collinearity)*						
Agriculture, forestry, fishing			-0.185***	-0.257***	-0.0828	-0.179***
			(0.0489)	(0.0941)	(0.0790)	(0.0654)
Energy & water			0.228***	0.223***	0.177***	0.199***
			(0.0388)	(0.0626)	(0.0661)	(0.0576)
Manufacturing			0.115***	0.180***	0.0805	0.0230
			(0.0337)	(0.0556)	(0.0578)	(0.0477)
Construction			0.154***	0.152***	0.0932	0.141**
			(0.0357)	(0.0584)	(0.0590)	(0.0605)
Distribution, hotels, restaurants			-0.104***	-0.101*	-0.0664	-0.0863*

			(0.0329)	(0.0550)	(0.0570)	(0.0463)
Transport & communication			0.171***	0.208***	0.110*	0.122**
			(0.0339)	(0.0557)	(0.0589)	(0.0481)
Banking & finance			0.156***	0.169***	0.127**	0.0287
			(0.0330)	(0.0542)	(0.0566)	(0.0469)
Public admin, education, health			-0.0365	-0.0144	-0.0203	-0.0694
			(0.0327)	(0.0537)	(0.0565)	(0.0462)
Other services			-0.0831**	-0.0987*	-0.00502	-0.103**
			(0.0338)	(0.0558)	(0.0584)	(0.0475)
Does now know			-	-	-	-
Part-time			-0.0541***	-0.0283***	-0.0484***	-0.0207***
			(0.00428)	(0.00732)	(0.00851)	(0.00562)
Permanent job			0.0588***	0.0420***	0.0477**	0.0864***
			(0.00895)	(0.0144)	(0.0206)	(0.0112)
Public sector			0.117***	0.0841***	0.0230*	0.0776***
			(0.00536)	(0.00832)	(0.0118)	(0.00740)
Managerial status *(Base as not manager or supervisor)*						
Manager			0.312***	0.193***	0.202***	0.236***
			(0.00525)	(0.00701)	(0.0118)	(0.0120)
Foreman or supervisor			0.0842***	0.0448***	0.0365**	0.0511***
			(0.00651)	(0.00976)	(0.0143)	(0.00909)
Does not apply			-0.495**	-	-0.408	-0.553**
			(0.200)	-	(0.254)	(0.233)
No answer given			0.117	-0.00345	0.154	0.130
			(0.0798)	(0.0993)	(0.357)	(0.124)
Ethnic Group *(Base as White British)*						
Mixed/Multiple ethnic groups	0.00533	-0.00410	-0.00454	0.0131	0.0133	0.00695
	(0.0241)	(0.0217)	(0.0201)	(0.0311)	(0.0451)	(0.0260)
Indian	-0.0244	-0.0595***	-0.0425***	-0.00723	-0.0130	-0.0523***
	(0.0164)	(0.0148)	(0.0137)	(0.0197)	(0.0322)	(0.0194)
Pakistani	-0.200***	-0.204***	-0.144***	-0.132***	-0.0954**	-0.0780***
	(0.0248)	(0.0223)	(0.0206)	(0.0356)	(0.0459)	(0.0245)
Bangladeshi	-0.214***	-0.170***	-0.111***	-0.100	0.00439	-0.0792*
	(0.0468)	(0.0421)	(0.0390)	(0.0667)	(0.0805)	(0.0479)
Chinese	0.0826**	-0.0155	0.0189	-0.00202	0.0190	0.0415
	(0.0348)	(0.0313)	(0.0290)	(0.0389)	(0.0679)	(0.0463)
Any other Asian background	-0.154***	-0.147***	-0.0960***	-0.105***	-0.0106	-0.0380
	(0.0239)	(0.0216)	(0.0200)	(0.0317)	(0.0511)	(0.0244)
Black/African/Caribbean/Black British	-0.143***	-0.132***	-0.0959***	-0.110***	-0.116***	0.00259
	(0.0159)	(0.0143)	(0.0133)	(0.0214)	(0.0329)	(0.0162)
Other Ethnic Group	-0.148***	-0.123***	-0.0854***	-0.0903***	-0.108**	0.0122
	(0.0240)	(0.0217)	(0.0201)	(0.0340)	(0.0457)	(0.0240)
Constant	0.902***	1.482***	1.628***	1.418***	1.458***	1.544***
	(0.0325)	(0.0299)	(0.0410)	(0.0720)	(0.0781)	(0.0543)
Observations	41,584	41,584	41,584	17,856	8,050	15,678
R-squared	0.131	0.296	0.398	0.254	0.196	0.163

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1