Wage discrimination revisited – new methodologies and approaches to wage discrimination for the United Kingdom.

by

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Abstract

The thesis is a compilation of essays on labour market wage disparities. It consists of three distinct empirical chapters related to wage and gender discrimination with evidence from the United Kingdom Labour Market.

The first empirical chapter analyses wage discrimination between groups with the same academic background in the UK labour market. The chapter compares nine income quartiles for higher education graduates using the Oaxaca-Blinder decomposition techniques. The results indicate that even after controlling for different worker individual determinants, there is gender discrimination. The results show that the total pay gap decreases in higher incomes quartiles. Interestingly, the effect of internal characteristics, the explained portion of the gender pay gap, diminishes at higher income quartiles. So even though there is less of a total pay gap at higher income levels. Most of that gap comes from discrimination rather than the individual determinants between groups (graduates vs. non-graduates).

The second empirical chapter is an extension of the first empirical chapter. In the second chapter, the Oaxaca-Blinder decomposition is used to calculate remuneration amounts in a hypothetical question *"what would happen if there was no gender discrimination?".* After the remuneration amounts are calculated, the paper uses an aggregated version of the Socio-Economic Impact Model for the UK (SEIM-UK) (Input-Output multi-regional model) to model four distinct (two sectoral, two regional) scenarios. Comparing the Input-Output analysis from SEIM-UK at the NUTS1 level and ONS Input-Output at the national level, the paper finds that output could potentially increase by 0.113% to 0.980% nationally by removing gender wage discrimination in the UK labour market.

The third empirical chapter analyses the Covid-19 effects on the UK labour market discrimination. Its main research question focuses on *"How did Covid-19 affect males and females differently?"*. In particular, the paper enquires, *"who faced economic adversity during the Covid-19 pandemic?"*. To analyse these research questions, the paper merges the latest data releases from the *UK Household Longitudinal Study Covid-19* and *the UK Understanding Society Covid-19* waves. The study uses discrete choice econometric estimations to determine if the pandemic affected men and women equally. In particular, income, age, occupation, and ability to telecommute were all critical factors in avoiding economic adversity during the Covid-19 pandemic, and the results show that both genders were equally affected.

Declaration

I hereby declare that this thesis is my own original work except where stated otherwise by reference in the text. It has not been submitted, in whole or in part, for any other degree or qualification at this or any other university. Further, I have acknowledged and correctly referenced the work of others.

Dedication

This thesis is dedicated to my family.

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First, I must acknowledge City-REDI for funding my PhD. This allowed me to focus solely on my studies, and thereby has led me to learn different techniques and aspects of research which otherwise would not have been possible.

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Chapter 1: Introduction

1.1 The gender pay gap

This research undertakes three distinct empirical studies on the gender pay gap in the United Kingdom (UK). In order to fully comprehend the research, the importance and definition of the gender pay gap must be understood. This is essentially the purpose of this chapter. Firstly, the topic's importance and the general definition of the gender pay gap are discussed. Then the introduction goes from a general definition of the pay gap to a more scientific definition adding further information about specific sub-categories. Finally, the introduction section sets out the scope and structure of the thesis.

Women play a significant role in today's business and workforce in the UK. Research suggests that female labour force participation in the UK stood at 58.09% 2019, (World Bank, 2019), the highest since the records began in the 1970s. In addition, the number of full-time female workers has also increased in the previous five years (Powell and Mor, 2019). Consequently, women have become essential to total employment in the UK.

However, despite the recent integration of women into the workforce, they still face many issues in the labour market (Batool, 2020). One of the issues is known as the gender pay gap. The gender pay gap refers to the average difference between men's and women's earnings (Leaker, 2008).

Batool (2020) considers it is one of the most prominent issues of the 21st-century market economy. Subsequently, the topic, due to its importance and impact on society, has received much research and media attention (Bargain et al., 2019). Hence, a vast amount of literature addresses the topic of gender discrimination in the workplace and labour market, both internationally and in the UK.

The gender pay gap can be further divided into two categories: the non-adjusted gap and the adjusted pay gap. The non-adjusted gender pay gap refers to the gross average income difference between men and women. The adjusted pay gap considers multiple factors such as occupation, hours worked, job experience, and education. An example can best explain this. Consider a large company with over 1,000 employees with a 50/50 ratio of women and men. If the average income of men is taken and subtracted from the average income of women, we have a non-adjusted wage gap. Consider now that 30% of the women in the company are part-time whereas just 10% of the men are part-time. Of course, it seems incorrect now to compare the average salaries since we know that many women's salaries are lower than men's, not because of discrimination but simply because they work part-time. Considering these factors, along with experience, education, and others, leads to the adjusted wage gap.

It is usually agreed in the literature that the unadjusted measure is not the best (Heinz et al., 2016), for the gender pay gap since crucial factors, like those mentioned above, such as working hours, work experience and education, are not accounted for in the un-adjusted wage gap. Therefore, most studies that look at discrimination do so by considering an array of variables that affect the wage gap (such as experience, education, region, number of children, and so forth).

The unadjusted wage gap has decreased over the years. Let us take the United States and the UK as examples. Both countries saw a decrease in the raw, unadjusted gap. Blau and Kahn (2017) show that over the years in the USA, the unadjusted gap in the USA has decreased from 37.9% in 1980 to 20.7% in 2010. Similar research has been conducted in the UK using the Annual Survey of Hours and Earnings (ASHE). Office of National Statistics (ONS) finds that the gender pay gap for the median gross hourly salary in the UK has reduced from 27.5% in 1997 to 15.5% in 2020 (ONS, 2020).

This absolute difference of 15.5% cannot be attributed to discrimination. Researchers argue that wage differences are only partially the result of gender discrimination. They argue that the adjusted wage gap is a much better and comparable figure for wage differences between men and women. Hence, it is also a better measure for measuring discrimination. Therefore, discrimination comes after productivity differences are accounted for. However, even after productivity differences are accounted for, men earn more than women. For example, Heinz et al. (2016) and Blau and Kahn (2017), amongst others, find that men earn more than women even after productivity differences are accounted for.

To answer the question of how much of the wage gap is due to discrimination and how much is due to productivity is challenging. Research suggests that it is different and varies with various factors such as type of occupation, number of dependent children, and size of the company, amongst others. However, these factors are still highly relevant to understanding the gender pay gap in general and for the UK in particular (Leaker, 2008; Olsen et al., 2018).

There are two specific sub-sets of the wage gap, the "glass ceiling" and the "sticky floor". The “glass ceiling” refers to an invisible barrier for women preventing them from moving up beyond a certain level in the hierarchy. Simpson et al. (2004) researched an elite education program in an elite university to demonstrate this. The research by Simpson et al.

(2004) found that even MBA-qualified women after graduation lag in their careers as compared to their male counterparts (in term of salaries). So, even given equal education, there is still a gender pay gap. This is also evident to see in the FTSE100 list of 2018, where only 7 percent of females were CEOs (Statista, 2019). In aggregate, women, for some reason, are considered less competent (due to prejudice, negative attitude towards women managers, and, exclusive network amongst men) for a higher management position in private organisations. This, of course, affects women's productivity and motivation and, in turn, might make it more difficult for them to get a higher position (Batool, 2020).

The other sub-set of the wage gap is the “sticky floors”. “Sticky floors” can be considered opposites of the glass ceiling and refer to a wide income gap between men and women at the bottom of the distribution. One explanation of why sticky floors exist is provided by Belley et al. (2015). They argue that [1] (Arrow, 1973), especially at the start of the career, is the reason behind it. This is discussed in detail later in the theory chapter of the thesis. The authors argue that more regulation in the labour market influences the wages of low-skilled workers.

These sub-sets are separate problems in themselves and are important to understanding the details of the gender pay gap.

1.2 Research problem and overarching research question:

My thesis, ‘Wage discrimination revisited – new methodologies and approaches to wage discrimination in the United Kingdom’, can be expressed as the following over-arching question.

“How can quantitative methods be used to analyse the persistence of gender disparities in pay, even when education levels are held constant, as well as the potential benefits of reducing the gender pay gap? Additionally, how can we determine the determinants of job loss during economic adversity during the Covid-19 pandemic?.”

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[1] Statistical discrimination arises from imperfect information about a particular group of individuals. Since employers have insufficient information about a group’s productivity, they use historical statistical information on the group they belong to in order to infer productivity.

The thesis's main focus is the development of new quantitative methods to measure and assess the effects of the gender pay gap in the UK labour market. The thesis aims to highlight the underlying factors that drive this persistent issue. By using these proposed methodologies, my thesis aims to bring novel strategies to monitor and address the gender pay gap. With these, I hope to contribute to broader efforts to promote gender equity and social justice.

1.3 Novelty of the thesis:

The thesis contributes to the literature on gender discrimination in the labour market by using novel data and methodologies to provide greater insights into the determinants of wage inequality and economic adversity. The thesis's empirical applications of the analysis of gender discrimination in the UK labour market offer valuable contributions to the field, and its findings can help inform policy decisions aimed at promoting greater gender equality and reducing economic inequality.

Each paper provides a unique perspective and methodology to the analysis of gender wage discrimination, with a focus on highly educated labour markets, regional analysis, and the impact of a global pandemic. By expanding the granularity of data and exploring the sources and nature of the gender pay gap, these papers provide new insights into the persistence of gender inequality despite higher education and the importance of considering regional variations. Furthermore, the papers offer theoretical and practical implications for policymakers, employers, and researchers in gender inequality and labour economics.

Chapter 3 adds to the literature by expanding the understanding of gender wage discrimination in highly educated labour markets with a high level of data granularity. Specifically, the paper adds to the knowledge of the presence of glass ceilings and sticky floors for the highly educated labour market. At the same time, the paper provides greater granularity in determining how the effect of discrimination changes along the income distribution. The paper's novelty also lies in the granularity of its analysis; it analyses the cross data of individuals with a similar background (graduates) but at different quartile levels to observe potential wage disparities.

The study gains uniqueness by evaluating individuals with a similar background (graduates) at nine income quartiles, providing insight into the sources and nature of the gender pay gap across the UK for graduates. Specifically, it examines the existence of glass ceilings and sticky floors across the entire wage distribution, which addresses a fundamental question:

can the wage gap be attributed to differences in returns to characteristics of graduates (discrimination), or is it down to labour market characteristics that we observe in the two sexes?

The study finds that despite achieving higher education, UK female workers do not escape discrimination, challenging the common belief that higher education eliminates the gender pay gap. The paper also highlights the increasing trend in the highly educated population, where the overall gap has decreased. Still, the discrimination component needs to be. This is in contrast to the overall population.

Chapter 4 contributes by introducing multi-regional input-output modelling techniques to analyse the wage gender gap in the UK labour market. The chapter uses the novel Socio-Economic Impact Model (SEIM) multi-regional input-output model for the UK to analyse wage discrimination scenarios using an underexplored methodology (Ghosh). It sets a case for using the Ghosh model, specifically when under-utilized potential or discrimination effects (as in this case) are involved. An argument for the use of Ghosh to be incorporated when analysing changes in value-added such as seen with the compensation of employees is incorporated in the chapter. It also proposes a new method to balance the resulting output of the Ghosh model.

The paper is also novel due to the model it uses. The paper uses the multi-regional UK Socio-Economic Impact Model (SEIM-UK). The SEIM-UK provides the ability to conduct a regional analysis at the NUTS 2 level. This is demonstrated and used with Regional Scenario 1 and Regional Scenario 2 (henceforth known as RS#1 & RS#2). Since this regional disaggregation is not presented with the national input-output model of ONS, the paper simulates RS#1 and RS#2 using the SEIM-UK model only.

This Chapter is also novel as it compares (by aggregating Standard Industrial Classification (SIC) codes) two input-output models for sectoral scenarios (SEIM-UK and ONS IO). This provides a comparison between the models and the eventual results alongside robustness. This also allows future researchers to get output from the two models and compare it. The paper proposes aggregating the SIC codes from ONS 64 sectors IO to SEIM-UK 30 sectors.

Another novelty of the paper is using female wages instead of female labour force participation (FLFP) to approximate an increase in GDP. The thesis uses female wages to calculate and approximate the effect on GDP. The methodology used in this paper is similar to that commonly employed in minimum wage research, where a hypothetical increase in wages is estimated, and its impact on the Gross Domestic Product (GDP) is analyzed. This approach involves approximating the potential effects of a wage increase on economic outcomes, which is akin to the approach taken in this study to estimate the influence of various factors on job-related outcomes. However, the methodology of minimum wage calculation differs from this paper in that it applies just to low-income workers and is not just subject to females.

Chapter 5 also provides much novelty, mainly due to the time component of the paper. The study is novel as it was one of the earliest studies to look at economic adversity during the early periods of Covid-19 and uses the April 2020 Covid-19 UK Understanding Society survey wave. The study is novel in its approach (taking a gendered perspective of economic adversity in the UK). It uses (relatively) recent data to analyse the impact of Covid-19 on gender in the UK. The study is limited because it analysed just the early part of Covid-19 (April 2020); (this reflects data availability at the time of the analysis). The paper provides evidence that young people with low incomes were the most likely to face economic adversity during the pandemic. Being in a key sector was the highest contributing factor to an individual being safe from economic adversity.

The paper adds to the theoretical literature by supporting Becker's theory through its findings. One of the interesting findings of the study was no gender discrimination in the early days of Covid-19 regarding layoffs and furlough. Correlating the results with the theoretical frameworks substantiates the argument by Becker's (1971) theory of taste of discrimination. This result substantiates Becker's theory because the early phase of Covid-19 represented a "panic" decision by firms to let go of individuals and save themselves. This "panic" caused the firms to act rationally, and based on that, we see no evidence of discrimination in the early days of the pandemic. So when "panic" set in, firms behaved more rationally as opposed to the gender gap, which we see, providing support for taste-based theories and credibility to those stating that the problems about gender are in hiring systematic or taste-based discrimination. The study adds to the novel and ever-growing literature on Covid-19.

1.4 Motivation:

My fascination with the issue of the gender gap began when I first read about the neo-classical theory of economics. The theory focused on the free market and relied on supply and demand as the optimal forces for equality in the labour market and beyond. Hence, it seemed quite unusual to me how despite these very principles, the gender pay gap still existed in the labour market, with women earning less than men. I found this discrepancy fascinating, which sparked my initial curiosity to study the topic in the first place.

I was particularly fascinated by the free labour market in most of the world and the UK, where theoretically at least, employees are paid based on their productivity, experience, and skill. How, then does the pay gap still exist? Hence, I wanted to study and understand the gender pay gap and how it co-exists with the principles of the free labour market. I also wanted to find out how this has perpetuated over time. This all led me to explore the academic literature on the topic, and I began to study and understand the different facets of the gender pay gap.

As I continued to do my research, I began to realise that many factors are responsible for the gender pay gap. These include cultural and social biases, differences in education, experience and discriminatory hiring practices, amongst others (See chapter 2 for a detailed discussion on the topic). While I was learning how much of a multi-faceted problem the gender pay gap is, I also learned that it could have significant social and economic implications for women regarding issues such as reduced retirement savings, increased poverty rate and lower lifetime earnings. Hence, the more I learned about the topic, the more I realised how important it is to bring gender equality into the workforce. I became passionate and excited about conducting research to understand the causes and the eventual consequences of the gender gap. All this is in an effort to ultimately identify and bring insights to the wage gap issue to eliminate it.

This interest in the topic has driven me to pursue this thesis. I hope this thesis will make a meaningful contribution to this topic and provide unique and actionable insight to bridge the gender pay gap. This is my overall motivation for doing this thesis. The reason is given later in the thesis for the selection, motivation and timing of each of the three individual empirical chapters.

The first chapter of the thesis, which focused on the wage gap for educated individuals, was selected for two particular reasons. One is the increasing costs of education, and the second is due to more women than ever obtaining higher education. This led to the first chapter, which focused on a detailed nine-income quartile distribution for equally educated people along with a time component to see whether the wage gap has increased or decreased over time. Another aim of this chapter is to investigate how the wage gap in highly educated individuals differs from the general labour market and to identify sticky floors and glass ceilings. These aims serve to highlight whether, even after obtaining high levels of education (a recent societal change) women have achieved gender parity. The first chapter also helps to support the empirical work in the second chapter, as remuneration amounts in the second chapter are determined by the Oaxaca-Blinder decomposition. So, the first chapter also serves as a gateway to the second empirical chapter.

For the second empirical chapter of the input-output model, I was particularly interested in exploring the benefits and impact of reducing the gender wage gap in the UK at a regional level. This was made possible due to my access to the first multi-regional input-output model of the UK developed by City-REDI. This state-of-the-art model allowed me to investigate the potential effects of no-discrimination and reduced discrimination scenarios across different regions of the UK. It also allowed me to see other sectoral effects at a multi-regional level, which was impossible before. Furthermore, I was interested in finding out empirically how much the UK would benefit if women were paid the same as men. Using the multi-regional Socio-Economic Impact Model (SEIM), I could estimate the potential effects of such a scenario on output and employment. This provides empirical insight into the economic benefits of bridging the wage gap at regional and national levels.

Another factor influencing my choice of the second chapter was that I wanted to compare the multi-regional input-output model with the Office for National Statistics (ONS) input-output model. This comparison would increase the robustness of the findings and instil greater confidence in the results, alongside checking how close or far the models are to each other in terms of their results.

Initially, I had planned for the second chapter to lead into a third chapter on computer-generated equilibrium models. However, the unforeseen onset of the Covid-19 pandemic changed this plan. When the pandemic happened, I returned to my home country and my supervisors and decided to change the third chapter (since I did not have access to many resources required for the CGE model). Hence a decision was taken to pivot the third chapter to examine Covid-19 and economic adversity with a gendered lens.

This decision was motivated by a desire to provide a timely and relevant contribution to the ongoing discussions surrounding the pandemic's economic fallout (specifically regarding gender). By examining how the pandemic has affected genders differently, we hoped to shed light on the unique challenges faced by women in the labour market during this crisis. (Further details on this can be found in Appendix 1).

1.5 Structure of the thesis:

The thesis is structured as set out below. The next chapter, "Theories of labour discrimination," sets the background for all chapters that succeed. The chapter summarises of efforts made by international organisations, governments, and firms to combat gender discrimination. This is followed then by the three empirical chapters.

The first chapter, titled “Gender pay gap for graduates in the United Kingdom – An Oaxaca-Blinder decomposition approach at nine income quartiles", introduce the reader to a national analysis of the wage gender gap decomposition. The second chapter, titled “What would happen if female wages became equal to males? A Socio-Economic Impact Multi-Regional Input-Output Model (SEIM-UK) application - A methodological case for a Gaussian approach”, by the use of scenarios, compares the situation of a more gender-balanced pay structure in the UK labour market. The third empirical chapter, “Determinants of economic adversity for men and women in the United Kingdom during early stages of Covid-19”, compares the labour market situation for women and men in the UK during Covid-19. Finally, chapter 6 provides an overall conclusion to the thesis.

1.6 The scope of the thesis

The first empirical chapter poses the question: “For males and females with higher education (i.e., educated to at least graduate level), what is the gender pay gap?". The question is expanded further in the paper by analysing not just the mean gap, but the upper-income quartiles and lower-income quartiles as well. Hence, the question becomes, at *different income* *quartiles* for males and females with equal education, what is the gender pay gap? The paper uses nine income quartiles to answer the question.

The topic of the gender wage gap extends beyond just the individual. It is also important from an economic point of view. The gender pay gap can reduce the economic output of a country and can (further down the line) cause problems for the country in terms of females being more dependent on the state with welfare payments (in old age). This reduced or missed economic output forms the basis for the second chapter of the thesis. The second empirical chapter asks, "What would happen if there was no gender discrimination in the UK?". The paper measures this lost economic outcome using two input-output models. First, it uses the multiregional input-output model built by City-REDI (at a higher granularity) that is aggregated to NUTS1 level. Secondly through the ONS model, which is a national IO model. created by City-REDI and the Office of National statistics. The paper makes a case for the Gaussian inverse method in input-output to find the economic outcome for the United Kingdom under four different scenarios of no gender discrimination. The paper finds that output can increase by 0.113% to 0.980% nationally because of removing gender discrimination.

The third empirical chapter of the thesis reflects the occurrence of Covid-19. Continuing with a similar theme to the earlier two papers, the third paper asks: "*Did gender inequality increase due to Covid-19?".* The paper expands on the question further down the line and looks at "Determinants of economic adversity during the early stages of Covid-19". This study is unique in that it focuses on the gender dimension in the context of economic adversity during Covid-19 times (and the data used reflect challenges faced during Covid-19 lockdown restrictions and their aftermath). (Appendix 1: Role of Covid-19: Explanation of third empirical chapter provides the reason and rationale behind the selection and writing of this chapter). To answer these questions, the paper uses a merged data set of the Understanding Society Covid-19 and the UK Household Longitudinal Study Covid-19. The paper finds that men and women were more or less equally affected by the pandemic. Income, age, occupation, and ability to telecommute were all key factors in avoiding economic adversity during Covid-19 times.

Chapter 2: Literature Review - Theories of Labour Discrimination

2.1 Introduction

This chapter discusses different theoretical schools of thought regarding labour market discrimination. The theories discussed serve as a guide to understanding why despite an emphasis on market efficiency and government legislation, discrimination in the marketplace still exists. After providing an overview of the discrimination theories, a note on the ethnic pay gap is provided (and how it relates to gender discrimination). Then practical tests for these theoretical models are discussed, and a summary of the current literature on real-life scenarios of discrimination is provided. Finally, efforts made by the governments, unions, and different organisations are discussed to combat discrimination. The themes and theories presented in this chapter run through all three of the empirical chapters and hence are extremely important to the thesis.

2.2 Overview of theories of discrimination

All theories of labour market discrimination have come about because the neoclassical model has failed (A. Smith, 1776). According to the neo-classical economic theory, if markets were to be left alone (*laissez-faire*), they would self-correct and eradicate all discrimination on their own. However, this has not happened. The pay gap between gender and ethnicity has persisted over time. Due to the persistent pay gap in the marketplace, different theories have emerged, explaining why and how it could remain when neo-classical points to the opposite.

There are two pioneering models of labour discrimination: 1) Taste and preference for discrimination (Becker, 1971) - in these types of models, there is an inherently racist and sexist element to the wage gap; 2) Statistical discrimination (Arrow, 1973; Phelps, 1972) models - these models attempt to explain the problem by asymmetric information (Lang and Lehmann, 2012). These models explain why even when firms are assumed to be acting rationally, wage discrimination might exist. These are arguably the two most predominant theories in the literature for the economics of discrimination. Both of these have been built upon years of research.

Becker (1971) led the work on the economics of discrimination. Arguably, Becker developed the first economic model of discrimination in his seminal work: the taste for discrimination model. In taste for discrimination, Becker argues that there is an unpleasant characteristic relating to dealing with minority female workers; many employers want to avoid interacting and dealing with minority (ethnic groups) and female workers. Becker argued that this bias would result in not hiring certain ethnic groups and females. In these models, he argued that people with specific characteristics form a group. Then that group acts against another group causing discrimination. Becker's theory also argues that employers are willing to let go of profits to do this. Hence, the discriminated worker has to "compensate" by being extra productive for her/his employer. The discriminated worker has two choices: he/she can either be extra productive or work for a lower wage.

Interestingly Becker (1971) argued that the reason for discrimination is best left to sociologists and psychologists rather than economics. Becker (1971) himself was only interested in the result of this discrimination. However, the earlier version of the theory came into heavy criticism as the theory predicts that firms that practice *taste-based* discrimination are going to be less profitable compared to non-discriminating firms.

Even though Becker's model explains current discrimination, it does not explain the persistent wage gap since the model predicts that firms will let go of profits and hence be overtaken by non-discriminatory firms. However, this did not happen, and questions started to emerge as to why. Arrow (1973) provided the answer in part to some of these questions. He extended the Becker model and argued that because white employees dislike working with non-white employees, the other workers are relegated to just poor-paying jobs. These discriminated workers have a higher productivity level compared to the job (and pay) they are earning. This, in turn, leads to increasing the productivity of the entire workers on average in the firm. This enables the white workers and firms to benefit from these discriminated workers. The firms and white workers both benefit at the expense of the discriminated worker; the firm gets to keep its profits, and the white workers benefit from overall increased productivity.

Further support for taste-based models is provided by Akerlof (1985). He answers this criticism of firms losing profits by arguing that there is a social custom amongst businesses for discrimination. He argues that since everyone is a trader and markets are assumed to be small, discrimination can persist. Anyone who violates this social custom of discrimination will be punished by the discriminatory group by boycotting the business. Even if the number of boycotting firms is few, the non-discriminatory business will experience a loss of profit. So, if a firm becomes non-discriminatory, that firm loses profits and businesses. Hence it is in its economic interest to keep up discriminatory behaviour despite the majority of the business being unprejudiced.

In sharp contrast to the taste-based models are models presented by Arrow (1973) and Phelps (1972), who argue that inequality in the labour market is due to imperfect information. These models are known as *statistical discrimination models,* which contrast with a taste of discrimination which uses sexism and racism to explain the labour market condition. The statistical discrimination theory models first assume that economic agents are non-prejudiced and rational. The theory assumes that since the employer has imperfect information about the applicant, the employer uses statistical information to infer the productivity of the applicant. Here history, perception, and social standing come into effect. So, if the minority group is less productive historically, each individual in it is presumed to be less productive. This causes discrimination. This can lead to a vicious cycle where the discriminated group is always discriminated against. This can, over time, lead to the people from the discriminated group being discouraged from participating in the marketplace or from investing in education (since their average return is going to be less than for the non-discriminated group). Another important inherent assumption of statistical discrimination is risk aversion. The employer always goes for the individual, given a choice of two almost equal candidates, for the one that has previously been shown to work. For example, if white people make for better workers than black people on average, we should, given similar characteristics of an individual, go for a white worker.

The imperfect information theory is another theory that does not rely on prejudice but explains the wage gap through lack of available information Arrow (1973). Arrow argues that there is an informational and transactional cost to employing an individual. He expanded on the statistical discrimination theory. He argued that employers already have a stereotype of worker characteristics to reduce the cost of information that is required to make a full decision on hiring. His model relies on the fact that the screening process for hiring a new worker is costly and risky. So, employers use pre-based group stereotypes to help with the decision.

Some of the stereotypes are an expectation of productivity which is used as a proxy for future work. A presumption of lack or low education based on skin colour and/or gender (Darity and Nembhard, 2000) causes wage differences to remain despite identical productivity. Borjas and Goldberg (1978) criticize Arrow's theory, arguing that it has left out a critical source of wage difference: productivity. Arrow’s model does not take into account actual productivity; his theory can explain the wage gap even without considering productivity levels.

Another popular theory is presented by Barbara Bergmann (1974). Her theory, called the *crowding model,* takes history into account and argues that since women were once not allowed in many occupations, they are crowded into a limited number of remaining occupations. This leads to lower wages in those particular *crowded* sectors. This argument is explained using the labour supply and demand curve. Bergmann explains that since the supply of workers for these jobs is high, wages are comparatively low. Although easy to understand on the labour market supply and demand graph, the phenomenon itself is challenging to understand and explain in real life. The inherent fundamental economic assumption of the model is that the surplus supply of females in particular fields is leading to low wages. This means that occupations that are predominantly hiring women workers will be characterized by lower wages. However, this raises a question. *Would not wages for men be low as well in those particularly crowded occupations, thereby effectively eradicating the gender pay gap specifically in those occupations?* Bergmann's arguments against this are that there are very few men coming to these overcrowded female jobs, and the labour market should be looked at as a whole, not divided by occupation. The theory is useful to understand why in the entire labour market, females earn less than males. The theory does not answer the fundamental question concerning why certain occupations have female crowding.

Breen and Garcia-Penalosa (2002) propose an answer to this. They look at the market from the perspective of the individual entering the labour market. These individuals have imperfect information about the labour market and base their career choices on previously held beliefs. Past differences affecting current generations are the underlying assumption in their model. Career choices of women and men are based on their observations of previous generations, which results in, and maintains, crowding.

One of the most controversial views on the gender pay gap is from Farrell (2005). Farrell argues that women pay the price for seeking a less risky, more flexible, and fulfilling career. These jobs typically tend to pay less. He gives an example of a librarian, which is a white-collar job earning less than someone who is a sanitation worker (despite the librarian having a graduate degree), and the sanitation worker having none. The sanitation worker is compensated extra for his work due to the problematic nature of the job, plus the unpleasant conditions. According to Farrell, the pay gap is a myth, and women earn less because of their lifestyle choices which affect their ability to earn a high wage. In his book "Why Men Earn More," he gives concrete steps for any woman to increase their wages. Amongst his recommendations are that women need to choose a career with a higher emotional and financial risk, such as a venture capitalist. They should seek out more specialised fields, such as a surgeon, and relocate if the company asks. He rejects the idea that women are discriminated against in the marketplace altogether and maintains the reason for the low payment for women is choices rather than discrimination.

Another famous theory regarding wage discrimination is called *monopsonistic wage discrimination* (Robinson, 1969) (or *Robinsonian Discrimination*). Robinson was the first to coin the term "monopsony" demand-side of the standard economic term monopoly, which means a market with a single buyer. This refers to the power of a monopoly in setting up wages. She argued that female wages are more inelastic as compared to males; hence females earn less as per their productivity levels. Farrell (2005) also found this in his research. The wage setters (which are the companies) can take advantage of this fact and keep the wages of females lower.

Monopsonistic wage discrimination provides an economic analysis of why the gender wage gap persists, even after accounting for the productivity of workers. Since the companies can earn a profit utilizing this fact (women being less sensitive to pay), the pay gap continues to exist, and companies continue to exploit female workers. Here, it is essential to note that the underlying motive is not prejudiced against women as is the case with taste-based discrimination; instead, the motive is profits. So even if all sexism and racism were to disappear, differences in pay might continue to exist. Table 2.1 summarizes the most popular theories in the literature.

Table 2.1 Theories of discrimination

Theory	Founder	Advocates and Supporters	Brief Explanation of Theory
Neoclassical	Adam Smith (1776)		The labour market will eventually eradicate discrimination in the long run and should not be intervened with.
Statistical Discrimination	Arrow & Phelps (1972)		Employers have imperfect information about individuals they interact with. Even though employers are rational. e.g. home mortgage against African Americans
Taste for discrimination	Becker (1957)	Holzer and Ihlanfeldt (1998)	Employers don't want to interact with minority groups and/or females and don't hire them. This reduces their employability options. They become more willing to work for less.
Asymmetric information	Ichino (2002)		Agents have insufficient information to make optimal choices and hence apply the rule of thumb, e.g., a white skin colour person is more educated.
Bounded rationality	Ferguson (1992)		The decision-making capacity of humans cannot be fully rational because of the number of limits that we face. Females are less productive than men assumed, and then that assumption is never challenged, as it would require work and decision-making resources. So optimal decision is ignored.
Principal/agent	Maskin and Tirole (1990)		The principal (Shareholder) has different values than the agent (manager). Prejudice by the manager may affect hiring the best person available.
Robinsonian discrimination	Joan V. Robinson (1934)	Boris Hirsch (2016)	Employers are exploiting their wage-setting power over women—rather than any sort of prejudice. Also known as "Monopsonistic" wage discrimination

To make matters more complex, innate personality differences have a role to play in the gender pay gap. In psychology, there is a conceptual link between labour market outcomes and personality traits. The conceptual framework is based on the *five-factor model* (also known in the literature as "*the big five*") (McCrae et al., 1985). The big five traits, as defined in the literature, are conscientiousness, agreeableness, openness to experience, extraversion, and emotional stability. Conscientiousness is defined as the ability or tendency to be hard-working, disciplined, organised, responsible, and efficient. Agreeableness is the tendency to be forgiving, cooperative, compromising, altruistic, tolerant, and trusting. Openness to experience is the inclination toward being open to new cultures, ideas, and aesthetic experiences; this is primarily characterized by being imaginative, broad-minded, curious, and creative. A person's inclination and interest toward the outer world and things, represented by being social, talkative, and active, defines *Extraversion.* Emotional stability is the degree to which an individual's emotional reactions are predictable and consistent - this is shown by being eventempered and calm. Agreeableness and conscientiousness are the main predictors of earnings amongst the big five. The gender-based studies that evaluate these differences show a consistent pattern. They found agreeableness and conscientiousness both positively correlated with the earnings of an individual.

Braakmann (2009), Nyhus and Pons (2012) both applied decomposition analysis and found that women have a higher level of *agreeableness* than men. They discovered that agreeableness leads to lower lifetime earnings for an individual. Furthermore, Mueller and Plug (2006) discovered that exhibition of the trait of agreeableness in women is penalized more in women than men. In many studies, conscientiousness was found to be positively correlated with earnings (Barrick and Mount, 1991; Furnham and Cheng, 2013; SunYoun and Fumio, 2014) . More recently, Janowski (2018) found that lifetime earnings for both females and males have a negative association with agreeableness and a positive association with extraversion and conscientiousness. One contrary study to this is by Heineck and Anger (2010), who found that agreeableness of women over the long term can have a positive impact on earnings.

2.3 Why the chosen themes are relevant to the gender pay gap?

The issue of unequal pay between genders is at the heart of this research, and the thesis primarily revolves around that. Explicitly, this study aims to explore different aspects of gender discrimination in the labour market; to identify areas of inequality and help to eliminate or mitigate them.

The first empirical paper focusing on the Oaxaca-Blinder decomposition examines whether labour market discrimination for women still exists in the UK labour market, even if education levels are kept constant. This is highly relevant as it helps to identify the main source of the pay gap between women and men. The decomposition aids us in understanding the factors that contribute to the gender pay gap, such as employee experience, hours worked disparities or occupation belonging.

Using Oaxaca-Blinder decomposition with nine- income quartiles for individuals with similar educational backgrounds allows us to have more of a granular and nuanced understanding of where the pay gap varies across the income distribution. Another important aspect of using Oaxaca-Blinder decomposition at nine income quartiles is its use to uncover whether sticky floors and glass ceilings exist in the UK. Therefore, this method of analysing individuals with similar backgrounds with a nine-income quartile disaggregation provides a more comprehensive understanding of the pay gap in the UK labour market, which is vital for assessing, designing and implementing policies to address this issue.

Furthermore, the paper uses time element components by taking different waves of the UK Understanding Society Survey data to capture how the gender pay gap has changed over time for the highly educated group. By conducting a detailed assessment of different time periods, the paper helps examine how the gender pay gap has shifted and how it has varied for the selected three periods.

The second paper uses an Input-Output model in a hypothetical scenario where gender discrimination is eliminated from certain selected regions and sectors in the labour market. This paper is extremely relevant to the gender pay gap as it shows how reducing the gender pay gap would be advantageous for the whole society, not just women.

The input-output model highlights the supply chain, inter-industry linkages and the multiplier effects of eradicating gender discrimination in the labour market. It also shows how it can benefit the broader society. This proves how gender equity is not just related to social justice but also has widespread implications for the development and growth of a country. In the case of London (regional scenario) and the professional and scientific sector (sectoral scenario), the paper shows how reducing the wage gap impacts the demand and output across multiple regions and sectors. By following these specific sectors and regions that are affected, the model can advise policymakers about the potential effects and trade-offs associated with various policy interventions to promote gender equity in the labour market. This can serve as valuable insight for policymakers as it allows them to focus their efforts based on the highest-yielding sectors and regions for gender inequality in the workforce in the United Kingdom. The second paper hence provides empirical evidence of the role that gender equality has on both economic development and prosperity.

The third paper continues analysing the UK labour market by focusing recent evidence about the probability of job loss during the early months of the Covid-19 pandemic, with special focus on gender.

The study sheds light on how the pandemic affected men and women differently in the labour market. It provides valuable information and insight into how women's and men's experiences varied during the pandemic. The findings suggest that even though women were not disproportionately impacted by Covid-19 (when it comes to job loss), the unique challenges they shared regarding mental health, child-care and housework were different from men. The study overall found that for both genders, the main determinants of economic adversity were being a key worker, the ability to do their job remotely and occupational differences. The factors identified in the study bring attention to the issue of the gender pay gap, as they highlight the common occupational classifications that exist between men's and women's jobs. Specifically, women tend to be overrepresented in certain occupations, while men are overrepresented in others. This underscores the need to address the underlying factors that perpetuate gender-based occupational segregation and its impact on unequal pay between genders. The results suggest policymakers look at the promotion of remote work and occupational categorisation as an important strategy to maintain the genders being disproportionally affected by another pandemic.

In conclusion, all three chapters, even though unique in their methodologies, follow the theme of the gender pay gap and aim to provide possible insights to policymakers as to the avenues to reduce it.

2.4 Ethnic Pay gap

The arguments for the ethnic pay gap are similar to those for the gender pay gap (on which there is much more literature). MacKenzie and Forde (2009) argue that keeping workers' pay low is difficult unless there are conditions of insecurity, temporal, and causal work. They argue that these types of work are usually over-represented by minority groups. Similar to the crowding effect mentioned earlier, they argue that most companies cannot discriminate (since it is illegal) amongst jobs that are seen as equal. Thus, they have sorting processes whereby minority groups end up in low-paying occupations. e.g., a teaching assistant rather than a full classroom teacher. So, bias or discrimination is against entry/promotion into certain higher-level occupations. This leads certain ethnic groups into certain occupations which are low-paying, and hence the ethnic pay gap exists.

Although there are certain similarities in theories of gender and ethnicity, some marked differences can also be noted. The first significant factor is family commitments. Family commitments often lead women to accept work with lower wages (Hakim, 2000). They also place constraints on many opportunities in the marketplace that require relocation. These factors are not necessarily relevant to the case of ethnicity.

Interestingly, immigration policy might also be a factor in this. Many minority ethnic groups are immigrants with specialized skills that are needed. This might result in these ethnic groups being in high-paid professions. Despite these factors, occupational discrimination remains a relevant issue for both ethnicity and gender. A complication in all this segregation is the question regarding *whether this segregation is positive or negative?.* Hakim (1996) argues that, at least in the case of women, the answer is clear. Segregation is detrimental since women are not working in different occupations than men but merely have a lower ranking or lower-paying job in the same occupation as men. Another argument is presented by Elliott and Lindley (2008) for ethnic groups; in supporting the segregation argument, they find polarizing evidence amongst immigrants. They find that immigrants are overrepresented in both low and high-paying jobs.

Brynin and Güveli (2012) make a crucial distinction in this regard. They divide the pay gap into two categories, across occupation (pay differences in different occupations) and within occupation (pay differences in the same occupation). They argue that if there are observed differences within the occupation in favour of white (British) employees, then this might be the result and evidence of wage discrimination. If, on the other hand, the reason for the pay gap is mostly occupational differences, then the reason for the low pay is segregation (minorities working in lower-paid occupations). This distinction is much clearer in theory than in practice. For example, there might be a clustering of ethnic groups in high-paying professions, which would make the average pay higher for ethnic groups. However, these workers might be within the occupation pay gap (pay gap for the same type of job). On the other hand, in a low-paying occupation, there might be no within occupation pay gap since the job is already close to minimum wage.

2.5 Testing theories of discrimination

The extensive theoretical literature on labour discrimination has been followed by attempts to test them empirically. Since none of the theories explain all variations observed in society, real-life testing for theories of discrimination remains very difficult (Olsen et al., 2014). The main reason for this is that in real life, a multitude of the factors described in the theories co-occurs. For instance, in practice, it is tough to distinguish between statistical discrimination and discrimination arising from prejudice. Some selected attempts to capture different theories of discrimination are mentioned below.

In experimental economics, *audit studies* are commonly used to see whether taste discrimination exists or not Altonji and Zhong (2021). Audit studies are studies where the researcher trains an employee such that all characteristics match the characteristics of another person except the one being under question, that is, discrimination. The "auditors" then send out their applications for jobs and check for discrimination. The primary purpose of the audit study is to see whether equally qualified individuals get the same or equal access to jobs as other demographic groups or not. One of the interesting experiments in this regard was conducted by Fershtman and Gneezy (2001). The experiment was conducted in Israel, and two groups were formed. One was the ethnic minority group which comprised of Asian and African immigrants in Israel. The second was of European and American immigrants (white group) in Israel. They paired ethnic minority group individuals with white individuals in a series of strategy experiments. Through these experiments, they were able to ascertain that white people tended not to trust people of eastern origin, which they labeled as "incorrect stereotyping."

Another interesting approach to pinpointing discrimination in real life involved the game show *The Weakest Link* on television (Levitt, 2004). In the show, players cast a vote against each other and fight for a winner take all prize. The player who gets the majority of the vote must leave the show. In earlier rounds, it is beneficial to vote for the weakest competitors, whereas in later rounds, the strongest competitors become the logical choice as targets. So, both the information-based and taste-based theory can be tested. Controlling for other factors, both theories predict that discriminated groups will get more votes than non-discriminated groups in earlier rounds. In later rounds, the statistical model predicts that fewer votes will be cast for the targeted group, whereas taste-based models predict that the targeted group will continue to get excess votes. The authors found evidence in the US case (although small) that there is information-based discrimination against Hispanics (meaning that other players assume/perceive that they have low ability). Taste-based discrimination was found against older people. No evidence of any kind of discrimination was found against black people and women.

In a recent study conducted by Ahmed and Hammarstedt (2021), an experiment was conducted with 1,406 university students from Sweden to discover whether people's decisions were affected by the sex and ethnicity of potential coworkers. This was to test Becker's taste for discrimination theory, as mentioned above. The experiment asked university students to state the lowest starting salary they would be willing to accept for a job at a campus food truck. They would be working alongside the owner of the truck. The sex and ethnicity of the owner were randomised across participants. Results showed no sign of prejudice for both interest in the job and minimum starting salary.

Pager et al. (2009) conducted a study to analyse discrimination using a field experiment for low-wage workers in New York (USA). They recruited black, latino, and white job applicants. The applicants were given equivalent resumes and asked to apply to hundreds of data entry jobs. In their study, they collected additional qualitative evidence from the applicants, allowing the researchers to see subtle yet systematic discrimination. They characterized this systematic discrimination in three distinct parts: shifting standards, race-coded job channeling, and categorical exclusion. The categorical exclusion was an immediate rejection of a minority (in this case, black) candidate for a white one. Shifting standards reflected cases in which employers viewed the same qualification levels/deficits and strengths differently based on the applicant's colour. Race-coded channeling went beyond hiring and was linked to occupational segregation. The minority candidates they observed were steered towards jobs that required greater physical strength and less customer contact.

Pager et al. (2009) noted a categorical exclusion case in which one of their black applicants, named Zuri, was asked to leave along with two other candidates (one Latino and one white male) only to be called back later in the office. Zuri explains, "All three of us went over….. She looked at me and told me she 'needed to speak to these two' and that I could go back" (Pager et al., 2009, p. 787). Zuri went back while the other two candidates were both asked to report back at 5 pm to start work on the very same day. Simon, the white applicant, later remarked that the women interviewer asked them to stay behind to sign something. "So as not to let them know she was hiring us. She seemed pretty concerned with not letting anyone else know." (Pager et al., 2009, p. 787)

However, all these experimental and audit studies are not real-life situations. The major criticism regarding these studies arises from the fact that they lack critical information on productivity (for audit studies) and do not represent the actual population (for experimental studies). Self-reported studies and questionnaires are also criticized since there is a perceived stigma of being racist. So even though people might be racist, they are not likely to show themselves to be so in a public survey, questionnaires, or any public forum (Dustmann and Preston, 2001). That is why most economics studies tend to focus on the actual labour market data and empirical evidence attempting to account for productivity differences.

2.6 Combating Discrimination

To combat the effect of discrimination that firms may have on employees, many countries developed Equal Pay Acts and Anti-Discrimination Laws, e.g., United Kingdom

Equality Act 2010, Sweden 1980 Equal Opportunity Act, Israel 1998 law for option equality at work. In contrast, other countries provide the right to equal pay in the constitution, e.g., Spain constitution article 35, Finland 1995 constitution. The United States has the Equal Pay Act (EPA) 1964 that prohibits employers from discriminating against ethnic groups and sexes.

The UK government has been especially active in combating discrimination. The government has taken active steps to stop this discrimination through legislation, notably the Equality Act 2010, which provides equal rights to all women in the workplace. However, realizing this is not enough, further laws to deter gender discrimination have also been implemented in the UK. According to later legislation (effective from April 2017) in the UK, a company with 250 or more employees is required to publish gender pay gap data each year. This serves two purposes: one, it directly tackles the gender pay gap, and second, it removes phenomena such as glass ceiling. According to a study by the UK Office for National Statistics (ONS), ever since the Equal Pay Act of 1970, the gender pay gap has narrowed, and the overall gender pay gap has been reduced. However, it still exists and persists (Olsen et al., 2018).

Unionization is another channel to fight this discrimination. A case for unionization is made by Blau and Kahn (1997). They find that countries with high unionization have lower wage dispersion, and it might imply a lower wage gap (Blau and Kahn, 1997). On the contrary, Booth and Francesconi (2003) argue that even with more trade unions, the gender pay gap is bound to remain. Since women are less likely to be members of trade unions than men, trade unions uphold the agenda for males much more than females. On top of that, trade union representatives themselves are males Booth and Francesconi (2003).

Arulampalam et al. (2007) argue that unions are less interested in members at the lower end of the wage distribution. Interestingly, they find that national minimum wage increases profoundly affect the wage distribution at the lower end of the distribution. Furthermore, they find that such policies reduce sticky floor effects. However, despite all efforts by unions, individuals, and the government, the gender pay gap persists.

In the private sector as well, the gender pay gap issue is gaining prominence. At the same time, the realisation that discrimination can be unintentional or, at the very least systematic is growing (Bertrand et al., 2005). Since outright discrimination against ethnic groups or between the sexes (and on other protected characteristics) is illegal, there are underlying structural issues within organisations that cause wage gaps. In the last twenty years, there has been a focus on providing equal opportunity policies to combat discrimination alongside legislative acts (Dobbin et al., 1993). This is an active initiative in which firms are encouraged by policy to review their practices and actively attempt to remove discriminatory organisational procedures (Equal Opportunity Act (EOC), 1998). The definition of equal opportunities, entails making political and philosophical assumptions. The objective can range from equal opportunity policies that ensure equal representation of each sex or demographic at different hierarchies to giving workers an environment where they can perform to their maximum potential (Jonsen et al., 2015). The International Labour Organisation (ILO) definition of equal opportunities is "a commitment to engage in employment practices and procedures which do not discriminate, and which provide equality between individuals of different groups or sex to achieve full, productive, and freely chosen employment" (ILO, 1998, p. 109).

There is significant controversy on how to go about implementing equal opportunities policies. Policy approaches can take two routes: equality of results and equality of opportunity. The equality of opportunity approach includes firms adopting standard procedures like actively recruiting certain ethnic groups and women and providing training for these discriminated groups along with child-care facilities for women, as well as flexible working hours or arrangements such as the provision of parental leave. The primary purpose of these is to provide non-discriminatory wages, and it is through the encouragement of these policies that equality in wages is achieved. The second type of policy takes a more intrusive role. They are called affirmative action or positive action. The aim of these policies is mainly to remove past discrimination. There is also an inherent assumption in this type of approach that the equality of opportunity approach cannot correct labour market disadvantages due to unequal starting points and a discriminatory history in the marketplace. Here countries also differ in their approach. The UK adheres to the ideology of equality of opportunity, whereas the US and Canada opt for equity legislation. These policies and their effects are still poorly understood (Hahn et al., 1999).

Additionally, these policies may be controversial (Fryer Jr and Loury, 2005). General opinion regarding these policies is divided. Advocates for these policies point to the wage gap and argue that the market has failed to correct itself and thus actively needs amendments to level the playing field (Davidov, 2016). Detractors argue that these policies might cause reverse discrimination, and firms might become less productive due to hiring less-skilled workers. There is an inherent assumption in policies enforced by the government: they imply that the group subject to these quotas and protected against discrimination is less qualified than others. These quotas eventually lead to inefficiencies in the marketplace (Farrell, 2005; Labaton, 2014).

Policies that target equal opportunity can range from simply having a document in a firm about its policy of non-discrimination. Other firms take a much more active route; these firms set out active measures to find sources of discrimination, remove them, and take special consideration while hiring discriminated groups.

Another dilemma in this equation is that an equal opportunity policy might be a way for some companies to divert attention away from their discriminatory behaviour, whereas for other firms, it might genuinely reflect their non-discriminatory nature. To decipher which company lies in the former category and which in the latter is complicated. For instance, some firms might start adopting the policy after someone complained, went on strike, or questioned the employer. The other option is leaving firms alone and letting them voluntarily opt for equal opportunity acts. This also has issues in that employers might think their company does not discriminate and does not actively check for wage gaps and remove discriminatory practices. In the UK, if a firm has laid out a statement of non-discrimination, there is no legal obligation on them to check actively against bias in their hiring practices and decision of promotion (Noon and Hoque, 2001). This means that companies can have written documents and still be involved in discriminatory practices.

There are many reasons why firms may opt to have a written document stating that they are equal opportunity employers but still be involved in discriminatory practices. Noon and Hoque (2001) argue that firms might do this to make themselves look like equal opportunity employers and to have perceived benefits such as improved employee relations, positive company image, and competitiveness in the labour market. Other issues for consideration when "showing" themselves as equal opportunity providers are to avoid penalties or investigations by the Commission for Racial Equality (now superseded by the Equality and Human Rights Commission (EHRC) and Commission for Equal Opportunity. The public backlash, the author points out, is another consideration. The policy idea, while having critics and drawbacks, as mentioned above, also has positives. The ILO (1997) report points out that the 300 organisations that actively participated in the activity, including police, government departments, and educational institutions, and set statistical targets did achieve (at least in the case of females) more equality than their peers.

In summary, this chapter has examined theories of discrimination along with practical attempts to measure it. The chapter lays the foundation for the following chapters and aids the reader in understanding common themes for the subsequent empirical work. Without the context of this theoretical chapter, it would be hard to understand the conceptual framework of the following chapters. Themes and theories from these chapters are referenced throughout the following thesis.

Chapter 3: The gender pay gap for higher education graduates in the United Kingdom – An Oaxaca-Blinder decomposition approach

3.1 Abstract

Despite substantial women's integration in the United Kingdom (UK) workforce, gender pay gap issues remain. This present in the UK labour market. The chapter estimates the gender pay gap for individuals who obtained at least a graduate degree in the UK using, using the Oaxaca-Blinder decomposition to dissect the pay gap between graduates to unexplained components (discrimination) and explained components (attributes). The paper novelty lays in the granularity of its analysis, it analyses the data for individuals with a similar background (graduates) but at different quartile levels to observe wage disparities.

Using data from *The UK Understanding Society* mainstage survey (wave 9), nine quartiles are used to distinguish the gender pay gap between different income levels. The results indicate that there is less of a total pay gap at higher than at lower incomes. However, the effect of characteristics (explained gap) diminishes as we progress up the income quartiles. On the other hand, the effect of discrimination increases as we progress the income level. So, at lower income levels, characteristics can explain more of a total pay gap. However, there is less of a total pay gap at higher income levels, but it is unexplained.

3.2 Introduction

Even though gender equality has received much public attention recently, the gender wage gap persists (Altonji and Zhong, 2021). Attaining gender equality remains a challenge for many governments worldwide, including the United Kingdom. The Office of National Statistics (2019) reports the gender pay gap to be 8.9% for full-time employees in the UK. It is even higher when all employees (full-time and part-time) are considered. The gender pay gap for all employees stands at 17.3% (ONS, 2020).[2]

Many papers have tried to understand what component of this gap is related to discrimination. Measuring the unexplained pay gap has fascinated researchers for more than three decades now (Blau and Kahn, 2017; Kunze, 2018) provide a comprehensive review). A large portion of these studies endeavors to study the source of inequality by observing the pay gap regarding determinants of pay. The Oaxaca-Blinder (OB) decomposition has been of utmost importance in understanding the source of inequality and is widely used (Blinder, 1973; Oaxaca, 1973). The decomposition technique allows researchers to segregate the gender pay gap into explained and unexplained components. Weichselbaumer and Winter-Ebmer (2005) document that most of these studies use the OB decomposition to study the mean unexplained gender pay gap[3].

Despite being a handy tool, most application research contains several limitations and restrictions. Paramount is the education returns issue (Wunsch and Strittmatter, 2021). Returns to education are often accepted to be similar across experience, age, and occupation. Nevertheless, according to Wunsch and Strittmatter (2021, p. 4), this "contradicts both theory and empirical evidence".

Further support to this is provided by Lemieux (2014), who argues that while returns to education can be substantial on average, they vary greatly based on individuals. He investigates why these disparities exist between equally educated individuals on paper. For that, he looks at how university education translates to earnings. Lemieux (2014) argues that there are three possible channels with which education increases earnings. First, the general skills one obtains

[2] The reason for choosing to report 2019 data instead of 2020 and 2021 figures is due to the disruptions caused by Covid.
[3] Fortin et al. (2011) provide a review of different employed methodologies.

while studying for university (in any field of study) might affect wages and productivity regardless of occupation. Secondly, the direct effect of a university degree helps individuals land a high-paying occupation. Third, specific skills obtained in university are a good match for a valuable job. The first channel does not rely on a field of study, while the second and third are particular and work on matching occupation and educational skills.

Another concern when dealing with this topic is the phenomenon of “glass doors” and “sticky floors”. Since most studies run a mean OB decomposition, valuable information is lost regarding these two phenomena. This paper fills in the gap between these two problems. The paper analyses a homogenous group (educated people defined by graduation) and looks at the gender pay gap in different quartiles. Thus, encompassing the issue of “sticky floors” and “glass ceiling” among these graduates.

Although there have been studies that study the gender pay gap across the whole wage distribution, the presence of studying just graduates for this purpose (surprisingly) has not received much attention. In such a context, OB decomposition can shed light on whether the resulting male-female wage gap results from characteristics or some other phenomena.

Hence the paper presents the approach of OB at nine income quartiles to gain insight into the sources and nature of the gender pay gap across the UK for graduates. Specifically, we are looking at the existence of glass ceilings and sticky floors across our entire wage distribution. This will answer a fundamental question. Can the wage gap be attributed to differences in returns to characteristics of graduates (discrimination), or is it down to labour market characteristics that we observe in the two sexes?

It gives the study a baseline to measure discrimination among individuals with a similar background entering the marketplace. The explained portion for the pay differential is due to productive characteristics of the individual (also known as the endowment effect). The unexplained portion of the differential is attributed to unobservable factors between men and women. This is often deemed as discrimination in the literature.

Of course, discrimination can occur in many ways (discrimination in hiring, housing, racism, sexism). However, this study contains and restrains itself to labour market discrimination. A formal definition of "discrimination" in the labour market is complicated due to the multitude of factors involved. Hence, most researchers in economics avoid giving a formal definition of the word (Oaxaca, 1973). Cain (1984, p. 2) describes discrimination as differences in pay for "equally productive" members. The term equally productive is critical here. Essentially, Cain allows differences in pay, provided they are based on productivity. Thus, labour market discrimination is the difference in wage outcomes after considering the productivity differences (such as education, workplace experience, etc.). Many researchers have this "implied" definition in their work while decomposing the wage gaps. This chapter takes this definition and proceeds to test it in later chapters empirically.

3.2.1 Research aim

The research aims to answer the following questions 1) What is the gender pay gap for individuals who obtained at least a graduate degree?. Do how you define ‘graduate’ matter while assessing the gender wage gap?. 2) How has the gender pay gap evolved over time? Has it increased or decreased?. 3) At *different income quartiles* for males and females with equal education, what is the gender pay gap?. 4) Is there presence of sticky floors or glass ceilings?.

3.2.2 Uniqueness and scope of the study

The study gains uniqueness by evaluating individuals with a similar background (graduates) at nine income quartiles. The study is constructed for individuals with a certain level of academic background. The results might be completely different if the scope of the study had been for individuals with a different academic background.

3.3 Literature Review - Empirical Approaches

The literature review of discrimination is vast. There are many techniques to measure discrimination. Table 3.1 summarises relevant studies that are prominent in the literature. The table is organised chronologically and covers these papers' names, country, year, data, technique, and main results. The papers provide a snapshot of the most relevant literature on discrimination and encompass many countries.

Table 3.1 shows a variety of papers using the OB decomposition and some other commonly used techniques (see Brown et al., 1980; Hirsch, 2016; Simister, 2000). The OB approach is the most widely used in the gender pay gap empirical techniques. Essentially, the OB technique measures the wage gap after accounting for differences in skills and/or productivity between the groups. The regression analysis decomposes differences between males and females (or ethnic groups) into two distinct categories. One is the observed wage differences caused by differences in skills and productivity (measured by coefficients). The other is the unexplained gap attributed to discrimination (measured by different rates of returns for those coefficients).

Of course, the method is not without its own set of problems. Over the years, the OB approach and its many extensions (despite being widely used) have received a variety of criticism. As mentioned earlier, researchers argue that the decomposition is limited, as it can only provide information about the average unexplained difference between wages (Card and Krueger, 1992; Fitzenberger and Wunderlich, 2001; Ospino et al., 2010). Suen (1997) argues that since the decomposition factors are not fixed, we must be careful in concluding discrimination based on the method. This thesis has a detailed discussion on the topic in the methodology section.

As is evident from Table 3.1, there is no single approach to discrimination, and even within the OB literature, there are different methods and extensions. To add further complication, many researchers believe that there are both macro and micro-determinants of discrimination. Those are dealt with separately in this literature review. Hence, the empirical literature review is broken down into macro-determinants and micro-determinants. After Table 3.1, micro-determinants and variables commonly used in the literature are discussed, followed by a discussion on the macro-determinants.

Table 3.1 Labour discrimination studies summary (using different methodologies)

Ref	Country	Year	Data	Technique	Results
Blinder, A. S. (1973)	Country-level (USA)	1973	Michigan Survey Research Center's "Panel Study of Income	Ordinary Least Square	White workers earn 50.5% more than black workers
Brown (1980)	Country-level (USA)	1966	Survey of economic opportunity	Multi-Nominal logit	14 to 17 per cent of the total differential is attributable to differences in the end
Cotton (1988)	Country-level (USA)	1980	1980 Census	Ordinary Least Square	48% difference in wages due to discrimination
Christie & Michael (2001)	Country-level (Canada)	1985 & 1990	1986 and 1991 Canadian censuses	Ordinary Least Square	Just 3.4% more of the wage differential is explained by educational dummies. Education differences do not explain earning gap in 1990 or 1985. Differences in the field of study are more helpful.
Swaffield (2000)	United Kingdom	1991-97	British Household Panel Survey	Random-effects (GLS) and OLS estimators	Discrimination occurs in the formation of human capital.
Simister (2000)	United Kingdom	1962-1998	British Election Study, British Social Attitudes	Survey data used. Results coded 1 and 0. Then seen over a long-term percentage	Dislike of immigrants is at 58% (1998). Reduced initially from the high 70 to 80s, but the reduction has radically slowed down.
Simister (2000)	United Kingdom	1971-1995	General Household Survey	Ratio of the wage earned by white /non-white	non-white wages were much lower than those of whites
Brookes et al. (2001)	Two countries (UK and Germany)	1991-1993	British Household, Panel Study (BHPS), Sozio-Oekonomisches, Panel/Bundesrepublik Deutschland (GSOEP)	panel data series random-effects panel models (REM)	gender wage differential was found to be more abundant in the UK than in Germany at 20 percent of the male wage compared to 9 percent

Ugidos (2003)	Spain	1995	Spanish Survey of Wage Structure	OLS estimators	The observed male-female average wage ratio is 21% higher than that in a non-discriminatory labour market.
Voon & Miller (2005)	Two countries (the US and the UK)	1978 to 2000	cross-sectional data (Current Population Survey (CPS) for the US and Family Expenditure Survey (FES) for the UK).	Pooled wage regression	Experience explains 39 percent of the US and 37 percent of the UK's wage gap. Yet the convergence in employment rates does not appear to have been a dominant factor in reducing the wage gap
Biltagy (2014)	Country-Level (Egypt)	2006	Egypt Labour Market Panel Survey 2006	Ordinary Least Square	30.8% discrimination effect between the genders in Egypt.
Boris (2016)	Multi-Country	1989-2004			Employers can save on labour costs by engaging in monopolistic wage discrimination against women who are less sensitive to wages when supplying labour to a single employer, and they do that
Ejaz (2016)	Country-Level (Pakistan)	2008	Pakistan Social & Living Standard Measurement (PSLM) Survey. Data pooled for the years 2004-05, 2006-07 and 2008-09	Multinomial logit (MNL)	59% is attributable to the differences in the unexplained component
Ismail et al., (2017)	Malaysia	2011	7135 working households in Peninsular Malaysia	Cross-sectional analysis	Wage discrimination within occupations plays an essential role in the gender wage gap
Olsen et al. (2018)	Country-Level (UK)	2009-2010	British Household Panel Survey (BHPS) and the United Kingdom Household Longitudinal Survey (UKHLS)	Cross-Sectional and Panel Data	The biggest driver of the GPG in 2014/2015 concerns differences in the labour market history of men and women, which accounts for 56% of the pay gap
Chen (2018)	Rural and Urban China comparison	2002–2013	China Household Income Project Survey (thereafter CHIPS), for the years 2002, 2007, and 2013.	Ordinary Least Square	The total discrimination index against migrants increased quickly over the early period as China witnessed rapid economic growth after entering the WTO and then dropped after anti.

Chinara, M. (2018)	Rural and Urban level India	2009-2010	Employment and Unemployment Survey 2009-2010 - 66th Round	Ordinary Least Square	The explained gap is one-third of the total gap in the log of wages (0.103 out of 0.333), and the unexplained gap (0.229 out of 0.333) is two-thirds of the total gap.
Piazzalunga and Tommaso (2019)	Country-Level (Italy)	2008-2012	EU-SILC (European Union Statistics on Income and Living Conditions) for 2004-12	Ordinary Least Square	The Italian gender pay gap increased from 3.8 to 8.6% between 2008 and 2012. 100% of it was due to a wage freeze in the public sector.

3.3.1 Micro-Determinants of Discrimination

Olsen et al. (2018), using the wave of the British Household Panel Survey (BHPS) (2014-2015), found that the difference between male and female pay in the UK was 13.40% in 2014-2015. However, the difference is on a slow, gradual decline as the study also looked at the BHPS survey from 2009-2010 and found the gap to be 14.40%. These estimates are significantly lower than the Office of National Statistics (ONS, 2016), where gender pay is estimated at 19.30% using the Annual Survey of Hours and Earnings (ASHE) data. One reason that might explain the difference is the methodology used in the respective studies. The ONS study takes median wage as a benchmark, whereas the Olsen et al. (2018) study takes mean values. Nevertheless, both represent essential information and can be used for analysis. The choice and reason for the final selection in this paper are discussed in the data section.

Garcia et al. (2001) propose using quartile regressions to compare the male and female wage distribution using the same characteristics for each regression. Their decomposition for the Spanish labour market uses the characteristics of men and women at the mean regardless of which quartile they run the regression. Gardeazabal and Ugidos (2005)consider assigning different weights to different characteristics. For instance, they give primary education at a certain quartile according to the proportion of individuals with those characteristics. Even though Gardeazabal and Ugidos (2005) used a different methodology, their finding matched Garcia et al. (2001). Both results showed that gender wage discrimination increased at higher quartiles.

Scarpetta et al. (2012) for the UK and Greece use survey data to determine the impact of education on gender wage discrimination. First, they use micro-data from the Labour Force Survey for 2004 to compare female and male returns to higher education. Then they analyse the effects of higher education on the unexplained part of the gender gap. For this purpose, they use an extension of the Oaxaca-Blinder decomposition using linear regression. They find that the unexplained part of the gender pay gap is lower for graduates than for individuals with secondary education in both countries.

Goy and Johnes (2012) analysed the macroeconomic factors and their roles in gender wage discrimination. The authors apply the OB decomposition methodology to an extensive micro database of 38 countries and find that a country's trade openness and development level are associated with lower wage discrimination. On the international scale, different applications of quantile regressions demonstrate the presence of a phenomenon known as the "glass ceiling". Arulampalam et al. (2007) argue that the glass ceiling occurs when there is more wage discrimination toward the top of the wage distribution than at the median or lower quartiles.

They analysed ten countries using data from the European Union Household Panel 2003. The data from the European Community Household panel covered the period from 1995 to 2001. The countries covered by the study were Austria, Britain, Finland, Germany, and Spain, amongst others.

Using the quantile regression technique, the authors study the effect of job characteristics (industry, private/public etc.) and individual worker characteristics (gender, education etc.) at different points in the wage distribution. They had two key observations. First, the gender wage gap was higher at the top than at the bottom of the distribution. Although the wage increase was not proportional, it increased as they went further across the wage distribution to a higher quartile. Secondly, each EU country's gender pay gap was significantly different across the public and private sectors. In the private sector, women earned significantly less at the bottom end of the distribution than in the public sector. For all countries in the analysis except Austria, Germany, and Ireland highest wage gap (for the public sector) was found at the 90^{th} percentile of the wage distribution. This points to the glass ceiling effect, an example of which is Finland, with highest wage gap of 31% at the 90^{th} percentile.

Arulampalam et al. (2007) found the raw average gap to be above 20% in the public sector and less than 13% in Britain's private sector. So, for public sector workers in Britain, the gender wage gap is wider for both the top and bottom ends of the distribution. However, for the private sector in Britain, they found that the wage gap did not increase as we moved up the wage distribution.

Piazzalunga and Di Tommaso (2019) for Italy conducted a quartile regression analysis on data from the Italian Income and Living Conditions panel from 2004-2012. The study aimed to determine why the gender pay gap had increased during the financial crisis. The Gender Wage Gap (GWG) in Italy increased from 3.8% in 2008 to 8.6% in 2012. They discovered the reason primarily a wage freeze in the public sector. Results of their quantile decomposition show two different trends. Between 2008 and 2010, GWG increased along the distribution, with the unexplained and explained components increasing. After 2010, GWG increased largely in the upper quartiles. [4]

[4] Other studies that analyse geographical comparisons in the wage gap are presented in Appendix 2.

Table 3.2: Micro-Determinants variable list in the literature (selected variables)

Variable Name	Studies
Education	• Blinder, A. S. (1973) • Cotton (1988) • Christie & Shannon (2001) • Brookes et al. (2001) • Paul (2004) • Ismail et al. (2017) • Arulampalam et al. (2007) • Boll & Lagemann (2018) • Olsen et al. (2018)
Occupation	• Blinder, A. S. (1973) • Christie & Shannon (2001) • Swaffield (2000) • Brookes et al. (2001) • Arulampalam et al. (2007) • Olsen et al. (2018) • Boll & Lagemann (2018)
Vocational training	• Blinder, A. S. (1973) • Ismail et al. (2017)
Work experience	• Cotton (1988) • Brookes et al. (2001) • Ismail et al. (2017) • Voon & Miller (2005) • Olsen et al. (2018)
Married	• Cotton (1988) • Brookes et al. (2001) • Ejaz (2016) • Ismail et al. (2017) • Landmesser (2019)
Industry	• Cotton (1988) • Swaffield (2000) • Christie & Shannon (2001) • Boll & Lagemann (2018) • Ejaz (2016)
Children	• Brookes et al. (2001) • Voon & Miller (2005) • Olsen et al. (2018)
Urban/rural	• Ismail et al. (2017) • Ejaz (2016) • Cotton (1988) • Christie & Shannon (2001)
Age	• Blinder, A. S. (1973) • Voon & Miller (2005) • Arulampalam et al. (2007) • Ejaz (2016) • Boll & Lagemann (2018) • Landmesser (2019)
Region	• Cotton (1988) • Christie & Shannon (2001) • Ejaz (2016)

Many different determinants contribute to the explanation of the wage gap at the micro level. Different researchers use different determinants depending on the scope of the study. One of the main determinants is the level of education. Hence, as observed in Table 3.2 most studies use education as the primary variable to explain wage differences. However, the education factor is used differently.

In his seminal paper, Blinder (1973) creates six dummies for education, distinguishing between lower levels of education (0-5) and higher levels of education up until advanced degrees. Cotton (1988) takes another approach to education. He uses education as a scaler comparing total years of education between men and women. Like Blinder (1973), Christie and Shannon (2001) use educational dummies in much greater depth than Cotton. Christie and Shannon (2001) use 19 dummies ranging from less than grade 5 to Doctorate, arguing that the key to understanding wage differences lies within understanding educational differences. They explain, "our results suggest that allowing for greater educational detail does help explain variation in wages" (Christie and Shannon, 2001, p. 180).

Age is another crucial determinant of OB decompositions. Often it is used as a proxy for experience (Arulampalam et al., 2007; Oaxaca, 1973). Many studies with age take it as a scaler (Landmesser and Policy, 2019). Most studies that use age also add the variable age^2 to demonstrate diminishing returns to experience. However, some papers use age but not age^2. Arulampalam et al. (2007) restrict their age sample from 22-54 years old's and do not use age^2. Another example of this is the approach taken by Boll and Lagemann (2018); they create six different categories to age instead of using age^2 where the youngest category is aged 14-19 years, and the oldest category is more than 60 years old.

Whereas most studies use age as a proxy for experience, some do not use this substitution and directly use work-experience (Cotton, 1988). Ismail et al. (2017) use work experience as a scalar (years of work experience) and add the square value of work-experience for capturing potential diminishing returns to experience.

The other two essential micro-determinants of OB decomposition are occupation and industry. Occupation refers to the type of jobs a person does, e.g. in the case of the original paper by Blinder (1973), managers, farmers, self-employed, craftsmen, sales etc. In contrast, the industry refers to the type of business that a company does. There are multiple classifications of industry, and the papers often select the most relevant ones as to the scope of the study. For instance, Arulampalam et al. (2007) use finance, manufacturing, property, hotels, communications, retail, energy, education, social services, construction, administration, and other industries.

Marital status/Married and the number of children indirectly affect the wage gap. Hence, they are also included. Married is included as a dummy variable, coded as 1 if the individual is married and otherwise 0 (Ismail et al., 2017; Landmesser and Policy, 2019). For the variable children, two methods are used. One is a dummy variable method. Olsen et al.

(2018) measure the number of children as 1 if an individual has children and 0 otherwise. The second is using the number of children instead of a dummy variable (Brookes et al., 2001).

Further analysis of key papers and their determinants is presented in Appendix 2: Analysis of key determinants.

3.3.2 Real-life scenario to observe discrimination

More recent papers try to use real-life scenarios to observe discrimination. Jackson (2018) investigated supply-side discrimination by using Boston taxi driver data. He used data from 2010-2015 from millions of trips to observe whether statistical and/or taste-based discrimination exists. He tracked the behaviour of taxi drivers by different age and ethnic groups to see whom they picked up. He found discrimination to be statistical rather than taste based. He also observed that as drivers gained more experience, discrimination decreased. His analysis pointed out that discrimination was based on facts like tipping behaviour, so as drivers learned to anticipate wage variation, discrimination decreased.

Another recent study by Brock and De Haas (2020) implements a loan exercise for 334 Turkish loan officers. They test for the presence of gender discrimination. They found that approval rates for females and males were the same. However, they found it was 30% more likely that loan approvals were conditional in the presence of a guarantor when coming from a female entrepreneur. Furthermore, they found that inexperienced and young loan officers mainly caused this discrimination. The worrying issue is that in this kind of discrimination, the bank does not lose. Only female entrepreneur is at a disadvantage.

3.4 Data

The data for the empirical study here comes from UK Household Longitudinal Study (UKHLS), also known as *The UK Understanding Society* survey. Understanding Society is an annual survey that captures valuable information about the economic and social circumstances of people living in the United Kingdom and replaces the former British Household Panel Survey (BHPS) in 2009. Figure 3.1 illustrates how Understanding Society has evolved over the years.

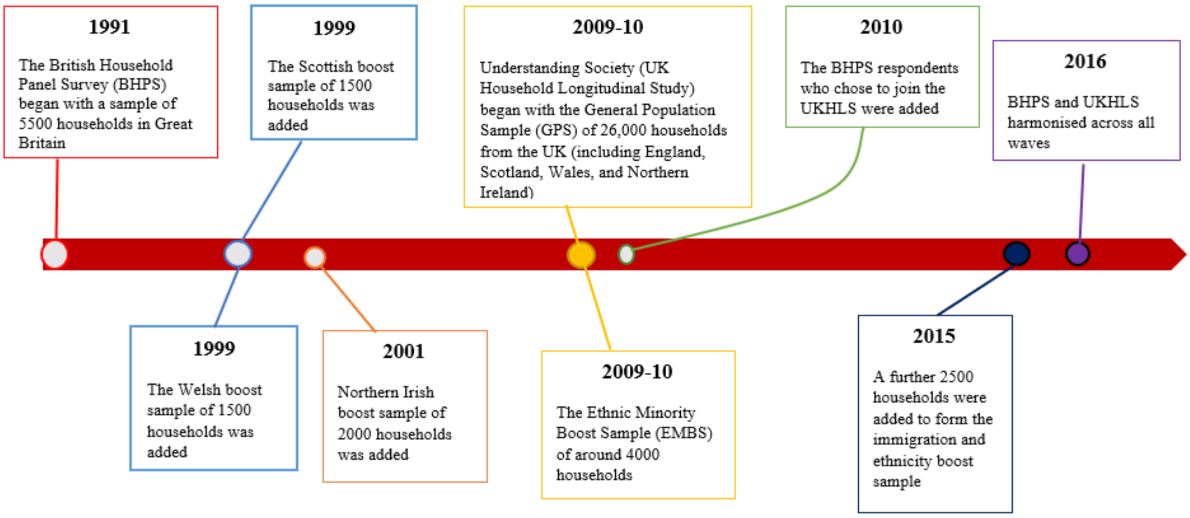


Figure 3.1 How Understanding Society has evolved over the years?

Source: Institute for Social and Economic Research (2021), Image: Own https://www.understandingsociety.ac.uk/documentation/mainstage/user-guides/main-survey-user-guide/study-design

The UK Understanding Society survey is suitable for our analysis for many reasons. One, it covers all ages and this makes it suitable to analyse the gender pay gap and develop comparisons in the different quartiles of the UK wage distribution. Second, since the data is time series, we can gauge how the wage gap for our specific group has changed over time. In order to achieve this, we use multiple waves in our study, which allow us to produce comparable results. Third, the education category for individuals is granular so that we can distinguish different types of individuals according to their education (less educated to more educated). Lastly, the sample size is significant for drawing meaningful conclusions. UK Understanding Society wave 9 (hereafter UKUS9) has a sample that covers 36,055 individuals.

Although the sample size is significant, one disadvantage of using the publicly available UKUS data instead of the secure micro-data available by the Office of National Statistics is that we lose a chance to have significantly more observations. Unfortunately, at the time of the research, micro-data access was unavailable (See Appendix 1: Role of Covid-19). UKUS9 is used as our main reference point for the most recent data.[5] UKUS9 covers the period of 2018-2019. Multiple sub-samples out of wave 9 are created to understand the graduate pay gap.

First, we create an all-worker sample of wave 9. This sample is restricted to individuals who are in the labour market. Then the sample is further restricted to individuals currently working rather than the entire labour market since the paper focuses on gender pay gap.[6] After we restrict our sample to employed individuals, we make further restrictions on our sample based on individuals who do not respond to our key independent variables.[7] After making these omissions, we are left with 11,119 individuals. The sub-sample includes education variables and all individuals in the workforce (with jobs) and for whom we have the relevant information. In our paper, this is referred to as the "All Worker Dataset" (AWT9). We add the term 9 as a suffix to indicate that this data set is from wave 9.

The second sub-sample is a further restricted version of the first sub-sample and includes individuals who have completed a bachelor's degree equivalent, master's, or Doctor of Philosophy (PhD) and any other higher education. Our paper refers to this as broad graduates ("BG9"). Broad graduates are defined as individuals who have completed any sort of university higher degree (masters, PhD), Post Graduate Certification in Education (PGCE), 1st degree or equivalent (bachelor's in arts, bachelor's in science), diploma in higher education, a teaching qualification (excluding PGCE), nursing or other medical qualification and other high degrees. These correspond to the highest level of education the individual has received, meaning that an individual's highest education is considered while making this determination. This sample constitutes 6,200 individuals. This serves as a benchmark for our analysis of the graduate pay gap in the UK in 2018-2019.

The third sub-sample is derived from the second data set and further restricts our sample. We restrict the sample based on educational parameters in the third data set (wave 9). A stricter definition of our key term, "graduates". We include individuals with a 1st degree or equivalent (undergraduate) (bachelor's in science, bachelor's in arts). Along with individuals who have completed bachelors, we add individuals who have obtained a higher education than bachelors in this sample. That is the completion of MSc and PhD. In our study, we refer to this

[5] Although wave 10 (UKUS10) data access is available, it's avoided in the analysis because of the possible impact of Covid-19.
[6] The entire labour market consists of individuals who are unemployed and hence are not paid. This makes them invalid for the pay gap analysis.
[7] A detailed discussion of variables is provided in this thesis's methodology and model section.

sample group from wave 9 as Graduate, Masters and PhD ("GMP9"). This sample has 4,624 observations.

The fourth sub-sample is derived from the third sub-sample set and places further restrictions. This sub-sample set contains individuals who are graduates in the strictest definition. Here we define graduates as individuals who have been granted an undergraduate degree or equivalent as their highest education. The difference with the third sub-sample set of GMP is that this sample set excludes masters or PhD students and looks at undergraduates only. This sub-sample set contains 2,613 observations. This is referred to as "Just Graduate" (JG9) in our study.

The fifth sub-sample of the study uses wave 1 of understanding society. Wave 1 covers the period of 2009-2010. The reason for using wave 1 in conjunction with wave 9 is two-fold. First, wave 1 provides a time element to the study. Second, it serves as a robustness check. This sample mimics the wave 9 data set of Broad Graduates (BG) but for wave 1. We are looking at individuals who have obtained a graduate degree (or equivalent) and above to analyse time differences with our 2018-2019 sample. This 10-year time difference provides valuable insight into the changing nature of the gender pay gap at different quartiles. We refer to this data set as "BG1". We use suffixes to indicate which wave the data belong to (e.g., suffix 1 corresponds to *The UK Understanding Society* wave 1. This sample contains 9,300 observations.

To add more context to our study and understand the time element in more detail, we add a sample from wave 5 of the Understanding Society database. Like wave 1, wave 5 adds further robustness check and serves to create a time element to the study. Wave 5 covers the period of 2014-2015. To keep our results consistent, we construct a sample that mimics that of wave 1 and wave 9's Broad graduate. We refer to this data set as BG5. The suffix 5 indicates wave 5. This is our sixth sample set. The number of observations in this sample stands at 7,486.

Table 3.3 Summary of sample sub-sets

Wave	Wave 9	Wave 9	Wave 9	Wave 9	Wave 1	Wave 5
Sub-Sample	All Worker Data-set	Graduate Masters/PhD	Just Graduate	Broad Graduate	Broad Graduate	Broad Graduate
Abbreviation	AWT9	GMP9	JG9	BG9	BG1	BG5
Number of Observations	11,119	4,624	2,613	6,200	9,300	7,486

3.4.1 Descriptive statistics

For description, the six data sets are broken down into two groups. The first group includes AWT9, GMP9 and JG9, while BG1, BG5, BG9 are included in the second group. Table 3.4 displays the descriptive analysis covering the model's demographic, labour market and socio-economic variables. The descriptive analysis is broken down by gender and arranged in two categories. The first category includes demographic and socio-economic variables, and the second focuses on labour market variables.

Table 3.4 covers the demographic characteristics of sub-samples AWT9, GMP9 and JG9. Individuals aged 40-49 years are the highest representative, and the same pattern continues with just graduates (JG9). In the sub-sample JG9, 26.9% of our sample belongs to 40-49 years old. This sub-sample has the same percentage for 30-39 years old. For the sub-sample GMP9, 30-39 years old constitute the highest proportion of the group, 28.2%. The percentages of 60+ individuals are far below any other group and stand at 5.4%.

Concerning the ethnicity distributions of three sub-samples, we find that 70% of the individuals are British (white). The second-highest ethnic group is Indian (4.3- 4.8 %), which is followed by Pakistanis. The selected ethnicities shown in table 3.4 were based on the highest proportion.

Regarding education, the all-worker sub-sample contains all educational variables with O levels and the lower group constituting 30%. The second highest group is that of bachelors with 23.5%. For the graduate/master's group, we have all other educational variables removed except that of BSc and MSc/PhD students. Just graduate sub-sample is restricted to bachelor's in education, and hence we observe 100% frequency for bachelors.

The legal marital status shows us that compared to all workers, we have a higher proportion of married individuals who have attained MSc and PhD qualifications. Overall, 53.7% of individuals have married *in all workers sub-sample*, while this percentage rose to 58.7% for graduates and master's group. The percentage is lower for just graduates (JG9) at 56%.

Table 3.4 Descriptive characteristics of AWT9, GMP9 and JG9, frequency percentages

	All workers (AWT9)			Graduate Masters (GMP9)			Just graduates (JG9)		
	Male	Female	Total	Male	Female	Total	Male	Female	Total
Number of Observations	4890	6229	1119	2018	2606	4624	1072	1541	2613
Age									
16-29 years old	20.80%	21.70%	21.30%	16.60%	19.30%	18.10%	18.40%	23.00%	21.10%
30-39 years old	22.40%	21.70%	22.00%	27.30%	28.80%	28.20%	25.80%	27.10%	26.60%
40-49 years old	25.70%	25.00%	25.30%	29.20%	26.60%	27.70%	29.90%	24.70%	26.90%
50-59 years old	23.30%	24.80%	24.10%	20.20%	20.80%	20.60%	19.60%	20.50%	20.10%
60+ Years	7.90%	6.90%	7.30%	6.70%	4.50%	5.40%	6.30%	4.70%	5.40%
Ethnicity (Selected)									
British/English/Scottish/Welsh/ northern Irish (white)	77.10%	76.40%	76.80%	70.30%	71.80%	71.10%	73.70%	74.20%	74.00%
Indian (Asian or Asian British)	5.10%	3.90%	4.40%	7.60%	4.30%	5.80%	6.40%	3.70%	4.80%
Pakistani (Asian or Asian British)	3.30%	2.40%	2.80%	3.40%	2.30%	2.80%	3.50%	2.30%	2.80%
any other white background (white)	2.80%	3.30%	3.00%	4.10%	4.60%	4.30%	2.90%	2.70%	2.80%
African (black or black British)	2.20%	2.70%	2.50%	2.90%	3.70%	3.40%	1.70%	3.80%	2.90%
Education									
Masters/PHD	19.30%	17.10%	18.10%	46.90%	40.90%	43.50%			
Bachelors	21.90%	24.70%	23.50%	53.10%	59.10%	56.50%	100.0%	100.0%	100.0%
Other degrees equal Bachelors	11.40%	16.30%	14.20%						
A levels and lower	14.60%	14.00%	14.30%						
O level and lower	32.70%	27.80%	30.00%						
Legal marital status									
Single	33.70%	34.50%	34.10%	29.60%	33.20%	31.60%	30.80%	36.10%	33.90%
Married	57.40%	50.80%	53.70%	63.70%	54.80%	58.70%	63.20%	51.00%	56.00%
Divorced	5.50%	9.50%	7.70%	3.90%	7.70%	6.00%	3.30%	8.20%	6.20%
Number of Children									
	Male	Female	Total	Male	Female	Total	Male	Female	Total
0	63.70%	64.30%	64.00%	58.80%	60.50%	59.80%	59.80%	62.40%	61.30%
1	14.90%	16.50%	15.80%	16.20%	16.40%	16.30%	16.20%	16.30%	16.30%
2	16.90%	15.90%	16.40%	20.40%	19.30%	19.70%	19.50%	17.50%	18.30%
3+	4.50%	3.30%	3.80%	4.70%	3.80%	4.20%	4.50%	3.80%	4.10%

We observe that most individuals do not have children (64%). For the *all worker dataset*, 15.8% of individuals had only one child. This proportion is higher for both the graduate group and the graduate and master's group at 16.3%.

Figure 3.2 provides an insight into how people who are pursuing more advanced degrees over time. Compared to 2009-2010 (Wave 1), the percentage of men completing master/PhD increased from 34.2% to 36.7% in 2018-2019. The change is even more significant in women increasing from 24.5% to 29.4% in BG9 (Wave 9). Appendix 3: provides complete Demographic descriptive statistics for BG1, BG5 and BG9.

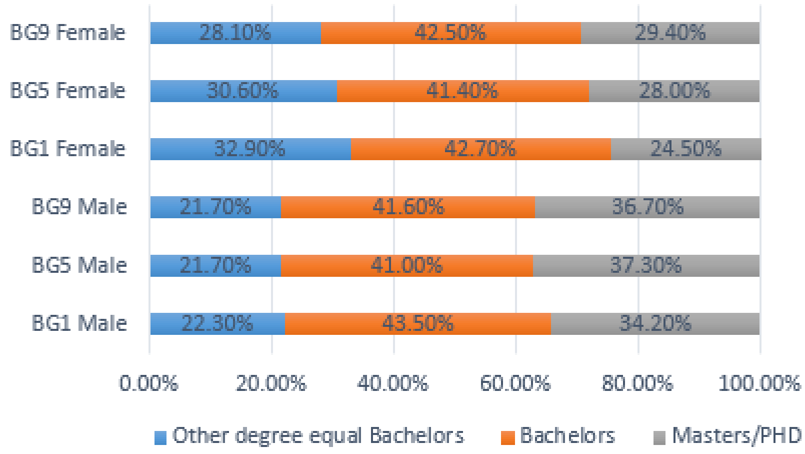


Figure 3.2:Education comparison over time for males and females

Table 3.5 incorporates information on the labour market characteristics for our sub-samples. As returns to education literature suggests, the gross pay per month is highest for graduates and MSc students, with 2,932 pounds. The second highest is just graduates falling about 196 pounds compared to graduates and master's group. Coming to all workers, we see a massive drop of 452 pounds per month with just graduates. The mean for all workers was 2,284. The average number of hours follows a similar pattern with graduates and those with masters qualifications putting in the most hours while all worker dataset worked the lowest number of hours. Looking at Table 3.5 for full and part-time employment, we observe that 83.8% of graduate and master's workers were full-time. This proportion reduces only slightly with just graduates at 82.3%. Looking at the *all-worker dataset*, we see 77.6% of individuals working full-time. This is also an important factor in why the average earnings of JG9 and GMP9 groups are higher than the all-worker dataset.

The male-to-female wage comparison is shown in Figure 3.3. The graph shows the average (unadjusted) pay gap between males and females for AWT9 to be around 878 pounds. When we move to just graduates, we observe the wage gap as approximately 995 pounds. When we include higher degrees (such as post-graduate and PhD), the gap decreases slightly to 991 pounds. Males in all three sub-samples earned more than females. The difference, as explained earlier, did not shrink but grew after similar academic backgrounds were considered.

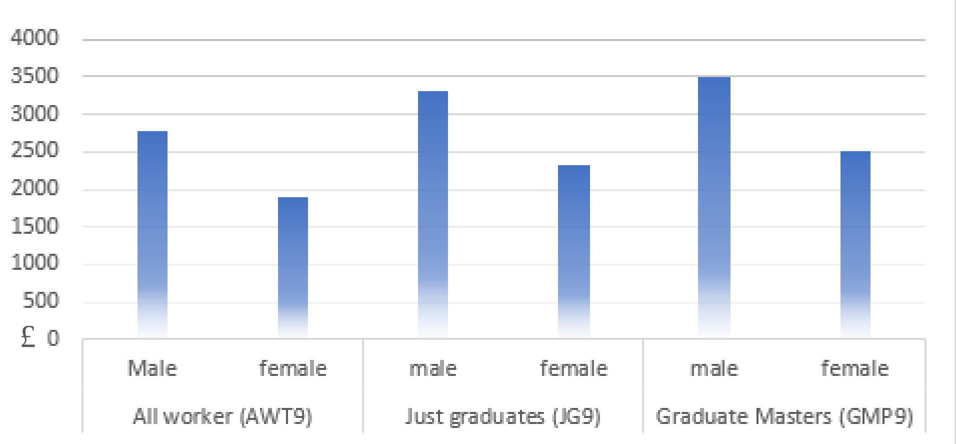


Figure 3.3:Male to female comparison of monthly wages AWT9, JG9 and GMP9

A factor in this is the number of hours worked and full-time employment rates undertaken by men and women. As shown in Figure 3.4, men are much more likely to be full-time employees than females. As expected, the percentage of full-time work increases from 90.5% for all worker datasets to 93.3% for masters/PhD for men. A similar but much more significant rise is also seen for females, with female employment increasing from 67.5% to 76.4%. As can be seen from the graph, individuals spending more money on education tended to opt for full-time work at a much greater rate than the public. This information is just for individuals already in the labour market.

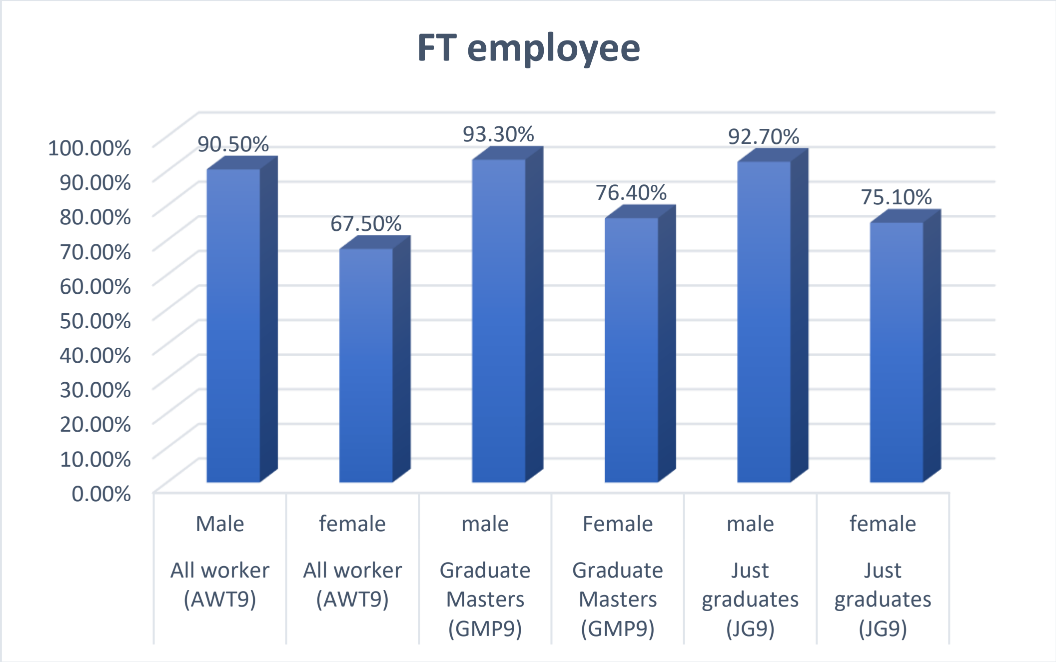


Figure 3.4: Percentage of full-time employees by gender (AWT9, GMP9, JG9)

The organisation size variable in Table 3.1 hints that the small companies are the major employer of individuals who do not possess higher education qualifications. This can be observed with all worker dataset having 28.6% of individuals in small companies whereas graduates and master's group only has 21.9% of individuals in this group. A similar pattern can be observed in just graduates, with 22.2% of individuals in the small company. The reverse is true for big companies. For the 500+ group, 29.5% of individuals from graduates masters/PhD group, 26.6% from just graduates and 22.4% for all workers. Looking at organisation type, the AWT9 sample, we observe 61.9% employed in the private sector, which is higher than our GMP9 51.5% and JG9 52.5% sub-sample.

Table 3.5 Labour Market determinants All workers, Graduate Masters and Just graduates samples

	All worker (AWT9)			Graduate Masters (GMP9)			Just graduates (JG9)		
	Male	Female	Total	Male	Female	Total	Male	Female	Total
Number of Observations	4890	6229	1119	2018	2606	4624	1072	1541	2613
usual gross pay per month: current job									
Mean	2775.74	1897.46	2283.71	3490.64	2499.01	2931.77	3323.35	2327.38	2735.98
No. of hours normally worked per week									
Mean	37.05	30.19	33.21	37.4	32.22	34.48	37.17	31.88	34.05
Full or part-time employee									
FT employee	90.50%	67.50%	77.60%	93.30%	76.40%	83.80%	92.70%	75.10%	82.30%
PT employee	9.50%	32.50%	22.40%	6.70%	23.60%	16.20%	7.30%	24.90%	17.70%
Organisation Size									
1 to 24	26.80%	30.00%	28.60%	20.20%	23.30%	21.90%	20.10%	23.70%	22.20%
25 to 99	24.80%	28.00%	26.60%	22.80%	26.30%	24.80%	24.40%	28.60%	26.90%
100 to 499	25.00%	20.30%	22.40%	25.80%	22.20%	23.80%	26.30%	22.90%	24.30%
500+	23.30%	21.70%	22.40%	31.20%	28.20%	29.50%	29.10%	24.90%	26.60%
Private firm or business, a limited company	73.50%	52.80%	61.90%	65.60%	40.60%	51.50%	67.50%	42.10%	52.50%
Other type of organization	26.50%	47.20%	38.10%	34.40%	59.40%	48.50%	32.50%	57.90%	47.50%

Figure 3.5 (for BG1, BG5 and BG9) illustrates percentages of individuals working in the private sector for both men and women. First, a clear trend is evident; more men tended to work in the private sector compared to women. Second, for men and women, the percentage of individuals involved in private sector work has increased over the years. Complete labour market analysis for our BG1, BG5 and BG9 sub-samples is provided in Appendix 4 of the thesis.

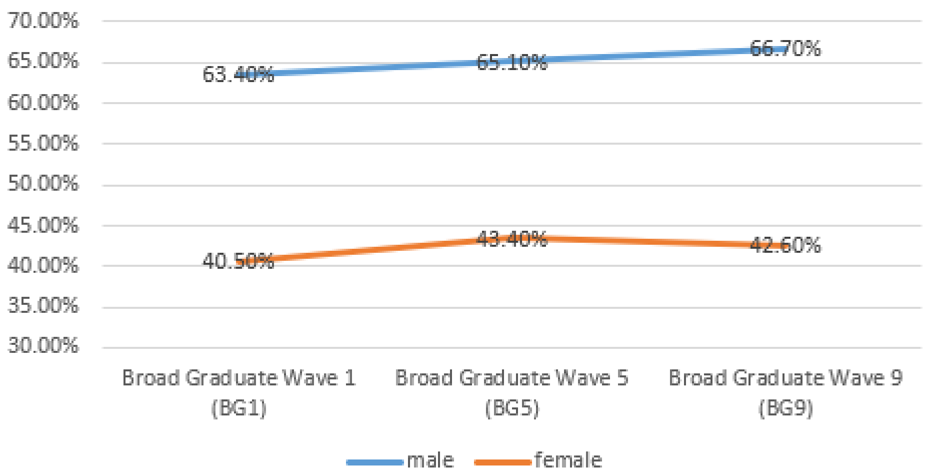


Figure 3.5 Gender segregated percentage of individuals working in Private firm or business, a limited company for BG1, BG5, BG9

3.5 Model

We use three cross-sectional data sets (wave 1, wave 5 and wave 9) of *The UK Understanding Society* survey for our empirical model. Mathematically we can represent our models in the following equation.

$$LN\ (Pay)_i = f(D_i + L_i + O_i) \ldots.. \quad (3.1)$$

Here LN stands for Log, D for Demographics (individual characteristics), L for Labour Market variables while O is for Organisation determinants. Our dependent variable is log of pay in the equation. Log of pay is used to normalise the salary distribution. Since log of pay cannot take negative values, we drop observations of salary that are less than 1£. The reason for this drop is that log 0 to 0.99 generates negative values. In order to counter this, all observations below 1 are dropped from the equation.

Table 3.6 Categorical Breakdown of Independent Variables

D = Demographic variables	L= Labour Market characteristics	O = Organisation type and sector
Gender (Male/Female)	Working Hours (Number of working hours each week)	Occupational size (Number of individuals in the organisation)
Age / Age Squared	Position (Part-Time or Full-Time)	Organisation type (Private or Public sector)
Married		
Education		
Location		
Number of Children		

3.5.1 Model 1

We use six different models to study the graduate pay gap in the UK. We first start the analysis with all AWT9. The reason for using this data set is to note whether essential differences between genders exist at the graduate level or not. This serves as a basis for our following models. If the model predicts substantial differences due to education, our analysis continues testing the graduate pay gap. Model 1 is different to all other models, it is the only model that contains education variables. This provides a base model for comparison. In addition, it provides a benchmark to study differences between highly educated individuals (studied) in this paper versus the general labour market. This model is considered the full model as it contains all the demographics, labour market and organisation type variables.

3.5.2 Model 2 and Model 3

Models 2 and 3 use the data set GMP9 and JG9, respectively. These models are different to model 1 in that they contain education level as our filter. Model 2 (GMP9) contains observations of individuals that are either graduates and/or masters, PhD. JG9 contains observations of strict graduates. Here, our analysis focuses on differences within educational groups.

3.5.3 Mode 4 A, Model 4B and Model 4C

Model 4A, 4B and 4C correspond to sub-samples BG1, BG5, BG9. Here we want to see a time dimension to the study and how the graduate pay gap has progressed. These models also serve as a robustness test. The quartiles for these models and the above models let us look at differences in the graduate pay gap at different income levels. This helps deepen our analysis and understanding of median income level over time and at the extreme distribution edges (highest income quartile versus lower-income quartiles).

3.5.4 Dependent variable

3.5.4.1 Log of Pay (Usual Pay per month)

The dependent variable for our equation is the log of salary. Using the log of salary instead of just salary as a scaler variable controls for having an income variable rightly skewed due to high earners. Since we want to mitigate that effect, we use the log of salary. The paper uses the usual variable pay per month for the analysis.

To convert our variable to Log, we first need to consider individuals with zero as their salary. 0 is a legitimate salary (indicating that the person did not receive any money last month). However, when converted into logs, it results in an error. Since Log of 0 is undefined. Hence, to resolve this issue, first, all 0's were converted to 1 pound in the data set. This assumption helps us do two things:

1) This assumption does not hinder our results as 1 pound is no significant value (especially for a month) and still helps us keep the 6.5% of the individuals who reported a salary of 0.
2) It also keeps the log normalised. Suppose we had taken the 0.01 log value of the addition. It would have been -4.6, and our normalisation would have been negatively skewed.

The standard procedure in the literature is to just ln (variable +1). Here we follow the standard procedure and convert our variable from salary to log of salary. We use the log of salary per month for all the sub-samples and models as our dependent variable.

3.5.5 Independent Variables

3.5.5.1 Demographic Variables

3.5.5.1.1 Age

Age is used as a proxy for experience and is a scaler variable in the analysis. Age positively correlates with wage to a certain point, after which the effect takes a diminishing and eventually negative value. This is captured by age squared.

3.5.5.1.2 Age Squared

We take age squared in our analysis to capture the effect of the negative correlation between age and wages after a certain point. This shows the inverted U-term relationship between age and wage. This is noted in the literature by Blinder (1973), Voon and Miller (2005), Arulampalam et al. (2007) and Landmesser and Policy (2019).

3.5.5.1.3 Gender

Gender is a binary variable, taking the value 0 for females and 1 for males. However, this variable does not appear in the explained or unexplained portion of the analysis owing to OB decomposition. Instead, it is an inherent and endogenous part of the model.

3.5.5.1.4 Education

The education variable is only present in the AWT9 sub-sample. For the AWT9 sub-sample, this variable ranged from general certificate of secondary education (GCSE) or lower up to masters and PhD. Since this is a dummy variable, we have GCSE and lower qualifications selected as our base variable. For the rest of the sub-samples, we have consistent education variables. The education variable for BG (1,5,9) groups includes a bachelor's degree and above. This also includes not necessarily formal bachelor's degrees but degrees to a similar level (for example, education variable). For the JG9 sub-sample, the education variable is Just Graduates.

For GMP9 group, graduates plus masters and PhD students are merged to form a bigger group. So, while in the AWT9 analysis, the variable serves as a dependent variable, for other sub-samples, it serves as a base variable upon which the entire analysis is rested —providing us with an opportunity to compare the gender pay gap amongst individuals with an academic background. This is noted in the literature by Arulampalam et al. (2007) and Olsen et al. (2018).

3.5.5.1.5 Children

Since the number of children affects parents' time allocation at home and work, we consider this variable to be included in our models. Evidence suggests that this might affect the gender pay gap (Ferrant et al., 2014). Therefore, we expect a positive correlation between having children and women's pay gap. For our analysis, we choose children between 0 and 16.

The number of children is included in the analysis as a binary variable. It is coded as 1 if the individual has children within these ages and 0 otherwise. The time component is the purpose of such coding and selecting just children below this age. As Ferrant et al. (2014) indicate, we anticipate that having children will impact wages. This is also noted by Ismail et al. (2017) and Olsen et al. (2018).

3.5.5.1.6 Location

We include the regional variable for London versus the rest of the UK to understand potential regional effects. Here, we want to observe whether being in London affects the gender pay gap. London is a binary variable coded as 1 if the individual works in London and zero otherwise.

3.5.5.1.6 Married

We include the marriage variable in our analysis for the same reasons mentioned in children. It measures many unobserved aspects of the gender pay gap, such as women working fewer hours than men. Being married was coded as 1 in our analysis. According to Landmesser and Policy (2019), the variable is an integral component in the unexplained component of OB decomposition for all European States.

3.5.5.2 Labour Market Variables

3.5.5.2.1 Working Hours (Number of working hours in each week)

Hours worked is a continuous variable that measures the "*No. of hours normally worked per week".* Therefore, we expect a positive relationship between wages and the number of hours worked, as pointed out in previous analyses in Christie and Shannon (2001) and Boll and Lagemann (2018).

As referenced in Tables 3.6 and 3.7, men's mean number of working hours is far greater than women. One of the reasons is the male proclivity towards working full-time (thereby increasing the number of working hours – see Figure 3.3). The second is related to the abovementioned factors like females tend to dedicate more hours to household-related activities.

3.5.5.2.2 Type of contract (Part-Time or Full-Time)

One of the main reasons for wage differences is the type of contract - working part-time or full-time (Olsen et al., 2018 ; Landmesser and Policy 2019)). Hence, it is essential to consider this variable in our model. This binary variable is coded as 1 for part-time and 0 for full-time.

3.5.5.3 Organization type and sector

3.5.5.3.1 Occupational size (Number of individuals in the organisation)

The question “No. employed at the workplace: a current job” was analysed for organisation size. The variable contained multiple options for response ranging from 1-2 to 1000 or more. This variable was recoded into four categories: 1-24, 25-99, 100-499, and 500+. It is also a dummy variable. The value of "less than 25 employees" was taken as the base, and it was coded 0, while the rest of the classes were coded as 1. The variable is widely included in OB decomposition Arulampalam et al. (2007), Olsen et al. (2018), Boll and Lagemann (2018) .

3.5.5.3.2 Organization type (Private or Public sector)

The question “work for a private firm or business or other limited company or do you work for some other type of organisation?” was chosen for organisation type. The question's wording does not distinguish between government and other types of non-profit (governmental) organisations. So, essentially it is a binary variable with two options. Private or other. Here we select the public sector as the base variable. The data was coded as 1 for private and 0 for other. The variable is also included in Brookes et al. (2001), Olsen et al. (2018), Boll and Lagemann (2018).

3.6 Methodology

As mentioned, comparing female and male pay on average (or median) provides only a partial picture of the situation. In addition, women and men have different individual and job characteristics, which might affect pay. Consequently, we develop a linear regression model to comprehend the difference to increase our understanding of the situation. For this purpose, we use the Oaxaca-Blinder technique explained below.

Alan Blinder and Ronald Oaxaca, in 1973, decided to address wage differentials between different groups (men and women, black and white) using an econometric framework. The framework would later be known as the OB decomposition (Blinder, 1973; Oaxaca, 1973). The method explains differences between average wages by different groups, separating those into composite and structural components.

Suppose we have individual data on education level, gender, work experience and wages. The gender wage gap (termed the overall effect) is the difference between the average female and male group. However, even if this difference is sound and shows the relative wages of men and women, it does not address the possible reasons behind this phenomenon. This is crucial if we wish to understand and combat labour market inequality.

This is where the OB decomposition provides us with additional information. The decomposition assumes a linear wage structure that links to an individual's observable variables. The observable variables are usually at the discretion of the researcher. Some common ones are work experience (age), education levels, urban, sector or industry belonging, and certain unobservable variables like potential (for a detailed discussion on determinants, refer to section 1 of this thesis). The critical aspect is that these observable and unobservable characteristics can differ between genders. This difference between wage structures is called structural effect (unexplained part) and is often called discrimination. This implies that a woman having the same characteristics as a man would earn different wages.

If this is the case, then the college diploma for a woman may be considered of less value in the labour market than the man. However, this is not the only logical assumption here. It may be that wage structures (e.g. diplomas) are equal in value for men and women. In this context, the gender wage gap would be observed by differences in observable characteristics. For example, the average man differs in their qualification and work experience. This difference between the observable variables in the labour market is known as *the composite effect* (explained part). (For this thesis, we focus on men and women, however, as shown in the original papers by Oaxaca (1973) and Blinder (1973), this method could be applied to different ethnic groups (e.g. black and white, Hispanic vs non-Hispanic etc.)). This can be written as

$$LnW(Males) - LnW(Females) \ldots\ldots\ldots\ldots (3.2)$$

where Ln= Log and W=salary. The log is necessary to normalise the wage parameter. Usually, the parameter is positively skewed. This can further be divided into the following.

$$LnW_{males} - LnW_{females} = X_{males} - X_{females}\beta^{M} + X_{females}^{(\beta_{males}-\beta_{females})} \ldots\ldots (3.3)$$

X is the explanatory variable e.g. education, the number of hours worked, etc. X(Males) - X(Females)B^M is the explained part of the equation, and X(Females) (^B(Males) - ^B (Females) is the unexplained part. The vectors ^B(Males) and ^B (Females) are obtained after running a regression equation 3.4. The same equation is estimated for females (equation 3.5).

$$LnW_{M} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + e \qquad (3.4)$$

$$LnW_{F} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + e \qquad (3.5)$$

The equations imply that the difference between the log of wages between females and males can be decomposed into two parts: the difference due to the X's (the independent variables) and the remaining difference, which is termed the "unobserved" or discriminated part. The standard assumption of OLS remains in both equation 3.4 and 3.5 where we assume that the error term is not related to the independent variable.

3.6.1 Limitations of the decomposition model

Before proceeding, it is important to note several fundamental limitations to the OB decomposition mentioned below. One of the fundamental problems often with this decomposition is that the goal of the decomposition is quite ambiguous. Precisely, the decomposition methods follow a partial equilibrium approach. Take, for instance, the example of unions. In the absence of a union, wages for workers within and outside of the union would change. In this scenario, the wage structure for non-union workers is not a good counterfactual that we can use (H. G. Lewis, 1986). This is further discussed in assumption 3 in detail.

We maintain the partial equilibrium approach throughout the thesis, indicating that we can use the wage of one gender to construct a counterfactual wage for the other gender. This is not limited to gender. The same methodology can be applied to different regions and periods to construct various counterfactual scenarios for the other group. A second limitation of the OB model is that it does help us quantify the main factors causing the wage difference between the two groups. However, it does not give us an understanding of why those factors are critical and does not enhance our understanding of the relationship between outcome and factors.

In this sense, it is important to note that OB decomposition does not give us a deep understanding of why the relationship exists. However, it does help us quantify which factors are essential and to be explored in more detail later. For example, consider a situation where after conducting the decomposition, one finds that occupational differences are why the gender pay gap persists. Therefore, one can further examine why men and women choose certain occupations over others. This can also lead to the question of checking the choices of subjects at university since they might affect eventual occupational choice. The main advantage hence of the decomposition lies in providing a simple quantified number for an estimator.

3.6.1.1 Assumptions inherent in Oaxaca-Blinder

3.6.1.1.1 Assumption 1: Mutual Exclusivity

One of the main assumptions of the model is that of mutual exclusivity. We restrict it by just having two mutually exclusive groups. This helps remove overlapping wage differentials, such as might be the case with Hispanics, whites or blacks, since some people might be a combination of both categories, such as Black and Hispanic. In the case of gender decomposition, the problem does not exist. This is not very restrictive since almost all decompositions fall into this category.

Since we are assuming mutual exclusivity, thus for an individual I, DAi +DBi=1, where either the person belongs to group A or group B. We can also write it as Dgi=1 (where g=A, B). For the wage-setting mathematically put, the assumption can be denoted by the simple equation Yi=DgiYgi. Over here, we are interested in comparing wage distribution for the two sets of workers A and B. So g=A, B. Ygi is the wage the worker would receive if the individual were in group g., e.g. If the worker is in group A, the wage that would be observed would be YAi. Thus, an individual has two potential outcomes, if Dai=1, then YAi and if DBi=1, then YBi. This is what we observe. The critical counterfactual question then becomes what would be the wage YA for workers in groups in B. Since we do not observe YA|DB, we make some assumptions for estimating this counterfactual.

3.6.1.1.2 Case Number 1: Structural Form and Overall Wage Gap: The Aggregate Decomposition:

The aggregate decomposition methodology is general and holds for a distribution statistic. Suppose we consider the distribution statistics of interest, v (FYg|Ds), where v is a real-valued function. We are interested in our case to know the distribution of potential outcomes of FYg|Ds where yg represents the potential outcome of workers in group s. FYg|Ds is an observed distribution where g=s and counterfactual when g≠s. The overall difference between the two can be measured using the earlier mentioned function v. Considering as is our case with just two groups A and B.

$$\Delta \mathrm{v0} = \nu\,(\mathrm{FYB|DB}) \;-\; \nu\,(\mathrm{FYA|DA}) \;\ldots\ldots\ldots(3.6)$$

The standard measures for these wage differentials are the median and the mean. The literature has also focused on differentials between 90th percentile and 10th percentile, 50th percentile and 10th percentile, 90th percentile and 50th percentile. These later measures provide insight into what occurs at the top end of the distribution and bottom end of the wage distribution. The choice of appropriate statistics depends on the problem one is trying to resolve. A standard aim of the decomposition usually lies in dissecting the overall wage gap between the two mentioned groups into components of differences in wage structure and components attributed to the observable characteristics of the workers. In this setting, wage structure is the link to unobservable and observable characteristics.

The decomposition into these two components requires the use of meaningful counterfactual wage distribution. For instance, we could postulate what the wages of a specific group of workers would look like if they had different returns to observable characteristics. Continuing with our two-group example of groups A and B, we may ask what the worker would pay for group A if they had returns to characteristics of group B. We could also ask what the pay of women would be if they were paid like men. When the groups belong to different time periods, we may ask what workers would earn in 2000 if they had the same returns to observable characteristics as in 1980. All the examples mentioned above show that manipulating structural wage-setting functions is required to compose counterfactuals and link them to observed and unobserved characteristics. We make a formal structure using the following assumption

3.6.1.2 Assumption Number 2: Structural Form of the wage equation

Suppose we have worker i, which belongs to either group A or B and is paid according to the following wage structure, m(A) and m(b), which are functions of the workers' observable characteristics (X) and unobservable characteristics (ε). Mathematically the equation becomes

$$YAi = mA(Xi, \varepsilon i) and\ YBi = mB(Xi, \varepsilon i) \ldots \ldots .. (3.7)$$

Here εi has a conditional distribution (since it is unobservable) with Fε|X given X and knowing that g=A, B. This wage differential is very general, but it is important to note that the wage differential implies only three reasons why wage distribution between A and B can differ. Those are

1) Differences between the wage-setting function of mA and mB
2) Differences due to distribution of observable characteristics
3) Differences due to unobservable characteristics

The main aim of the OB is to separate the contribution of the first factor (difference between mA and mB) from the other two factors. When we make the counterfactual assumption based on <u>alternative</u> wage structure (e.g. using the observed wage structure of group B as a counterfactual for group A), decompositions can provide us with valuable counterfactuals.

Other counterfactuals are based on hypotheticals and hence may involve general equilibrium effects. For instance, let us take an example of the distribution of wage for group A workers if there were no group B workers. What would the pay structure look like in this case for group A workers? Another similar question would be the pay structure if there were no union workers. Another relevant question for the thesis is the question of non-discriminatory pay. What would the wage be of women if they were paid according to some non-discriminatory wage structure (different to that of men). The following assumptions help answer some of the questions and the type of counterfactuals that we are working with.

3.6.1.3 Assumption 3: Simple counterfactual treatment

Following from the earlier discussion, if we assume that m^c (a counterfactual wage structure) is said to be the simple counter-factual treatment. So $m^c = mA$ for workers in group B and workers in group A $m^c = mB$. To illustrate the point further, we continue with our earlier example. So that Yg|Ds is g=A, B potential results (outcome/wage) and s=A, B indicates group membership. Continuing, we observe that if s=A then observed wage for group A becomes YA|DA while the counterfactual wage becomes Y_b^c|DA. For group B similarly, we will observe YB|DB while the counterfactual wage would become Y_a^c|DB.

The superscript C is added to the equation to highlight the counterfactual wages. For example, let us consider a case where workers in group B belong to a union while workers in group A do not belong to any union. The dichotomous variable DB represents the status of workers (whether they are in a union or not). For worker i hence, if the worker belongs to the union so that DB=1, the observed wages under the union is YB|DB,i = mB (Xi, εi). The counterfactual wage that would exist in this case would be (if there were no union) Y_a^c|DB, i = m^c(Xi, εi) = mA(Xi, εi), i ∈ B. Looking at the alternative question and going by the same question, one could ask what the wage of non-union worker j will be in the presence of a union.

It would be Y_b^c|DA, j = m^c (X j, ε j) = mB(X j, ε j), j ∈ A. The choice of which counterfactual to use is the same (analogous) as the choice reference group in the OB decomposition. Looking at assumption 3, we can see its limitation as well. Assumption 3 rules out another counterfactual in this case of unions for getting the wage of the market without any unions in the labour market. Unless there are no general equilibrium effects m*, a wage structure without any union is not equal to mA.

3.6.2 Criticism of Oaxaca-Blinder

The model proposed by Oaxaca and Blinder, though having widespread recognition, has also received many criticisms specifically for selecting independent variables and model specifications (Riach and Rich, 2002). It can significantly change depending on what the interest of the researcher is. Rosenzweig and Morgan (1976) argued that using age parameter (age and age squared) instead of experience and experience squared in the equation developed by Blinder (1973) results in a bias. The bias they argued results in expansion of the size of the education variable in explaining the difference between male and female wages, whereas more of a difference would have been explained by experience if it were incorporated in the equation.

Heckman (1979) argued that there is an inherent selection problem with describing the wage offer for women. He argued that the decision to enter the labour market might differ for men and women. Therefore, their wage structure and setting might be different. Hence, if that is the case, both unobserved and observed components may be different for the two genders. They reflect the fact that men who participate are different from women who participate in their characteristics. This is not just a problem in setting up a similar wage equation to men but also to conduct counterfactual.

F. L. Jones (1983) argued that incorporating and using the constant term was defective. He argued that in the presence of offset fictional variables, the magnitude of the constant term depends on of sample (reference group - which is white males) group. So, the constant term introduced and the residual term in the decomposition cannot be interpreted. In summary, his argument relies on the fact that the discrimination (residual term) cannot be determined uniquely because the intercepts themselves depend on the measurement decision and the reference group.

Ronald L. Oaxaca and Ransom (1999) responded to the criticism by arguing that the main problem is the researchers trying to evaluate the contribution of each variable to the overall discrimination. They secondly argued regarding the dummy variable that mainly the issue arises when researchers randomly assign reference groups. Still, the estimates and their effects are not affected by the out of sample group. They acknowledged that while the estimates might still be unbiased, the intercept might be affected. They said that all wage equations contain categorical variables, and it is a problem for all wage equations. So, the problem of seeing the relative effect of a dummy variable on the decomposition of wages will remain a problem.

Other critics have claimed that the Oaxaca-Blinder approach is limited to the labour market while measuring discrimination. If there are endowment differences, for example, women are stopped/discouraged from going into eventual high paying subjects, that is also a type of discrimination affecting the labour market. So the model underestimates the amount of discrimination that is in the labour market (Madden, 2000).

Further criticism has come from Atal et al. (2009) who argued that the methodology has three main flaws. The first one is that the average wage gap is considered, which omits the different distribution of the wage gap between the same group. Secondly, they argued that recent data has suggested that the relationship between wages and characteristics might not be linear. This violates the Mincerian equation, which is the primary input of the decomposition. Thirdly, the compared individuals often do not possess similar characteristics, leading to an upward bias when measuring the equation. They argued that taking comparable individuals in the final data set improves the equation.

Finally, the most severe problem of the Oaxaca-Blinder approach is that estimates of the coefficient might have a bias due to variable errors, information problems and selection problems. This leads to whether the final discrimination residual can be interpreted as discrimination or not (Ospino et al., 2010). However, here it is essential to mention that all empirical work in the social sciences is with methodological problems and hence even though the approach is not perfect, we proceed with the thesis using the approach.

3.6.3 Improvements in Methodology

Studies have built upon the above-explained model of Oaxaca-Blinder (1973) and removed many of the problems that were in the original model. For example, one of the earliest criticisms laid on the model was that it did not consider occupational segregation (J. P. Smith and Welch, 1986). Nurses, doctors, and all people were pooled together in the same group and treated the same. The seminal paper from Brown et al. (1980) also takes and uses occupational segregation. As advancements grew in the literature, the need to further dissect the discrimination into quartiles became important. In this regard, the papers by Fortin et al. (2011) considered quartiles also became important.

3.6.3.1 Index Problem:

The disaggregation technique relies on wage differentials between groups by two distinct parts. One is that of productive characteristics (such as experience and education), and the other is that of remuneration of these characteristics between groups. To achieve this, The OB decomposition presumes a labour market advantaged group beforehand. This random choice of disadvantaged/advantaged group is known in the literature as the index problem. The index problem presents constant criticism to the decomposition model as there is no reason to assume the coefficient of a specific group of people.

The issue has been widely dealt with in the literature. Reimers (1983), for example, gives one way to solve the index problem. He proposed using the average (mean) of all groups involved in the study to get the non-discriminant coefficients. Mathematically this can be represented by the following.

$$\beta^{\wedge} *= 0.5B^{\wedge}H + 0.5\beta^{\wedge}M \ldots\ldots(3.8)$$

Here $\beta^{\wedge} *$ corresponds to the new non-discriminatory estimator. $B^{\wedge}M$ corresponds to the coefficient of men (estimated in the equation 3.4) and $\beta^{\wedge}F$ corresponds to the coefficient of women (estimated in equation 3.5).

Cotton (1988) expands on Reimers (1983) idea and proposes that rather than taking the means of all groups. A better way is to take the weighted average of the group distribution. Mathematically, this can be represented.

$$\beta^{\wedge} *= \frac{NM}{NM+NF}BM + \frac{NF}{NM+NF}BF \ldots\ldots(3.9)$$

Here $\beta^{\wedge} *$ corresponds to the new non-discriminatory estimator. NM corresponds to the number of males in the sample, and NF refers to the number of females. The rest of the terms are the same as in equation 3.8.

3.6.3.2 Extensions to limited dependent variable models

OB decomposition is not just limited to outcome variables where the dependent variable is continuous. For example, it has been used to study change of labour force participation over time in the case of the UK by Gomulka and Stern (1990). Fairlie (2005) researched racial gaps in computer ownership and self-employment. Liao and Paweenawat (2020) analysed Thailand using this methodology more recently. They researched the probability of women being in the top 10% of the earners using the probit model for Thailand utilising data from official national statistics of Thailand from 1985 to 2017. The methodology is summed up below.

Firstly, the probit model establishes the correlation between top 10% of women and individual characteristics. The individual characteristics include years of schooling, marital status, age etc. The following equation shows this.

$$\Pr(Yi = 1|\text{Xi}) = \varphi(\text{Xi}\beta\text{i} + \text{Ei}) \ldots..(3.10)$$

Here Yi is a variable that equates to 1 if the individual is in the top 10% earning group and assumes the value of 0 otherwise. Xi is a set of explanatory variables and includes all the aforementioned characteristics. Since age is a major factor in the distribution of top earners (meaning it is heavily skewed to the right). Two distinct models are run.

Model 1 is a binary variable where 1 is the value of the binary variable if an individual is female and in the top 10% of the earner group. Here the rest of the people in the sample are given a value of 0. Again, in the second model, if the individual is a female and in the top 10% of the earner group, she is given the value of 1. However, in this case, 0 is given to the males in the top 10% of the earner group. The next step is to run an OB decomposition. This is to study changes in the gender wage gap for the top earners. The equation for log hours wage is run as shown in equation 3.4 and equation 3.5.

The non-linear models suffer the same difficulty as the same linear models in their appropriate counterfactual choice. In addition, precaution must be taken while verifying the counterfactual. The counterfactual must lie within the bounds of a limited dependent variable. Fairlie (2005) checks that using White coefficients for the black average self-employment rates does not yield a negative result. The non-linear decomposition might be preferable to the linear decomposition when the gap lies at the ends of the distribution (at the tails). Also, it might be more useful when there are large differences between the explanatory variables themselves.

However, non-linear models also come with their set of problems. The non-linear models are difficult to compute as the contribution of each variable does not add to the total in the non-linear model. Fairlie (2005) proposes a solution to this. He proposed that the coefficient of each variable should be switched to the reference group value in sequence (based on a series of counterfactual).

3.6.4 Regressed Influence Function

Firpo et al. (2007) extend this idea and propose a decomposition beyond the mean. They argue for a new regression method to estimate the effect of variables at different quantiles. The model is called the regressed influence function (RIF) and uses three distinct regression estimators. The first regression is based on standard OLS. The dependent variable, in this case, is the refocused influence function (RIF-OLS). The second is the logit regression (RIF-Logit), and the third is non-parametric logic regression (RIF-NP). This method has the advantage of surpassing the analyses of averages, but its limitation is the assumption that the covariation of the variables is independent. The authors also admitted this.

Data aggregation and salary decomposition are key for Fortin et al. (2011). They do not rely on parametric assumptions. Their method allows the effects of the covariates to be studied independently. This is very similar to Oaxaca-Blinder decomposition and adds one additional step to the approach. Before proceeding with the OB decomposition and calculating its coefficient. The coefficient is calculated by a RIF regression, as mentioned above. The RIF coefficients become the new coefficients, and the OB decomposition is performed using those estimates.

The approach comes with one disadvantage. The issue with the RIF regression coefficient is that it contains just a local approximation, which means that important information is provided at one value of the function and its derivatives simultaneously. However, it does not solve the index problem, and it does not provide valuable information across the distribution of interest. The RIF's advantage is that it provides detailed distribution calculations for different distribution parameters.

3.6.5 Quantile Regression

Machado and Mata (2005) propose an extension of the OB decomposition. They argue that decomposition should be completed on the entire wage distribution. This method relies on the estimation of wage density function in each period. They applied it on Portuguese wages for the years 1986 to 1995. The counterfactual nature of their proposal required wage distribution conditional on variables using quantile regressions. So, quantile model estimates are calculated. These quantile regression estimates can capture the impact of covariates across the wage distribution. This method relies on the impact that wage is supposed to have on wage density. It does not, however, force a relationship between different variables.

Here it becomes essential to note that while we can decompose the mean using standard regression. We cannot decompose the quantiles using simple quantile regression. To grasp this point, we first look at the interpretation of the B coefficient. The B coefficient has two distinct interpretations. The first is the conditional mean interpretation, where the B coefficient is simply the effect of X on the conditional mean E(Y|X) in the model E(Y|X)=BX. Using iterated expression law (the expected value of X should be the same as the conditional expected value of X given Y is the same as X), we can also say that E(Y)=EX[E(Y|X)]=EB(X). This yields the interpretation that unconditional mean B is the effects of an increase in the mean value of X (on the unconditional) mean value of Y. This interpretation of B and particular property of regression is used in the OB decomposition. Only the conditional quantile interpretation is valid by contract for the quantile regression. Continuing the analogy of the simple regression mentioned earlier, suppose we have the ith conditional quantile which means that Qi(X)=Bi(X). This can be interpreted as Bi the effect of X on the conditional ith quantile of Y given X. However, the main difference is that the law of iterated expression is not valid here. Consequently, we cannot interpret Bi as the effect of increasing the mean value of X given the unconditional quantile Qi. For this paper, we utilise this quantile regression.

3.7 Results

Table 3.7 summarises the OB decomposition at the mean for all the models in the analysis. The output table reports the average log of wages for men and women, the unadjusted wage gap (difference), and the explained and unexplained gap. The mean log of the male was higher than the mean log of females, indicating that men earned more in all the models. The unadjusted wage gap was the largest in Model 1 (AWT9), with a log difference of 0.412. The unadjusted wage gap was lowest in Model 4A (BG1), with a difference of 0.346.

Table 3.7 Oaxaca-Blinder decomposition for all six models, summary of overall results.

	Model 1 All worker wave 9	Model 2 Just graduate wave 9	Model 3 Master PhD wave9	Model 4 A Broad graduate wave1	Model 4 B Broad graduate wave 5	Model 4 C Broad graduate wave 9
Overall						
Male	7.728***	7.945***	7.990***	7.727***	7.811***	7.930***
	(0.00997)	(0.0195)	(0.0146)	(0.012)	(0.0127)	(0.0129)
Female	7.316***	7.576***	7.641***	7.381***	7.415***	7.549***
	(0.00937)	(0.0164)	(0.0131)	(0.0106)	(0.0111)	(0.0111)
Difference(D)	0.412***	0.370***	0.349***	0.346***	0.396***	0.381***
	(0.0137)	(0.0255)	(0.0196)	(0.016)	(0.0168)	(0.017)
Explained(E)	0.266***	0.246***	0.218***	0.213***	0.243***	0.225***
	(0.0113)	(0.019)	(0.014)	(0.0121)	(0.0132)	(0.0125)
Unexplained(U)	0.146***	0.124***	0.130***	0.133***	0.153***	0.157***
	(0.0103)	(0.0205)	(0.0161)	(0.0128)	(0.0134)	(0.014)
N	11119	2613	4624	9300	7486	6200

Standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01

The unadjusted wage gap is further subdivided into two parts for all models; Explained (characteristics) and Unexplained (discrimination). The explained part of the results indicates the average increase women would have if they had similar characteristics to men. The unexplained part is attributed to discrimination. Consequently, the mean difference between the log of wages, D contains two components (E and U). Therefore, if we assume that there are no unobservable explanatory variables, then the total difference, D is equal to E + U. The base of the first component € comes from the difference in the degree of the independent variables. The second part of the equation (the U component) emanates from the differential effect of these covariates (discrimination component). We observe a total difference in the all-worker model (model 1), D of .412. This is the highest amongst all the models, followed by broad graduate wave 5 with .396 and broad graduate wave 9 with .381, respectively. The lowest difference was observed in Model 4A for broad graduates' wave 1 (BG1) of .346. Detailed results for each model are presented in Appendix 5 to Appendix 10.

Figure 3.6 compares each model's explained and unexplained component of the wage gap. The explained portion is calculated as explained gap / total gap, and the unexplained portion is calculated as unexplained gap / total gap. These calculations provide us with the percentage of the wage gap explained and the percentage that is down to discrimination for each characteristic and discrimination variable. The highest explained percentage in our models was observed with just graduates at 66.49%. This means that 66.49% of the total gap in log average of men and women can be explained by our characteristics. The second-highest percentage for explanation is in the AWT9 group, with 64.56% of the wage gap explained. The lowest wage gap explanation came from BG9, with 59.06%. This is smaller when compared to other models for earlier years using similar variables and data. In BG 5, 61.36% and BG 1, 61.56% of the component of the wage gap was explained. Our education group, including masters and PhDs, had 62.46% explained results, while 37.54% remained unexplained.

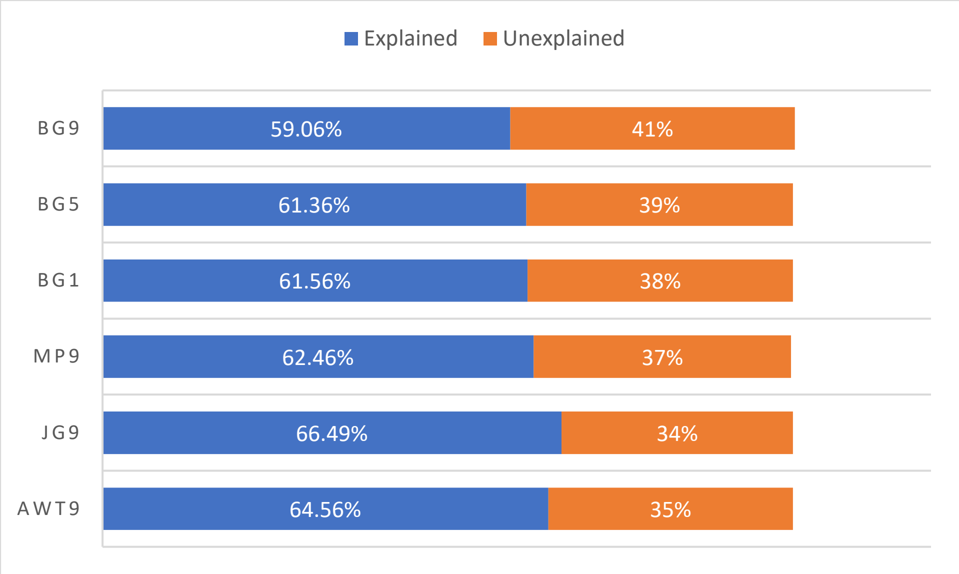


Figure 3.6 Explained component and unexplained component of six model

Table 3.8 OB decomposition presents the contribution of each variable in the explained and unexplained components. The magnitudes of each variable in the explained portion equal the total explained component. The same is true for the variables in the unexplained component. Looking at Table 3.8 OB decomposition, we observe working hours, working status (part-time, full-time), age, married, and organisation size as key components that comprise most of the explained portion. Table 3.8 OB decomposition demonstrates that the key role in explaining the gap for most models is working hours and being part-time. Working hours were most significant for AWT9 and BG1, explaining 0.176/0.266 and 0.141/0.213 of the log mean gap. The working status also explained the wage gap and was most significant for our BG1 and BG5 groups. Working status (with full-time as the reference group) explained 0.0726/0.213 of the gap in BG1.

Similarly, for BG5 model .0847/0.243 of the gap was explained. In the explained portion of the analysis, we see negative values (in the case of education and age squared). This is reasonable and means that women were older and had more educational experience on average. If we remove these advantages, the wage gap will increase further. Regional disparity came to be insignificant for all models except BG1 and BG5. For BG1, London is significant at P<.0.01, and for BG5, it is significant at P<.0.10, although the magnitude (0.00552/0.213 for BG1 and 0.00144/.243 for BG5) of the explanation is low for both. Being married was significant in all the models. Ranging from explaining 5.7% of the gap (JG9) to 1.85% (BG1).

Table 3.8 Oaxaca-Blinder decomposition full results

	Model 1	Model 2	Model 3	Model 4 A	Model 4 B	Model 4 C
	All worker wave 9 (AWT9)	just graduated wave 9 (JG9)	Master PhD wave 9 (MP9)	Broad graduate wave 1 (BG1)	Broad graduate wave 5 (BG5)	Broad graduate wave 9 (BG9_
Age	0.00941	0.108***	0.0975***	0.00835	0.0699***	0.024
	(0.0162)	(0.0405)	(0.0302)	(0.0199)	(0.0241)	(0.0239)
Age squared	-0.00702	-0.0891**	-0.0879***	-0.0141	-0.0682***	-0.0215
	(0.0139)	(0.0358)	(0.0274)	(0.0179)	(0.0217)	(0.0216)
Working hour	0.176***	0.117***	0.113***	0.141***	0.145***	0.130***
	(0.0085)	(0.0136)	(0.00991)	(0.00942)	(0.0101)	(0.00943)
Part time	0.0773***	0.0693***	0.0627***	0.0726***	0.0847***	0.0656***
	(0.00521)	(0.00914)	(0.0067)	(0.00608)	(0.00672)	(0.00605)
Private	0.00198	0.0109**	0.00635*	-0.0142***	-0.0111***	0.00102
	(0.0021)	(0.00506)	(0.00385)	(0.00294)	(0.00281)	(0.00317)
London	-0.000123	0.00134	0.00178	0.00552***	0.00144*	0.000949
	(0.000843)	(0.00237)	(0.00189)	(0.00117)	(0.000789)	(0.00162)
Married	0.00628***	0.0142***	0.0122***	0.00394***	0.00884***	0.0103***
	(0.00114)	(0.00368)	(0.00257)	(0.00106)	(0.00169)	(0.00204)
Children	0.000124	-0.000101	-0.000125	0.0000378	0.0000035	-0.0000312
	(0.00022)	(0.000615)	(0.000333)	(0.000351)	(0.000142)	(0.000234)
25-99	-0.00298***	-0.00560**	-0.00501**	-0.00671***	-0.00712***	-0.00425***
	(0.000889)	(0.00265)	(0.002)	(0.00158)	(0.00173)	(0.00162)
100-499	0.00844***	0.00624*	0.00758***	0.0127***	0.00957***	0.00903***
	(0.00156)	(0.00332)	(0.00283)	(0.00233)	(0.00237)	(0.00257)
500+	0.00464**	0.0138**	0.0103**	0.00352	0.00952**	0.00895**
	(0.00236)	(0.00586)	(0.00462)	(0.00297)	(0.00383)	(0.00404)
Masters & PHD	0.00955***					
	(0.00316)					

Bachelors	-0.0104***					
	(0.00299)					
Other High degree equal bachelors	-0.00853***					
	(0.00132)					
A levels and Lower	0.000489					
	(0.000602)					
Unexplained						
Age	0.677**	-0.102	0.456	0.267	0.248	0.651
	(0.266)	(0.606)	(0.54)	(0.346)	(0.386)	(0.441)
Age squared	-0.353**	0.0976	-0.231	0.015	0.00319	-0.301
	(0.147)	(0.324)	(0.288)	(0.179)	(0.208)	(0.239)
Working hour	-0.523***	-0.338**	-0.391***	-0.728***	-0.652***	-0.474***
	(0.0681)	(0.143)	(0.108)	(0.0983)	(0.0956)	(0.095)
Parttime	-0.0658***	-0.0259**	-0.0246**	-0.0982***	-0.0680***	-0.0354***
	(0.00857)	(0.0127)	(0.00986)	(0.0121)	(0.0111)	(0.00929)
Private	0.0410***	0.106***	0.0522***	0.105***	0.0895***	0.0568***
	(0.0134)	(0.0231)	(0.0173)	(0.0134)	(0.0144)	(0.0153)
London	-0.00431	-0.00982	-0.00944	-0.0135**	0.00267	-0.00769
	(0.00368)	(0.00872)	(0.00698)	(0.00607)	(0.00536)	(0.00563)
Married	0.0230*	0.023	0.0141	-0.0201	0.0362**	0.00566
	(0.0122)	(0.0325)	(0.0241)	(0.0164)	(0.0173)	(0.0197)
Children	0.00873	0.0356*	0.0244	0.0222*	0.0203*	0.0266**
	(0.0083)	(0.019)	(0.0153)	(0.0119)	(0.0122)	(0.0129)
25-99	0.00821	-0.0041	0.00784	0.00749	0.0191**	0.00439
	(0.00665)	(0.0152)	(0.0113)	(0.00861)	(0.00896)	(0.0097)
100-499	0.00118	-0.019	0.00252	0.0022	0.00305	-0.00226
	(0.00612)	(0.0157)	(0.0116)	(0.00777)	(0.00861)	(0.00943)

500+	0.00823	0.0183	0.0291**	0.00908	0.0283***	0.0173
	(0.00637)	(0.0157)	(0.0144)	(0.00921)	(0.0095)	(0.0114)
Masters and PHD	-0.0116**					
	(0.00572)					
Bachelors	-0.0104*					
	(0.00622)					
Other High degree equal bachelors	-0.000977					
	(0.0038)					
A levels and Lower	-0.000448					
	(0.00438)					
_cons	0.349***	0.343	0.201	0.565***	0.423**	0.214
	(0.135)	(0.316)	(0.273)	(0.19)	(0.208)	(0.221)
N	11119	2613	4624	9300	7486	6200

Standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01"

3.7.1 Quantile regression results

In panel (a), (b), (c), (d), (e), (f) of Figure 3.7, quartile OB decomposition are shown for all six of our models. Each panel shows a line graph with three lines at 9 income quartiles going from 0.1(lowest quartile) to 0.9 (highest quartile). The blue line indicates total wage gap, red indicates the effect of characteristics (explained gap), and green indicates discrimination (unexplained gap).

Panel A depicts quartile decomposition for all worker data set (AWT9). Observing panel A, we discern that the total wage gap decreases as we move up the income quartile. However, the effect of characteristics (the explained portion of the wage gap) also decreases as we move up the income quartile, whereas the opposite is true for the discrimination effect. The effect of discrimination increases as we move up the income quartile.

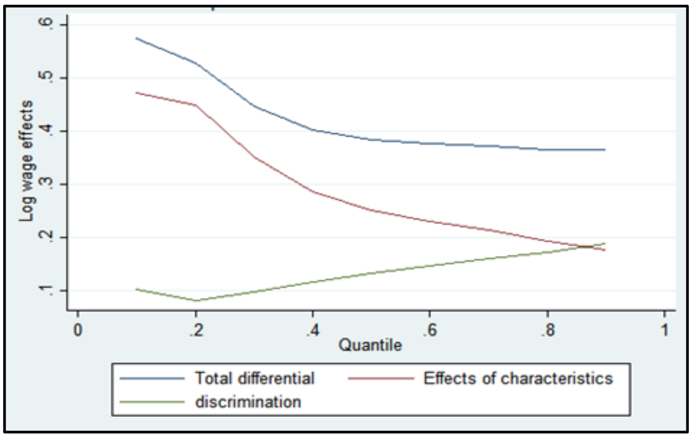
For our Just Graduate (JG9), represented by panel b, we notice the total wage gap decreasing at higher income quartiles but a less rapid rate than in the AWT9 model. Eventually, at higher levels of the income quartile, the total difference lines smooth and become almost constant before going up again. Coming to our characteristic and discrimination trend, we notice effects similar to panel A in that effect of characteristics decreases and discrimination increases as we move up the income quartile. However, in JG9, compared to AWT9, the effect of discrimination becomes more than the effect of characteristics at a much earlier quartile (near to 6th quartile).

For our GMP9 group, represented by panel c, we notice the total differential to be like that of JG9. However, in contrast to JG9 and AWT9, the effect of characteristics is greater but decreasing, whereas the effect of discrimination increases. Discrimination takes over characteristics at around .75, which is similar to AWT9.

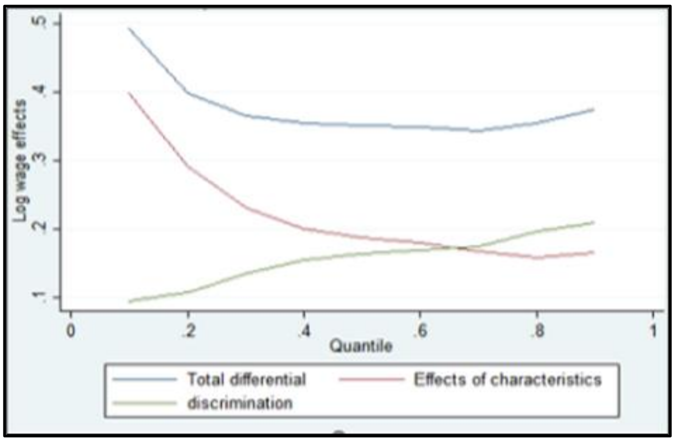
Regarding Broad graduates' wave 1 (BG1), panel d, we observe the total difference from lower to upper quartiles decreasing rapidly. The effect of characteristics diminishes quickly, whereas discrimination increases rapidly in the early quartile and about 40th percentile of the quartile, overtaking the effect of characteristics indicating higher discrimination from the early quartile group of .4 onwards. Comparing it to broad graduate wave 5 (BG5), the total difference decreases more rapidly than in BG1. More of the total difference is due to characteristics and remains so until the income quartile of .7 where discrimination again takes over. The pattern and trend of the lines in the characteristics and discrimination portion are similar to our GMP9 model. Finally, in our last panel F Broad Graduate wave (9), the total log wage difference line follows the pattern observed in JG9, GMP9 all graduate wave 5. However, this differs from all graduate wave 5 in that discrimination takes over characteristics much earlier at .6. Detailed results for quantile decomposition are represented in Appendix 11 to Appendix 16 of the thesis.

In summary, similar patterns were observed for all six models. The lower quartiles had the highest wage differential, which co-variants can mainly explain, and discrimination levels are low at those quartiles. However, as we move up the income quartiles, we notice that total wage differentials decrease until the 8th quartile. At this point again, we see the total differential rising. The characteristic line also displays a related trend amongst models, sharply decreasing from 1st quartile to 4th quartile and then steadily decreasing. We observe a slow and gradual increase in most cases (except all graduates wave 1) throughout the income quartiles for discrimination.

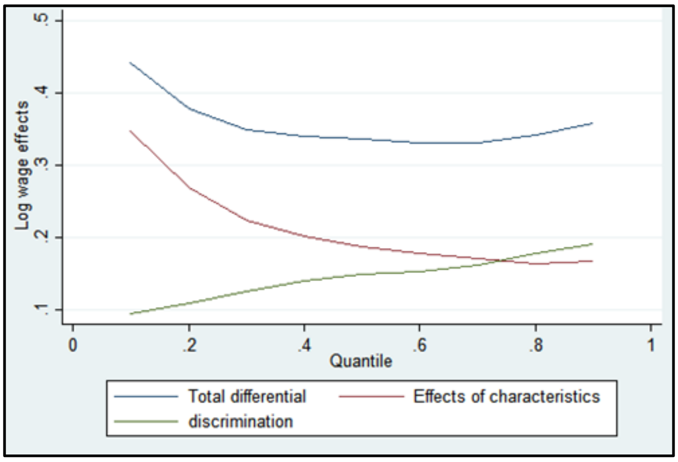
Figure 3.7: Quartile OB Decomposition Panel (a),(b),(c),(d),(e), (f)



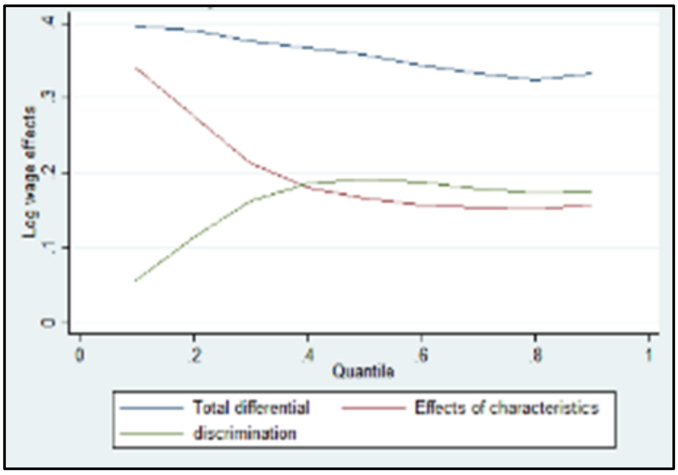
All worker dataset (AWT9)



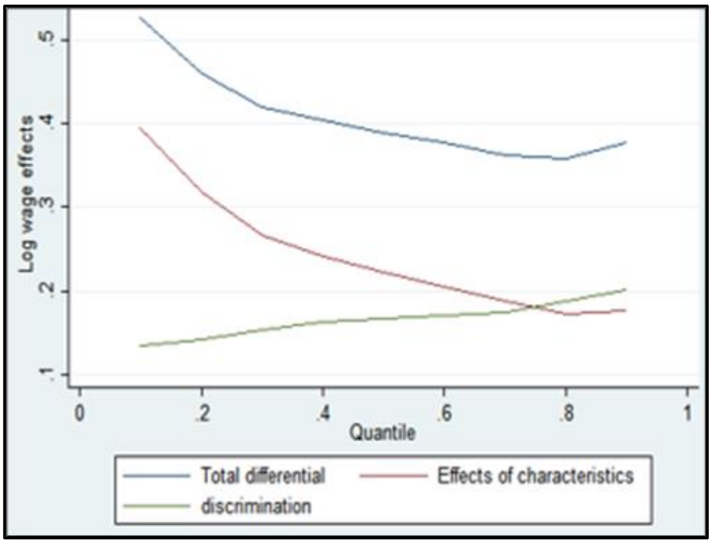
Just graduate (JG9)



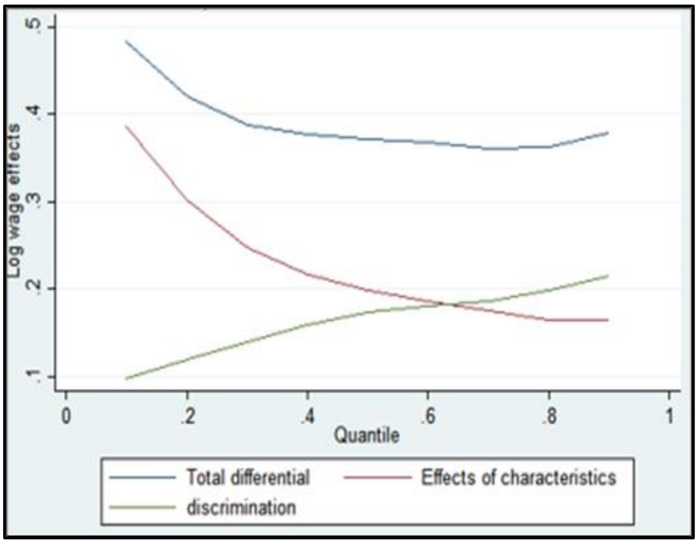
Graduate/ Master PhD (GMP9)



Broad Graduate (BG1)



Broad Graduate 5 (BG5)



Broad Graduate 9 (BG9)

3.8 Discussion and Conclusion

We analysed six models with Oaxaca-Blinder, five with varying levels and definitions of education and a sixth overall model to provide robustness and comparison. We selected a model of all worker dataset for wave 9 of *The UK Understanding Society* survey. The analysis found that the total unadjusted wage gap was the highest for the all-worker model (AWT9) compared to other models. However, even though the difference is the highest for this group, it is not unjustified as the proportion of explained gap is also high in the model. The results found gender discrimination to scale up to 35% in the all-worker model. This is substantiated by Olsen et al. (2018) who also found an unexplained gap of 36% for UK. The results, however, are much lower than those Landmesser and Policy (2019) reported for the UK, which found the unexplained effect to be 52.1%.

For the graduate pay gap, the highest discrimination was found in Broad Graduate 9 (BG9) at 41%, whereas the lowest was observed in our Just Graduate (JG9) model. Increasing education levels and including masters/PhD into the calculation did not decrease the magnitude of discrimination; however, it did decrease the overall wage gap. This indicates that despite achieving higher education, women do not escape discrimination. As for our similar educated background models, we saw high rates of unexplained components. Interestingly, the overall wage gap (unadjusted gap) for educated individuals has increased. This is in stark contrast with the general population, which shows the total overall gap (unadjusted) decreasing between men and women over the years. Our analysis found that while the wage gap is decreasing for the general population, the result does not hold true for highly educated individuals. (Since we use multiple datasets for educated graduates, the results are also robust)

Coming to the proportion of the gap explained and unexplained, it is hard to evaluate whether the estimate is overstating or understating the unexplained gap. One crucial factor missing from the analysis is the inclusion of the occupation variable. That might have a significant effect in explaining more of the gender pay gap. This will most likely decrease the unexplained part of the analysis and improve the explained portion. Due to the lack of number of observations, this key variable was ignored, but as is suggested from the literature, it might help explain the gender pay gap in more detail. As a result, it is appropriate to be skeptical about interpreting the unexplained portion as discrimination, though, as mentioned throughout the paper, this does play a role in it.

The analysis was further expanded with all six models analysed at 9 different income quartiles. From our models, we can say that while the total wage gap decreases at the upper level of the income quartile, there is more of a discriminatory component at the top income levels. For instance, the paper found the opposite true at the lower levels. At the lower-income quartiles, the total wage gap was the highest. However, the effect of characteristics explained most of the disparity in the gap at lower income quartiles. The results were valid for the overall population (AWT9) and highly educated groups. This substantiates much of the literature and confirms the glass ceiling hypothesis. Arulampalam et al. (2007) found the presence of glass ceiling in Britain's public and private sectors. For sticky floors, our analysis found no statistical evidence. Like our results on sticky floors, Arulampalam et al. (2007) also found no evidence of sticky floor in Britain for both the private and public sectors.

These results are also substantiated by Landmesser and Policy (2019), who found the effect of characteristics going down and the unexplained gap increasing as we move up the income quartile. The only difference between our study and Landmesser and Policy (2019) was at 0.2 and 0.9 income quartile. At both these income quartiles, the effect of characteristics was noticed to increase by Landmesser and Policy (2019) whereas our study found no such effect.

The paper adds to the literature as it provides valuable insights for the gender pay gap in highly educated individuals at nine income quartiles. The paper is also important since it proves that the way you define high education changes the results. Lastly, the paper adds to the literature by looking at how the adjusted and unadjusted gap has changed over-time.

Chapter 4: What would happen if female wages became equal to males? A Socio-Economic Impact Multi-Regional Input-Output Model (SEIM-UK) application: A methodological case for a Gaussian approach

4.1 Abstract:

Labour market discrimination creates wage differentials unrelated to productivity, constituting an economic cost to society (Teignier and Cuberes, 2014). This paper attempts to measure the effects of removing gender wage discrimination on the regional economy and reports changes to gross value added and number of new jobs created. In order to do that, the paper use a multi-regional input-output model (2016) for the UK. The chapter is essentially composed of two main parts.

The first is an extension of the Oaxaca-Blinder (1973) approach to measure wage discrimination, which allows us to calculate the remuneration amount for the individuals by region and sector. The second part sets up a series of assumptions (hypothetical) to calculate the impact of equal gender remuneration on the economy using an input-output model. After the remuneration amounts are calculated in the first part, we assume and compare four different scenarios. The first two are "benchmark" scenarios of complete wage equality in one region and one sector. The other two scenarios are no-gender discrimination scenarios in which all people are remunerated as per their productivity levels.

All the scenarios increase labour and production costs. The input-output model uses this labour and production cost increase as vector shocks to the economy. All these four scenarios produce an exogenous (hypothetical) shock that increases female compensation effects in the UK economy. We use two input-output models to calculate the effects of these changes. The effects are first analysed at the regional level based on the Socio-Economic Impact Model (SEIM-UK). Secondly, we simulate nationally using the ONS input-output model for comparison. Our results imply that removing discrimination from the workplace against women improves output and employment significantly for UK with GVA ranging from 0.08% to 0.98%.

4.2 Introduction

The United Kingdom has seen a gradual increase in female labour force participation (FLFP) over the last three decades. In 1990, FLFP stood at 52.02% compared to 58.09% in 2019 World Bank (2019). Goldin et al. (2006) term this increase as the "quiet revolution" in gender roles, which signifies the narrowing of labour market differences between males and females. Before the revolution, he argues that women's identity was defined by their fathers or after marriage by their husbands. However, since the revolution (which he believes started in the 1970s), women formed their identity by themselves, marrying late and starting their careers.

Many different explanations have come forward to explain this rise in FLFP. From a health and medical point of view, these include a significant decrease in fertility (by the birth control pill) (Bailey, 2006), substitutes for maternal lactation (Albanesi and Olivetti, 2016), and a reduction in post-birth disability. In addition, these medical advancements allow women to plan for their professional careers.

This has been coupled with decreased total labour input required in households due to technological advancements (automatic washing machines, dishwashers, etc.) (Attanasio et al., 2008). Simultaneously the technological progress in the workplace has meant that the need for non-manual skills compared to manual skills has increased. Heathcote et al. (2010) argue that this post-industrial phase shift explains part of the reason why the labour supply has increased for women. In addition, they argue that this post-industrial phase leads to a growing service sector, associated with jobs suited to women's preferences and skill sets. This has led to a change in social norms.

Fernandez et al. (2004) investigate this change in social norms by looking at the sons of working women. They find that sons of working women preferred working wives. This indicates a change in men's perception which, over time, affects societal norms. According to the same work, women's perceptions are also changing. They find that gender stereotypes are slowly weakening with the presence of women in the labour market.

As a result of these societal changes, women have had greater labour market aspirations, increased return on education and have continued to get graduate degrees from professional schools.

Interestingly most of these studies focus on individual effects of gender-based discrimination. However, the presence of the gender wage gap (in any way) is a costly phenomenon not just for the individual but the country as well. This is a much rarer topic for research. Very few studies try to understand the macroeconomic outcome of this discrimination. Even fewer have these at the center of their research. For example, the study of Tertilt and Doepke (2016) talks about female empowerment for economic development. Even though they identify female empowerment as key to development, they do not analyse the macroeconomic effects of this discrimination. Studies are limited on this topic, even in developed countries. García-Meza (2021) paper contributes to the literature by adding valuable macroeconomic outcomes of this discrimination. It specifically adds value in its approach and methodology (input-output model).

Few studies target macroeconomic variables, like employment, growth and labour market discrimination. The following paper tests these theories and ideas empirically by creating a hypothetical scenario in which no gender discrimination exists and the effects on macro-economic variables such as GVA and number of jobs are studied. The paper empirically computes the costs of discrimination in the UK labour market by using an Input-Output (IO) model at the regional level.

4.2.1 Purpose of the study/Motivation of the study

Labour market policies and gender wage gaps have been extensively studied recently. However, despite the recent focus on these labour market issues and policies, very few studies estimate the benefit of removing this discrimination from the labour market. Even fewer studies try to calculate the impact of eliminating these discriminations at regional and sectoral levels (Domingue, 2014). The paper analyses the possible benefits of removing gender discrimination in the labour market. That is the motivation of the study.

The paper finds potential benefits of removing this discrimination at the macro level for the country. The study's contribution is to analyse the sectoral level and regional effects of a hypothetical scenario in which no gender discrimination exists in the UK. Since much public effort, attention and funds are being spent on this issue, and it is interesting to observe the potential benefits of its eventual abolition.

4.2.2 Aim of the paper

The paper aims to answer the question of what would happen if there was no gender discrimination in the UK labour market. The paper tries to answer this question by running six distinct scenarios through a multi-regional input-output model Socio-Economic Impact Model (SEIM-UK) for the UK and the ONS Input-Output Model. The four proposed scenarios are presented below.

What are the economic effects for the UK if the compensation of employees for female employees was exactly equal to men in London? (Regional Scenario #1)

What are the economic effects for the UK if everybody was paid per their productivity level in London? (Regional Scenario #2)?

What are the economic effects for the UK if the compensation of employees for females was exactly equal to men in the Professional, scientific, and technical activities sector (Sectoral Scenario # 1)?

What are the economic effects for the UK if everybody was paid per their productivity level in Professional, scientific, and technical activities sector (Sectoral Scenario # 2)?

Scenarios 1 through 4 are run through the SEIM-UK Input-Output Model. Scenarios 3 and 4 are run through the Input-Output model by ONS alongside SEIM-UK[8]. Here economic effects refer to overall changes in value-added, output and number of jobs amongst other important economic indicators such as final demand.

4.2.3 Novelty of the paper

The paper is novel in several ways. The first is using female wages instead of female labour force participation (FLFP) to approximate an increase in GDP is novel. In the literature, the usage of minimum wage increases is observed. The literature has other examples of analyses that also look at the relationship between FLFP and economic growth (Lechman and Kaur, 2015; Tsani et al., 2013; Yıldırım and Akinci, 2020). The main reason for this is the nature of economic growth with respect to female labour force participation. There appears to be a U-shaped relationship between economic growth and FLFP. As economic growth increases, so does FLFP, but until a certain point. After that point, as economic growth increases, FLFP decreases. Then as countries grow even more (GDP increases), FLFP starts increasing again. Recently meta-studies Tsani et al. (2013),Yıldırım and Akinci (2020), show evidence of the effect in higher-income countries, some evidence in middle-income countries and finally, little evidence in lower-income countries.

However, the thesis uses female wages to calculate and approximate the effect on GDP. The closest thing to the approximation used in this paper is minimum wage literature which approximates a hypothetical wage increase and its effect on GDP. However, the methodology of minimum wage calculation differs from this paper in that it applies just to low-income workers and is not just subject to females. Detailed discussions on these two topics and previous work are provided in the literature section of this paper.

[8] Reason for why scenarios 1 and 2 are not run through ONS input-output model are presented later on in the data portion of the chapter

The paper is also novel due to the model it uses. The paper uses the multi-regional UK Socio-Economic Impact Model (SEIM-UK). The SEIM-UK provides the ability to conduct a regional analysis at the NUTS 2 level. This is demonstrated and used with Regional Scenario 1 and Regional Scenario 2 (henceforth known as RS#1 & RS#2). Since this regional disaggregation is not presented with the national input-output model of ONS, the paper simulates RS#1 and RS#2 using the SEIM model only.

The paper is also novel as it compares (by aggregating Standard Industrial Classification (SIC) codes) two input-output models for sectoral scenarios (SEIM-UK and ONS IO). This provides a comparison between the models and the eventual results alongside robustness.

4.3 Literature Review

Labour market discrimination has individual as well as country costs associated with it. Mostly, these costs are referred to in relation to the individual and not as a country overall. For example, Lang and Kahn-Lang Spitzer (2020) provide a detailed analysis of discrimination literature review and note how it affects the individual. Their paper, primarily focuses on discrimination as a problem of the individual and not at an aggregated scale. It does not show how wage discrimination can directly affect a country.

For instance, Giuliano et al. (2011) argue that discrimination leads to higher turnover amongst employees but once again, the issue of how it affects a country is not addressed since the primary concern is individual discrimination.

Discrimination through a macro lens requires that we observe the cost that a country faces because of discrimination. A country might miss valuable output and GDP by not addressing discrimination. It is easier to understand the context of the paper if we see discrimination as much as an issue for the individual as we do for the country. In the paper, we focus on the opportunity cost that a country is bearing (loss output, GDP) due to labour market discrimination. We specifically focus on gender discrimination but leave the door open for further enhancements to the model for ethnic discrimination costs.

Before going into the literature on economic growth and the gender pay gap, it is essential to mention and clarify one crucial fact. The gender pay gap can often come from preferences (Farrell, 2005). For example, Neyer and Stempel (2019) note that the time women allocate to household activities versus men is different. OECD (2019) data also substantiates this and shows a clear difference between women's unpaid and paid working hours. On average, men spend 110 minutes on unpaid work, while women spend 276 minutes per day on unpaid work. The difference is just as stark when it comes to paid working hours. Men spend, on average, 266 minutes on paid work, whereas women spend 152 minutes on paid activities. This is the average found by observing data from 75 countries across time-surveys from 2006 to 2015 (Charmes, 2019). This indicates systematic gender differences, according to Neyer and Stempel (2019). On the other side of the argument, theoretically, these principles can be boiled down to preferences for women and men regarding the labour market and household work.

However, studies since the 2000s show that these differences might not be preference based. J. Lewis et al. (2008) report that fathers in Western Europe want to work less, whereas mothers reported a greater desire for full-time and more working hours. This is an indication that there is a disparity between preferences and work-time allocation between genders.

Boye (2009) provides further support for this. He concludes that the differences in unpaid housework and paid working hours for men and women constitute one of the reasons why the well-being of European women is lower than women. This again indicates that preferences result from factors outside of women's control, and we can conclude that at least one of those factors is discrimination in the labour market.

4.3.1 Economic growth and discrimination

Dabla-Norris et al. (2015) link discrimination, productivity and growth for a country. They argue that labour market discrimination affects both growth and productivity. They argue that the misallocation of resources is the main reason behind it. They state that misallocation of resources is responsible for productivity and income differences within countries.

The mechanism they propose is that of a feedback effect. So, women or any group discriminated against lowers investment in education (since they receive less benefit from it). This leads to a country's lower productivity and growth (Klasen and Lamanna, 2009). They also correlate it to the country receiving less talented people since there is a presence of discrimination in the labour market.

Further adding to this is the opinion of Stiglitz (2012) who argues that economic growth and increased equality in the labour market complement each other. He argues that we should look beyond GDP as a measure of wealth and consider increased living standards for the country's citizens to be a benchmark for economic performance. He argues that we must think of stronger workers' rights, anti-discrimination laws and anti-trust laws to do this. Amongst these, he especially highlights the role of worker's rights for the betterment of the country.

Economic growth can be affected by demographic effects, which can be a result of gender inequality, according to Cavalcanti and Tavares (2016). For example, they suggest that gender inequality in the labour market determines women's education which affects fertility rates which in turn affect economic growth.

In support of these studies, research published by the World Bank (King and Mason, 2001) points out that women are less prone to corruption than men and that having more women employed is beneficial for the economy. Empirical literature supports these ideas. Studies such as Galor and Tsiddon (1996) and Cavalcanti and Tavares (2016), suggest that gender equality in wages increases a country's overall economic growth. These researchers mention another way that economic growth is affected by gender equality. They point out that economic growth increases labour force participation, decreasing the fertility rate. A lower fertility rate is also one sign of economic growth Cavalcanti and Tavares (2016). In addition, women tend to invest more time in their children's health and education (Sinha et al., 2007). This means that human capital is negatively affected by the reduction in women's wages.

Altuzarra et al. (2021) also add their opinion to this. They argue that giving women more income allows them more "bargaining power", which also affects long-term economic growth for the better. They also argue that women are better savers than men, thereby increasing the overall (aggregate) savings of a country.

Here it is important to mention a few very controversial studies which found a positive relationship between lower female salaries and economic growth. One such study is by Karoui and Feki (2018) for Africa. The countries studied are usually export-oriented countries which are semi-industrial. They use in their industries a large amount of female labour with no/low education). They argue that lower salaries for females increase competitiveness by reducing production costs. This favours exports and, in turn, stimulates investment. Seguino (2000) also finds this is true for some Asian countries. They also argue that exports are promoted by inequality in employment and education. They argue that these conditions increase growth in lower-middle-income countries, at least as far as exports are concerned. This export surplus contributes positively to the economy.

4.3.2 Macro determinants of labour discrimination

Usually, determinants of labour discrimination are evaluated with individual micro-data. However, there have been few studies conducted at the national level. Table 4.1 provides a list of macro-determinants found in the literature.

Table 4.1 Macro-Determinants of Labour Market Discrimination (selected studies)

Seguino (2000)	• growth rate of technological change • gender wage gap • Female human capital • Male human capital
Klasen (2009)	• Per capita annual compound growth rate in purchasing power • Real GDP per capita in PPP-terms in 1960 (2000) • Growth rate of total population • Average of exports plus imports as a share of GDP • Growth rate of working-age population (15–64) • Level of fertility 1960 (2000) • Under 5 mortality rate 1960 (2000) • Life expectancy measured in years • Number of years of schooling for the population • Absolute (annual) growth in male and female years of schooling • Absolute growth in total years of schooling • Female–male ratio of schooling • Female–male ratio of the growth in the years of schooling • Female share of the total labour force (15–64)
Schober (2011)	• Raw gender wage gap • Unexplained gender wage gap • Meta wage residual • Human capital • GDP growth • Exports/GDP • Manufactures exports • Life expectancy • Exports plus Imports divided by GDP • log(GDP)
Ferrant (2016)	• Income per capita for country • SIGI - Social Institutions and Gender Index (SIGI) • Human Capital • Physical Capital • Trade Openness • Population Size • Religion • Fertility and Life expectancy • Urbanisation Rate • Labour Force Participation • Unemployment Rate

Klasen and Lamanna (2009) conducted one of the most significant studies involving a 93-country analysis of the following regions: Latin America and the Caribbean (LAC), East Asia and Pacific (EAP), Middle East and North Africa (MENA), OECD countries, South Asian (SA), Eastern Europe and Central Asia (ECA) and Sub-Saharan Africa (SSA) from 1960-2000. Their focus was mainly to analyse and compare countries with the highest gender pay gap between MENA, SA and SSA. They found that education and employment play a significant role in female discrimination, which has important implications for the country's economic growth. The authors found that the education gender gap and employment gender gap both decreased economic growth. They reported that economic effects were much higher for the employment gender gap than the education gender gap. Their analysis shows that in MENA countries the gender gap is linked to disparities in employment, while in SA regions the main reason is education.

Seguino (2000) further investigated the gender pay gap and its effect on economic growth in semi-industrialised export-oriented countries. To determine semi-industrialised export-oriented countries (SIEO), he developed a SIEO index. The index was created by adding the natural log of shares of exports in GDP, the share of manufacturing in output, and the ratio of transport and machinery to non-oil primary commodities. The analysis was conducted for low- and middle-income countries as defined by the World Bank. He analysed a total of 20 countries. The countries analysed were Brazil, Greece, Hong Kong, Singapore, Taiwan, and Turkey, amongst others. The data covered GDP growth rates from 1975-1995 along with wage gap, male human capital, female human capital and technological change.

She analysed "affirmative action"[9] on the gender pay gap and found that affirmative action for targeted group reduced disparities in pay gap although it came at the cost of older workers. Seguino very controversially argues that a 0.1% increase in the gender pay gap resulted in an average 0.12% GDP growth rate. She argued that depending on the country, the effect could be as high as 0.72%. In Seguino's study, the gender pay gap was treated as the difference in the average wage of males and females.

Ferrant and Kolev (2016) studied the effect of social institutions on gender discrimination for a country's long-term growth. They measured discrimination using the OECD's Social Institution and Gender Index (SIGI). The SIGI index was developed in 2007

[9] Affirmative action refers to active steps (including legislation) by the government to increase the participation rate of minorities and women in areas of education, employment, and culture. (Robert, 2018)

by the OECD. It focused on the role of women and men in the context of societal values, norms, and attitudes. The SIGI index analysed discrimination in social institutions in non-OECD countries with the use of five key determinants: Familial code (patriarchy), Ownership rights (unfair share in property for males and access to resources), Son preference (missing women due to abortion), Civil Liberties (equality of law) and Physical integrity (violence and cases of harassment against women). The authors concluded that discrimination in social institutions had a profound and negative effect on a country's income. Moreover, the effect was found to be stronger in lower-income countries. This effect lowered female productivity (often not paid equally for their labour) and decreased female labour force participation rate and access to education. The author estimated that discrimination caused the world to lose 12 trillion USD (16% of the world economy).[10]

4.3.2.1 Criticisms of Macro-Studies of gender

Schober and Winter-Ebmer (2011) criticised the Seguino (2000) study because aggregate data analyses are inadequate to analyse the impact of the gender pay gap on the economy. They advocated that micro-data is better suited to study the gender gap's economic consequences rather than macro-data. Furthermore, they argued that individual characteristics and capital differentials amongst the genders could only be controlled by using micro-data. Building their argument, Schober and Winter-Ebmer (2011) analysed 16 out of the 20 countries analysed in Seguino (2000) paper – the selection was based on the availability of the data for these 16 countries. Their results were unlike the ones in Seguino (2000) study, showing that the gender pay gap decreases economic growth instead of increasing it.

Bandiera and Natraj (2013) also criticised these macro-level studies for several reasons. He argued that reverse causality might exist between economic growth and gender pay gaps. He argued that differences in the level of discrimination could be related to differences in the stages of development. For instance, as the technology level increases (which is assumed to be directly proportional to economic growth), it decreases the comparative advantage men have due to their physical strength. Thus, technological development and economic growth promote gender equality. Secondly, cross-sectional studies omit important time variables in studying the gender gap and its effect on economic growth. Another critical factor, according to him, is that the studies do not distinguish between discrimination and the pay gap. The study treats them interchangeably.

However, the terms are different; discrimination can mean many things, while the pay gap is a statistical measure. The authors also argued that health, fertility, and trade liberalisation are frequently omitted in macro-studies, but they must be included; otherwise, the growth regression is incomplete. Another criticism of the macro-studies is that they assume that all countries are affected the same way by pay gaps which is not a reasonable assumption. Time-specific characteristics and country-specific characteristics are probably the most significant variables in each country. Thus, the cross-section study conducted by Klasen and Lamanna (2009) does not have the correct unique coefficient. Since the effects of time series (which are essential and different for each country) are not captured, the coefficients might be biased. Independent variables used in regression might have distinct effects on one country while having completely different effects on another. This is not captured in the Klasen and Lamanna (2009) work. Lastly, macro-analysis can only capture patterns for different countries and cannot serve as policy implications. Hence research should be performed using micro-level data (Bandiera and Natraj, 2013).

Table 4.2 Summary of criticisms of Macro-Determinants studies on the wage gap

Schober et al., (2011)	• Macro-data, micro-data is better suited to study the gender gap's economic consequences gender wage gap. • Individual characteristics and capital differentials amongst the genders could only be controlled by using micro-data Male human capital
Bandiera et al., (2013)	• Reverse causality might exist between economic growth and gender pay gaps • Cross-sectional studies omit important time variables that are important in studying the gender gap and its effect on economic growth • Time-specific characteristics and country-specific characteristics (technological advancement, for instance) make a study of one country entirely different from another • Macro-analysis can only capture patterns for different countries and cannot serve as policy implications. • Independent variables used in regression might have distinct effects on one country while having completely different effects on another country.

4.3.3 Economic benefits of removing the gender pay gap

As mentioned earlier, there are very few studies that measure the effect of reduction in the pay gap on GDP as opposed to the effect of FLFP on GDP (Cavalcanti and Tavares, 2007; Morais Maceira, 2017; Schober and Winter-Ebmer, 2011; Severini et al., 2019; Tzannatos, 1999). Cavalcanti and Tavares (2016) estimate the cost of gender discrimination in the US using national accounts information (2008). Their study finds evidence that discrimination adversely affects the country. They find it lowers output and female labour force participation. Furthermore, they find that it increases population and negatively affects the steady-state output. They calibrate a growth model where the labour market, fertility and savings are endogenous. The model has two assumptions pertaining to gender discrimination. First, the model assumes that women earn less than men despite having similar productivity levels. The second is that women provide better child-rearing than men. Their model is for the US economy. They find that if we increase the gender pay gap by 50%, we will see a 35% reduction in income per capita.

Teignier and Cuberes (2014) also conduct similar research. They endeavour to find out the cost of the gender gap, specifically in labour force participation and entrepreneurship in the US. They prove that income has a negative effect due to these gaps. They show this using a general equilibrium occupational model. The model assumes that occupation is a result of the individual talent of a human being. They start by assuming that there are two genders in the labour market: men and women. These two genders are allowed to enter any occupation except for certain occupations that involve friction for women. Secondly, they assume that the labour market expels certain women. The results for them show that steady state output reduces by 11%. Furthermore, under extreme conditions where no women are allowed to enter the labour market, there is a 50% decrease in steady state output.

A study by Ngai and Petrongolo (2017) shows that the service sector reduces the gender pay gap for women in terms of wages and hours worked in the US. They find that two factors constitute this shift. One is the marketisation of the economy, and the second is the reallocation of labour from the manufacturing side (structural transformation). Their model consists of three sectors: market services, home services and goods. They argue that there is a competitive advantage for women regarding services. For the US, they find that marketisation and structural transformation account for a 50% increase in women's working hours and a 20% rise in gender wage ratio over the last 40 years.

Ma et al. (2016) report that if fathers are to increase time spent on child rearing and gender policies by the government that decrease discrimination contribute towards increased income per capita and female labour force participation. The paper's central premise comes from the fact that gender equality affects a wide array of activities. They argue that it affects child education, child-rearing, household production and time allocated for work. Their model for Korea assumes two things: one, women earn less than men despite equal productivity, and two, men spend significantly less time than women on child education and child-rearing. Once they remove these gender differences, they find that income per capita has increased from 3.6% to 4.1%, and female labour force participation has increased from 54.4% to 67.5%.

Lee (2019) provides another model of Korea, studies the glass ceiling and examines its cost -effects at a macroeconomic level for the country. The model like some of the earlier models, is based on Lucas (1978) span of control framework. They assume that the reason for the glass ceiling for women is that they do not have managerial skills comparable to men to advance their careers. Their model assumes that the glass ceiling has completely disappeared and that aggregate output has increased by 8.4%. (of course, the share of female managers has increased in this scenario).

Finding direct comparable studies that calculate the number of jobs created is also difficult as they are rare. However, estimates from the paper by Morais Maceira (2017) for European Institute for Gender Equality (EIGE) provide an estimated increase of 3.5 million to 6 million jobs by 2050 for increasing female labour force participation and reducing inequality in the European Union.

4.3.4 Minimum Wage Literature

Since the hypothetical in this paper assumes no labour market discrimination for women in an input-output setting, it is appropriate to compare it to similar work on minimum wage literature. Since no direct studies with the input-output, apart from the some mentioned above (Souza and Domingues, 2015; Morais Maceira, 2017; Lee, 2019; Severini et al., 2019) can be directly found. However, the effect, in theory, can be correlated to the effect of raising labour costs. Therefore, for comparison numbers, it is the most relevant literature.

Wolff and Nadiri (1981) were amongst the first to run a simulation of minimum wage via the input-output model. They estimated changes in prices, output, and employment. They used data from US current population survey (CPS) from 1972 and 1979 to analyse minimum wage increase effects on the economy. Assuming no employment effects and full pass-through effects, they found that a 10 to 25 percent wage rise increases prices by 0.3 to 0.4%.

In studies for the UK, McGuinness et al. (2011) find gender wage gap for part-time workers is reduced by increasing the national minimum wage. Their analysis for Ireland uses a different number of national minimum wage workers across many different firms in Ireland. Controversially Robinson (2002) for the UK finds that the national minimum wage does not affect the wage gap or the removal of sticky floors. They found this by employing a quantile regression methodology. Another study by Robinson (2005) later substantiates this fact. The only difference between the two studies is that they found a very small effect for the national minimum wage on growth this time. They find that the gender pay gap has reduced in areas of the UK where women form most low-paid workers by 1 to 2 percentage points.

Ganguli and Terrell (2006) find that doubling the national minimum wage has profoundly affected Ukraine. They find that the national minimum wage increase has led to the closing of the wage gap in Ukraine. Blau and Kahn (1997) earlier found similar results for 1979 and 1988 in the US, where they said there was a sharp decline in the gender wage gap.

4.3.5 Gender and Input-Output

Recently, input-output and computer-generated equilibrium (CGE) models have been modified to include gender decomposition of labour. This is because of growing interest in inequality and recognition that women are integral to economic development. Fontana and Wood (2000) first introduced the literature on gender decomposition. Further additions were made by Fofana et al. (2003), and since then, further work has been done on the topic (Severini et al. (2019). A detailed discussion, including the different use cases and methodology for these earlier models Fofana et al. (2003), is provided in Appendix 17: Origin and subsequent models of Fotana and Wood (2000).

Papers dealing with increased female wage costs using input-output models are scarce. A paper that attempts to do so is Tsani et al. (2013) for middle-easter countries. They find while using a general equilibrium model (GEM-E3-MEDPRO) that a 5% increase in FLFP increases GDP by an average of 1.3%. They also discussed how the increase of FLFP will eventually decrease wages by 3.5% over a period of 2015 to 2030.

Two other papers analysing the same are by Souza and Domingues (2015) and Severini et al. (2019). Souza runs a hypothetical of an increase in wages for women as per their remuneration levels. This is done by disaggregating households and compensation of employees by gender. They find that this increase yields (for Brazil) a positive impact on the economy. They observed a GDP growth of 0.42% and an increase in household consumption and real wages in the next 19 years. The data for their study comes from the National Household

Survey and Brazilian Institute of Geography and Statistics (IBGE) input-output matrix. This input-output matrix had 110 commodities and 55 industries. They converted the input-output matrix to the social accounting matrix and finally to the CGE to see a long-term increase in female labour costs.

A similar approach to the one by Souza is taken by Severini et al. (2019). They developed a gender-aware CGE model based on the Italian economy to assess the impact of a fiscal policy. They analyse the fiscal policy of reducing taxes on hiring females (thereby essentially reducing female labour costs). This is done by using sectors that have a higher gender disparity. They find that impact of such a policy would be an increase in GDP of 0.10% for Italy, which would also reduce unemployment by 0.52%.

4.4 Data

The data for this paper comes from multiple sources. The input-output model comes from City-Region Economic and Development Institute (City-REDI) based at the University of Birmingham. City-REDI's core objective is to help accelerate economic growth in the West Midlands city region. Simultaneously it focuses on studying inter-regional inequality across the UK and intra-regional inequalities in the West Midlands. In pursuit of this goal (amongst others), City-REDI created the first United Kingdom Socio-Economic Impact Model (SEIM-UK) multi-regional input-output model.

The Socio-Economic Impact Model for the UK was created to focus on three main different features: (1) globalisation, technological and structural change in the labour market; (2) household heterogeneity and socio-demographic change; and (3) the evolution of trade patterns and value-added chains. The SEIM – UK Model was constructed at the NUTS 2 level. The multi-regional model covers 41 regions and 30 sectors (NUTS-2 classification) of the UK and includes foreign trade flows with other countries.

4.4.1 Background of SEIM-UK:

The Socio-Economic Impact Model (SEIM-UK) is a multi-regional input-output model (MRIO) that covers 30 sectors (Table 4.5) and 41 regions (Table 4.3) in the UK. The model is based on Supply and Use tables (SUTs) for the UK 2016. The total output and demand components are equal to the sum of the individual component of NUTS-2 regions. We disaggregate the final demand, imports, and primary inputs etc., by regional weights for the MRIO based on ONS estimates.

The reason for constraining the number of sectors to 30 is due to data limitations in value-added components (gross operation surplus, mixed-income, and compensation of employees) for NUTS-2 regions. That is why the 68-sector economy is turned to 30 sectors and 41 regions in NUTS-2 SEIM model rather than the 68 sectors (industry). When we aggregate our sectors to 30, the differences we observe within the industries result from varying demand and production structures within those 30 industries. Consequently, regional industry specialisation and sectoral mix are the key elements forming regional economic structures (Carrascal-Incera et al., 2020).

The Cross-Hauling Adjusted Regionalisation Method (CHARM) (Többen and Kronenberg, 2015) is employed to construct the SEIM-UK model. Along with SUTs, multiple other databases are used to develop the mode, e.g., Public Expenditure Statistical Analysis (PEA), Living Cost and Food Survey (LCFS), amongst others. To make the values correspond to the SUT, the final adjustment method uses the widely used RAS method (Stone, 1961).

We use SEIM-UK as our model for analysis of different scenarios of no discrimination. We focus primarily on how the change in female labour compensation affects different aspects of the UK economy for final demand, output and new jobs gained. SEIM-UK is preferred to the standard Input-Output UK national model because it allows one to observe and understand the effects of the increase of GVA at a multi-regional level. Since we presume the shock to be in both sectors and regions, we need a multi-regional model.

The SEIM - UK Multi-Regional Input-Output (MRIO) model also provides different extensions regarding the labour market and demographics, as well as distinguishing between the socio-economic characteristics of households and their consumption patterns. This allows for much more detailed, sector and place-sensitive economic analyses to be undertaken than would be available with the national Input-Output provided by the Office of National Statistics (ONS). Hence, SEIM-UK better serves in understanding the question *"What would happen if female labour force participation became equal to men?"* which is the paper's fundamental question. In the latter part, we run the same analysis sectoral for the ONS input-out model to compare results. This can only be done based on the sectors because the ONS model is an entire UK model. Essentially, we are running Sectoral scenarios # 1 and # 2 for both SEIM-UK and Input-Output Model ONS (2016) to see and compare results. Regional Scenarios # 1 and # 2 cannot be run because the ONS model is not disaggregated regionally.

The MRIO framework helps us better understand removing discrimination's sectoral and regional effects. This, combined with the feedback effect (indirect effect), gives us an idea of how the effect of the wage increase in the sector or region affects other industries and regions in UK. The feedback has two components: one is the impact on other regions, and secondly it shows how the initial effect eventually loops back to the region of origin. This helps us to take account of both direct and indirect effects. Considering all these things, IO models are the most appropriate for this study as they allow for the estimation of effects (both direct and indirect) at the macroeconomic level. For example, we can estimate an increase in labour compensation output, number of jobs and final demand at the industry level (López et al., 2016). In contrast to computer general equilibrium, the input-output model allows for a straightforward interpretation of results, transparency and ease of use. This is what makes it the most used tool for these types of evaluation studies (Carrascal Incera et al., 2022).

4.4.2 Aggregating regions from NUTS 2 to NUTS 1

SEIM-UK disaggregates value-added services by net taxes on production, compensation of employees, gross operating surplus, and mixed income. Since compensation of employees is included in value-added services for SEIM-UK, we can disaggregate it by gender to run our analysis. However, due to data limitations, the model must first be converted to NUTS 1 and then disaggregated by gender[11]. This is value-added because gender pay gap data is only available at the NUTS 1 level. The following section explains how the model was converted from NUTS 2 regions to NUTS 1 regions using the 30 sectors. The extension to disaggregate compensation of employees by gender is discussed.

To converge NUTS 2 regions to NUTS 1 region. The programming language R was used. R was preferred to Python, given that the package "ioanalysis" was available. The package ioanalysis in R provides a module specifically written to merge regions in the input-output analysis. The package was written by John Wade and Ignacio Sarmiento-Barbieri and allows the user to work with different facets of the input-output(I-O) model. This includes region aggregation and important I-O information like Leontief inverse, key sectors, backward and forward linkages etc. In order to accomplish this, the user is guided to create "An object of class Input Output created from as. input".

Once this initial step of creating an input-output model in R was completed, we merged the regions using the ONS classification presented in Table 4.3. Table 4.3 shows NUTS 2 regions and their NUTS 1 region used in the classification. All the regions were aggregated at the NUTS 1 regional level making our new SEIM UK I-O model with 12 regions and 30 sectors. The Z matrix contained a total of n x m = 360 rows and 360 columns. We also obtained

[11] List of data used for conversion is presented in appendix 18 of the thesis.

the corresponding Export, Import, value-added, final demand and output matrices at the NUTS 1 level. Once all of the matrices were obtained, we checked for accuracy.

Table 4.3 Nuts 2 regions with their NUTS 1 classification

Number	Code	Region	Aggregated to	Code
1	UKC	Tees Valley and Durham	**North-East**	UKC
2	UKC	Northumberland and Tyne and Wear	**North-East**	UKC
3	UKD	Cumbria	**North-West**	UKD
4	UKD	Greater Manchester	**North-West**	UKD
5	UKD	Lancashire	**North-West**	UKD
6	UKD	Cheshire	**North-West**	UKD
7	UKD	Merseyside	**North-West**	UKD
8	UKE	East Yorkshire and Northern Lincolnshire	**Yorkshire and the Humber**	UKE
9	UKE	North Yorkshire	**Yorkshire and the Humber**	UKE
10	UKE	South Yorkshire	**Yorkshire and the Humber**	UKE
11	UKE	West Yorkshire	**Yorkshire and the Humber**	UKE
12	UKF	Derbyshire and Nottinghamshire	**East Midlands**	UKF
13	UKF	Leicestershire, Rutland & Northamptonshire	**East Midlands**	UKF
14	UKF	Lincolnshire	**East Midlands**	UKF
15	UKG	Herefordshire, Worcestershire and Warwickshire	**West Midlands**	UKG
16	UKG	Shropshire and Staffordshire	**West Midlands**	UKG
17	UKG	West Midlands	**West Midlands**	UKG
18	UKH	East Anglia	**East of England**	UKH
19	UKH	Bedfordshire and Hertfordshire	**East of England**	UKH
20	UKH	Essex	**East of England**	UHI
21	UKI	Inner London – West	**London**	UKI
22	UKI	Inner London – East	**London**	UKI
23	UKI	Outer London - East and North-East	**London**	UKI
24	UKI	Outer London – South	**London**	UKI
25	UKI	Outer London - West and North-West	**London**	UKI

26	UKJ	Berkshire, Buckinghamshire, and Oxfordshire	**South-East**	UKJ
27	UKJ	Surrey, East and West Sussex	**South-East**	UKJ
28	UKJ	Hampshire and Isle of Wight	**South-East**	UKJ
29	UKJ	Kent	**South-East**	UKJ
30	UKK	Gloucestershire, Wiltshire and Bristol/Bath area	**South-West**	UKK
31	UKK	Dorset and Somerset	**South-West**	UKK
32	UKK	Cornwall and Isles of Scilly	**South-West**	UKK
33	UKK	Devon	**South-West**	UKK
34	UKL	West Wales and The Valleys	**Wales**	UKL
35	UKL	East Wales	**Wales**	UKL
36	UKM	North-eastern Scotland	**Scotland**	UKM
37	UKM	Highlands and Islands	**Scotland**	UKM
38	UKM	Eastern Scotland	**Scotland**	UKM
39	UKM	West Central Scotland	**Scotland**	UKM
40	UKM	Southern Scotland	**Scotland**	UKM
41	UKN	Northern Ireland	**Ireland**	UKN

4.4.2.1 Checking for accuracy and correctness of the aggregated model

To check for accuracy and correctness of convergence of the model. We used individual matrices output. So, each matrix in NUTS1 was compared to the original matrix of NUTS 2. This means we compared the sum of Z (Intermediate matrix), I (import), V (Value added), E (Export) F (Final demand) and X (output) matrix. Mathematically, we can represent this via the following. The same equation was checked for all other matrices, and the following equation was tested.

$$\mathbf{\Sigma Z(NUTS1) = \Sigma Z(NUTS2)} \ldots\ldots..(\mathbf{4.1})$$

$$\mathbf{\Sigma E(NUTS1) = \Sigma E(NUTS2)} \ldots\ldots(\mathbf{4.2})$$

$$\mathbf{\Sigma I(NUTS1) = \Sigma I(NUTS2)} \ldots\ldots.(\mathbf{4.3})$$

$$\mathbf{\Sigma F(NUTS1) = \Sigma F(NUTS2)} \ldots\ldots(\mathbf{4.4})$$

$$\mathbf{\Sigma V(NUTS1) = \Sigma V(NUTS2)} \ldots\ldots.(\mathbf{4.5})$$

$$\mathbf{\Sigma X(NUTS1) = \Sigma X(NUTS2)} \ldots\ldots(\mathbf{4.6})$$

4.4.2.2 Construction of new Input-Output Model at NUTS 1 Level

The data provided by the R package gives us each matrix individually. All individual matrix equations from 1 to 6 were checked for accuracy. All came out to be true (correct to 2 decimal points). Each matrix was then used to create a new Input-output model at NUTS 1 level. The dimensions of the new input-output model at NUTS 1 were the following.

Z matrix = 360 X 360

X matrix = 360 X 1

Export Matrix = 360 X 1

Final Demand =360 X 48

Value added = 4 X 360

Import Matrix = 30 X 360

The final model contained 30 sectors and 12 regions. Table 4.4 below shows the 12 regions along with their code.

Table 4.4 Regions of NUTS 1 model

Code	Region	Code	Region
UKC	North-East	**UKI**	London
UKD	North-West	**UKJ**	Southeast
UKE	Yorkshire and the Humber	**UKK**	Southwest
UKF	East Midlands	**UKL**	Wales
UKG	West Midlands	**UKM**	Scotland
UKH	East of England	**UKN**	Northern Ireland

4.4.2.3 Checking of Output

To calculate and check the total output of the new model we followed two methods. First, we used the total output generated automatically by the package ioanalysis. This was first compared to the original output (see equation 4.6) to check for correctness. In the second method, we calculated output in the following two ways in the newly created NUTS 1 model.

$$\mathbf{\Sigma Z + \Sigma F + \Sigma E = \ X} \dots \dots \dots . . (\mathbf{4.7})$$

$$\mathbf{\Sigma Z + \Sigma V + \Sigma I = X} \dots \dots \dots . (\mathbf{4.8})$$

Equation 4.7 states that the sum of the Z matrix, Final demand (F) and Export (E) should be equal to the model's total output. Equation 4.8 states that the sum of the Z matrix, Value added (V) matrix and Import (I) should be equal to the sum of the model's total output. Equations 4.7 and 4.8 were compared to the original output of the NUTS 2 model. They were both the same. So, we satisfied the condition that equations 4.7 and 4.8 are equal to equation 4.6. Mathematically, we can represent this as the following:

$$\mathbf{\Sigma Z + \Sigma F + \Sigma E = X \dots \dots (4.7) = \Sigma X(NUTS1) = \Sigma X(NUTS2) \dots\ (4.6)}$$

$$\mathbf{\Sigma Z + \Sigma V + \Sigma I = X \dots (4.8) = \Sigma X(NUTS1) = \Sigma X(NUTS2) \dots (4.6)}$$

4.4.3 Industry categorisation

The industry classification with 30 sectors followed the same structure as the SEIM-UK (NUTS 2 model), which can be seen in Table 4.5

Table 4.5 Industry classification in the SEIM-UK model

Number	Code	Industry name
1	A	Agriculture, forestry and fishing
2	B	Mining and quarrying
3	CA	Manufacture of food, beverages and tobacco
4	CB	Manufacture of textiles, wearing apparel and leather
5	CC	Manufacture of wood and paper products and printing
6	CD-CF	Manufacture of petroleum, chemicals and pharmaceuticals
7	CG	Manufacture of rubber, plastic and non-metallic minerals
8	CH	Manufacture of basic and fabricated metal products
9	CI	Manufacture of computer, electronic and optical products
10	CJ	Manufacture of electrical equipment
11	CK	Manufacture of machinery and equipment
12	CL	Manufacture of transport equipment
13	CM	Other manufacturing, repair and installation
14	D	Electricity, gas, steam and air-conditioning supply
15	E	Water supply; sewerage and waste management
16	F	Construction
17	G	Wholesale and retail trade; repair of motor vehicles
18	H	Transportation and storage
19	I	Accommodation and food service activities
20	J	Information and communication
21	K	Financial and insurance activities
22	L	Real estate activities
23	M	Professional, scientific and technical activities
24	N	Administrative and support service activities
25	O	Public administration and defence; compulsory social security
26	P	Education
27	Q	Human health and social work activities
28	R	Arts, entertainment and recreation
29	S	Other service activities
30	T	Activities of households

4.4.4 Estimation of compensation of employees by gender at NUTS 1 level

SEIM-UK (NUTS 2) divides value-added services in the following categories 1) Compensation of employees 2) Net taxes on production 3) Gross operating surplus and finally 4) mixed income. Figure 4.1 shows the state of the IO model.

Region	Sector	Tees Valley and Durham	Tees Valley and Durham	Tees Valley and Durham
		UKC1	UKC1	UKC1
		s1	s2	s3
UKN0	s23	0.00	0.00	0.02
UKN0	s24	0.00	0.00	0.04
UKN0	s25	0.00	0.00	0.00
UKN0	s26	0.00	0.00	0.00
UKN0	s27	0.00	0.00	0.00
UKN0	s28	0.00	0.00	0.01
UKN0	s29	0.00	0.00	0.01
UKN0	s30	0.00	0.00	0.00
	Intermediate inputs	188.00	342.00	242.00
v1	Net taxes on production	-28.14	4.73	3.89
v2	***Compensation of employees***	***53.37***	***91.12***	***206.07***
v3	Gross operating surplus	80.54	115.97	67.07
v4	Mixed income	25.23	1.18	0.97
v5	Value added total	131.00	213.00	278.00
Dom	Total Domestic Inputs	319.00	555.00	520.00
I1	Total Imports	62.76	275.34	246.90
Tot	Total Inputs	381.76	830.34	766.90

Figure 4.1 State of I/O Model (Compensation of employees at NUTS2 level)

4.4.4.1 Extension of I/O model to disaggregate by gender

After the aggregation at NUTS 1 level, we have the compensation of employees in 12 regions, and 30 sectors of the economy. To extend the I/O model by gender, we break down the compensation of employees to males and females. This is explained in Figure 4.2. For each column, Compensation of employee's males (Cm) + Compensation of employee's females (Cf)= Compensation total (Ct) (already in SEIM-UK NUTS 1). This can be represented mathematically by the following.

$$C_m + C_f = C_t \dots\dots\dots..(4.9)$$

Sector	UKC1	UKC1	UKC1
	s1	s2	s3
s25	0.00	0.00	0.00
s26	0.00	0.00	0.00
s27	0.00	0.00	0.00
s28	0.00	0.00	0.01
s29	0.00	0.00	0.01
s30	0.00	0.00	0.00
Intermediate inputs	188.00	342.00	242.00
Net taxes on production	-28.14	4.73	3.89
Compensation of male employees			
Compensation of female employees			
Compensation of employees	***53.37***	***91.12***	***206.07***

Figure 4.2 Extension of I/O Model to disaggregate by gender.

4.4.4.2 Annual Survey of Hours and Earnings

In order to disaggregate the compensation of employees by gender, we use the Annual Survey of Hours and Earning (ASHE) (edition 2016), which allows us to have a disaggregation for 30 sectors broken down by NUTS 1 region. ASHE contains regional and industry data disaggregated by gender covering 109 industries. Since the SEIM-UK contains some industries that are merged, we do the same with the ASHE data. The data for the regions matches with our SEIM-UK (NUTS 1 classification) except of the unavailability of data on Northern Ireland (UKN) (see later discussion). For each industry (109) and region (11), ASHE gives a value of the gender pay gap. ASHE also provides the national average for each of the industries. Each estimate provided by ASHE also comes with a measured quality. There are four types of measures used in the data. 1) Estimates of good quality, 2) Estimates of reasonable quality, 3) Estimates of lower quality and 4) Estimates that are unreliable and/or of poor quality[12]. This is mainly due to the extent of data, as 109 industries are considered in each region.

To make the 109-industry data usable, we merge industries present in SEIM-UK and disregard industries that are irrelevant to us. For instance, many sectors in manufacturing were a combination of different manufacturing sectors in the 109 industries of ONS. They were merged in NUTS2 SEIM – Model and subsequently SEIM – Model NUTS 1. For dealing with these merged manufacturing sectors, an average of the merged sector was taken.

To find the pay gap of the merged industries, we take the average of the individual industries. For example, in the case of Manufacture of wood the merged industry constitutes

[12] All of these are colour-coded in the data file provided by ASHE.

of and of products of wood and cork, (except furniture; manufacture of articles of straw and plaiting materials) (Mw), Manufacture of paper and paper products (Mp), and Printing and reproduction of recorded media (Mr), these 3 sectors are merged in our SEIM-UK NUTS 1. All these three manufacturing industries have different individual gender pay gaps. However, as SEIM-UK combines these terms in "Manufacture of Wood and Paper products and Printing (Mwpp)", we take the average of these individual industries to come up with a new gender pay gap for our analysis. This can be represented mathematically by the following equation 10.

$$Averagegp(Mw + Mp + Mr) = gpMwpp(SEIM - UK) \ldots\ldots..(4.10)$$

Where GP = gender pay gap. All industries that are merged in SEIM-UK go through a similar process of an averaging of individual industries. Once we obtain all-region and industry values for the gender pay gap, we proceed to the next step of using this gender pay gap to disaggregate the compensation of employees.

Here it is important to note that data was provided for the mean and median of the gender pay gap. Since more reliable data existed for the mean, we selected the mean as our working gender pay gap. Data was also provided for full-time and part-time employees separately. However, we use the average of full-time and part-time workers. The reason for this is two-fold. 1) In our data of SEIM-UK, we do not distinguish employees by part-time and full-time work. 2) More reliable estimates existed for all workers than just part-time or full-time workers.

Table 4.6 Breakdown of gender pay gap by NUTS 1 regions and sectors (sample data shown here)

Description	**Code**	**Median (%)**	**Mean (%)**
North-East, public administration and defence; compulsory social security	O	7.1	7.6
North-East, public administration and defence; compulsory social security	84	7.1	7.6
North-East, education	P	12.6	13.4
North-East, human health and social work activities	85	12.6	13.4
	Q	12.1	20.6
North-East, human health activities	86	2.3	20.2
North-East, residential care activities	87	8.2	7.6

4.4.4.3 Calculation of compensation of employees by gender

Equation 4.9 gives us a starting point to calculate the compensation of employees. Since we know that total compensation of employees must equal to compensation of females + compensation of males. We also know the two values' percentage difference (gender pay gap). Knowing this information, we can formulate our second equation to solve for Cf. Let gp= gender pay gap.

$$C_f = gpC_m \dots \dots (4.11)$$

Equation 4.11 states that $C_f = Compensation\ of\ female\ employees$ is dependent on $C_m = Compensation\ of\ male\ employees$. The opposite is also true. Therefore, given equations 4.9 and 4.11, we can solve for Cf and subsequently Cm or vice versa. This was done for all NUTS 1 regions and their sectors.

4.4.4.4 Dealing with missing data

As mentioned above, ONS provided estimates for all regions of our SEIM-UK except Northern Ireland. There was no information provided for Northern Ireland, which is region UKN. Since no information was available for Northern Ireland, the national average of the industries was taken and applied to all Northern Ireland sectors. This gives us the gender pay gap. A similar methodology, as mentioned in part 4.4.3 of this thesis, was applied to obtain compensation for employees by gender.

We also used national averages for unavailable data of a region's sector. The national average is a good benchmark since all sectors at that level are termed "good quality data" from ONS. Table 4.7provides a list of all sectors within different regions of our model that had missing data and for which national averages were used.

Table 4.7: Sectors in regions with missing values

East Midlands, Manufacture Of Machinery And Equipment NEC.
East, Mining And Quarrying
London, Agriculture, Forestry And Fishing
London, Manufacture Of Machinery And Equipment NEC.
London, Manufacture Of Motor Vehicles, Trailers And Semi-Trailers
North-East, Water Supply; Sewerage, Waste Management, Remediation Activities
North-West, Arts, Entertainment And Recreation
Scotland, Arts, Entertainment And Recreation
Scotland, Manufacture Of Electrical Equipment
Scotland, Manufacture Of Motor Vehicles, Trailers And Semi-Trailers
Scotland, Water Supply; Sewerage, Waste Management And Remediation Activities
South-East, Arts, Entertainment And Recreation
South-West, Other Manufacturing
Wales, Manufacture Of Machinery And Equipment NEC.
Wales, Mining And Quarrying
West Midlands, Arts, Entertainment And Recreation
West Midlands, Mining And Quarrying
Yorkshire And The Humber, Mining And Quarrying
Yorkshire And The Humber, Other Manufacturing
London, Manufacture Of Coke And Refined Petroleum Products
North-East, Manufacture Of Basic Metals
Scotland, Manufacture Of Coke And Refined Petroleum Products
South-East, Manufacture Of Textiles

4.5 Methodology

The paper uses the Input-Output (IO) approach to answer its questions. The IO model was developed by Noble prize winner Wassily Leontief and captured different relationships amongst various sectors of the economy. Adding different regions within a country yields a multi-regional input-output table used in this paper. This model can aid in answering many hypothetical questions, such as the one presented in the paper.

The paper represented schematically can be seen in Figure 4.3. There are two sides to the figure. First, it shows the interconnection between the input-output and wage decomposition models. From the decomposition results, we can calculate the adjustments in wage for each (Oaxaca and Ransom, 2003).This makes all the workers remunerated according to their observable characteristics.

There are many steps involved in calculating how the increased wages of women (in our case) affect output. First, there is a direct effect between the old and the new wage.

Secondly, we have the indirect effects on the economy, and finally, there is an induced effect on the economy. In total, we have the three effects for changes in output.

$$Total\ effect\ =\ Direct\ effects\ +\ Indirect\ effect\ +\ Induced\ effect\ \ldots\ldots(4.12)$$

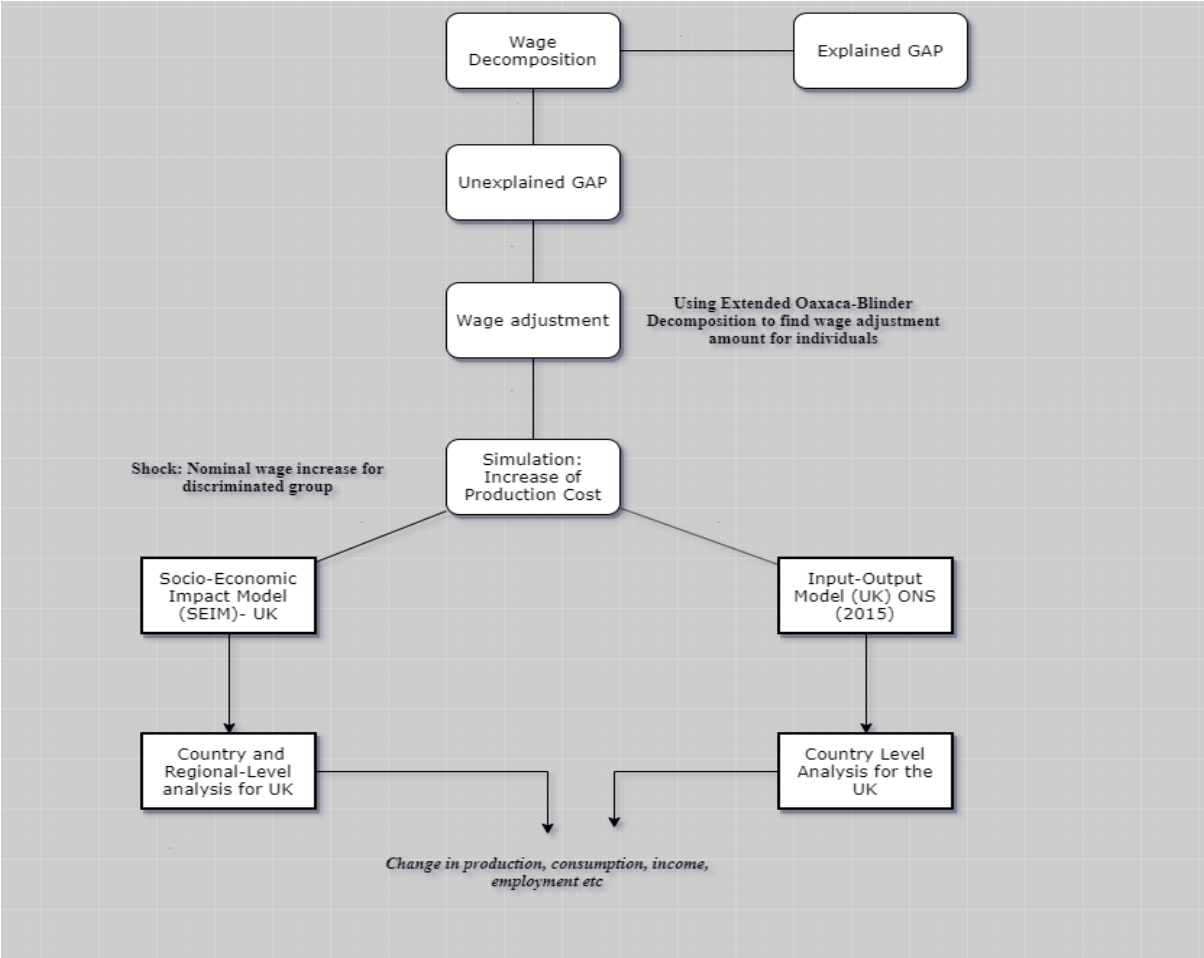


Figure 4.3:Linking wage decomposition model with the input-output model

Figure 4.3 shows the link between our four different potential scenarios for removing gender discrimination. These estimates are used as vector shocks for increasing labour costs (nominal). These shocks are imposed for the year 2016 for our SEIM-UK multi-regional input-output model. This vector shock in the model will be used to analyse the effect on the entire economy and the regional level. SEIM-UK also allows us to analyse the effects sectorally. We use our models to analyse the effects of eliminating discrimination on output, final demand, employment, and value-added.

We use the Ghosh model to simulate the changes based on the initial wage increase (change in the primary input cost). The Ghosh model is a supply-side input-output model as opposed to the more common demand-side IO models. In the demand-driven models, we have equation 4.13, where A is the technical co-efficient, Z is the intermediate demand, and x is the output. Equation 4.13 leads to equation 4.14 (Leontief) where x is the new output, I is the identity matrix, f is the final demand, and L is Leontief.

$$\mathrm{A} = \mathrm{Zx\hat{}} - 1 \ldots\ldots\ldots\ldots (4.13)$$

$$\mathrm{x} = (\mathrm{I} - \mathrm{A}) - 1 * \mathrm{f} = \mathrm{Lf} \ldots .. (4.14)$$

In this scenario, we have the final demand guiding output. The supply side model is an alternative version in which value-added determines output. The Ghosh model is made possible by transposing our view from column to horizontal. Rather than divining each column of Z with the output of that column x, we have a division of each row of Z divided by the gross output of that row. B is used to denote the direct-output coefficient matrix; mathematically, it can be defined as

$$\frac{Z(row)i1}{x(gross\ row\ sum)i} = B \ldots .. (4.15)$$

Similar to equation 4.13 in the Leontief, we have equation 4.15 in the Ghosh.

Continuing with equation 4.15, we have

$$x = (I - B) - 1 * v = G^{/} v \ldots\ldots (4.16)$$

Where $\mathrm{G}^{/}$ is Ghosh inverse, v is value-added, and x is the final output. Equation 4.16 is used to find the resulting change in output for this thesis chapter. [13]

4.5.1 Regional Scenario# 1

In the first regional scenario, we use London as a benchmark. The reason for using London is its total compensation. As can be seen from Figure 4.4, the compensation of London is greater than any other region. Also, its heavy trade with other regions makes it the ideal region to test our scenario. In the first regional scenario, we assume that the compensation of male employees has become equal to the compensation of employees for females in London. Then we observe the changes in the economy for the hypothesised change.

[13] A detailed discussion on the plausibility of the model and the solution to the problem of no increase in value added is provided in chapter 7.

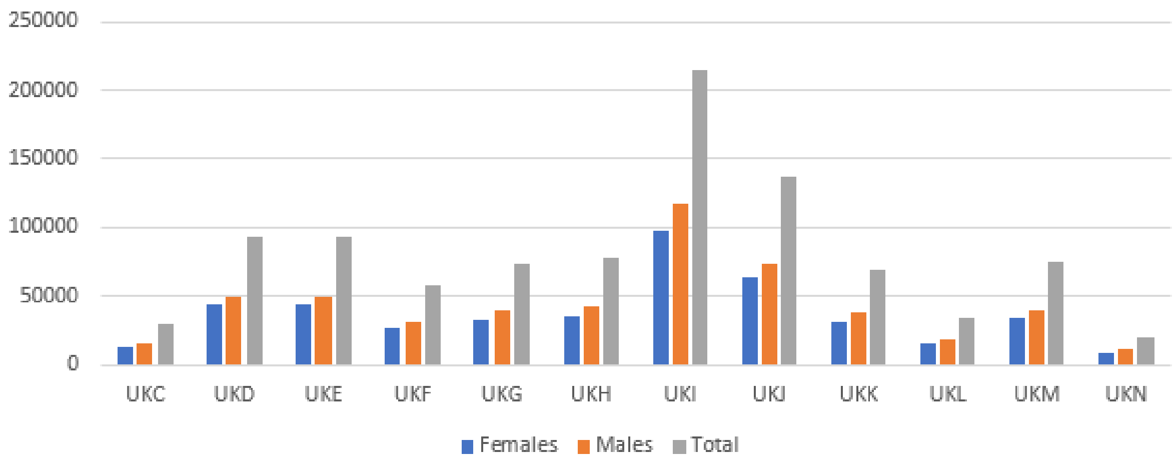


Figure 4.4: Compensation of employees broken down by males and females at NUTS 1 level (Millions of Pounds)

4.5.1.1 Value added for Regions Scenario#1

In RS #1, UKI (London) compensation of employee (male) is equal to compensation of employee (female). Out of the 30 sectors modelled in the economy, there is an increase in female wages for 28, while 2 (Water supply, sewerage and waste management and Activities of households) experience a decrease. Table 4.8 represents the changes broken down by sectors. The most significant change was observed in the financial and insurance sectors, with female wages increasing by £ 4,881 million to match male compensation.

Table 4.8 Increase in female compensation based on total equality in wage scenario (RS #1)

Number	Code_30	Sector	Change In compensation of females (Million £)
1	A	Agriculture, forestry and fishing	0.921
2	B	Mining and quarrying	10.425
3	CA	Manufacture of food, beverages and tobacco	93.154
4	CB	Manufacture of textiles, wearing apparel and leather	61.447
5	CC	Manufacture of wood and paper products and printing	28.122
6	CD-CF	Manufacture of petroleum, chemicals and pharmaceuticals	36.686
7	CG	Manufacture of rubber, plastic and non-metallic minerals	25.948
8	CH	Manufacture of basic and fabricated metal products	49.965
9	CI	Manufacture of computer, electronic and optical products	38.683
10	CJ	Manufacture of electrical equipment	33.313
11	CK	Manufacture of machinery and equipment	4.608
12	CL	Manufacture of transport equipment	31.880
13	CM	Other manufacturing, repair and installation	20.101
14	D	Electricity, gas, steam and air-conditioning supply	35.506
15	E	Water supply; sewerage and waste management	-124.714
16	F	Construction	695.055
17	G	Wholesale and retail trade; repair of motor vehicles	1425.505
18	H	Transportation and storage	290.839

19	I	Accommodation and food service activities	229.910
20	J	Information and communication	1642.474
21	K	Financial and insurance activities	4881.035
22	L	Real estate activities	448.874
23	M	Professional, scientific and technical activities	4175.573
24	N	Administrative and support service activities	180.303
25	O	Public administration and defence; compulsory social security	624.930
26	P	Education	1277.797
27	Q	Human health and social work activities	1685.189
28	R	Arts, entertainment and recreation	498.847
29	S	Other service activities	539.557
30	T	Activities of households	-67.035

4.5.2 Regional Scenario #2

While regional scenario#1 assumes that there is complete equality in wages, in regional scenario#2, we take a much more realistic approach and assume that the compensation of female employees has increased based on the discrimination women experience. This discrimination amount is calculated by OB decomposition (The methodology for running OB decomposition is in chapter 3 of the thesis). The paper uses the same methodology with slight modifications to calculate London's regional discrimination.

4.5.2.1 Value added for Regions Scenario#2

To calculate regional discrimination, we used a subsample from Understanding Society wave 9. The subsample is filtered for all working individuals who are residents of London. Then OB decomposition is calculated at the mean for these filtered individuals. We use the following equation.

$$Ln(wage) = B_0 + age + age^2 + workinghours + parttime + private + married + children + organisation\ size + e_0 \dots\dots\dots\dots (4.17)$$

Where Ln (Wage) is a log of wage, working hours are a total number of over hours worked, including overtime. Part-time represents the status of work and is a dummy variable. Married, private, children are also dummy variables, with children representing individuals having a child less than 16 years old. Organisation size is a categorical variable describing the number of employees, with four categories of 1-24, 25-99, 100-499, 500+. The results for the OB decomposition are shown in Table 4.9.

Table 4.9 OB decomposition London - Regional Scenario # 1 discrimination

Blinder-Oaxaca decomposition, Model=Linear # of observations total = 1452

Number of observations males = 636 Number of observations females = 816

Lnwage	Coef.	Robust Std Err.	z	P>z	[95% Conf.	Interval]
Overall						
Males	7.89	0.03	291.01	0.00	7.84	7.94
Females	7.53	0.03	291.21	0.00	7.48	7.58
Difference	0.36	0.04	9.50	0.00	0.28	0.43
Explained	0.24	0.03	8.36	0.00	0.18	0.30
Unexplained	0.12	0.03	3.82	0.00	0.06	0.18
Explained						
Age	0.02	0.05	0.42	0.68	-0.08	0.12
Agesquared	-0.02	0.04	-0.38	0.70	-0.10	0.07
working hour	0.12	0.02	5.98	0.00	0.08	0.16
Parttime	0.08	0.02	5.59	0.00	0.05	0.11
Private	-0.01	0.01	-0.98	0.33	-0.02	0.01
Married	0.01	0.00	2.47	0.01	0.00	0.02
Children	0.00	0.00	0.46	0.64	0.00	0.00
organisation size	0.02	0.01	2.43	0.02	0.00	0.04
Unexplained						
Age	-0.25	0.86	-0.30	0.77	-1.95	1.44
Agesquared	0.25	0.47	0.53	0.60	-0.68	1.17
working hour	-0.51	0.20	-2.50	0.01	-0.91	-0.11
Parttime	-0.07	0.02	-2.66	0.01	-0.11	-0.02
Private	0.07	0.04	1.95	0.05	0.00	0.15
Married	0.00	0.03	-0.11	0.91	-0.07	0.06
Children	0.02	0.02	0.81	0.42	-0.03	0.07
organisation size	0.00	0.07	-0.05	0.96	-0.13	0.13
_cons	0.61	0.44	1.39	0.16	-0.25	1.47

Table 4.9 shows the OB decomposition at the mean for males and females. The absolute difference between the log of males – log of females is 0.356094. The explained component of this difference is 0.2401. The explained component represents a portion of the total pay gap that can be accounted for by our independent variables. The unexplained difference component

(discrimination) is 0.11596. This is termed as discrimination and forms part of the pay gap that our independent variables cannot explain. The discrimination percentage is found to be 32.565%. This is calculated by dividing the unexplained component by the total wage gap 0.11596/0.356094. This value forms the basis of our work in RS #2.

Furthermore, it is assumed to be removed from London (for female compensation). This forms the new vector shock that we use in our SEIM model. Essentially, we add this amount to female compensation for all 30 sectors of the London region. As an illustration, we take the sector of London, agriculture, forestry, and fishing which has a pay gap of 10.5 (ASHE, 2016). Our OB decomposition calculation shown in Table 4.9 shows that not all of the pay gap is down to attributes or co-efficient (independent variables used in the model). In fact, there is an explained portion and an unexplained (discrimination) component. Since we are assuming a scenario in which no gender discrimination exists in London. Hence, we re-calculate the female compensation of employees while the male one remains constant, as found in the earlier chapter (see 4.4). Mathematically, we observe the following.

$$Total\ pay\ gap * (1 - \ discrimination\ amount)$$
$$= new\ compensation\ of\ employees \dots \dots (4.18)$$

Continuing with our illustration of the agriculture, forest and fishing sector, we calculate 1- 32.565% of our 10.5 and eventually end up with the remaining 7.08 pay gap. Once this new gap is found, we employ the methodology mentioned in chapter 4.4.4.1 to find new compensation for female employees. Table 4.10 shows the change in the compensation of females for all sectors of London.

Table 4.10: RS #2 Change in compensation of female compensation based on calculated discrimination amount

No.	Code_30	Sector	Change In compensation of females (Million £)
1	A	Agriculture, forestry and fishing	0.14
2	B	Mining and quarrying	1.52
3	CA	Manufacture of food, beverages and tobacco	14.48
4	CB	Manufacture of textiles, wearing apparel and leather	8.83
5	CC	Manufacture of wood and paper products and printing	4.38
6	CD-CF	Manufacture of petroleum, chemicals and pharmaceuticals	5.44
7	CG	Manufacture of rubber, plastic and non-metallic minerals	3.95
8	CH	Manufacture of basic and fabricated metal products	7.26
9	CI	Manufacture of computer, electronic and optical products	5.5
10	CJ	Manufacture of electrical equipment	4.72
11	CK	Manufacture of machinery and equipment	0.73
12	CL	Manufacture of transport equipment	4.92
13	CM	Other manufacturing, repair and installation	3.18
14	D	Electricity, gas, steam and air-conditioning supply	5.58
15	E	Water supply; sewerage and waste management	-22.65
16	F	Construction	106.29
17	G	Wholesale and retail trade; repair of motor vehicles	219.17
18	H	Transportation and storage	46.54
19	I	Accommodation and food service activities	36.75
20	J	Information and communication	255.87
21	K	Financial and insurance activities	716.7
22	L	Real estate activities	67.79
23	M	Professional, scientific and technical activities	628.99
24	N	Administrative and support service activities	28.38
25	O	Public administration and defence; compulsory social security	98.24
26	P	Education	196.21
27	Q	Human health and social work activities	254.24
28	R	Arts, entertainment and recreation	72.41
29	S	Other service activities	82.22
30	T	Activities of households	-11.17

4.5.3 Sectoral Scenario #1:

In sectoral scenario no. 1, we take the sector with the highest employee compensation difference between men and women. To calculate this, equation 4.19 is used

$$Total\ sectoral\ compensation\ for\ sector\ 1$$
$$= \Sigma \text{ Sector 1 compensation of employees for all regions } \ldots \ldots. (4.19)$$

The same was done for sectors 2, 3 and so on. The results of this exercise yield in Table 4.11. Table 4.11 shows the sector with the smallest pay gap was sector 30 Activities of households and sector 13 - other manufacturing, repair and installation. A reverse gap (female compensation was higher) was observed in sector water supply, sewerage, and waste management. The sector with the highest compensation of employee difference was sector 23, Professional, scientific, and technical activities denoted by "M". Once we identified this sector, a hypothetical was set up. We assumed that there is no wage gap in this sector[14].

Table 4.11 SS#1 Total sectoral compensation (sorted by lowest to largest) for the UK

National	***Sector***	***Sector name***	***Compensation of Employee Difference***
UK	s15		-406.99
UK	s30		31.38
UK	s13		126.26
UK	s2		166.94
UK	s1		193.89
UK	s11		374.69
UK	s4		458.36
UK	s10		460.77
UK	s24		479.03
UK	s5		496.01
UK	s8		643.56
UK	s14		692.73
UK	s9		705.59
UK	s7		833.53
UK	s6		974.18
UK	s22		1041.89
UK	s12		1188.84
UK	s3		1321.98
UK	s19		1454.34
UK	s28		1687.02
UK	s18		1735.31
UK	s29		1800.57
UK	s25		3038.87
UK	s16		3287.68
UK	s20		5000.05
UK	s26		7258.96
UK	s21		8799.77
UK	s17		10499.26

[14] We set up a similar scenario in RS #1, where the compensation of males and females was equal.

UK	s27	11350.34
UK	s23	11928.02

4.5.3.1 Value added for Sector Scenario 1

To calculate value added in each sector in SS1, sector 23's compensation of female wages is increased to match male compensation. This is done for all 12 regions in sector 23. The exercise is similar to RS#1, where London's sectors were changed. In this case, we increase compensation in sectors. The resulting value added in all 12 regions for sector 23 is represented in Figure 4.5.

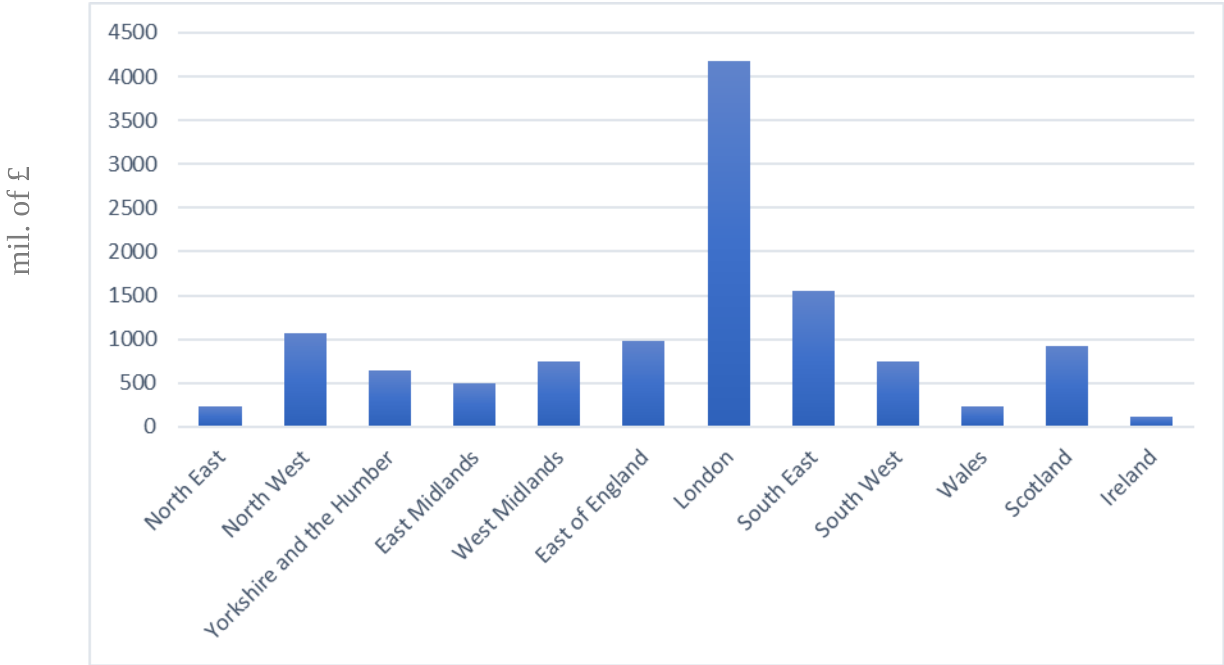


Figure 4.5 Change in compensation of female employees sector 23, in each of the 12 regions for sectoral scenario 1

4.5.4 Sector Scenario 2

In sectoral scenario 2, we use the same methodology mentioned in regional scenario no 2 but for sector 23 only. We used the OB decomposition to find the discrimination percentage in Sector 23. Once this is found, we increase female compensation by this amount, thereby representing each female's actual productivity.

Like RS #2, we use the all-worker dataset from wave 9. However, in wave 9, we create a sub-sample of individuals only in the Professional, scientific, and technical activities. Standard Occupation Classification 2000 (SOC) is used to create the sub-sample. First, we analyse the occupations that belong to sector 23 from the SOC 2000 and then create a filter with just these individuals. The list of professions and their frequency identified in these steps is given in Table 4.12.

Table 4.12 Identifying sector 23 in Wave 9 Understanding Society from SOC 2000

Name of profession	Frequency
Science professionals	81
Engineering professionals	217
Information and communication technology professionals	331
Health professionals	286
Teaching professionals	1116
Research professionals	96
Legal professionals	122
Business and statistical professionals	211
Architects, town planners, surveyors	100
Public service professionals	172
Librarians and related professionals	23
Science and engineering technicians	194
Draughts persons and building inspectors	37
It service delivery occupations	137
Health associate professionals	649
Therapists	163
Social welfare associate professionals	246
Protective service occupations	200
Artistic and literary occupations	154
Design associate professionals	108
Media associate professionals	128
Sports and fitness occupations	115
Transport associate professionals	43
Legal associate professionals	59
Business and finance associate professionals	516
Sales and related associate professionals	325
Conservation associate professionals	18
Public service and other associate professionals	343

Table 4.12 represents a total of 3,890 observations. The largest category within sector 23 was teaching professionals, with 1,116 observations. The smallest sample was found to be of conservation associate professionals. Now that we have individuals inside sector 23 of the economy. We run our OB decomposition. The results of the OB decomposition are presented in Table 4.13. Table 4.13 shows a total log gap of 0.2758, between male and female earnings in sector 23. Of this 0.275 gap, our independent variables explain 68.4 of the gap. The

unexplained gap is (Discrimination percentage of total) 31.591%. = 0.0871353/0.2758199. This is lower than our RS #2 where the unexplained gap was 32.565%.

Table 4.13 OB decomposition for sectoral scenario 2, sector 23 pay gap

Blinder-Oaxaca decomposition, Model=Linear — # of observations total = 3890
# of observations males = 1681 — # of observations females = 2209

Ln wage	Coefficient	Robust Std.Error	Z	P>z	95% Confidence Interval	
overall						
Males	7.94	0.01	537.11	0.00	7.91	7.97
Females	7.67	0.01	625.82	0.00	7.64	7.69
Difference	0.28	0.02	14.36	0.00	0.24	0.31
explained	0.19	0.01	13.05	0.00	0.16	0.22
unexplained	0.09	0.02	5.24	0.00	0.05	0.12
------------------+-- ----						
explained						
age	0.00	0.03	-0.05	0.96	-0.07	0.06
agesquared	0.00	0.03	-0.07	0.94	-0.06	0.06
working hour	0.12	0.01	10.41	0.00	0.10	0.14
parttime	0.05	0.01	7.89	0.00	0.04	0.07
private	0.01	0.00	2.89	0.00	0.00	0.02
married	0.00	0.00	2.31	0.02	0.00	0.01
children	0.00	0.00	-0.05	0.96	0.00	0.00
organisation size	0.01	0.00	1.62	0.11	0.00	0.01
------------------+-- ----						
unexplained						
age	0.03	0.52	0.05	0.96	-0.99	1.04
agesquared	0.06	0.27	0.20	0.84	-0.48	0.59
working hour	-0.36	0.12	-2.93	0.00	-0.59	-0.12
parttime	-0.03	0.01	-2.88	0.00	-0.05	-0.01
private	0.04	0.01	2.60	0.01	0.01	0.06
married	0.02	0.02	1.02	0.31	-0.02	0.06
children	0.02	0.01	1.37	0.17	-0.01	0.05
organisation size	0.12	0.04	3.28	0.00	0.05	0.20
_cons	0.19	0.29	0.67	0.50	-0.37	0.75

4.5.4.1 Value added for sectoral scenario # 2

Table 4.13 shows that sector 23 experiences discrimination at 31.591%. Proceeding from this, we assume that the sector 23 pay gap is reduced by this percentage from the original pay gap. Mathematically this can be achieved through equation 18, as shown in RS #2. This new calculation provides us with a new compensation for female employees. Male compensation is assumed to be constant as per the original pay gap. This increase in labour costs, in turn, gives us new value added. The increased value added for sectoral scenario # 2 is shown in Figure 4.6.

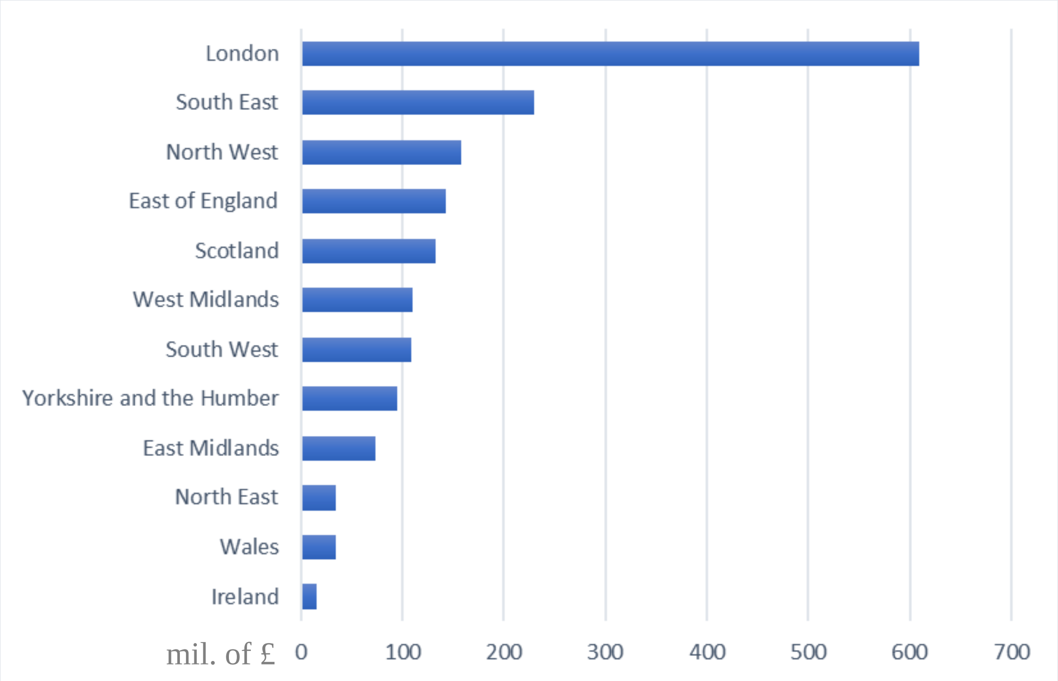


Figure 4.6 Change in compensation of female employees sector 23, in each of the 12 regions for sectoral scenario 2

Sector 23 in London, the South-East and North-East showed the most significant change in value added. Ireland and Wales showed the most minor change in sector 23 with increases of 15.9 million and 33.9 million pounds respectively.

4.5.5 Input-Output ONS

To compare SEIM results for consistency and goodness, we used the Input-Output model from ONS. The IO model for ONS represents 64 sectors and accounts for the UK. It does not provide regions; hence regions scenarios cannot be compared. However, we can compare sectoral scenarios of SEIM with the IO model of ONS. This was undertaken in the study to compare national results with multi-regional level results.

4.5.5.1 Imbalance in the number of sectors

While SEIM-UK contains 30 industries/sectors (we use the terms interchangeably), IO Model of ONS uses 64 sectors. This provides an imbalance that needs to be considered while running and comparing results. As mentioned earlier, the sectoral formation of the SEIM-UK of 30 sectors inside SEIM-UK are aggregated of the 64 sectors that are presented in IO national model of ONS. The sectors for models IO and SEIM are derived from Standard Industrial Classification (SIC 2007). The IO model of ONS aggregates these 99 SIC 2007 into 64 sectors, aggregated further into 30 sectors. To address this issue of imbalance, two approaches can be taken.

1) We can aggregate the sectors in the IO Model to the 30 sectors of the SEIM-UK. This can be done using R or Python. Also, this can be done manually by Excel; however, doing it manually requires a great deal of time and the chances of error are high.
2) The second method involves using the 64-sector disaggregation as presented in the input-output model of ONS and the disaggregated version of M (sector 23). In this method, we can retain the information kept in IO model and use sector 23 as it currently exists. For example, sector M is divided into Legal and accounting services; services of head offices; management consulting services, Architectural and engineering services; technical testing and analysis services, Scientific research and development services, Advertising and market research services and Other professional, scientific, and technical services; veterinary services. This is aggregated in SEIM to sector 23, Professional, scientific, and technical activities. If we were to disaggregate this, we would get the eventual IO (ONS) model usage of sector 23. Table 4.14 shows how sector M/23 corresponds to IO (ONS) sectors.

Both methods mathematically will yield the same results. As method 1 would just aggregate sectors 46 – 50 into one whole sector (23). This can be represented by equation 4.20

$$Aggregated\ sector\ 23 = sector\ 46 + sector\ 47 + sector\ 48 + sector\ 49 + sector\ 50 \ldots\ldots (4.20)$$

We are interested in overall output and GVA, so either method can be used. In this thesis, the second method is preferred to the first one, since it allows the original data to be retained. Also, it provides further information on different sectors (indirect effects) as all the original 64 sectors are retained.

Table 4.14 Sector M (Identification of Sectors)

Sector Identification	***Sector code in IO (ONS)***	***Sector Name***
Sector M / 23	46	Legal and accounting services; services of head offices; management consulting services
Sector M / 23	47	Architectural and engineering services; technical testing and analysis services
Sector M / 23	48	Scientific research and development services
Sector M / 23	49	Advertising and market research services
Sector M / 23	50	Other professional, scientific, and technical services; veterinary services

4.5.5.2 Disaggregating IO ONS by gender

The IO ONS, like SEIM UK, does not have gender disaggregated employee compensation. Hence, first, we disaggregate the compensation of employees by gender. This is explained previously in section 4.4. We use equation 4.9 and 4.11 to disaggregate the compensation of employees into female and male compensation of employee. To check for accuracy, we satisfy equation 4.9, as mentioned earlier.

$$C_m + C_f = C_t \dots\dots\dots..(4.9)$$

Here C_f refers to female compensation of employees; C_m refers to male compensation of employees, whereas C_t refers to compensation of employees' total. Equation 4.9 states that after the decomposition of compensation of employees. Therefore, male employee compensation and female employee compensation must equal total employee compensation.

4.5.5.3 Sector Scenario 1 (ONS)

Once we have the disaggregated compensation, we set up our model to find the new value added. In the first scenario, we recreate the hypothetical that the compensation of females is equal to the compensation of males. Recall that this is similar to our SEIM-UK sector 1 scenario. This is because, eventually, we want to compare the results of the ONS model to SEIM-UK. This serves as a robustness test and provides us with much-needed information compared to our multi-regional model. To set up the scenario. First, we extract values of sectors 23 of male's compensation. Our ONS IO model corresponds to sectors 46, 47, 48, 49 and 50 (see table 4.12 for details). Then we assume that female compensation in these sectors has become equal to male compensation. Mathematically, we can represent this by the following.

$$\begin{aligned} &Sector\ (23/M) Male\ Compensaiton \\ &= Sector\ (23/M) Female\ Compensation \dots\dots(4.21) \end{aligned}$$

This setup of equation 13 causes increases in labour costs for the economy. This increase, in turn, affects value added. The value added for this scenario, along with the second sectoral scenario, is presented in the next section[15].

4.5.5.4 Sector Scenario 2 (ONS)

To run sectoral scenario 2 for ONS, the methodology for SEIM-UK sector scenario 2 is used. We assume that the compensation of female employees has gone up (while male compensation remains the same). The difference is the increase in female compensation corresponds to the pay gap based on productivity. To find the new pay gap based on

[15] The new value added is then used to run the methodology explained in chapter 4 using the Ghosh approach. We present the output and overall changes in the results chapter of this paper.

productivity, we use the OB decomposition from scenario sector 2 set-up for SEIM-UK. The results of the Oaxaca-Blinder showed a discrimination amount of 31.591% (see 4.11). Therefore, in our analysis of Sector Scenario 2 (SEIM-UK), we reduced the gender pay gap of 23.2 (total unadjusted gap in sector 23) by 31.591% to find a new gender pay gap for the sector. This new gap represents the gap between the genders based on their productivity levels. Mathematically, we do so by the following equation.

$$New\ GP\ (Sector\ 23) = Sector\ 23\ pay\ gap * \ (1 - discrimination\ (of\ pay\ gap) \ldots\ldots (4.22)$$

Equation 4.13 gives us the new gender pay gap for the compensation of females. In our analysis of sector 23, we have the new gender pay gap as (23.2 * 0.68409 = 15.871). Hence, the new pay gap for calculation is 15.871. With this percentage, we calculate the new compensation of females based on equation 4.9 and equation 4.11, like mentioned before. The reason for selecting and keeping sector 23 / sector M is twofold. First, it is the sector with the highest overall compensation of employee difference. Secondly, to compare the ONS IO model with the SEIM-UK model, we keep the sectors the same.

4.5.5.5 Value Added for the two ONS sectoral scenarios

The results for the female value added in the two scenarios are presented in Table 4.15. Table 4.15 shows significant differences in increases when productivity differences are accounted for versus when the compensation of employees is assumed to be exactly the same as men. The highest compensation change for females was observed in legal, accounting, management, consulting and head office services, with an additional income of £ 4092 million in scenario 1 and 598.8 million pounds in scenario 2. The last change was observed in the scientific and technical services sector with increases of 1057 million pounds and £154 million for scenarios 1 and 2, respectively. Note that we do not have regions in the ONS input-output model, and the data represents changes for the UK.

Table 4.15: Value added for ONS sectors scenarios (Millions of pounds)

Industry	***Sectoral Scenario # 1***	***Sectoral Scenario # 2***
Legal and accounting services; services of head offices; management consulting services	4092.36	598.88
Architectural and engineering services; technical testing and analysis services	1687.59	246.96
Scientific research and development services	1306.93	191.25
Advertising and market research services	1159.97	169.75
Other professional, scientific and technical services; veterinary services	1057.57	154.76

4.6 Results

Table 4.16 summarises the results for all four scenarios using the two input-output models. Table 4.16 shows the highest initial value-added increase in regional scenario#1, accounting for a total increase of 0.908%. As is to be expected, scenarios of total equality (in which female compensation becomes equal to male compensation RS #1, SS #1, and SS #1 (ONS) are higher than scenarios of female compensation increase as per their productivity (RS #2, SS #2 and SS #2 (ONS)).

The scenarios showcased a total output increase of 0.980%, which is equivalent to an increase of 34.27 billion pounds in regional scenario#1. This is followed by Sectoral scenario#1 (SEIM-UK), with an increase of 27.13 billion pounds. This is followed by SS #1 (ONS), which showed an output increase of 19.1 billion pounds. Although RS #1 had more output increase than SS #1, total jobs created by SS #1 (SEIM-UK) were higher than RS #1. RS #1 saw an increase of 316,948, while RS #1 saw a job increase of 282,347 throughout the economy.

Sectoral scenario comparison between SEIM-UK and ONS model show higher output increases (following a higher level of value-added increase) for SEIM-UK as compared to ONS model. In SS #1, the output increase is 27.1 billion; with SEIM-UK running the same scenario with ONS Input-Output, we observe an increase of 19.1 £ billion. Similar observations occur for sectoral scenario#2. In SEIM-UK, we see an overall output increase of 3.96 billion pounds against ONS model increase of 2.79 billion pounds.

One reason the estimates may differ is due to different regional multipliers that are considered with SEIM-UK model. Another reason why there are differences in the models is that initial VA change is higher for SEIM-UK than in ONS models. In the SEIM sectoral scenario 1 initial VA change for was 2.62 billion pounds higher than in ONS model. While in SS #2, SEIM-UK saw a higher value-added change by a total difference of 382 million pounds.

Table 4.16 : Summary of results for all scenarios (VA, Output and Job increase)

	RS #1	***RS #2***	***SS #1***	***SS #2***	***SS #1 (ONS)***	***SS #2 (ONS)***
Va increase (%)	0.908%	0.137%	0.574%	0.084%	0.4495%	0.0658%
Output increase (%)	0.980%	0.148%	0.770%	0.113%	0.5696%	0.0834%
Job Increase (%)	0.944%	0.143%	1.060%	0.155%		
In Millions of £						
Va increase (£)	18874.90	2846.63	11928.02	1743.36	9304.45	1361.63
Output increase (£)	34270.51	5169.84	27134.66	3965.83	19106.80	2795.91
Job Increase (# of people)	282347	42720	316948	46326		

Table 4.17 provides a regional-level analysis of output and jobs for all scenarios. Regionally, in all our scenarios, London saw the most significant increase in output and jobs. The second largest change is observed in South-East for output and jobs in all scenarios. The third largest change comes from the Scotland in all the regional scenarios. At the same time, the sectoral scenarios saw the 3rd largest increase in North-West. The lowest change in output and jobs came from Northern Ireland for all the models. The second lowest change came from North-East. Table 4.17 does not provide a regional breakdown for ONS models since the regions are not included in the ONS models.

Table 4.17 Regional breakdown of output and jobs for all scenarios

Change In Millions of £	***RS #1 output***	***RS #1 jobs***	***RS #2 output***	***RS #2 jobs***	***SS #1 output***	***SS #1 jobs***	***SS #2 output***	***SS #2 jobs***
North-East	274.04	3081.31	41.31	464.10	529.76	7636.59	77.77	1121.66
North-West	672.17	7205.68	101.36	1085.40	2425.06	33881.32	355.75	4971.14
Yorkshire and The Humber	528.33	6305.43	79.52	948.39	1318.83	20287.95	192.70	2964.35
East Midlands	505.00	5932.08	75.81	889.67	1286.38	18731.97	189.92	2767.19
West Midlands	541.92	5765.65	81.55	866.84	1891.01	25492.44	276.07	3721.53
East	595.64	6373.43	89.32	955.38	2322.27	31101.49	337.85	4523.79
London	28253.55	217799.42	4264.52	33015.32	8549.90	77831.41	1248.23	11362.53
South-East	1127.51	10256.19	169.59	1542.13	3820.35	40233.00	561.70	5916.52
South-West	486.49	5392.31	73.33	812.08	1648.56	18989.87	241.77	2785.06
Wales	354.98	4187.17	53.43	629.82	628.16	8939.20	91.58	1302.83
Scotland	694.61	7436.18	104.58	1118.78	2307.29	28520.12	332.96	4113.59
Northern Ireland	236.27	2611.87	35.52	392.46	407.10	5302.47	59.53	775.43
Total	34270.51	282346.73	5169.84	42720.38	27134.66	316947.85	3965.83	46325.62

Output changes for the more realistic scenarios RS #2 and SS # 2 are provided in Figure 4.7 and Figure 4.8 side by side for comparison. As can be seen from the figures, the primary effect comes from London. However, the overall effect of London is smaller in the sectoral scenarios compared to the regional scenario. For RS # 1, we observe the South-East, and then Scotland being affected the most. For SS #1, the effect is most in London, the South-East, the North-West and East.[16] Appendix 19 to Appendix 24 show the rest of the maps with modified legend to pinpoint where the effect is the most dominant of increased output and jobs.

[16] Areas with a similar output change were grouped for a display of results.

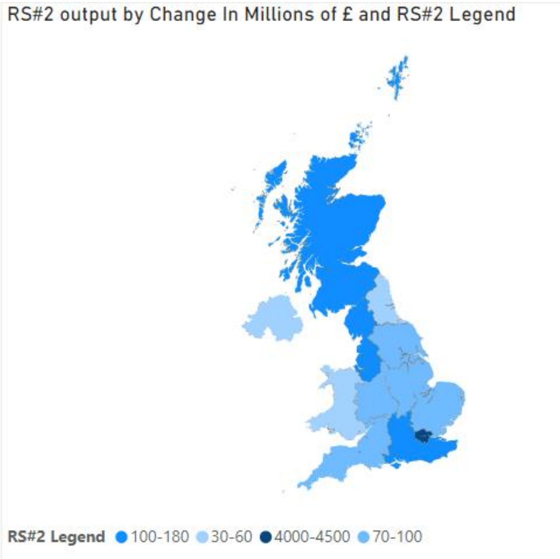


Figure 4.7 RS #2 output changes in millions of pounds

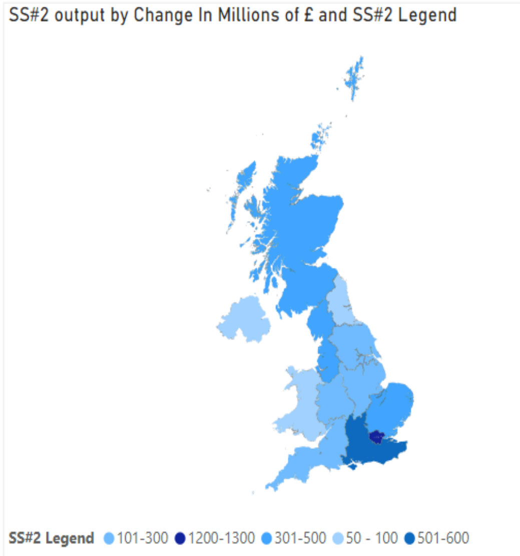


Figure 4.8 SS#2 output changes in millions of pounds

Figure 4.9 shows the highest changing sectors by output for regional scenario#1 and regional scenario #2. The biggest change is observed in electricity, gas and air conditioning supply (1086 million pounds) followed by construction (942 million pounds) and then manufacture of computer, electronic and optical products (483 million). The sectors with the highest changes in RS #1 and RS #2 appear to be male-dominated sectors.

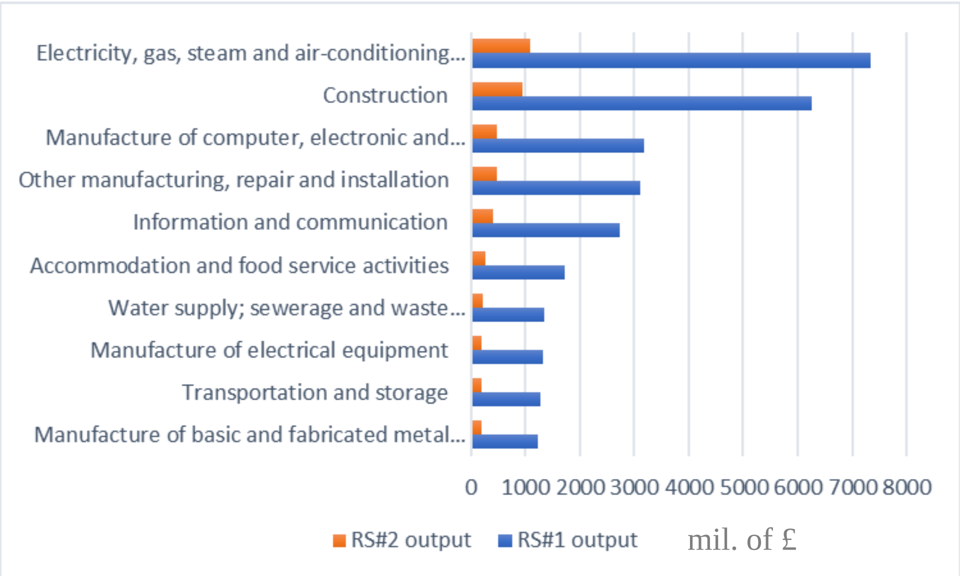


Figure 4.9 Sectors with highest output changes (RS #1)

4.6.1 ONS Input-Output model vs SEIM-UK Comparison of results (sectoral)

To compare the results of Input-Output model and SEIM UK, the 64 sectors of the ONS model need to be matched with the 30 sectors of the SEIM UK model. Since both models rely on UK SIC of Economic Activities 2007 (SIC 2007) (ONS, 2007). An exercise was taken to convert all the SIC classification codes from the ONS model to the 30 sectors in SEIM-UK. Appendix 25 provides the SIC codes and the conversion from sectors of ONS to SEIM-UK sectors (using SIC codes).

Once the conversions are complete, as shown in Appendix 25: Conversion of IO model ONS to SEIM-UK based on sectors (using SIC codes), we aggregate sectors from ONS based on the conversion sectors identified against SEIM-UK. For instance, in sector 23, we use equation 4.20 to find a comparison between ONS sector and SEIM-UK.

$$Aggregated\ sector\ 23$$
$$= sector\ 46 + sector\ 47 + sector\ 48 + sector\ 49 + sector\ 50 \ldots\ldots (4.20)$$

After these steps are completed, a check for correct aggregation to 30 sectors is undertaken per equation 23. Once equation 23 is satisfied, we can compare the results for ONS and SEIM-UK by sectors. This is shown in

$$\Sigma \text{ ONS 64 industries} = \Sigma \text{ 30 aggregated industries} \ldots\ldots.. (4.23)$$

Comparing the two more realistic scenarios of SS #2 and SS #2 (ONS), we observe that the top 3 largest sectoral changes for both models are the same, as shown in Figure 4.10. The difference is that the IO ONS model has the second largest sectoral change in financial and insurance activities and 3rd in wholesale and retail trade, whereas the positions are reversed for SS #2 (SEIM-UK). Comparing the two models, we also observed that SS #2 (SEIM-UK) estimates were higher for 22 sectors, whereas in 8 sectors IO (ONS) estimates were higher.

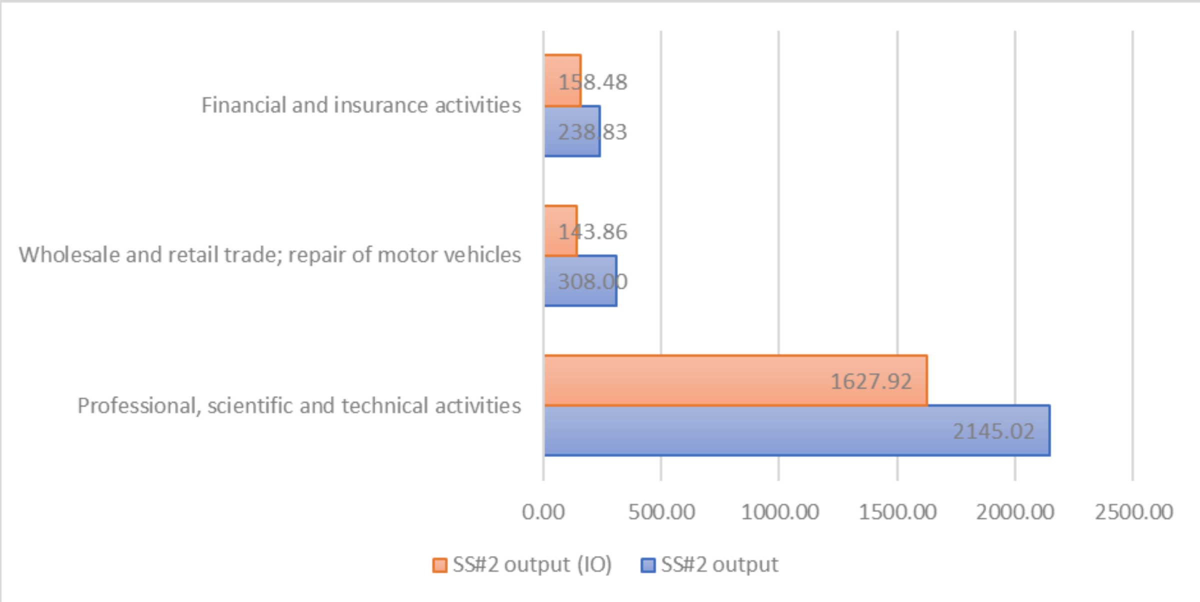


Figure 4.10 Top 3 largest changes in SS #2 and SS #2 (ONS)

The 8 sectors which were larger in terms of change were Construction, Electricity, gas, steam and air-conditioning supply, Manufacture of food, beverages and tobacco, Administrative and support service activities, Mining and quarrying, Agriculture, forestry and fishing, Arts, entertainment and recreation and, Manufacture of basic and fabricated metal products. Overall, SS#2 (SEIM-UK) predicted a change more significant than SS #2 (ONS) of 1169.92 million pounds. A complete breakdown of results by sectoral changes for all regional and sectoral scenarios is provided in Appendix 26: Sectoral results (change in millions of pounds by the 30 sectors including ONS model) of the thesis.

4.7 Does the model over-estimate results or under-estimate results?

4.7.1 Assumptions and over -underestimating the product

Despite offering many advantages, the input-output model does have a significant downside to it as well. The drawback lies in the model's assumption. The assumption is that the employment level is fixed and can be maintained despite increased costs. However, in real life, higher wages (labour cost increase) are bound to affect employment and output in negative ways as well. Hence, an argument can be made that our model overestimates the effect of an increase in labour cost for women on output.

Another equally valid argument could be that the model underestimates the result because of the no-spillover assumption. Once females start receiving more money, the families of females would also benefit from the increase. These advantages are not considered in the model, and although we can assume a sign for the assumption (positive- more growth), producing actual values would be difficult. Another equally valid argument is that increased wages for women open new avenues for businesses, hence new employment in the system. This again would imply that results are underestimated.

Due to the price and cost effect that was considered for the model, we presume an overestimate in our results. The reason being that in real life, these labour cost increases might result in a reduction of profits and employment. Despite these reservations noted above and the problems mentioned, the study still provides valuable empirical evidence for the hypothesised case, especially since that area is extremely limited.

There is another fundamental assumption inherent in the input-output model. That is full pass-through. All effect is passed on fully throughout the economy meaning that new labour costs do not reduce demand for workers and no workers lose their job to adjust to the new labour costs. This again produces estimates of the upper bound. One advantage of this is that the because the effect is passed on to the economy, we can observe the effects on intermediate goods. For example, even if a particular industry has few women working, the output might increase because of the supply chain effects of increases in other sectors. It is vital to note that while there are critics of the input-output model, they also point out that 1) the results of the estimates are comparable to the Phillips curve estimation and general equilibrium models and 2) That the magnitude and direction of results are in line with reports from other literature MaCurdy (2015).

4.7.2 Over-underestimate arguments from discrimination measures

To make matters more complex and confusing, the adjusted wage gap, which we are using as a proxy for discrimination, is a measure that is also disputed. Researchers dispute that measure does not consider many unobservable characteristics such as mental strength, preferences, and competitive attitude. Since these unaccounted-for variables might also affect wage differences, researchers argue that the value of discrimination is overestimated (Blau and Kahn, 2017).

On the other side, there are also reasons and arguments to suggest that the value measured after these productivity differences might be underestimated. Researchers on this side argue that control variables, such as industry and occupation, could be related to discrimination. While running the analyses, we put these control variables as productivity measures and hence lose some discrimination.

An interesting way to combat this in the literature is through studies of homogenous groups (e.g. members that share similar characteristics). The reason why these studies work better is that similar academic backgrounds might account for omitted variable biases. For example, one interesting study was performed by Noonan et al. (2005), who discovered a gender wage gap of just 11% between male and female lawyers from a selected cohort of the University of Michigan.

Booth and Francesconi (2003) perform a similar study keeping this philosophy using academic economists in the UK. He finds that the within-rank adjusted wage gap is 9% between these economists. He argues that there is a significant adjusted wage gap even in homogenised groups. This, combined with other studies that find the adjusted wage gap, indicates that there is discrimination against women. However, it is essential to clarify that the magnitude is much lower than the absolute gender pay gap. This methodology of the adjusted wage gap is used in our paper as a proxy for labour market discrimination.

4.7.3 A note on assumption and cost

We make an important assumption in the input-output model. Employment loss does not occur due to increased labour costs. Still, we must ask who pays for the increased labour cost? At the simple level, the employer's answer to who pays for the increase seems obvious. However, businesses do not always end up paying a higher cost. The literature suggests that they can often pass it to consumers MaCurdy (2015). Businesses have four possible choices of response to the increased cost imposed by our hypothetical. First, they can decrease employment (meaning they can lay off employees). The second option is reducing training and fringe benefits for employers. This is often coupled with the first one and presented as three options for businesses. The third option is to take a loss in profits. In this scenario, the owner is the one who ends up paying for the cost. The fourth option is to increase prices, in which case the consumers end up paying.

Here it is important to acknowledge that while the input-output model provides outstanding short-run results and estimates for our hypothetical, its nature has drawbacks. A fundamental assumption of the input-output model is a failure to account for long-term responses to the change. This is because the input-output model implicitly assumes that (even though prices might change) there is no substitution amongst goods and no employment changes (the system absorbs all the wage increases, and unemployment does not increase). The assumption that output will be fixed, and no unemployment will occur despite increased compensation for female employees are two big ones. It is also noteworthy to note that the criticism of Oosterhaven (1988) is valid over here as well. Since we assume output is changed but gross value added remains the same. This is unlikely as output increases will affect value added. These are well-renowned flaws of the model and have been acknowledged for a long time, e.g., Wolff and Nadiri (1981), Lemos (2004).

4.8 Plausibility of the model

Ghosh (1958) was the first to propose an alternative to Leontief's formulation in his article "Input-Output Approach in Allocation System". Similar to the Leontief model is a production model where output depends on the factor's income (value-added). This factor's income is usually affected by an exogenous variable. The model is an example of the supply-driven input-output model.

The Ghosh model, in essence, is a model that calculates the impact of a unit change in primary input (value-added) for the sectoral (and regional) output throughout the economy (Oosterhaven, 1988; Voon and Miller, 2005). Ghosh (1958) proposed the model as a solution to analyse the labour supply. He also hoped to use the model to plan for economies with limited resources, specifically where allocation of resources was challenging to achieve or maintain welfare. Another potential application when developing the model was that it might be a helpful way to study the structure of an economy dominated by monopoly markets. In these situations, a supply increase would be absorbed by the demand.

Despite Ghosh's novel model, the debate and empirical allocation did not start till the 1970s when Augustinovics (1970) presented her paper re-evaluating the supply side model. She argues that we should re-think the supply side model via the equilibrium features that W. Leontief (1944) talks about and disregard the questions and debate on its plausibility. From a methodology point of view, a single accounting framework is used to derive both the demand and supply formation. In essence, both Ghosh's and Leontief's versions are production models by different but analogous means. They both can be solved by the circular framework (Leontief, 1936).

Strong critics emerged because of her paper in the form of Giarratani (1980) and Oosterhaven (1988). Giarratani (1980) was the first to point out that these models are complicated to interpret and argued that the problem of interpreting the model in a conventional production theory has led to assertions and interpretations that challenge the meaning and structure of the model.(Oosterhaven, 1988, 1989) lays the most critical criticisms of using and interpreting the Ghaus model.

Oosterhaven, in support of Giarratani (1980), argues that the Gaussian model is implausible. He argues that it is a model that responds to changes in value-added in a sector of an economy that leads to output changes without affecting value added again. He argues that output increases in turn, no matter how allocated and produced, should affect (even if it is a little bit) value added. The premise of his argument lies in the model's flaw of not changing value-added despite increasing output.

Further support for these claims has been provided by De Mesnard (2009). De Mesnard argues that Gaussian models are "uninteresting" and lack plausibility as an output model. Furthermore, he argues that it is less informative than price and output models.

Despite the critique mentioned above, the Ghosh model is a valuable tool and can be used in many specific input-output applications, a sample of which is presented below. Guerra and Sancho (2010) have proposed to re-think the model. They argue that if we reconsider Ghosh's models as closed models, then the problem of no value-added increase disappears. They argue that closing the model solves the value-added problem and correctly computes changes from supply shocks.

Viñuela and Fernández Vázquez (2012) use the Gaussian to estimate immigrants' impact on the internal migration pattern in Spain. Using input-output analysis via Ghosh, they find direct and indirect effects of immigrants arriving in Spain and how it will affect production allocation amongst various regions. Expanding their analysis Viñuela and Fernández Vázquez (2012) also explore the effects of the Spanish definition of core and periphery region.

Still, though, critics remain of the model and question the model. The arguments boil down to two things from the critics, 1) The validity of results (interpretation), and 2) Value added not increasing because output increases. The following debate is organised to try to answer these issues. For the first point from the validity point of view, I will present an exercise showing that both this and the work from Dietzenbacher (1997) proposal reduced each other. To do this, we must take a standard open model configuration for Ghosh and Leontief. Both, as evidenced below, share common linearity assumptions and work best assuming that quantities are fixed. Here it is important to note that Dietzenbacher (1997) talks about the Ghaus model as equally good if it is taken as a price model, not as a quantity model for which we will argue.

The second task in the debate is explaining the model's plausibility theoretically, especially pertaining to and trying to answer the question (Oosterhaven, 1988, 1989), who points out the unresponsive value added as the main criticism. Firstly, it must be acknowledged that it is a valid criticism. Output increases without actual increases in value-added are theoretically a problem.

The problem can best be explained in the following mathematical example. Let us say that value added (in our case, it is due to hypothesised increase in labour cost – the mechanism is discussed in detail earlier in the methodology section of the thesis) under Ghosh model increases in a sector (j). The same rule applies to the case of regions as well. We are just taking sectors as an example. This sends a shock in the system and due to the input-output mechanisms, is absorbed in the system, thereby increasing the sector's output. Due to the system shock, other sectors are also affected. Let us say sector d is also affected due to this, and we see an increase in the output of sector d (d is not equal to sector j). The problem lies that even though sector d has seen its output goes up through endogenous nation of output allocation of an input-output model, sector d value-added does not see an increase. Consequently, we have a situation where the Output of sector d has increased while the value added of sector d has not increased due to a shock in the value added of j.

To compare this dilemma, we take a similar example for the case of the Leontief quantity model. In a hypothetical mathematical example, let us say that we have final demand for j increase (this can be for any reason). The system is shocked, and the input-output model gives new values of value added and output for all sectors. (While we continue with our simple example of one region economy, the case similarly applies to multi-regional input-output models in the economy). Even with the new value added to the system, the final demand for other goods does not change. This can be argued is the same flaw as in the above Gaussian model example where the value added was not changing because of output. Here, despite changes in output, the final demand does not change. It does not make sense that consumption by individuals remains the same after getting new additional income.

If the adversaries of the Ghosh model argue that output cannot change and value-added is unresponsive to that new output reallocation, a similar argument could be made for the Leontief model's implausibility. It could be argued that the Leontief model is also implausible since it is unresponsive to the income change of individuals.

Guerra and Sancho (2010) propose two solutions to these problems. One is that we make consumption endogenous to the model; the first final demand will also change the subsequent final demand. The second solution is to use a general equilibrium model considering price and income. These types of models also have consumption as endogenous. Guerra and Sancho (2010) have made a similar claim to the one proposed above in defending the plausibility of the input-output model.

For our analysis, however, we are not interested in prices and want to see the output and interregional effects of changes in female income. Therefore, we chose a closed multi-regional model. This has certain advantages and, of course, certain disadvantages as well. These are explained in detail above.

The solutions proposed (although not necessary for this study) might also serve to remove some of the problems with Ghosh's model since they are just as applicable to the Ghosh model as they are to the Leontief. The only difference would be that if we make demand endogenous in the Leontief model, we make supply (value added) endogenous in the Ghosh model Guerra and Sancho (2010).

Aroche Reyes and Marquez Mendoza (2021) provide one interpretation of how the model can be used. They argue that the model is the best fit to analyse underdeveloped countries where due to some factors, there is insufficient growth while the demand from the population is high. On the other side, the Leontief model is demand-driven, e.g., the Open supply Leontief model or Keynesian are constrained by final demand. So, whereas Ghosh assumes unused productive capacity, the production capacity is considered unlimited in the Leontief model.

Since these models share the same structure, there is a one-to-one correspondence between every limitation and mathematical property. However, the mathematical property and limitation go in opposite directions (Manresa and Sancho, 2020). While this has been widely accepted for the Leontief Model, it is rejected for the Ghosh model. Aroche Reyes and Marquez Mendoza (2021) provide further support by arguing that they do not find any methodological and mathematical flaws in the model. The most important thing is that it should make economic sense for its case. In this case, due to the nature of the question, it makes sense to use the Ghosh model.

4.9 Discussion and Conclusion

This chapter of the thesis answers a hypothetical question. What would happen if there was no discrimination in the labour market for women? The results show that removing discrimination can increase output (GVA) from 0.08% to 0.98% (depending on the scenario) for UK. On top of that a total of between 42,720 and 282,347 new jobs can be created.

To answer the question, input-output models from the SEIM-UK (created by City-REDI) and the Input-Output model (ONS) are used. The models use data from 2016, and the questions are answered for the UK's 12 NUTS1 regions and 30 sectors. Since the SEIM-UK was at the NUTS2 level and data for gender wage differences by sectors was unavailable for NUTS2 levels, we converted the NUTS 2 level multi-regional SEIM-UK model to the NUTS 1 level (12 regions).

To answer the research question, four scenarios are created, 2 (regional) and 2 (sectoral). The 2 scenarios are run through the SEIM-UK and ONS (regional scenarios cannot be run through ONS IO since it is not a multi-regional model). We find that scenarios in which male compensation became equal to female compensation performed better than no-discrimination scenarios. The range of output increase due to removing discrimination in the labour force ranged from 0.08 % (SS#2 ONS) to 0.98% (RS#1).

For the most realistic scenarios, we have an output increase of 0.15% (RS#2), 0.11% (SS#2) and 0.08% (SS#2) (ONS). This is in line with the literature where it is proposed that the gender pay gap is a cost to society (Altuzarra et al., 2021). Tsani et al. (2013) provide further credibility to our results by arguing that labour market discrimination affects both the economic growth and productivity of a country. These results are similar to those of Severini et al. (2019), who find that reducing hiring costs for females and increasing gender equality increases GDP by 0.10%. Our results are slightly lower than Souza's estimates, 0.42% increase for Brazil. Souza and Domingues (2015) and Severini et al. (2019) use IO/CGE models to run their scenarios. Our results are also slightly lower than the results produced by Tsani et al. (2013), who estimated a cumulative increase of 1.3% from 2015 to 2030 in middle easter-countries due to removing discrimination. However, since it is a cumulative result, actual results would be much closer to our results in the short run.

Our results contradict Seguino (2000), who found that a 0.1% increase in the gender pay gap increases GDP by 0.12%. We find the exact inverse to be true. One reason for this difference is the analysed countries. Seguino analysed middle-income countries, including Brazil, Greece, Hong Kong, Singapore, Taiwan, and Turkey. Another reason is the time frame of the study by Seguino (2000), as the data covered in that study included data only until 1995. For the UK, our study does not support the findings by Robinson (2002), who did not find any economic effect of an increase in the minimum wage for females. Our study finds that in all the models, there is a significant increase in output.

Job increase (in the number of people added to employment), measured by just SEIM-UK model, had a range of 0.14% increase (RS#2) (42,720) to 0.94% increase (RS#1) (282,347). For the most realistic scenarios, our results suggest a range of 0.14% (42,720) RS#2 to 0.16% SS#2 (46,326). Our results for job increase also support research by Ma et al. (2016), who noted that removing gender differences increases labour force participation from 54.4% to 67.5%. This is further supported by Altuzarra et al. (2021), who argue that women's increase in income has more long-term economic benefits than men since they are better savers.

Comparing IO model with the SEIM-UK model, we observed that overall output increases were higher for the SEIM-UK model than the IO model. Of the 30 sectors present in the model, 22 showed a larger increase in SEIM-UK as compared to the IO model (for SS#2).

One of the chapter's contributions is using the Gaussian inverse rather than the usual Leontief. The hypothetical and paper provide a use-case of the Gaussian under-utilised potential and argues that the Gaussian serves as a good use case for our hypothetical. To address the issue of no-increasing Value-added in other sectors (a supplementary paper is prosed in which value-added subsequently increases based on initial changes).[17]

[17] This is not part of this chapter as the math, and associated illustration, would take another complete chapter.

Chapter 5: Economic Adversity and Covid-19 in the UK Labour Market

5.1 Abstract

The Covid-19 pandemic forced locked down in many countries worldwide, including the UK. The UK government ordered the closure of businesses and urged people to stay at home, which had far-reaching implications for the labour market. Many workers faced the risk of losing their jobs permanently or seeing their working hours cut. Using a merged dataset from *The UK Understanding Society Covid-19* and the UK Household Longitudinal Study Covid-19 surveys, this study examines the UK labour exposure to Covid-19. In particular, the analysis compares men's and women's exposure to economic hardship during the first waves of Covid-19. The study has two main aims. Firstly, to comprehend, examine and compare the early impact (April 2020) of the Covid-19 pandemic on UK male and female workers. That is to understand the gender dimension of the impact of Covid-19 on workers' economic adversity, measured as the number of individuals laid off or put on furlough. Secondly, to analyse the main determinants of economic adversity during Covid-19. The results give indications that the pandemic affected both men and women equally. Among others, income, age, occupation, and ability to telecommute were the key factors that affected economic adversity the most during the first Covid-19 waves. The probability of economic adversity is reduced by 0.305 if an individual was a key worker. Hence, our study re-emphasised the narrative that being a key worker and having the ability to work remotely were the main reasons for being safe from economic adversity. Our results also suggest that occupation affected men and women differently. This means that sectors and occupations an individual was working in were far more crucial factors than any other in terms of the probability of facing economic adversity.

5.2 Introduction

The Covid-19 pandemic has had a significant effect on people's lives worldwide. The health effects, both directly and indirectly, have been severe. As of January 15, 2021, over 5.55 million have died, and over three hundred and twenty-four million have tested positive for Covid-19 (Science and University, 2021). Certain figures estimate that 40 to 70 percent of the global population may be contaminated (Baldwin and Di Mauro, 2020). Moreover, the infection has spread to 218 nations, making no nation immune.

During the first waves of the pandemic, most countries implemented special preventive care policies to combat the disease (Fong et al., 2020). The most common measures adopted included social distancing and closures of schools, businesses, non-governmental organisations and community centres. Mass gatherings were also curtailed. Even at weddings and funerals, only a certain number of individuals could attend. Travel became limited to a bare essential. These measures tended to compress the scale or lessen the cumulative number of instances associated with Covid-19 to avoid rapid growth and minimise stress on medical care (Science and University, 2021).

In addition to the pandemic's health effects, Covid-19 has also caused widespread unemployment (Bernstein et al., 2020). Early forecasts by the International Monetary Fund (2020a) predicted that as a result of the pandemic, the global economy would shrink by 3% in 2020. However, the International Monetary Fund (2020b) subsequently released a new version in June 2020, upgrading the statistic to 4.9 per cent. The changes were made due to: 1) lower activity during lockdowns; 2) persistence in social distancing activities; 3) uncertainty; and 4) decline in productivity amongst firms that were open for business.

The severity of these effects on a particular nation relies on social distancing (lockdowns and associated policies), the extent of enforcement, and, more significantly, the duration of enforcement.

Furthermore, school, work and daycare closures have led to a significant economic downturn and have caused massive labour shocks (Azcona et al., 2020), affecting the supply and demand side of the economy. The supply-side (goods and services produced) and the demand side (the demand for goods and services) have both been affected by the labour disruptions (investment and consumption) associated with Covid-19.

Another demand-side labour shock comes from employee's and people's consumption. In some situations (where they are laid off), employees have lower wages and will be more dependent on the state. As a result, people become more cautious about spending, resulting in a reduction in demand. These have a knock-on effect that shrinks the economy, which ultimately influences both companies and people. Similarly, certain people cannot access or conduct their employment due to border barriers, travel restrictions, and quarantine policies. This is especially true for casually employed and informal sector workers (Ahmad et al., 2020).

From a company perspective, all companies faced challenges during this pandemic, unlike anything they had faced before (ILO, 2020). Small and medium enterprises (SMEs) were the worst hit. The hospitality, transportation, and tourism sectors faced significant sales declines and, in some cases, insolvency (ILO, 2020). Individuals and companies' hardships are entangled.

Given this uncertainty, businesses and individuals feared investment and hiring new workers, thus, creating a shortfall of employment in the labour market. This is further augmented by a lack of quality and quantity of employment. In the UK alone, 17.8% of workers are classified as working in low-paying occupations, with low-paying employment described as one that pays less than two-thirds of the median hourly salary (ONS, 2018). These worrisome issues were further compounded by an impending global economic recession (ILO, 2020) which will, in turn, affect everyone, one way or the other.

Dealing with all these issues has been a massive hurdle for governments worldwide. Governments worldwide prioritised health over economics and have ordered complete or partial lockdowns (Waddell et al., 2021). The UK did the same. To reduce the spread of the virus, the UK government took extensive measures, including the closure of schools, restaurants, and non-essential businesses (Hupkau and Petrongolo, 2020). However, during the lockdown, the government designated specific economic sectors as necessary: pharmacies, groceries and primary retailers, delivery services and public health (ONS, 2020).

In short, the virus's negative impacts were detrimental. It has little regard for demographics such as gender, age, social status, or ethnicity. In a tweet, New York governor Andrew M. Cuomo (Jones, 2020) described the pandemic as the "great equaliser". The premise is that no one is exempt from Covid, regardless of their status, influence, or wealth, "It is a disease that transcends wealth, fame, prestige, or age. We are all at risk" (Mein, 2020, p. 2439).

Is the virus really the great equaliser? The answer to this question is where the motivation for this paper arises. Did Covid-19 further enhance inequalities? Was the Covid-19 effect the same for female and male workers? Who was affected most? The paper shows how the pandemic caused economic adversity differently for different people, specifically focusing on gender differentials.

5.2.1 The economic impact of Covid-19 (mechanisms through which people face economic adversity)

To comprehend the detrimental impact of Covid-19, it is essential to understand the mechanism through which the shock adversely affected the economy and the workers. According to Carlsson-Szlezak et al. (2020), there were mainly three primary transmitting channels. Lower usage of resources has a strong effect on reduced consumption of products. In tandem with the pandemic's extended duration, social distancing steps often lead to lower consumer trust, where consumers become sceptical about government expenditure and cynical about the long-term financial outlook. The implicit effect of the financial exchange on the economy is the second way the pandemic affected the economy. According to Carlsson-Szlezak et al. (2020), household wealth decreases, savings increase, and consumption decrease even further. Ultimately, Covid's supply disturbances bring activity to a halt. Hence, it negatively impacts the supply chain, impacting labour demand and contributing to reduced wages, layoffs, and long-term unemployment.

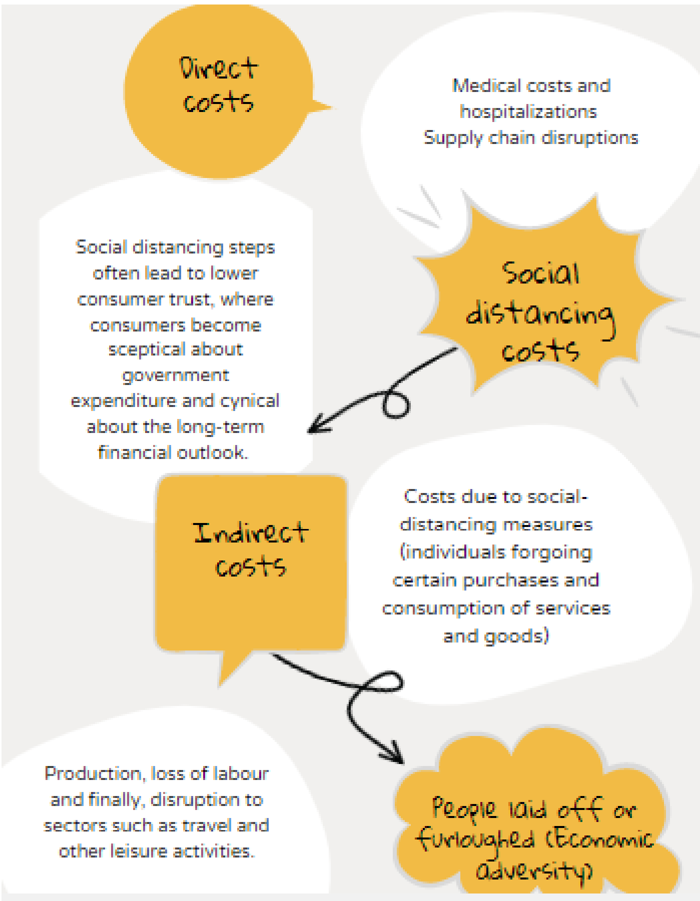


Figure 5.1:Mechanism through which individuals faced economic adversity

Source: Jonas (2013), Carlsson-Szlezak et al., (2020). Graph: own elaboration

This is backed by Jonas (2013), who argues that all pandemic impacts through first direct costs, secondly costs due to social distancing and finally, indirect costs. The direct costs are medical costs and hospitalisations. Then there are costs due to social-distancing measures (individuals forgoing certain purchases and consumption of services and goods). Thirdly, indirect costs (production, loss of labour) and finally, disruption to sectors such as travel and other leisure activities. All these eventually affect the individual.

Baldwin and Di Mauro (2020) elaborate on this theory, claiming that economic agents develop a "wait and see" mentality because of anticipation shocks. The author argues that this is natural during times of uncertainty. This is due to a lack of faith in trade transactions, currencies, and political uncertainty.

According to Baldwin and Di Mauro (2020), the magnitude of the shocks is characterised by three significant elements: consumer and firm behavior in the face of adversity, public policy response and finally, epidemiological properties of Covid-19 (risk of illness, death in exposed population). Baldwin and Di Mauro (2020) further argue that the modern economy is a complex web of interconnected parties. Firms, financial intermediaries, consumers, and suppliers are all linked together. Everyone is buying, lending or is a customer of someone. Due to the high level of interaction among all individuals, a supply chain collapse negatively affects all circular movements.

Baldwin and Di Mauro (2020) suggest a framework for this method to take place. First, households do not get paid, resulting in lower levels of savings and expenditure. This decrease in savings leads to less investment and diminishes capital stock. Secondly, imports decrease because households demand less for imported products. This reduces income for the rest of the world, considering the UK an endogenous country and the rest of the world as exogenous. Since most of the world's GDP has fallen, so has their desire for imports (the UK's export). Third, demand and supply changes trigger major disturbances in foreign and domestic supply chains. Finally, all these variables lower overall demand, which has a cascade impact on production variables, reducing everything from production to consumption to wages. In this scenario, labour is affected more than capital.

5.3 Literature Review

The literature review is broken down into sections. The sections reflect how the pandemic impacts the labour market. The labour market is divided into men and women where possible. Furthermore, the literature review explains how this pandemic crisis differs from past ones. The literature review proceeds to note factors that are not directly but indirectly connected to the labour market, such as household responsibilities, women's present status, lack of security, mental health, and gender-based violence. The literature review explores different facets of men's and women's lives and how this pandemic may have affected them. Recent diseases such as Ebola and Zika highlight the importance of including a gender context in times of an outbreak (Smith, 2019). Public health crises, according to Smith, intensify existing disparities. They have jeopardised women by restricting their access to care (Wenham et al., 2020). Hence this type of analysis, gender-segregated looking at different aspects of how Covid affects men and women, becomes essential.

5.3.1 Covid-19 and labour market effects on gender

Alon et al. (2020) argue that Covid-19 has substantial implications for gender equality during outcome and eventual recovery in the labour market. They argue that this pandemic is different from a regular recession. During a "regular" recession, men's employment is affected more than women. One possible reason for this is provided by Tertilt and Doepke (2016). The authors argue that women's labour supply is less uncertain than men. They found that the effect appears to be even larger when there is an economic fluctuation, for example, in a recession. Men accounted for more than three-quarters of the overall cyclical fluctuation[18], whereas women accounted for just a quarter from 1989 to 2014 in the US.

Tertilt and Doepke (2016) also found that men's working hours are more volatile than females. Women who are married have the smallest levels of uncertainty using the US current Population Survey for 2015. They contend that this is because married trained women have security. When the economy suffers a recession, many married women increase their labour market participation to cover their husbands' increased chance of being laid off. However, as per Alon et al. (2020), owing to social distancing initiatives, the main effect of this pandemic is shown in industries with high female job shares. Under recent economic downturns, such as

[18] Cyclical fluctuations are periods of expansion (increased business activity, economic growth) and contraction (low business activity, economic growth) from a trough (the lowest point in the cycle) to a peak (the highest point in the cycle) that represent the economic business cycle.

those in 2008-2009, male employees were impacted even more significantly than female employees.

In addition to Tertilt and Doepke (2016), Gausman and Langer (2020) also point out that a high ratio of women can be observed in caregiving roles, whether in the formal or informal sector. The frontline healthcare occupational positions like health technicians, nurses and community health workers are held mainly by women, making them more prone to infections, morbidity, and death. Aside from their occupational risk, females are often the main caregivers at home, making them increasingly susceptible to contamination when they interact with the people they care for. Women in the US perform around 65% of unpaid family caregiver roles, of which 80% care for people aged 50 or above. Apart from this, women are also seen in abundance in informal occupations.

Furthermore, females who serve in the informal sectors (particularly in low- and middle-income countries) have access to only basic healthcare for themselves and their families. Moreover, the closure of nurseries and day-care and no earned sick leaves, women are forced to work in less than favourable circumstances that put them at risk and expose their family to the disease (Gausman and Langer, 2020).

Hupkau and Petrongolo (2020) further add to the Alon et al. (2020)'s argument. They suggest the unique nature of this crisis would have an entirely different effect on employment than past economic downturns. Hupkau and Petrongolo (2020) observes in the UK, that women were highly represented in the service industries under lockdown and also key (critical) sectors. Hence it is unclear whether women's labour market would be affected more than men. However, if women are not in lockdown sectors, they are much more likely to work from home and be safe. Based on the UK Labour Force Survey data April-June 2019, the authors conclude that women are more likely than men to lose their jobs.

In their article, Kristal and Yaish (2020) attempted to address two important questions about Covid-19 and gender. *Would the crisis worsen current gender differences, or will the Covid-19 level up the gender disparity curve?* To answer these questions, they observed employed Israeli women and men before the lockdown (i.e., in the first week of March) and after (i.e., in the last week of April 2020). The authors found that women's income and employment were more severely hit than men's during the economic downturn. They concluded that the coronavirus epidemic had not resulted in a levelling up of the inequality curve in Israel. On the contrary, it has widened the gender gap in the labour market, with women being hit much harder than men in the crisis.

A study conducted by Lewandowski et al. (2021) sheds further light on the gender dimension of occupational exposure to contagious diseases. It was discovered that women, particularly in Europe, are at a greater risk of acquiring infectious diseases than men because their occupations necessitate regular and close contact with customers, exposing them to contagions. Gender, rather than education or age, was found to be a key factor in workers' susceptibility to such diseases. This gendered exposure can especially be observed in Continental European and Nordic countries.

Farré et al. (2020) using a sample of 5,000 households in Spain discovered significant job losses in non-essential and quarantined fields where remote work was not possible after the lockdown. Employment losses mainly were temporary; however, the lowest educated workers faced the largest impact. Using regression analysis, they found that women were more likely than men to lose their jobs. Women who were willing to retain their careers were more inclined to work at home. In the short term, Covid-19 expanded gender disparity in both unpaid and paying jobs.

Witteveen (2020) analyses gender and race inequalities in the UK. The lockdown imposed in the European countries led to many business closures. In certain conditions[19], the UK government provided a furlough scheme, in which staff could earn up to 80% of their daily wages while others faced shortened work time or unemployment. While analyzing the demographic characteristic inequalities, Witteveen (2020) reports that individuals in lower-earning communities faced twice as much economic deprivation as those in higher-earning groups. He notes that men have a higher probability of being dismissed from work as well as being furloughed. He found that men who fall most in this category are white males with middle-income jobs. His research found that wage disparities between men and women are mostly related to jobs and that racial and ethnic minority communities control the plurality of essential occupations and females. As a result, all of them could keep their jobs even though their life was at risk.

Furthermore, two papers using academic outputs (publication) data further corroborate a decline in women's efficiency during the first waves of Covid-19. Before going into concrete samples of these articles, it is important to remember that they're about a specific category of worker: female academics. Female researchers are a very small segment of the total female

[19] If you were taxed as an employee and reported by PAYE and, were let go by your employer. Your employer could file for the scheme.

employed, and perhaps their results might not be so easy to generalise to the rest of the employed female population.

According to Amano-Patiño et al. (2020), the Covid-19 crisis has dramatically reduced women's productivity growth in the short term. They look at how the policies have affected the competitiveness of economists. They explore working paper publication patterns using data from the CEPR discussion paper series, NBER Working paper series, Vox EU columns, and research repository Covid Economics: Vetted and Real-time papers. Their analyses show that the number of female authors working on non- Covid papers has remained steady (20%). In Covid-19 papers, women constitute only 12% of the total number of authors working Amano-Patiño et al. (2020). They also observe that senior economists are working on Covid-19 papers. Junior and mid-career economists still have the largest difference between Covid and non-Covid studies. At the mid-career stage, the gender gaps are important. Women in the middle of their careers have yet to begin working on Covid-related studies. In a dataset of articles by Amano-Patiño et al. (2020), only 12 mid-career females out of a sample of 647 distinct writers reported to the literature on Covid-19.

Adams-Prassl et al. (2020) provide further credibility to these findings. They discovered that the impact of Covid-19 on the labour force differed significantly across countries, dependent on a real survey of 20,910 participants from the UK, US, and Germany in March and April 2020. Also, within nations, the effect is unequal and amplifies differences that still occur. However, they observed that employees in Germany are the safest and least affected by the crisis since they have a well-established short-time work scheme.

They also noticed that the biggest disparity is due to workplace discrimination. Staff who can only do a limited part of the work from home, as per the scientists, are more willing to cut their working hours, lose pay, and, in the worst-case scenario, lose their jobs permanently. However, this crisis would affect women and less-educated workers the most.

Furthermore, Adams-Prassl et al. (2020) notes that women lost employment at a much higher rate than men, contributing to the widening gender wage gap. Most women, especially the younger ones, were adversely affected regarding jobs and working hours. This seriousness is mirrored in young women's excessively negative perceptions of the Coronavirus. Their pessimistic overview can be attributed to their young age and their first and only experience of an economic downturn so far. Similarly, women in older cohorts responded with far more optimism because they had witnessed previous crises. They understand and are more realistic that things will become better after a while.

5.3.2 Covid-19- Household and childcare responsibilities

Collins et al. (2020) took a unique approach to examine how Covid has impacted men and women regarding family obligations and childcare. They test the theory of whether this pandemic turns out to be an ¨equalizer¨, i.e., whether men would be willing to take more responsibility at home, thus balancing certain aspects of gender equality. Since child-rearing has historically fallen upon mothers, they argue that stay-at-home orders have provided many employers with the opportunity to allow telecommuting. Working from home has given men who have been historically indifferent to housework and childcare responsibilities the chance to consider and enjoy these menial activities. When childcare is unavailable, fathers can no longer neglect their children's needs, particularly when their provisional offices have been transformed into the child's playground (Schulte et al., 2020).

To answer whether the pandemic is making men more responsible for childcare and household, Collins et al. (2020) assessed how heterosexual dual earners (where males and females earn) and married couples with children coped with work during the outbreak. The question is pertinent since, during the lockdown, the parents must discuss and coordinate additional housework, homeschooling, parenting, and meeting their employers' intensified demands. Many that were still working during the pandemic could contribute to greater work-hour equality.

Collins et al. (2020) use panel data from the US current population survey to examine whether the hypothesised increase (in men working more hours at home) is true or not. The period analysed was from February 2020 (serving as the before pandemic period) to April 2020 (after the Covid-19 period). The data is used in the research to examine gaps in the working hours of mothers and fathers. Collins et al. (2020) discovered that small children worked four to five times fewer hours than fathers. As a response, the wage disparity between men and women has widened from 20% to 50%.

Farré et al. (2020) take a similar approach and document the pandemic's effects in Spain for gender. Spain was one of the pandemic's hardest-hit countries. Hence the lockdown in Spain was one of the strictest in Europe. Farré et al. (2020) analysed rich household survey data in May 2020. Like Collins et al. (2020), they found that men increased participation in childcare and housework during the lockdown. However, most of the burden fell on women. They also noticed that this was happening before the pandemic as well. Women were responsible for most childcare and household work before the pandemic.

Qian and Fuller (2020) also found results supporting Collins et al. (2020) and Farré et al. (2020). Qian and Fuller (2020) focused on Canada's work life during the pandemic. Using the public microdata Canada's Labour Force Survey (LFS) file, they show that the employment gap between genders widened considerably between February and May 2020 for parents of young children. The gender gaps were more significant for parents with elementary school-aged children than preschoolers. For parents with less schooling, the difference was much greater. In addition to this finding, Qian and Fuller (2020) suggested that following the epidemic, flexible leave programs for infants beyond adolescence were introduced to assist families in distributing caregiving needs fairly.

Alon et al. (2020) findings further support that of Collins et al. (2020) and Farré et al. (2020). They found that the closure of day-care centres and schools resulted in a massive increase in childcare needs. This has a significant effect on single mothers who must deal with reduced working hours. As the job market emphasises experience, the impact on mothers is inclined to maintain.

Interestingly Alon et al. (2020) are much more optimistic about the future, in sharp contrast to Collins et al. (2020) and Farré et al. (2020). Despite acknowledging that the pandemic has had an immediate negative effect on gender equality. They argue that the crisis will eventually promote gender equality in the workplace beyond the immediate effect. More companies are implementing flexible job arrangements such as work from home and flexitime. This encourages both parents to have a much better work-life dynamic. This change brought about by Covid-19 is likely to persist and hence can promote equality among the sexes when it comes to childcare and household responsibilities. Secondly, they contend that several fathers who are now solely responsible for their children's upbringing could be eroding social norms. This will potentially compensate for the unequal allocation of housework and childcare.

Hupkau and Petrongolo (2020) provide support to Alon et al. (2020). They contend that the closing of childcare and preschools has exacerbated pre-existing home production demands, potentially widening the gap between fathers' and mothers' childcare contributions. However, they argue that the pandemic may help erode social norms, just like Alon et al. (2020). They claim that parental household positions can be inverted in industries where a mother works in a vital sector and a father is made to stay at home due to lockdown. This will help move gender norms closer to equality in the long run. Secondly, this can be a testing opportunity to adopt flexible working solutions beyond the current crisis, which can further help gender equality.

5.3.3 Covid-19 and Telecommuting

Dingel and Neiman (2020) try to address a fundamental question in Covid-19 times. *How many jobs can be done at home?* They classify the feasibility of working from home for all occupations in the O*Net database. They find that almost 37% of the people can work from home in the United States within many industries and cities. They also observe that people who can telecommute have a higher salary than those who do not. These jobs accounted for 46% of all US wages. They extended the initial classification to various countries and noticed that lower-income societies have a smaller percentage of work that can be performed at home. They selected the 2008 version of an International Standard Classification of Occupations (ISCO) to conduct their research in other countries.

Mongey and Weinberg (2020) run a similar analysis to Dingel and Neiman (2020). They add to the earlier categorization of occupation methodology to measure proximity in the workplace. They analyse high personal proximity and low work from home occupations. The latter measure how soon work can revert to routine, whereas the former occupation measures test whether the work can be done under a lockdown or not. They find that, workers who cannot telecommute tended to be non-white. They also found that these workers were less educated and had little to no healthcare provided by the employer. While belonging to the lower quartile, these workers were also more likely to be single and less likely to be born in the US. They noticed that they were both in jobs requiring direct physical contact and much work from home. Although the lockdown could have a smaller effect on women, Mongey and Weinberg (2020) argue that those who are impacted are less inclined to reintegrate into the economy.

5.3.4 Other effects of Covid-19 on the labour market:

Cao et al. (2020) offer a distinctive analysis of the effect Covid-19 has on the labour supply side, while several surveys concentrate on the demand side of the labour market. This unique study approaches Covid-19from the labour supply side. The authors looked at a large online education platform with more than 100,000 gig workers and investigated how the lockdown affected the gig economy's labour supply. They discovered that the gig economy network expanded by 25% on average throughout the pandemic. The effect was felt worldwide, but it was felt more strongly in areas with more reported incidents.

Remarkably, they discovered that stay-at-home orders accounted for just 7% -16% of the total losses implying that simply removing the lockdown would not restore the economies without managing the pandemic. They also evaluated how male and female workers responded differently to the pandemic. Although both males and females increased labour supplied, a much higher increase was observed for males than females. Consequently, the gender gap in the labour supply further increased by 31%. Individuals in the 30 to the 50-year-old age group were primarily responsible for the rise, which Cao et al. (2020) attributed to a disproportionate share of childcare and household labour because of school closures.

Another interesting paper on the labour market comes from Chernoff et al. (2020). They conducted a study to see the effects of Covid-19 on automation. The authors believed that Covid-19 could accelerate the automation of jobs (which was already occurring). Employers' desire to accelerate automation safeguard against current and future pandemics. The authors identified occupations with a high degree of viral infection and occupations having a high potential for automation. They looked at geographic disparities in the United States to see which areas were the most at risk. Finally, the authors examined various professions at elevated threats of automation and viral infection. They found that females who had low to medium levels of wages and low education were at the highest risk for both automation and viral infection. Using similar data to check this for other countries, they found that the results held, and women around the world were in high-risk professions.

To investigate the effect of Covid-19 on the labour market, Lang and Kahn-Lang Spitzer (2020) analysed work vacancy data obtained by Burning Glass technologies and unemployment evidence from Unemployment Insurance (UI) original reports. They used the Bureau of Labour Statistics (BLS) to set a pre-Covid labour market. The reason for using job vacancy data was to allow them to track the economy by industry and occupation and get disaggregated geographic data. They observed that job vacancies significantly reduced in the second half of March, and by late April 2020, they had fallen over 40%. At first, the collapse hit all US states regardless of stay-at-home policies. These trends can also be seen in subsequent UI statements and BLS results. Whether the profession belongs to one of the key designated sectors, all professions and jobs witnessed rises in UI claims and declines in postings. The magnitude, however, differed. Essential, frontline jobs took a much smaller hit than hospitality and leisure activities which saw the biggest collapse. However, Lang and Kahn-Lang Spitzer (2020) claim that the economy would struggle even if stay-at-home measures were lifted because the economic crisis was not triggered entirely by stay-at-home rules.

Montenovo et al. (2020) contribute to understanding how pandemic and policy responses have affected the US labour market. To put things in perspective, they benchmarked their findings with 2008-2009 data. They used the Current Population Survey (CPS) data and found that employment shows a significant decline in April 2020 compared to February 2020 for the US. Among the worst-hit were Hispanic workers aged 20 to 25 and those with low education levels (some college or high school degrees). Secondly, they noticed that work reductions were higher in jobs that required interpersonal contact and could not be performed remotely. They claim that the pre-pandemic occupational category offered the key to understanding unemployment for ethnicity, age, gender, and education sub-populations. They find that most people were laid off because of occupation and that certain groups were present more in certain occupations, leading to unemployment inequalities. They do acknowledge that there is a significant unknown aspect when it comes to gender.

5.3.5 Covid-19 and mental health

The ramifications of this outbreak are not only limited to an increase in economic inequality but also to the mental health of individuals. According to a 2011 World Health Organisation report, mental health challenges are related to injustice, deprivation, and economic and social health determinants. As a result, economic hardship exacerbates mental health issues for people and their families.

Many studies (Brodeur et al., 2021; Etheridge and Spantig, 2020; Proto and Quintana-Domeque, 2021) document that Covid-19 has substantially affected people's mental wellbeing. According to the findings, Covid-19 has had an adverse impact on mental health, with women impacted more than men. Etheridge and Spantig (2020) seek to answer if this is true for the UK. Using data from the Covid-19 Understanding Society report for April 2020, they found a large decrease in mental well-being/mental health after Covid-19 in the UK's general population. Consistent with other evidence (Proto and Quintana-Domeque, 2021) there is a more considerable decline in mental health for women than men. They argue that Covid-19 has affected people's lives, including family, financial, and health issues. Furthermore, they investigated which of these three affects their lives the most.

The largest decrease is associated with financial circumstances, family responsibilities and age. The young are in a worse position than the old. Etheridge and Spantig (2020) contend that socioeconomic conditions play a crucial role in understanding the gender disparity in mental wellbeing. Before the pandemic, individuals with the biggest social networks were said to have a greater prevalence of mental illness than their peers. Women reported higher levels of loneliness after the pandemic compared to men. This could be due to females reporting more close friends before the pandemic. The paper has far-reaching consequences, as it indicates that women's declining wellbeing is due to a clear lack of social networks and connections rather than the wider economy or labour force.

Etheridge and Spantig (2020) are given additional support by Brodeur et al. (2021). Brodeur et al. (2021) claim that while lockdowns are important to stop the virus from spreading, they can affect the public's well-being. The researchers employed Google search term data to see whether the lockdown influenced mental health in Europe and America. Brodeur et al. (2021) found a significant increase in search terms related to boredom in Europe and America. There was also a significant increase in searches for worry, sadness, and loneliness. Suicide, divorce, and stress searches all decreased. Overall, the researchers discovered that the lockdown had a huge effect on people's emotional wellbeing.

Stuckler et al. (2009) report social welfare as a key variable to mitigate these effects. If the government supports individuals during economic adversity, then stress and mental health issues resulting from economic adversity can be reduced.

In addition to mental health, Gausman and Langer (2020) observed that the problems are compounded for women when looking at pregnancy and sexual health. Due to the imposed lockdown and restricted movement, many businesses' supplies chain has been disrupted. If women cannot access and use their normal contraception methods, this could lead to a rise in unwanted pregnancies. The epidemic's detrimental consequences on women's reproductive wellbeing go beyond pregnancy and motherhood. Furthermore, elective medical operations (including abortions) are being postponed in several US nations due to the epidemic.

5.3.6 Gender-based violence

COVID-19 has led to a shortage of human resources in many sectors. The police and law enforcement agencies are busy implementing public health measures, monitoring social distancing measures, and enforcing the quarantine. This means they cannot immediately respond to Gender-Based Violence Against Women and Girls (GBVAWG) incidents due to a lack of resources and time. In addition to this, countries facing economic constraints are also likely to see an increase in the incidents of public unrest, looting and other crimes resulting from this pandemic. Thus, police resources will also be diverted to respond to such situations. Furthermore, it influences the justice system. Legal hearings have been postponed or rescheduled. This will result in a backlog, affecting the standard of justice in the long term and slowing down the legal process.

Furthermore, programmes given to victims of violence (hotlines, hospitals, crisis centres, legal assistance, and safety) are expected to be impacted and could face reductions because of this pandemic. Women and young girls have also found it highly challenging to disclose GBVAWG events to the police and request protection because of the lockdown measures. Since individuals would be under the constant scrutiny of their abusers, it would be challenging for them to seek help from outside organisations either through hotlines or accessing support services in person.

According to Azcona et al. (2020) in their UN Women study, numerous women and girls no longer feel secure at home. They believe that Covid-19 would jeopardise the welfare of girls and women even more. They note that approximately 243 million women and girls aged between 15 to 49 were subjected to physical and sexual violence by an intimate partner 12 months before the survey worldwide (Azcona et al., 2020). According to the researchers, this figure is only supposed to rise as the virus exacerbates stability, financial burden, wellbeing, and higher tensions. For instance, it was observed that calls to domestic hotlines in Malaysia and Lebanon, for instance, more than doubled in March 2020 relative to March 2019, whereas an increase of 32% in France was noticed. It is important to note here that these are reported incidents, and it has long been known that domestic violence is under-reported.

Moreover, women’s reluctance to abandon abusive relationships when they are afraid for their health and their children's health can also be attributed to the lockdown. This lockdown has severed their ties with the outside world, and now they cannot gain support from their social network. They are unable to meet and ask for help. Another example of this in a high-income country is Canada, which struggles to meet the demands of those fleeing violence. The problem is far more challenging in low- and middle-income nations, which are still battling to satisfy the demands of reacting to domestic abuse cases, and now must fight for limited money as they transition to Covid-19.

Where women's safety is already in jeopardy, this pandemic has worsened the situation for women with disabilities. Azcona et al. (2020) emphasise the importance of focusing on women with disabilities. Women with disabilities are two to three times more likely to experience violence from their partners or family members. Considering their minimal contact or help outside, a forced lockout might jeopardise these people's ability to escape abuse. People with disabilities who are legitimised, according to the researchers, could be the worst affected category.

5.4 Data

The study uses two data sets: *The UK Understanding Society* and *The UK Understanding Society Covid-19* study surveys. UK Understanding Society launched in 2009 and is also known as the UK Household Longitudinal Study. It is a representative observational survey of 40,000 families and 100,000 participants (Burton et al., 2020).

To understand the implications of the Covid-19 pandemic, a new special study/wave of the survey was undertaken. Participants from the last two waves (waves eight and nine) of the primary annual UK Understanding Society sample were asked to complete a short web survey. This was to gather important information and changes in lifestyle due to Covid-19. Every month, the participants completed surveys specially intended to chart improvements and included questions modified as the coronavirus circumstance progressed.

The waves were April (first wave), May (second wave) and June (third wave). The first wave had a total of 17,452 respondents. While the second, third and fourth had 14,811 and 14,111 respectively (Understanding Society Covid Study, 2020). This paper uses the first wave for the Covid-19 study. Table 5.1 provides a full overview of the number of participants in each wave as well as a gender breakdown (both weighted and non-weighted).

Table 5.1 Weighted and non-weighted gender distributions

Without Weights								
April Wave			***May wave***			***June Wave***		
Men	***Women***	***Total***	***Men***	***Women***	***Total***	***Men***	***Women***	***Total***
N=7287	N=10165	N=17452	N=6112	N=8699	N=14811	N=5803	N=8308	N=14111
42%	58%	100%	41%	59%	100%	41%	59%	100%
With Weights								
April Wave			***May wave***			***June Wave***		
Men	***Women***	***Total***	***Men***	***Women***	***Total***	***Men***	***Women***	***Total***
N=6600	*N=7413*	*N=13743*	N=5712	N=6285	N=11997	N=5404	N=6064	N=11494
48%	52%	100%	48%	52%	100%	47%	53%	100%

Data Source: The UK Understanding Society Covid-19 waves

The overall response rate was 41.2% and 40.2% for the 1st and 2nd wave, respectively. (Understanding Society Covid Study, 2020). The research protocols were accepted by the University of Essex's ethics committee. The user framework provides more details (Burton et al., 2020).

5.4.1 Data Merge

The Covid-19 study conducted did not include some significant variables. Information on skills, occupation, and industry were not present in the Covid study. The study merged *The UK Understanding Society Covid-19* wave with the primary UK Understanding Society Wave 9. 17,452 individuals composed the initial sample for April 2020 Covid-19 study. To merge the Covid-19 April wave with the primary UK Understanding Society database (wave 9), the cross-wave Person Identifier was used to merge the two studies. After the data merge, there were 15,990 participants in the combined survey. Individuals left un-merged (1,462) were dropped from the study. This merge allowed us to combine the two datasets and include the missing variables that were available in the annual Understanding Society survey.

5.4.2 Data Weight

For the weighting exercise, two main options were considered. The Covid-19 weights (ca_betaindin_xw) and the wave-9 weights (i_indinui_xw). Here c represents that the survey was conducted monthly. It is a prefix used to show the frequency of the data collection. This contrasts with annual surveys with prefix i in the annual understanding society database. The next letter after c represents the wave. Here a represents April, as we proceed along the waves, we have cb (representing May), cc (representing June) and so forth. The w at the end of the variable represents that the data was collected by web. Other options included in dataset are t for telephone, however it is not applicable in our study since our data is a questionnaire and responses are web-based (Burton et al., 2020).

The Covid-19 weights were eventually selected as the user guide suggests using "cW_betaindin_xw”. Here W stands for Covid-19 wave number. For example, the April wave has a, the May wave has b and so forth. Our study uses the April wave, so our variable becomes ca_betaindin_xw. The user guide states, “cW_betaindin_xw is a product of the wave nine cross-sectional analysis weight for those who completed the main adult interview (i_indinui_xw), with an additional adjustment for differential nonresponse to the relevant wave of the COVID-19 web survey, conditional on wave nine response” (*The UK Understanding Society* User Guide, p. 27, 2020). Each person is given a single weight in the covid-19 web`s[20] sample weights. Variance non-response and disproportionate choice likelihood are both considered by the weights. The weights are a continuation of wave 9's annual sample weights.[21] After the weights, the study reduced the sample size to 13,743 individuals.

5.4.3 Descriptive analysis

The weighted sample characteristics by gender for the April wave are shown in Table 5.2.

[20] Since all these interviews were taken on the web and not in person that is why the word web is used over here
[21] Further details of how the weights were calculated can be found in the main Understanding society user guide. (Institute for Social and Economic Research 2020).

Table 5.2 Descriptive characteristics of men and women

	April Wave		
	Men	***Women***	***Total***
Age Group			
16/25	10.0%	10.3%	10.2%
25/34	14.5%	12.8%	13.6%
35/44	14.4%	15.5%	15.0%
45/54	17.2%	18.7%	18.0%
55/64	19.0%	18.7%	18.9%
65/74	15.2%	14.8%	15.0%
75 +	9.7%	9.1%	9.4%
Ethnicity (Selected)			
British/English/Scottish/Welsh/northern Irish (white)	85.8%	87.0%	86.4%
Indian (Asian or Asian British)	2.3%	1.6%	2.0%
Pakistani (Asian or Asian British)	1.7%	1.1%	1.4%
African (black or black British)	1.0%	0.9%	1.0%
Caribbean (black or black British)	0.4%	1.1%	0.8%
Living with a partner			
Yes	67.6%	60.4%	63.9%
No	32.4%	39.6%	36.1%

Data Source: The UK Understanding Society main survey (wave 9) and Covid-19 survey merged dataset

For both men and women, the April wave depicts relative descriptive features. There were marginally younger men about to enter the labour force in comparison to women. Overall, our analysis illustrates that the UK has an ageing population, with 41.3% individuals over age 55. In contrast to women, more men lived with a partner. 67.6% of men lived with a partner compared to 60.4% of women. Most of the sample was white, 86.4%. The second biggest ethnic group were Indians, with 2% (Asian or Asian British). The figures correspond to ethnicity regardless of whether they are Asian-British, or their background is from Asia. This also demonstrates that our weighted sample is adequate in representing the actual UK population by ethnic group. According to the Office for National Statistics (2011) for the entire United Kingdom, 86% of the population is White, while 2.5% are Indians. This is according to the last census data conducted in 2011 census (ONS, 2011).

For our weighted sample group, Table 5.3 shows labour market characteristics for the April wave. To understand the data in-depth, the labour market characteristics of our weighted sample group are compared with a baseline month of January-February 2020. The January-February baseline month provides us with the before Covid-19 condition for men and women, while the April data provides a snapshot of what happened after the pandemic had hit. Men had higher labour force participation than women during the baseline month. Men's labour force participation was 62.1%, while women's respondents worked 57.6% of the time. Although employment figures for men and women were close, there was a significant disparity between men and women self-employed. 9% of men reported being self-employed, whereas just 5.5% reported self-employment. Hours worked for men and women differed significantly. Men worked 20.10 hours a week, while women worked 13.86 hours per week. One factor for this is that more women work part-time in contrast to men. Only 8.8% of men worked part-time, while 23.2% of women worked part-time. There was also a significant difference in pay for men and women, with men earning 2,120 pounds per month compared to women who earned 1,531 pounds per month.

Table 5.3 Labour Market Characteristics of Men and Women

	Baseline (Jan/Feb 2020)			***April Wave***		
	Men	***Women***	***Total***	***Men***	***Women***	***Total***
Employment Status - Excluding NA & missing values						
Yes, employed	51.0%	50.5%	50.8%	47.7%	47.8%	47.7%
Yes, self-employed	9.0%	5.5%	7.2%	8.6%	5.2%	6.8%
Yes, both employed and self-employed	2.1%	1.6%	1.8%	2.1%	1.5%	1.8%
No	33.8%	39.8%	36.9%	35.1%	41.0%	38.2%
Number of observations	***N=2838***	***N=3125***	***N=5963***	***N=2634***	***N=2897***	***N=5532***
Earning amount (People on monthly wages)	2120.58	1531.12	1811.64	2020.78	1498.80	1747.35
Earning average of entire household (monthly)	3000.13	2829.64	2912.21	2966.18	2849.58	2906.86

From the April wave, it is apparent that both men and women suffered due to the pandemic. In April, men who were employees reduced from 51% to 47.7%. Women suffered greatly in the pandemic, with women employees reduced from 50.5% to 47.8% (Table 5.3). The proportion of men's self-employment declined by 0.4%, while women's self-employment fell by 0.3 per cent. The average monthly pay for men dropped from £2,120 to £2,020 in 2020, while the monthly average wage for women fell from £1,531 to £1,498.

5.4.4 Pre Covid-19 condition of men and women in the labour market

The following section discusses the pre-Covid-19 labour market characteristics of men and women. This is important to recognize how they changed during Covid-19. Figure 5.2 provides insight into the labour market difference between men and women in the UK. We analyse four employment status categories: "employed", "self-employed", both "employed and self-employed", and "not in the labour market".

Labour market characteristics of men and women were very similar when it came to employed work. 51.0% of the men were employees, whereas 50.5% of the women were employees. There were stark differences in being Self-employed, however. Men reported 9% of self-employment whereas females reported 5.5%, a gap of almost 3.5 percentage points. There were also differences in being both self-employed and employed, with men reporting 2.1% whereas females reported 1.6%. 33.8 per cent of men did not work, while 39.8% of women did not offer any labour market features. To discover who was affected most, we do not exclude workers over 60; see Table 5.2 for more information.

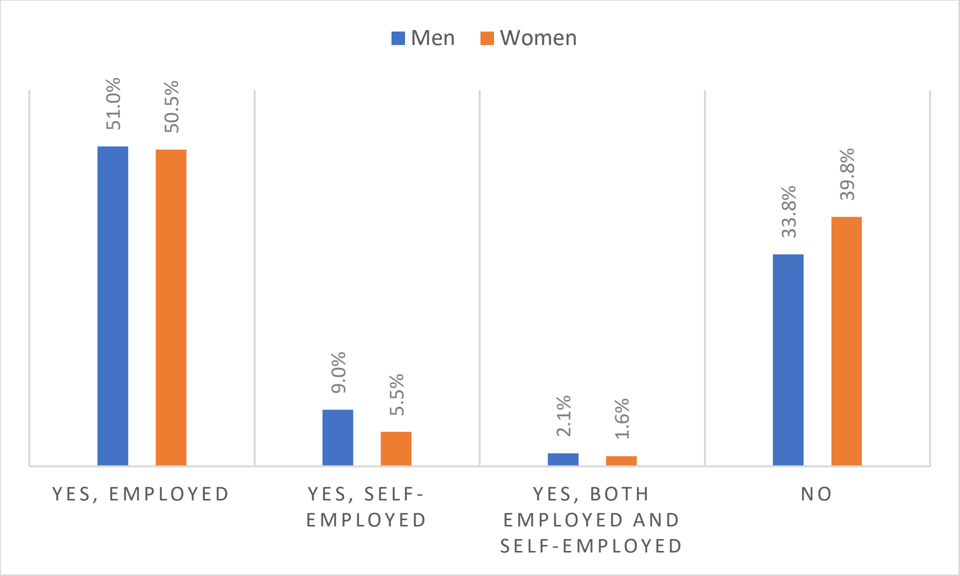


Figure 5.2 Employment status of men and women pre-Covid (Baseline month: Jan/Feb 2020): Own, Data Source: *The UK Understanding Society*

5.4.4.1 Labour Market analysis: January and February 2020 employed

Speaking specifically about the labour market characteristics, we narrow our sample to people who reported being employed in January and February 2020. We dropped individuals who are not employed and ended with a sample of 7,969 individuals.[22] Figure 5.3 provides the analysis with just individuals employed in January and February 2020, which are the base months in our analysis for pre-Covid times. Men and women differed significantly in how they were employed. Women opted to work for someone rather than self-employment, with 87.8% of females stating that they are employees. Men also preferred being employed (at a lower rate than women), with 82.3 per cent of men reporting being employed. There were significant disparities in self-employment, with men recording 14.5 per cent and women reporting 9.4 per

[22] Further details can be found in the data section of this thesis.

cent of self-employment. There was only a 0.4 per cent gap between males and females when it came to be both self-employed and employed.

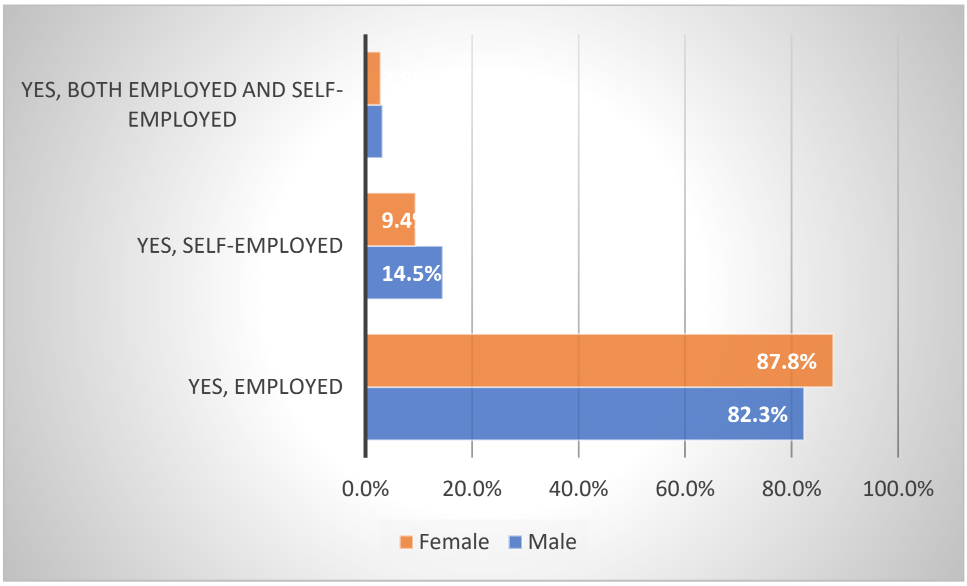


Figure 5.3 Employment status breakdown (January/February 2020) – Gender Segregated Graph: Own Data Source: *The UK Understanding Society*

5.4.4.2 Mean working hours

Figure 5.4 shows the mean weekly working hours for men and women before Covid-19. Overall, men worked more hours than women. Men worked 37.42 hours per week, whereas women worked 30.19 hours. The average number of hours for men and women was 33.80. Although not the focus of this research, working hour differentials are critical for understanding labour market characteristics for men and women in the lockdown. Research (Cooke and Hook, 2018) suggests that women allocate more time than men to unpaid work. Individuals who did not note their working hours or refused to note their working hours were dropped from the analysis and do not form a part of our analysis.

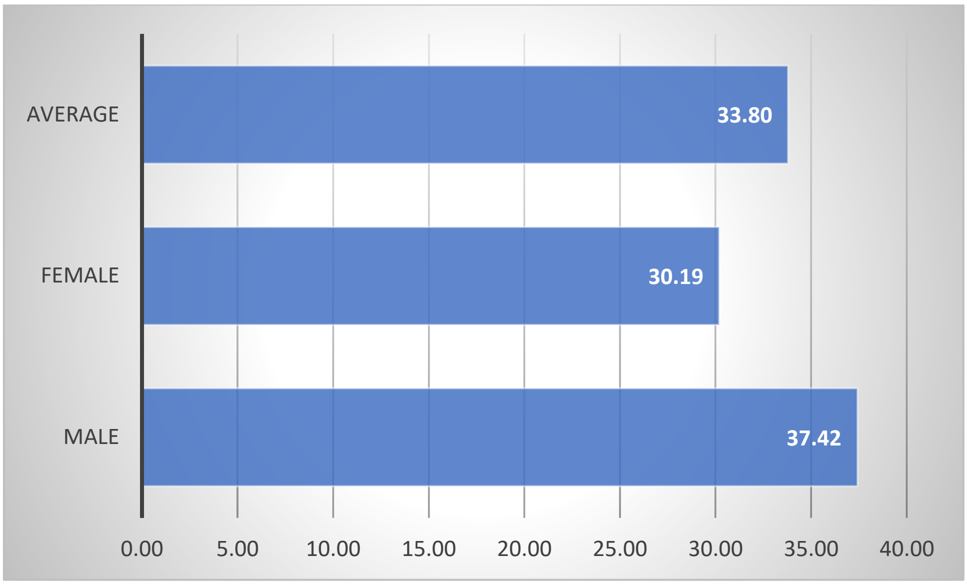


Figure 5.4 Mean weekly working hours for men and women in January/February 2020 (Pre-Covid) Data source: *The UK Understanding Society*

5.4.4.3 Education

The education level for men and women was not provided in *The UK Understanding Society Covid-19* wave. Therefore, for analysis, we use 2019 data from the understanding society to determine the education level of men and women before Covid-19. Figure 5.5 illustrates a comparison of men and women by highest qualification. As can be seen from the graph, more men than women in the labour market a degree. Females had a higher proportion of degrees by 1.8%. There were more men than women in other qualifications those men. The percentage for O and A levels was similar, with men having a slightly higher percentage in both.

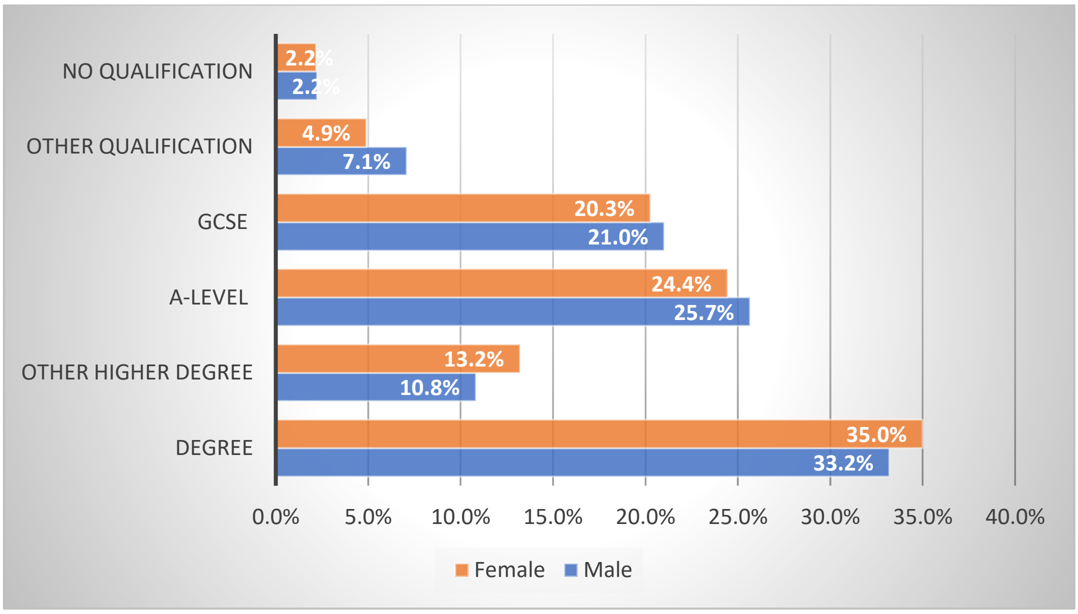


Figure 5.5:Education level of men and women – Pre Covid status (2019) Data source: *The UK Understanding Society*

5.5 Labour Market Situation after Covid-19

5.5.1 Male employment

The post-Covid-19[23] labour market scenario presents a bleak image. After the outbreak, employment was analysed before and after Covid-19 for comparison. The study only looks at people who worked before the pandemic[24]. It follows these individuals to see what occurred after the epidemic spread through the UK. First, we analyse the male workers in our sample group. As we can see in Figure 5.6, male employment and self-employment both fell. This led to a new category of unemployment. The unemployment category became 4.8% after the pandemic (Figure 5.6). Since we started with the individuals in the labour market, our pre-market analysis does not show any individuals unemployed.

The number of individuals stating to be self-employed and employed grew marginally. One plausible reason for this might be that people attempted to protect themselves from future unemployment. Individuals reporting self-employed did not change that much reducing by just 0.8%, which makes sense since the individuals in this category were likely still trying to cope in the early days of Covid without shutting down their business. The comparison month for

[23] The post Covid-19 period refers to the first wave of the pandemic. That is the period of March 2020 to May 2020. Throughout the following chapter, the mention of post Covid-19 refers to first wave of pandemic.
[24] Individuals stating labour market work before the pandemic

before and after Covid-19 used in this analysis are January/February 2020 and April 2020, respectively.

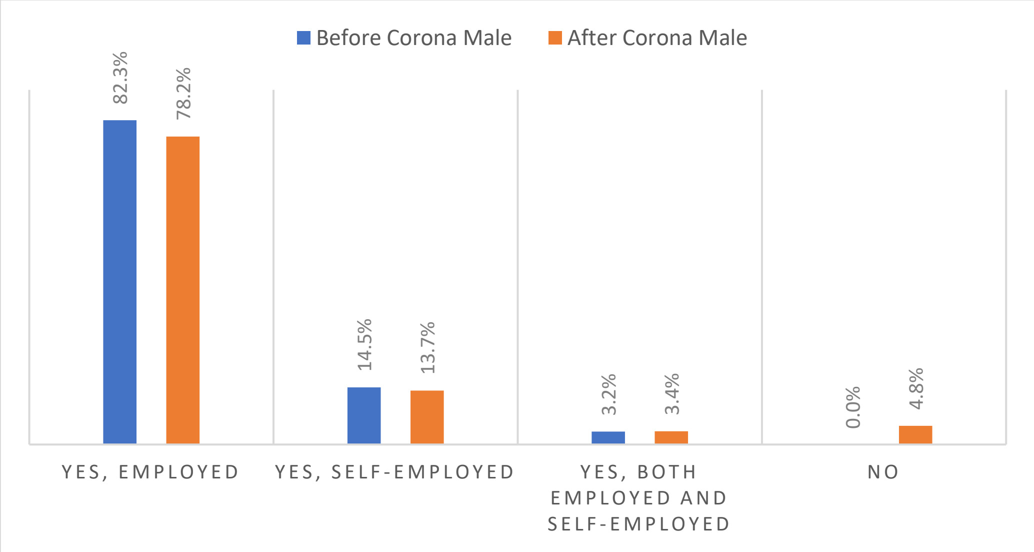


Figure 5.6 Labour Market Effects of Covid – Pre and Post Covid graph employment status for men – Unemployment added. Data source: *The UK Understanding Society*

5.5.2 Female employment

Figure 5.7 illustrates the situation for women. As we can see, it shows a similar picture to that of men. 4.7% of the women in our sample group became unemployed. Employment in all three categories fell. There were only minor differences in working and self-employed women; each declined marginally. Intriguingly, unlike men, women in the working and self-employed categories also dropped by 0.2 per cent. Self-employed females saw a decrease of 0.6% from January-February to April 2020.

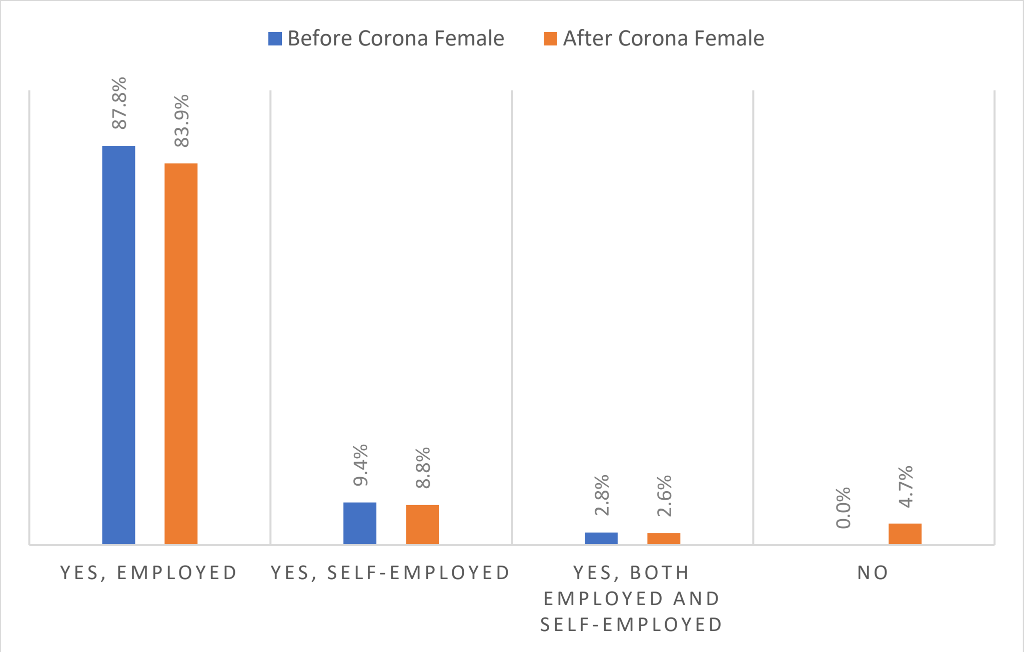


Figure 5.7 Labour Market Effects of Covid -Pre and Post Covid graph employment status for women. Data source: *The UK Understanding Society*

5.5.3 Working hours

Figure 5.8 shows a comparison of weekly working hours (gender-segregated) before Covid (immediately before the pandemic Jan/Feb 2020) and after Covid-19 (April 2020). During the pandemic, men and women's average working hours dropped sharply. Men's average working hours decreased from 37.42 hours to 25.34 hours, a net reduction of 12.08 hours. Women had a comparable condition, with mean working hours declining from 30.19 hours to 20.65 hours, a 9.54-hours cut. However, men suffered more in terms of total hours loss. The statistic can cause one to infer wrongly that men suffered more than women in terms of mean working hours. Since women started working hours are less than men, a percentage comparison is necessary. If we take a percentage of reduced hours, it is similar for men and women. The average working hours of men decreased by 32.3 per cent, while the average employment hours of women declined by 31.6 per cent. A third of a percentage point reduced working hours. It is important to note that roughly 4.75 percent of the population lost their employment after the pandemic. These individuals reported the working hours as "not applicable" (those that report “no” to participating in the labour market in Figure 5.6 and Figure 5.7). When calculating after Covid average mean hours, these individuals were dropped from the final sample.

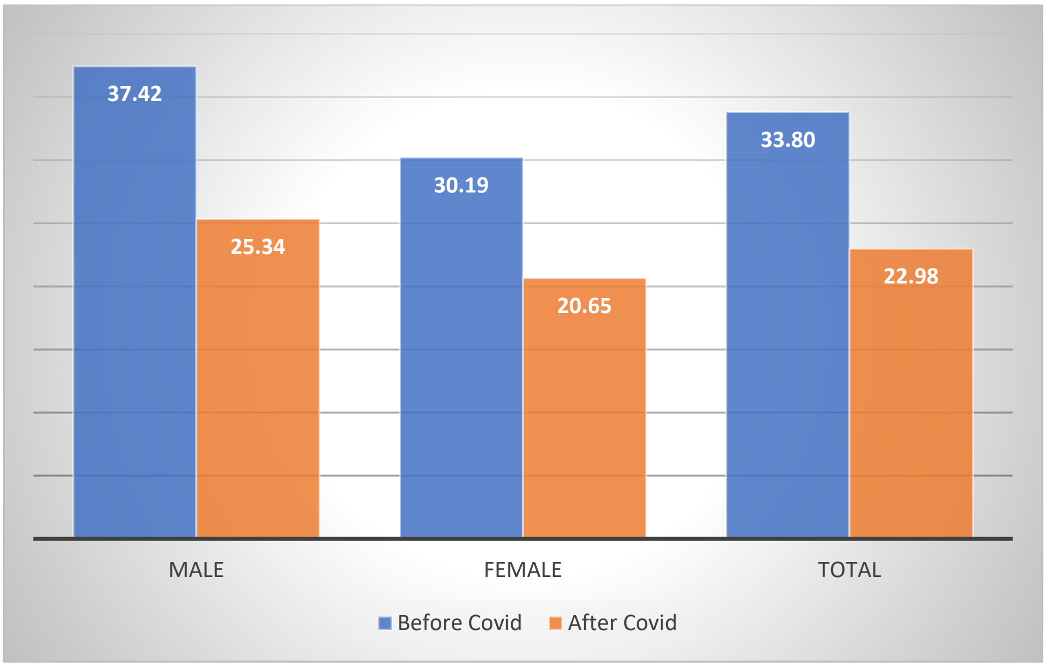


Figure 5.8 Mean weekly working hours – Before and After Covid analysis gender-segregated. Data source: *The UK Understanding Society*

5.5.4 Key workers analysis

The UK Understanding Society Covid-19-month questionnaire included a new question: "Are you a key worker?" to classify workers who had an essential occupation (NHS, refuse workers) during the Covid-19 regulations. The results are shown in Figure 5.9. Men were less likely than women to serve in key worker professions. Only 38.9% of males said they worked as key workers. Females made up a much higher percentage of key workers, with 51.1% reporting themselves as belonging to this category. This is essential for measuring economic adversity since we expect key workers to be relatively safe from economic adversity during Covid times.

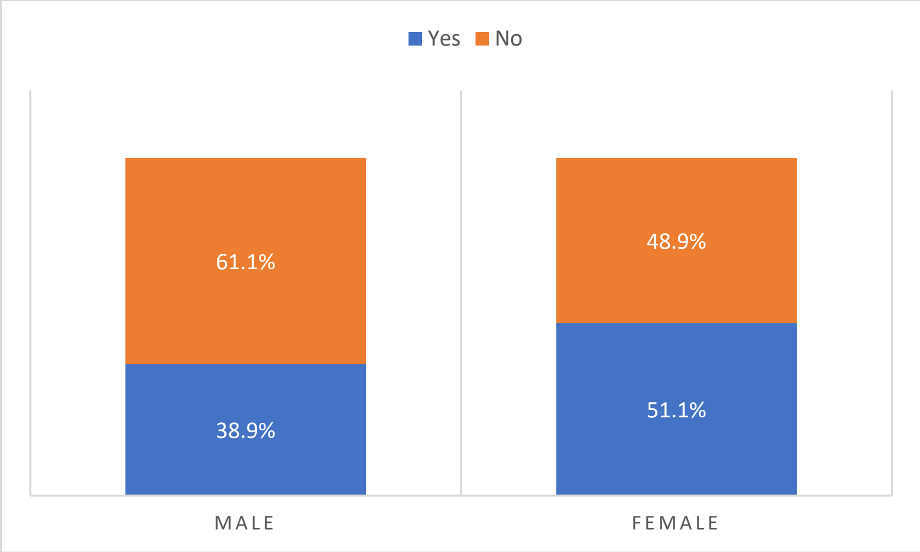


Figure 5.9 Keyworkers as a proportion of men and women in employment. Data: *The UK Understanding Society Covid-Months (April Survey)*. Graph: Own elaboration

5.6 Measuring Economic Adversity

The ONS (2020) termed the pandemic the "largest recession on record". GDP fell by 20.4% in the UK in the 2020 second quarter after an initial downfall in the first quarter of 2.2%. From April to May of 2020, the government furloughed (at least for a one to three-week period) a total of 8.9 million people (Francis-Devine et al., 2021). Furthermore, almost 2.6 million have used the government's Self-employment income support scheme (HMRC, 2020). These schemes and the number of people benefiting from them show how important they are.

However, these schemes make the task of quantifying economic adversity a problematic task. Employers were persuaded to retain more of their workers because of public policy, particularly the Coronavirus Job Retention Scheme, which gives 80% of individuals' salaries up to £2,500 (HMRC, 2020). As a result, unemployment figures themselves do not provide enough detail about individual's economic hardships during Covid-19. Hence, the study uses a combination of becoming furloughed and unemployed to measure economic difficulty. This is termed economic adversity in the study. Consequently, for the study, we define economic adversity during the Covid-19 times as the addition of the number of people unemployed and the number of people furloughed.

To calculate economic adversity, first, a new variable was created to calculate the economic adversity including people who were furloughed from the furlough variable. Secondly, we used the employment variable to calculate the number of unemployed people. After creating these two new variables, we merged them to establish the new variable economic adversity. This refers to a 1943 (24.4%) of the sample population in our analysis. Of these, 1,566 people (19.6%) identified themselves as becoming furloughed under the Coronavirus Job Retention Scheme, and a further 377 (4.7%) of these became unemployed. That is a total of 24.4% of our 7969 sample. These individuals were classified as having faced economic adversity in the paper.

5.6.1 Who faced economic adversity?

Now that our identification is complete for individuals who faced economic adversity, we move on to who experienced it (where possible, we try and disaggregate by gender). First, we look at the number of people who have experienced economic hardship by gender. Figure 5.10 indicates that both males and females endured economic hardship. Overall, men endured economic deprivation at a higher rate than women. 25.5% of men reported facing economic adversity compared with 23.2% of women. There are many reasons for this disparity. Some of the explanatory factors for these differences are being a key worker, occupation, and working part-time or full time. A detailed look at the determinants of economic adversity can be found in the results section.

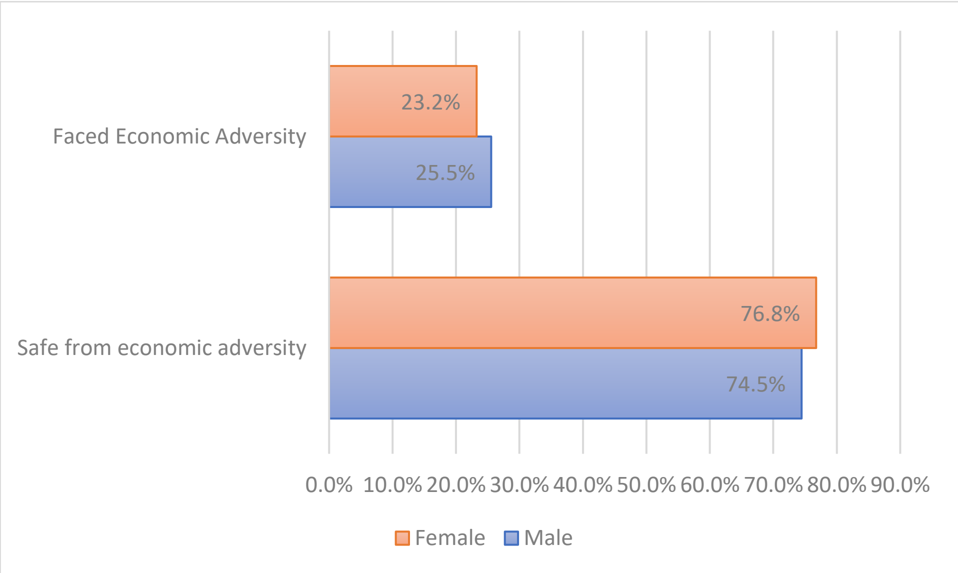


Figure 5.10 Male and female comparison of economic adversity during Covid-19

5.6.2 Economic adversity by age: Comparison of within groups (gender-segregated)

Figure 5.11 reveals insights into who faced economic adversity by age group. It is important to note that this is an analysis within the age group. Thus, we are looking at only differences within the age group. For example, 15-24 years shows how many males and females in that age group experienced economic hardship. It is also worth noting that the sum for each age group (both males and females) is 100 per cent. To illustrate, if we observe females aged 45 to 54, 17% of them have experienced financial hardship. This also means that 83% of the women in that age group were not affected by economic adversity (not shown in the figure but can be deduced).

Consequently, each age group is looked at separately, not together. Figure 5.11 shows that younger individuals were more vulnerable to economic hardship. The 15-24 age range was the most vulnerable to economic hardship. Males and females show varying patterns when it comes to economic hardship. Economic adversity was endured by 41.5% of females in the age group of 15-24 (the study's youngest age group) and 36.9 per cent of males aged 15 to 24. Compared to the existing literature, these findings correspond with that of Kristal and Yaish (2020). Kristal and Yaish (2020) papers provided a much higher percentage of women facing economic adversity (in Israel). They found that only amongst 18–24-year-old women only 39% remain employed in April 2020 compared to 61% amongst men of the same age group.

As we move further up by age spectrum, we can see in Figure 5.11 a reduction in economic adversity for both men and women. Men in the age groups of 25-34 and 35-44 faced economic adversity at 33.6% and 21.5%. These findings of younger men experiencing larger economic adversity are similar to that of Kristal and Yaish (2020). The rates were similar, although slightly lower for the same age groups for female workers, with 23.3% and 19.5%, respectively. One potential reason for this is the sectoral segregation (nurses, public administration, health and social work) between young men and women. As the literature suggests women occupy more of the key (critical) sector workforce (Alon et al., 2020; Hupkau and Petrongolo, 2020).

Moving further along the age group of 45-54, we notice the downward trend continues for women. Economic adversity for women aged 45-54 stood at 17%, the lowest for women in any age category. While for men in this age group of 45-54, we observe similar economic adversity stats as we did for the 35-44 age category. The economic adversity rate increased to 22.3%. The phenomena of reduced economic adversity as age progresses for women does not continue. The study found a non-linear effect, with higher economic adversity rates for the 55+ age group. Females in this age group encountered the second-highest degree of economic difficulty, with 24.3% of economic adversity age group. This age group also was third highest on the men's side, with 22.4% of 55+ reporting that they became unemployed or were furloughed. This is an important observation and, while not the subject of this study, must be investigated further in the future, since individuals aged 55 and up who are still employed may have wages as their primary source of income and fewer prospects for new projects at this point of their careers.

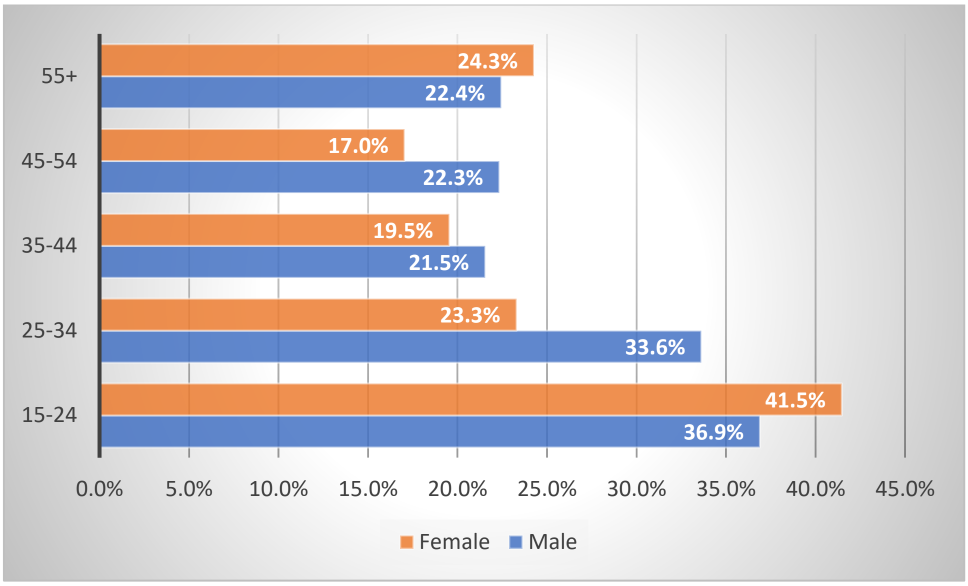


Figure 5.11:Economic adversity by age and gender – Graph: Own. Data source: *The UK Understanding Society*

5.6.3 Income group analysis

Figure 5.12 examines the economic adversity of individuals in different income brackets. The trends are similar for both men and women, as shown in Figure 5.12. As income increases, the number of people in the income category who experience financial hardship decreases. In lower-income brackets, both men and women have high rates of economic hardship, as seen in Figure 5.12. We observe a sharp fall as we progress from the wage classes to higher incomes. Observing Figure 5.12, for individuals who earned 0-1,500 pounds per month compared to individuals who earned 1,501-3,000 pounds per month, we see a massive drop off for males (31.6% to 24.5%) and females (29.3% to 22.7%). Perhaps not so surprising, as we move up the income scale, economic adversity drops even further. The adversity prevalence for men was about 12% in the high salary (3,501-4,500) and 12.8% elite income (4,500-plus) groups. Females' percentages dropped from 9.5 per cent for the 3,501-4,500 income group to 6% for the 4,500 plus income group overall. It is important to mention that too few women were a part of it for female’s elite income groups, so the analysis might give biased results.

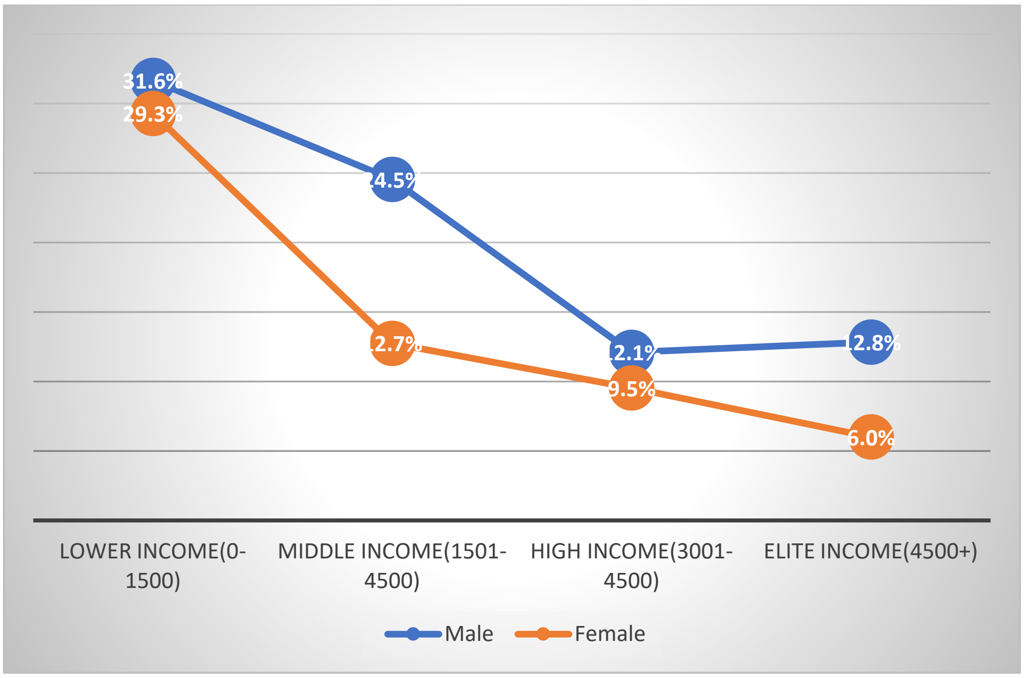


Figure 5.12:Economic adversity by Income group (within income group analysis) – gender-segregated – Graph: Own. Data source: *The UK Understanding Society*

5.7 Methodology

We use a conditional logistic regression framework to evaluate the factors that affect the likelihood of the occurrence. This is because our dependent variable has a binary outcome (0 or 1). So based on our independent variables, we are observing the corresponding probability of how our dependent variable varies from 1 (100% probability) to 0 (no probability). Logistic regression is like a linear regression model as it predicts an outcome for our binary Y from one or many different responses (explanatory) variables X. Using logistic regression serves one significant advantage over linear regression. The independent variables in logistic regression are not required to have a normal distribution. One major downside of using logistic regression over the ordinary least square regression model estimation is the potential difficulty in interpreting the results. Logistic regression uses log-odds rather than probabilities. The use of log- odds (the logarithm of odds) instead of a linear relationship like in the ordinary least square estimation makes it challenging to interpret.[25]

To resolve this, we report marginal effects (along with reporting log-odds) to calculate the exact effects of the regressors on the dependent variable these aids in the interpretation of the logistic coefficients. Marginal effects are preferred to log odds as I would like to interpret

[25] Cramer's econometric manual "Logit model from economic and other fields" provides further information.

the model in probability scale. This makes the interpretation more intuitive. Mathematically this can be thought of as a derivative. Derivative of our logistic function gives us marginal effect. Marginal effect also serves another benefit. They help us with magnitudes of the co-efficient which again remains unclear in odds-ratio. Hence for the purpose of this study, we use marginal effects. Analysis with odds-ratio is given in the Appendix 27 to Appendix 31 of this chapter.

5.7.1 Mathematical representation of logistic model

Mathematically, we can write the model, given Y as our binary variable; we start with the assumption that the probability of Y becoming P(Y=1) depends on our explanatory/predictor variables (x). So, the purpose of the model is the following:

$$p(x) \equiv P(Y = 1|x) \text{ …………(5.1)}$$

Effectively, we are looking for indicators that cause our dependent variable's likelihood to converge to 1. As a result, instead of using the equal to sign, the three nearly equal to signs are used. Since we know that Y is dichotomous, we are essentially modelling $E(Y|x)$, which is exactly what we do in the ordinary regression model estimation. If we model p(x) as a linear function of explanatory variables, we will arrive at the following

$$p(x) = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p \text{ …………..(5.2)}$$

However, as is evident from the linear regression line, this model is not bounded by 0 or 1. It can assume almost any value. Thus, adding the component of exponential to the equation results in the equation 5.3. Equation 5.3 is limited such that p(x) cannot be higher than 1. It is derived from equation 5.2 by adding the exponential variable.

$$p(x) = \exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p) \text{ …………..(5.3)}$$

Equation 5.3 has constraints of probability becoming greater than 0. Still though, the equation lacks a constraint for probability to be less than 0. To achieve this, we convert our equation 5.3 into equation 5.4 as the following.

$$p(x) = \frac{\exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p)}{1 + \exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p)} \text{ ………..(5.4)}$$

Now that we have defined the restrictions, the likelihood will be smaller than 1 and greater than 0. To understand it in context of OLS regression we can convert equation 5.4 to 5.5 by taking the log of the function mentioned in equation 5.4. We take the log of equation 5.4 and end up with the log version.

$$\log\left(\frac{p(x)}{1 - p(x)}\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p \text{………..(5.5)}$$

Equation 5.5 in log form hence is our final equation. This is the final regression best fit. To find the minimal difference between expected and observable values, maximum likelihood is used. In logistic regression, we employ chi-square rather than R2 to calculate the model's fit.

5.7.2 Model:

We use cross-sectional data for the following empirical model; mathematically, our empirical model can be written as the following equation:

$$Economic\ Adversity_i = f(D_i + L_i + O_i)\ldots\ldots(5.6)$$

Our dependent variable, *economic adversity* is a dichotomous variable that takes the value of 1 if the individual experiences economic adversity and value of 0 if the individual did not face economic adversity[26].

The regressors of independent variables encompassed in the model include a vector of socio-demographic variables (D); a vector of labour market variables (L) and a vector of the organisation type variables (O).

D= Demographic variables of individuals i

L= Labour Market characteristics

O= Organisation type and sector

Among the socio-demographic variables, the model includes:

- Gender (Male/Female)
- Age (Categorized in 10-year increments)
- Education (Level, A level, Degree etc)

Amongst the Labour Market variables, the model contains information on:

- Employment type (Employed/ Self-employed or both self-employed and employed)
- Working Hours (Number of working hours in each week)
- Fixed salary (Whether fixed salary per hour/ month or not)
- Contract type (Permanent or temporary)
- Income level (Dummy variable with 4 income categories)
- Keyworker (Whether key worker or not)
- Ability to Telecommute (Whether the individuals work showed previous ability to do work)

[26] A complete discussion on the definition and measurement of economic adversity can be found in section 5.6 and section 5.8.3.1 of this thesis.

Among the organisation variables, the model contains information on:

- Occupational classification (Major Groups)
- Organisation type (Private or Public sector)

Table 5.4 Category breakdown of variables

D = Demographic variables	L= Labour Market characteristic	O = Organisation type and sector
Gender (Male/Female)	Employment type (Employed/ Self-employed or both self-employed and employed)	Occupational classification
Age group dummies	Working Hours	Private or Government Sector
Education	Fixed salary (Whether fixed salary per hour/ month or not)	
	Contract type (Permanent or temporary)	
	Income dummy	
	Keyworker (Whether key worker or not)	
	Ability to Telecommute	

The probability of facing economic adversity depends on demographic, labour market, and organisational variables. We hypothesise that labour market variables are most crucial in determining economic adversity. Here it is important to note that the empirical model presented in the study investigates the determinants of economic adversity for individuals during the initial phases of Covid-19 (April 2020). Other factors might become necessary to be included as Covid-19 progress.

For this study, we use three specific models. First, three mixed-gender model requirements are estimated. Those are model 1, model 2 and model 3A. Then we divide model3A into two sub-samples of males and females. By using male worker sub-sample, model 3B explores the predictors of the male labour force. Similarly, in model 3C we use female worker's sub-sample. Finally, the results of model 3A and 3B are compared. We also specifically test for the following hypothesis in these models.

Hypothesis 1: Individuals' gender does affect economic adversity

Hypothesis 2: Being a key worker does not affect economic adversity

Hypothesis 3: Qualification/education does not affect economic adversity

5.7.2.1 Economic Adversity Determinants Analysis

In models 1 through 3, the study analyses the determinants of economic adversity for the UK. The estimation results are presented sequentially, including a series of additional determinants. The models go from simple (with few explanatory variables) to complex (with several explanatory variables). In the first model, the analysis is based on demographic variables (Model 1), and then the study adds labour market variables (Model 2). In Model 3, all factors, including organisation variables, are presented. Model 3 is then further subdivided into 3A (mixed-gender model), 3B (male-only model) and 3C (female only model). The first model is our baseline model, which includes the set of individual socio-demographic determinants. The second model adds to this by incorporating labour market characteristics. Finally, model 3A presents the full model estimation, including all variables in our analysis.

5.7.2.2 Gender disparities

For gender comparison and to test our hypothesis, we regress model 3A, the full model with the different gender sub-samples. Estimation 3B analyses the relationships only using the male workers' sub-sample, while estimation 3C uses only the female worker's sub-sample.

5.7.2.3 Filtered cases and constraints on the final sample

The final sample used to estimate models 1 and 2 contains 7,969 individual observations. These individuals were working in our benchmark time of January/February 2020. These observations were generated by combining data from *The UK Understanding Society Covid-19* wave with data from the general *The UK Understanding Society* survey and applying labour market constraints. For the sake of simplicity, we sub-divide our UK's labour market sample into three main groups of workers: employed (85%), self-employed (11.9%) and both employed and self-employed (3%). Furthermore, the study was limited by those who provided information on working hours.

Table 5.5 provides key descriptive of this sample. There were 7,969 people left in the survey after the constraints mentioned above were applied. The average number of hours worked a week was 34 for the whole study. The mean working hours for men were 37.42 hours per week, while the mean working hours for women were 30.19 hours per week. Men were slighter older than women in our sample group. Men had an average age of 44.71, whereas females had an average of 43.46. Monthly income varied significantly between our sample group. Men earned 2053 pounds per month while females earned 1480. The average monthly wage for our sample was £1,765.61.

Table 5.5: Descriptive of our sample group pre-covid (Jan/Feb 2020) baseline

Variable	Male	Female	Total
Number of Observations	3973	3996	7969
Age (average yrs)	44.71	43.46	44.08
Working Hours (average hr)	37.42	30.19	33.80
Monthly Income (average £)	2052.99	1480.23	1765.61

Model 3 required further information on variables. For model 3 (A, B, C), we removed individuals that did not provide information on their standard occupational classification (2010). This led to a reduced number of observations of 7,042.

5.7.3 Explanatory variables in the model

The study uses economic adversity as the dependent variable in the model. Economic adversity is a binary variable that takes the value of the one in the case of Covid-19 related economic adversity and zero otherwise. The model's variables are grouped into three distinct groups.

5.7.3.1 Dependent Variable

5.7.3.1.1 Economic Adversity

The dependent variable for our equation is economic adversity. Here economic adversity is defined as being unemployed or being furloughed. Overall, in our sample of 7,969 people working pre-Covid (Jan/Feb 2020). A total of 1,943 individuals were classified as facing economic adversity, a proportion of 25.25% of our sample size. Economic hardship here is defined as people who had to face any of the following. 1) Lay off – becoming unemployed (4.7%) of our sample, and 2) Being furloughed (19.6%). This amounts to 25.2% of our 7,969 observations. Our analysis aims to find out the determinants that explain the probability of facing a situation of Covid-19 economic adversity.

5.7.3.2 Demographic Variables

5.7.3.2.1 Age

The risk of experiencing economic hardship was split into sub-groups to detect age-related results based on age. Our mixed-gender study varies in age from 17 to 88 years old. Individuals are categorized as 15-24 (early career), 25-34 (mid-level career), 35-44 (established careers), 45-55 (late careers) and 55+ (close to retirement careers). Here, we are primarily concerned with experiences of economic adversity in different age groups. As our reference group, we have a 16-24 (early career) age group. The literature suggests that this age group was hit hardest (Adams-Prassl et al., 2020).

5.7.3.2.2 Gender

To include information about the gender of the individuals in our sample, a binary variable was constructed. Gender takes the value 0 if the individual is female and 1 for males. This is one of our main sample variables and the subject of our hypothesis. Our sample is composed of 49.9% males and 50.1% of females.[27] (Alon et al., 2020) suggests that women are the worst off in the pandemic. Hupkau and Petrongolo (2020) also find that women are more likely to lose their jobs than men in the UK.

5.7.3.2.3 Education

For this variable, the study looked at the individual's highest attained level of education. The variable contained multiple categories that included “No qualification” (2.2%), “Other qualification” (6%), “GCSE” (20.6%), “A-levels” (24.9%), “Other degree” (12%) and “degree” (34%). Degree and other degrees were merged as one variable labelled “degree” to provide a more balanced grouping. For all other categories, a dummy variable was created. The aim of introducing these variables is linked to our hypothesis. We expect economic adversity to decrease as the education level increases. The reference group for this variable was selected as GCSE (Levels). This is important since Montenovo et al. (2020) finds “polarization by education, with fewer job losses among high school dropouts and college graduates”. Haque et al. (2020) also points out that least educated people were more likely to suffer because of Covid-19.

5.7.3.3 Labour Market Variables

5.7.3.3.1 Employment type

The study looked at three categories of workers: working, self-employed, and both employed and self-employed. This categorization is based on their job status in January/February 2020. We use "employed" as our comparative group category because it is the most common job class. 85% of our final sample were employed, whereas 11.9% of our sample were self-employed. 3% of the sample reported both being employed and self-employed. Blundell et al. (2020) found that self-employed individuals are more likely to have lost their jobs than employed ones during the pandemic.

5.7.3.3.2 Working hours

Working hours (per week) were derived from *The UK Understanding Society Covid survey* wave. The variable represents the working hours of employed people in the UK in January/February 2020. Those that refused to disclose their working hours were excluded from the sample. The variable had a minimum value of 0 and a maximum of 168. We consider working hours vital since we hypothesise that individuals who are working more hours are more valuable to a company and would therefore have less chance of getting unemployed or

[27] This sample is weighted. See table 5.2 for more detail

furloughed. Xue and McMunn (2020) grant support to this and found that pre-pandemic working hours were essential to explaining post Covid-19 activity layoff.

5.7.3.3.3 Fixed salary

The fixed salary variable measures how individuals were paid for their work. The question was included in the April Covid-monthly wave and was formulated as multiple-choice. The options for the answers were fixed salary, for each job completed, by hours worked, by tops and commission only and finally, a salary or hourly wage plus tips or commission. For the fixed-wage type, we generated a binary variable. If the person was paid a fixed wage, the binary variable had a value of 1. The remaining indicators were all coded as 0. Individuals with a set income are likely to have greater stability and, as a result, have a reduced risk of being furloughed and of facing economic hardship. Adams-Prassl et al. (2020) find this true in their work. They find workers paid by the hour, and workers on flexible hours contracts were hit the hardest.

5.7.3.3.4 Ability to telecommute

One of the key factors in the pandemic was no interaction with other households. Consequently, the ability to telecommute became advantageous. To understand and use this trait, the *Understanding Society Covid-19 survey* added a new variable measured for January/February 2020 (before covid). The variable was whether the individual had worked from home previously. Overall, 5.7% of the individual respondents worked exclusively from home. 5.8% reported working from home often, whereas 17.7% of the individual reported having worked from home sometimes. This variable was used as a proxy. It showed an individual's ability to telecommute. Individuals showing any form of capacity to work from home (sometimes, often, always) were merged. A new dummy variable was created. The final dummy variable showed individuals who were able to telecommute. We expect a strong negative correlation between being able to telecommute and facing economic adversity. Alon et al. (2020) and Collins et al. (2020) emphasized the importance of telecommuting in this pandemic.

5.7.3.3.5 Key worker status

The April Covid-19 UK Understanding Society survey wave had an additional question asking respondents whether they were key workers or not. This allows us to control for keyworker status in our analysis. Upon examining this variable, we find that 42.6% of the individuals in the April wave reported themselves as key workers. Workers who reported that they did not know were dropped from the analysis. Employees who responded inapplicable to this question (because they were now out of the labour market) were coded as non-key workers. Hence, workers working in Jan/Feb 2020 baseline but due to Covid-19 were now out of the market. They reported that the question "Are you a key worker?" was not applicable; they were coded as not a key worker. Keeping the above-identified conditions in mind, we created a new dummy variable called keyworker that classified workers into key workers as one and those who were not as 0. We expect a strong negative correlation for workers who were key workers for economic adversity. Blundell et al. (2020) noted that individuals who were low-paid, female and from the ethnic background were more likely to be key workers. He noted that these workers were at less risk of facing economic adversity.

5.7.3.3.6 Contract type: (permanent or temporary)

Another major factor in determining whom to let go and/or furlough might be the ease of letting an individual go. As Adams-Prassl et al. (2020) find, firms protect permanent employees more than those on temporary contracts. Hence the contract becomes very important. We observed individuals who had a permanent contract with the company against individuals who were not given permanent contracts for our study. Overall, of our 7,696 individuals, 640 (8%) individuals had temporary contracts. We created a dummy variable with 1 representing a temporary contract and 0 (our reference group) as fixed-term contracts.

5.7.3.3.7 Income

Income from work is another variable that is of great interest. Witteveen (2020) points out that middle-income whites were more likely to be furloughed and/or dismissed from work. So, we hypothesized that the workers earning a higher income than our middle-income group are less exposed to economic adversity. We expect individuals who are earning more income to generate more productivity for the company. We also expect lower-income groups to have a positive sign since these are often key workers, as Blundell et al. (2020) mentioned. To create this variable, we looked at two separate variables: the last payment made to an individual (pay amount) and the payment period (period of payment). The first variable measures how much money individuals were paid, but it does not specify the payment period. Thus, the two variables were merged to create a new variable called monthly pay. This variable converted the amount received by the individual to a monthly payment. Individuals were mostly paid monthly (73.6%). For these individuals, their monthly payment was multiplied by 1. Keeping their values, the same representing monthly payment. Yearly payments were divided by 12 to get monthly payments. Weekly payments (14.9% of the individuals) were multiplied by 4. For people who got paid bi-monthly, their payment was multiplied by two after creating the monthly pay variable. Once we had monthly pay for all the individuals, we created dummy variables out of our new variable. Income dummies corresponded to 0-1500 (low-income group), 1501-3000 (middle income group), 3001-4500 (high income group), 4500+ (elite income). We selected the low-income group as our reference group.

5.7.3.4 Organisation type and sector

5.7.3.4.1 Occupational classification

We used the Standard Occupational Classification 2000 (SOC) to classify occupations. There are nine major groups at the top tier classification of the SOC. These are Managers and senior officials, Professional occupations, Associate professional and technical occupations, Administrative and secretarial occupations, Skilled trades occupations, Personal service occupations, Sales and customer service occupations, Process, plant and machine operatives and elementary occupations. This is the most aggregated level and can be further subdivided into minor groups. Our measure of SOC had 81 occupations. Full details and percentages for each group are shown in Appendix 32. These were carefully categorized into their nine major groups. Once categorized, these were turned into dummies with process, plant and machine as our reference group. The reason for selecting SOC 2000 instead of SOC 2010 is that there were more missing values in the later variables. Overall, 941 individuals reported data that was either missing, inapplicable or not mentioned. For creating dummy variables and grouping, these were dropped from the analysis.

Consequently, the number of observations in our final sample is reduced to 7028 (Model 3A). Qian and Fuller (2020) support this variable. They find that females (especially mothers) were in occupations that would likely lose their jobs or be furloughed.

5.7.3.4.2 Private sector or another sector (Government/NGO)

We added the private sector variable to our analysis to consider if the individual was working for a private or a public institution. This variable is included in the 2019 primary UK Understanding Society Survey wave. We used the variable job sector to identify individuals working in the private sector. Overall, 51.7% of the individuals were working in the private sector. Using this data, we created another dummy variable. The dummy variable represented work in the private sector against work in any other sector. One limitation of using this variable is the assumption that individuals were still working in the same place as in 2019. Oecd (2020) report points out the importance of this variable in job loss during Covid times.

5.8 Results

Table 5.6 and Table 5.7 present the marginal effects (dy/dx) for the determinants included in the models.[28] Since the study uses average marginal effects, all effects reported are specific to the predicted probability at the mean of the independent variables used.

5.8.1 Individual and Labour Market Effects

Table 5.6 shows the results of model 1 (individual determinants) and model 2 (individual and labour market determinants). The general goodness-of-fit, captured by the Nagelkerke statistic (R Square), for model 1 and model 2 is 0.065 and 0.387, respectively. Model 1 explains 6.5% of the variation in our dependent variable, whereas model 2 which also incorporates labour market determinants, explains 38.7%.

In model 1, there is a statistically significant correlation at 10% for males. The marginal effects for males of 0.0195 show that the expected probability of economic adversity is higher for males than for females by 0.0195 when all other independent variables in model 1 are held constant at their mean. For age, the reference group is 16 to 24. The results suggest that individuals of all age groups were less likely to face economic adversity than our reference group. In general, the probability of facing economic adversity decreases as age increases. The lowest probability of economic adversity was found in the 45 to 54 age group. The marginal effect shows that 45- to 54-year-old had 0.143 percentage points less probability of economic adversity than our reference group. The results were all significant at 5%.

In Model 1, we also looked at educational variables. The reference group for this variable was people with GCSE qualifications. The results suggest that individuals who obtained any academic degree were safer. Individuals with A-levels education were also less likely to face economic adversity than those with GCSE education. However, individuals who chose unconventional educational routes (other degrees) were more likely to be in an economic adverse condition.

In Model 2, labour market characteristics were added to individual characteristics present in Model 1. Model 2 found no significant correlation between gender and economic adversity. All age variables were also found to be non-significant. We notice a significantly lower probability of economic adversity of -0.077 percentage points for individuals with a

[28] The study presents from appendix 27-31 log-odds, betas, significance, and p-values for each of the model separately.

degree. This implies that the probability of economic adversity is lower than our base GCSE category, keeping all other variables at their mean.

For labour market variables, key workers, ability to telecommute, income levels, temporary employment, fixed salary, and self-employed were all significant at a 5% level. Self-employed individuals were less likely to face economy adversity as compared to individuals employed by organisations. They had a 0.395 percentage point less probability of facing economic adversity than employed individuals. Individuals with fixed salaries had a 0.102 less percentage point probability of facing economic adversity than other payments such as hours of work. Those who were temporarily employed had a -0.035 less probability than individuals who had permanent employment. Working hours did not have any significance on economic adversity.

Model 2 also shows the effect of income on economic adversity. The base reference group for this category was low-income individuals (0-1500 pounds). As compared to lower-income individuals, middle income (1,501-3,000 pounds), high income (3,001-4,500 pounds), and elite income (4,500+), all were less likely to face economic adversity. Two highly significant results were observed in the variables of key workers and their ability to work remotely. Both variables were negatively correlated with economic adversity. Key worker variable had a very high magnitude of the negative sign with a probability reduction of -0.343 percentage points of facing economic adversity.

Table 5.6 Model 1 and 2, Marginal Effects (dy/dx) of Demographic and Labour Market variables

	(Model 1) Individual Characteristics(I)	(Model 2) Labour Market +(I)
Individual Characteristics		
Male	0.0195**	0.0128
	(0.00946)	(0.00873)
25 to 34	-0.0434**	0.0118
	(0.0172)	(0.0153)
35 to 44	-0.123**	-0.00838
	(0.0176)	(0.0158)
45 to 54	-0.143**	-0.0145
	(0.0171)	(0.0155)
55+	-0.121**	-0.000418
	(0.0166)	(0.0149)
Degree holder	-0.142**	-0.0773**
	(0.0121)	(0.0111)
A Levels	-0.0293**	-0.0116
	(0.0130)	(0.0115)
Other degree	0.0507**	0.0248
	(0.0197)	(0.0178)
No qualification	0.0104	0.00622
	(0.0303)	(0.0270)
Labour Market Characteristics		
Self employed		-0.395**
		(0.0197)
Employed and self employed		-0.0198
		(0.0226)
Hours worked		0.000431
		(0.000364)
Fixed salary		-0.102**
		(0.00907)
Temporary employment		-0.0352**
		(0.0161)
Middle income		-0.0485**
		(0.0102)
High income		-0.124**
		(0.0206)
Elite income		-0.123**
		(0.0315)
Key worker		-0.343**
		(0.00782)
Ability to telecommute		-0.0982**
		(0.0103)
N	7969	7969
Nagelkerke (R Square)	0.065	0.387

Note: ∗p<0.1; ∗∗ p<0.05; standard errors in parenthesis

5.8.2 Organisational determinants effects

Table 5.7 shows results for Model 3, Model 3A and Model 3B. In Model 3, 3A and 3B, organisational variables are added to the variables already present in Model 2. The Nagelkerke (R Square) for models 3, 3A and 3B is 0.419, 0.420 and 0.437. This indicates that our model explains 41.9% of the variation in the dependent variable in the case of model 3, 42% in the case of model 3A and 43.7% in the case of model 3B. Similar to our observation in Model 2, gender remains insignificant in all three models. Hence, we reject our null hypothesis that there is gender discrimination of women facing more economic adversity in the first wave of Covid-19.

Looking at the Nagelkerke (R Square) for model 1, we see that it explains just 6.5% of the variation in the dependent variable. They indicate that the model is a poor fit in explaining the dependent variable. Model 1 includes just demographic and educational variables.

Once the labour market variables in model 2 are included, the Nagelkerke (R Square) goes from 6.5% to 38.7%. This indicates that labour market variables were key to understanding economic adversity. The Nagelkerke (R Square) rises to 41.9% when we include organisational variables. Looking at these statistics from a broader perspective, there is little discrimination, especially in the early days of Covid-19, considering that our first model accounts for 6.5% of the variation in the dependent variable.

Age shows a statistically significant negative correlation to economic adversity between ages 35 to 44 at 5% and 44 to 55 at 10% for models 3 and 3A. For ages 35 to 44, economic adversity is 0.036 percentage points and 0.087 percentage points less than our reference group (16 to 24) for models 3 and 3A, respectively.

Degree remained significant at a 5% level for all our variables, however there is a negative effect. Hence, we reject hypothesis 3 and find evidence that degree has a significant correlation to reducing the probability of economic adversity. Self-employed individuals had an inverse relation with economic adversity.

Variables of income, key worker, remote working, and fixed salary maintained their sign and significance in Model 3 similar to that of Model 2. The magnitudes were also similar to Model 2. Amongst these, the magnitude of the variable key workers was the biggest. The probability of economic adversity is reduced by 0.305 (Model 3), 0.303 (Model 3A) and 0.311 (Model 3B) as compared to not being a key worker. Consequently, we reject hypothesis 2 and conclude that the statistical evidence is that being a key worker had an inverse relation with economic adversity.

Moving to the organisational variables, in Table 5.7 we find that individuals working in a private company were more likely to face economic adversity for all models. This was highest for our male-only model, showing an increase of 0.122 percentage points to face economic adversity instead of working in a non-government or not-for-profit organisation. Continuing with occupational variables, we selected process, plant and machine operatives as the reference group. All occupational variables had a negative and significant relationship with economic adversity at a 5% significance level, which means that compared to individuals in plant, process and machinery, all other occupations were less likely to face economic adversity. Model 3 also included an interaction or cross-effect term, a product of middle income*male. The interaction term observes the effect of one independent variable changing due to another independent term, in our case this is individuals who are in the middle-income bracket and are male. The results suggest that males earning an income of 1,501 to 3,000 pounds per month were more likely to face economic adversity by 0.0414 percentage points.

Model 3A runs the same variables as Model 3 with only males. All age groups faced a lesser probability of economic adversity than the youngest age group, 15 to 24.

Model 3, Model 3A shows that self-employed individuals were safer from economic adversity. Hours worked for males had a very small negative correlation with economic adversity and fixed salary. Regarding income variables, we see negative signs for two higher-income groups but no significant relation with middle income. Remote working and key workers were both significant and negatively co-related. All organisational variables maintained their signs and significance, similar to Model 3.

Model 3B in Table 5.7 deviates from Model 3A and 3. Model 3B is our female-only model, and the marginal effects demonstrate no age significance. The degree variable is statistically significant at 5%. Labour market characteristics are similar to models 3 and 3A. For middle income group (1501 to 3000) pounds per month, we find a negative and significant correlation. In terms of organisational variables, we notice individuals in private companies maintaining their sign, magnitude, and significance; however, when it comes to an occupational category, all variables take an opposite sign to model 3 and 3A. Individuals in elementary, sales, skills, trade, technical, and managerial senior all had a higher probability of facing economic adversity when compared to plant and machinery occupation.

Table 5.7 Marginal Effects (dy/dx) of Model 3, Model 3A and Model 3B

	(Model 3) Mixed Gender	(Model 3 A) Male only	(Model 3 B) Female only
Individual Characteristics			
Male	-0.0168		
	(0.0116)		
25 to 34	-0.0120	-0.0466*	0.00209
	(0.0173)	(0.0270)	(0.0230)
35 to 44	-0.0362**	-0.0867**	0.000114
	(0.0180)	(0.0281)	(0.0235)
45 to 54	-0.0331*	-0.0559**	-0.0249
	(0.0175)	(0.0276)	(0.0227)
55+	-0.00781	-0.0584**	0.0211
	(0.0174)	(0.0270)	(0.0226)
Degree	-0.0579**	-0.0770**	-0.0387**
	(0.0118)	(0.0172)	(0.0161)
ALevels	-0.00466	0.0254	-0.0340**
	(0.0118)	(0.0166)	(0.0168)
Other	0.0268	0.0264	0.0310
	(0.0183)	(0.0251)	(0.0273)
Noqualifi	-0.0394	0.00123	-0.0723*
	(0.0303)	(0.0443)	(0.0412)
Labour Market variables			
Selfedummy	-0.324**	-0.338**	-0.301**
	(0.0237)	(0.0320)	(0.0356)
eandsedummy	0.0251	0.0104	0.0520
	(0.0232)	(0.0329)	(0.0324)
Hours worked	-0.000267	-0.00132**	0.000883
	(0.000405)	(0.000610)	(0.000546)
Fixed salary	-0.0659**	-0.0567**	-0.0829**
	(0.00987)	(0.0145)	(0.0136)
Temporary	-0.00453	-0.0276	0.00833
	(0.0162)	(0.0256)	(0.0207)
Mid income	-0.0651**	-0.0147	-0.0818**
	(0.0158)	(0.0146)	(0.0164)
High income	-0.137**	-0.119**	-0.160**
	(0.0218)	(0.0268)	(0.0404)
Elite income	-0.167**	-0.143**	-0.199**
	(0.0363)	(0.0428)	(0.0777)
Key worker	-0.305**	-0.303**	-0.311**
	(0.00823)	(0.0121)	(0.0114)
Telecommute	-0.0869**	-0.0764**	-0.105**
	(0.0110)	(0.0158)	(0.0154)
Organisation variables			
privatecom	0.112**	0.122**	0.104**
	(0.0106)	(0.0169)	(0.0134)
senior	-0.0431**	-0.0786**	0.124**
	(0.0199)	(0.0238)	(0.0485)
professional	-0.118**	-0.161**	0.0666
	(0.0230)	(0.0285)	(0.0518)
technical	-0.0700**	-0.0978**	0.0863*
	(0.0203)	(0.0250)	(0.0483)
administrative	-0.0846**	-0.103**	0.0677
	(0.0206)	(0.0294)	(0.0473)

Skilled trade	-0.0416**	-0.0716**	0.124**
	(0.0208)	(0.0226)	(0.0627)
Service care	-0.0752**	-0.0890**	0.0691
	(0.0227)	(0.0392)	(0.0482)
salescustomer	-0.0704**	-0.0956**	0.0876*
	(0.0217)	(0.0298)	(0.0484)
elementaryocc	-0.0449**	-0.0659**	0.103**
	(0.0200)	(0.0239)	(0.0483)
middleman	0.0414**		
	(0.0188)		
N	7028	3525	3502
Nagelkerke (R Square):	0.419	0.420	0.437

Note: ∗p<0.1; ∗∗ p<0.05; standard errors in parenthesis

5.8.3 Discussion and conclusion

There is not enough evidence from this analysis to suggest that female workers in the UK faced economic adversity at higher rates than male workers. In fact, model 1 reveals the opposite. Model 1 finds that males were more likely to face economic adversity. This contrasts with Hupkau and Petrongolo (2020), who find that women are more likely to lose their jobs in the UK.

The study shows that youngest individuals were hit the hardest, corresponding to the findings observed in the literature for other countries. For example, Adams-Prassl et al. (2020) discover the same results for UK. Our education findings align with the literature on the least educated people affected (Montenovo et al., 2020; Haque et al., 2020). Our finding on the self-employed variable contradicts current literature where it is hypothesized that self-employed individuals were the worst hit (Blundell et al., 2020).

As expected, the ability to work remotely has a negative association with economic adversity. Multiple authors, including Alon et al. (2020) and Collins et al. (2020), emphasised the importance of working remotely during the pandemic as a way to increase the resilience in the labour market. Also as expected, key workers were less likely to face economic adversity.

Adams-Prassl et al. (2020) found that firms were protecting their permanent employees as compared to temporary ones however we could not find any evidence for this. We did find contradicting evidence in model 2 of our paper. We discovered that temporary individuals were less likely to face economic adversity. Coming to organisational variables, we discover a consistent positive co-relation of the private sector with economic adversity. This was a consistent finding in all our models. Implying that individuals in governmental organisations and non-profit organisations were safer.

Regarding occupational classification, we found in model 3A, all occupations are less likely to face economic adversity than plant and machine operatives. Plant and machine operators are the most exposed occupational classification in our analysis for females.

Based on the literature (Witteveen, 2020), an interaction variable was included in model 3A, that of income and gender. In line with the literature, the interaction term also points to middle-income males in the UK have a higher probability of job loss and being furlough than other income groups. This is in line with Witteveen (2020).

One of the interesting findings of the study was no gender discrimination in the early days of Covid-19 pertaining to layoffs and furlough. Correlating the results with the theoretical frameworks, this substantiates the argument by Becker (1971) theory of taste of discrimination. The reason that this result substantiates Becker's theory is because the early phase of Covid-19 represented a "panic" decision by firms to let go of individuals and save themselves. This "panic" caused the firms to act rationally and based on that, we see no evidence of discrimination in the early days of pandemic.

In summary, the study looked at differences between men and women before and after Covid-19 struck. The paper analysed different labour market components of male and female lives after Covid. In addition to this, the paper looked at determinants of economic adversity. The paper used *The UK Understanding Society* annual datasets with special data released by *The UK Understanding Society* to study Covid-19. The early months of Covid-19 were used for the analysis (April, 2020). In contrast to much of the literature, we did not find evidence that females were more likely to face economic adversity in the UK. Labour market variables were the key characteristics in determining economic adversity. Having a degree had a negative and significant relation with facing economic adversity. We found young people with low incomes as having the most probability of facing economic adversity. We also found, being a key worker, having a degree, being self-employed, and having the ability to work remotely as the prime factors for economic safety. We also found evidence for the higher probability of economic adversity for individuals working in the private sector.

Chapter 6: Conclusion

6.1 Main results and implications:

6.1.1 Oaxaca-Blinder Decomposition:

The Oaxaca-Blinder decomposition analysis finds that the mean log of wages for men is higher than for women, indicating that men earned more in all models. The unadjusted wage gap was highest for Model 1 (AWT9) with a log difference of 0.412 and lowest for Model 4A (BG1) with a difference of 0.346. The wage gap is further divided into explained (characteristics) and unexplained (discrimination). The explained portion indicates the average increase women would have if they had similar characteristics to men, while the unexplained part is attributed to discrimination.

In the empirical application, key components that comprise most of the explained wage gap include working hours, working status (part-time, full-time), age, marital status, and organization size. The explained portion of the wage gap was highest for just graduates at 66.49%, indicating that this percentage of the gap can be attributed to these characteristics. The lowest percentage of the explained wage gap was observed in BG9, at 59.06%. Working hours and part-time status were the major contributing factors to the explained wage gap in the UK labour market..

Notably, the analysis also reveals negative values for education and age squared in the explained portion, suggesting that women were older and had more educational experience on average. Removing these advantages would lead to an even larger wage gap. The regional disparity was insignificant for most models, except for BG1 and BG5, and being married was significant in all models, with its contribution to the explained wage gap ranging from 5.7% (JG9) to 1.85% (BG1).

Even though at the lower-income quartiles, the total wage gap was the highest, the effect of characteristics explained most of the disparity in the gap at lower-income quartiles. The results were valid for the overall population (AWT9) and highly educated groups. This substantiates much of the literature and confirms the glass ceiling hypothesis. Arulampalam et al. (2007) found the presence of a glass ceiling in Britain's public and private sectors. For sticky floors, our analysis found no statistical evidence. Like our results on sticky floors, Arulampalam et al. (2007) also found no evidence of sticky floor in Britain for both the private and public sectors. These results are also substantiated by Landmesser and Policy (2019), who found the effect of characteristics going down and the unexplained gap increasing as we move up the income quartile.

The decomposition results show that the unexplained wage gap due to discrimination against women is significant in all models, ranging from 0.124 to 0.157 in log points. This suggests that even after controlling for various observable characteristics such as education, experience, occupation, and industry, there is still a substantial portion of the gender wage gap that cannot be explained by these factors alone. This could indicate the presence of other factors, such as gender bias, stereotypes, or other forms of discrimination that affect women's wages.

Furthermore, quartile OB decomposition was carried out for six different models, and the results were plotted on a panel, with each graph plot showing a line graph representing the total wage gap, the effect of characteristics (explained gap), and discrimination (unexplained gap) in 9 income quartiles (from 0.1 lowest quartile to 0.9 highest quartile).

In all the models (see Figure 3.7), the total wage gap decreases as the income quartile increases, although at different rates for each model. The effect of characteristics also generally decreases as the quartile increases, while the effect of discrimination increases. Discrimination becomes more significant than the effect of attributes at varying quartiles depending on the model, indicating that discrimination plays a vital role in the wage gap in higher-income groups.

The patterns observed across the six models show that lower quartiles have the highest wage differentials, which mainly co-variants can mostly explain, and low discrimination levels. As the income quartiles increase, the total wage differentials decrease, although there is a slight increase in the 8th quartile for some models. In general, the effect of characteristics decreases, whereas the effect of discrimination gradually increases throughout the income quartiles.

The analysis presented here has several larger implications. Firstly, it confirms the existence of a gender wage gap in individuals with equal academic background. The wage gap persists even after controlling for various observable characteristics such as experience, occupation, and industry. This indicates the presence of other factors, such as gender bias, stereotypes, or other forms of discrimination, that affect women's wages. Secondly, the analysis reveals that the wage gap is not uniform across different income quartiles. The highest wage differentials are observed in the lower income quartiles, and these can mostly be explained by co-variants and low discrimination levels. As income quartiles increase, the total wage differential decreases, and the effect of discrimination gradually increases. This implies that discrimination is vital to the wage gap in higher-income groups.

The analysis also sheds light on the factors contributing to the explained portion of the wage gap. Working hours, working status (part-time, full-time), age, marital status, and organization size are the key components that comprise most of the explained wage gap. The percentage of the wage gap attributed to these characteristics varies across different models, with just graduates having the highest explained portion at 66.49%. It is also noteworthy that removing the advantages of education and age squared would lead to an even larger wage gap. This finding implies that policies aimed at reducing the wage gap need to focus on addressing discriminatory practices and biases rather than just improving women's education or work experience.

Finally, the analysis confirms the glass ceiling hypothesis, which suggests that women face significant barriers to career advancement and promotion to higher-paying jobs. This finding is consistent with previous research on the topic. However, the analysis did not find any evidence of sticky floors, which suggests that women are not disproportionately concentrated in low-paying jobs. Overall, the analysis provides valuable insights into the nature and determinants of the gender wage gap and can inform policies to reduce the gap.

6.1.2 Input-Output Model using Ghaus:

The thesis chapter answers a hypothetical question: What would happen if there was no discrimination in the labour market for women? To answer the question, input-output models from the SEIM-UK (created by City-REDI) and the Input-Output model (ONS) are used. The models use data from 2016, and the questions are answered for the UK's 12 NUTS1 regions and 30 sectors. Since the SEIM-UK is at the NUTS2 level and data for gender wage differences by sectors was unavailable for NUTS2 levels, the thesis converted the NUTS 2 level multi-regional SEIM-UK model to the NUTS 1 level (12 regions).

To answer the research question, four scenarios are created, two regional and two sectoral. Each scenario is run through the SEIM-UK and ONS models, with regional scenarios only possible through the SEIM-UK model. These represent two types of scenarios. One in which male and female wages become equal. Second, productivity differences are considered and just the amount calculated through Oaxaca-Blinder decomposition for discrimination is increased for females. These are more realistic scenarios. We find that scenarios in which male compensation became equal to female compensation performed better than in non-discriminatory scenarios.

The results show that removing discrimination can increase output (GVA) from 0.08% to 0.98% (depending on the scenario) for the UK. On top of that, a total of between 42,720 and 282,347 new jobs can be created.

The range of output increases due to removing discrimination in the labour force ranged from 0.08 % to 0.98%. For the most realistic scenarios, where productivity differences are adjusted, we have an output increase of 0.15% in our regional scenario and 0.11% in our sectoral scenario. Job increase (in the number of people added to employment), measured by just the SEIM-UK model, had a range of 0.14% increase of 42,720 to 0.94% increase of 282,347.

Overall, the highest initial VA increase was observed in regional scenario #1, accounting for a 0.908% total increase. Scenarios with total equality (RS #1, SS #1, and SS #1 (ONS)) had higher results than those where female compensation increased as per productivity (RS #2, SS #2, and SS #2 (ONS)).

The highest output increase was found in regional scenario #1, with a 0.980% or 34.27 billion pounds increase. SS #1 (SEIM-UK) had the highest job increase with 316,948 job increases.

Regional analysis showed that London had the most significant increase in output and jobs across all scenarios, followed by the South-East and either Scotland (in regional scenarios) or North-West (in sectoral scenarios). The lowest change was observed in Northern Ireland and North-East.

Comparing the input-output model with the SEIM-UK model reveals that the latter yields higher output increases. Explanation of this is difficult since MRIO provides greater regional depth, whereas IO (ONS) model provides greater sectoral depth. The paper is novel in many ways. First, using female wages instead of female labour force participation (FLFP) to approximate an increase in GDP is novel and is rarely used. This finding underscores the importance of considering different models when studying the potential effects of reducing labour market discrimination. Using the Gaussian inverse rather than the Leontief inverse in this research showcases a novel approach to analysing hypothetical scenarios and their implications. Further research could build on our findings by examining the effects of value-added increases in individual sectors due to reduced gender wage differences.

The study shows that removing discrimination can significantly affect the economy, resulting in more jobs and increased output. The job increase estimates from the SEIM-UK model support research that suggests eliminating gender differences will improve labour force participation rates. They can address some of the limitations of the paper of no job loss due to increased wages. Furthermore, Altuzarra et al. (2021) argue that women’s income has more long-term economic benefits than men’s, as women tend to be better savers. This indicates that reducing gender wage differences will have lasting economic advantages.

The study’s implications are significant for policymakers, business leaders, and society as a whole. The study suggests that removing discrimination in the labour market can lead to increased output and job creation, which can positively affect the economy. It provides evidence that gender wage differences can significantly impact the economy, and reducing such differences can lead to long-term economic benefits. The study also underscores the importance of considering different models when studying the potential effects of lowering labour market discrimination.

The chapter's findings suggest that policymakers and business leaders should consider policies and practices that promote gender equality in the workplace. This could include measures to reduce gender wage differences, such as pay transparency, diversity and inclusion training, amongst others mentioned in the paper. The study also highlights the need for more research to explore the potential effects of reducing gender wage differences in specific sectors and regions.

The study's findings also have implications for society as a whole. They suggest that reducing gender wage differences can lead to more equitable and inclusive communities where everyone has access to equal opportunities and benefits. Furthermore, the study suggests that promoting gender equality can have lasting economic benefits, particularly for women, who tend to be better savers. This highlights the need for broader societal changes that promote gender equality, such as promoting women's education and career opportunities.

In conclusion, the chapter's findings suggest that reducing gender wage differences can have significant positive effects on the economy, resulting in more jobs and increased output. The study underscores the importance of considering different models when studying the potential impact of reducing labour market discrimination. It provides evidence to support policymakers and business leaders in promoting gender equality in the workplace.

6.1.3 Covid-19 and Economic Adversity:

The third empirical chapter analyses the impact of Covid-19 on the UK labour market discrimination, focusing on the gender dimension of the effects of Covid-19 on workers' economic adversity. The study merges the latest data releases from the UK Household Longitudinal Study Covid-19 and the UK Understanding Society Covid-19 waves to examine the exposure of male and female workers to economic hardship during the first waves of Covid-19. The paper uses discrete choice econometric estimations to determine if the pandemic affected men and women equally.

The results of Models 3, 3A, and 3B show that organizational variables explain 41.9%, 42%, and 43.7% of the variation in the dependent variable, which is the probability of facing economic adversity during the first wave of COVID-19. The likelihood of facing economic adversity decreases with age, as those in the 35 to 44 age group had a lower probability than the 16 to 24 age group. The results show that the pandemic affected both men and women equally. Income, age, occupation, and the ability to telecommute were the key factors that affected economic adversity the most during the first Covid-19 waves.

The study found that being a key worker and having the ability to work remotely were the main reasons for being safe from economic adversity. The results also suggest that occupation affected men and women differently, with sectors and occupations an individual was working in being far more crucial than any other in terms of the probability of facing economic adversity. Contrary to some previous literature, there needs to be more evidence to suggest that female workers in the UK faced economic adversity at higher rates than male workers. The youngest individuals were hit the hardest, corresponding to findings observed in the literature for other countries. Education findings align with the literature on the least educated people affected. In contrast, the study's conclusion on the self-employed variable contradicts current literature where it is hypothesized that self-employed individuals were the worst hit.

As expected, the ability to work remotely has a negative association with economic adversity. The study found that key workers were less likely to face economic adversity. The study also discovered that individuals in temporary work were less likely to face economic adversity, contradicting previous literature. The study found a consistent positive correlation between the private sector with economic adversity, implying that individuals in governmental organizations and non-profit organizations were safer.

Regarding occupational classification, the study found that all occupations are less likely to face economic adversity than plant and machine operatives when it comes to men. However, plant and machine operatives are the most exposed occupational class in the analysis for females. Based on the literature, an interaction variable was included in the model of income and gender, pointing to middle-income males in the UK having a higher probability of job loss and being furloughed than other income groups. This was found to be true.

One of the interesting findings of the study was no gender discrimination in the early days of Covid-19 pertaining to layoffs and furlough. This substantiates the argument by Becker's theory of taste of discrimination, as the early phase of Covid-19 represented a "panic" decision by firms to let go of individuals and save themselves, causing the firms to act rationally.

The implications of this study are significant in understanding the impact of Covid-19 on the UK labour market, specifically in terms of gender discrimination. The study found that men and women were affected equally by the pandemic, with key workers and those who could work remotely being the most protected from economic adversity. The study also highlights the importance of individual characteristics such as age, occupation, income levels, and employment security in determining exposure to economic adversity.

These findings have several implications for policymakers and employers. Firstly, policymakers need to target policies that enhance education, income levels, and employment security to improve the overall economic well-being of individuals. Secondly, employers need to prioritize the safety and protection of key workers and those who can work remotely during economic uncertainty. Thirdly, employers need to consider occupation-specific factors when designing their employment policies to ensure that all workers are adequately protected from financial adversity.

Moreover, the finding that there was no gender discrimination in the early days of Covid-19 layoffs and furlough is significant. It supports Becker's theory of taste of discrimination and highlights the importance of firms acting rationally during times of economic crisis. This implies that firms should focus on protecting their businesses during times of uncertainty while ensuring that their employment practices are fair and non-discriminatory.

Overall, this study provides valuable insights into the impact of Covid-19 on the UK labour market, highlighting the importance of individual characteristics and labour market determinants in determining exposure to economic adversity. These findings can help inform policy decisions and employment practices to ensure that all workers are protected and supported during economic uncertainty.

6.2 Policy implications

Based on the results of the three empirical chapters, along with the theoretical framework provided in chapter 2, here are the policy recommendations.

6.2.1 Mandatory disclosure of the gender pay gap for companies with over 50 employees:

One of the potential solutions to address the pay gap is making it mandatory for companies with 50 or more employees to disclose the gender pay gap publicly. In the UK, companies above 250 employees must disclose this information. This is relevant to solve issues in all three papers. (Equality Act 2010 (Gender Pay Gap Information) Regulations 2017).

In the first paper, for instance, the Oaxaca-Blinder decomposition helps pinpoint the contribution of different factors, such as experience and education, along with discrimination, to the pay gap. By requiring companies with above 50 employees to disclose the gender pay gap, it would automatically force the companies to gather intelligence on it and confront it. This should help solve any discrimination practices (whether known or unknown) that are taking place in the workplace. Additionally, this can be useful to the company to see what is driving the wage gap: is it hours worked, experience, education or some other factor at play

The second paper highlights how reducing the pay gap has potential benefits for not just women but the economy as a while. Requiring companies with above 50 employees to disclose pay gap information creates an incentive for companies to face the issue and hence resolve it. Since this also affects how they are viewed by potential employees and candidates looking to work for them. This also sets a benchmark for companies to measure their progress and see their performance against other companies. This consequently benefits women and the overall economic growth of a country.

The third paper on the impact of Covid-19 on economic hardship in the labour market can be helpful to as it will hold medium/large companies accountable for any adverse effects that might diss-appropriately affect women or men. It would also allow for a better understanding of the extent to which women are concentrated in sectors that are more vulnerable to economic shocks, which could inform targeted policy interventions to support these industries.

Overall mandating that medium-sized and large-sized companies disclose their gender pay gap can aid and serve as a multifaceted solution to address issues raised in all three papers. Promoting this practice would encourage companies to look at their discriminatory practices, provide insight into the root of the discrimination and ultimately help resolve them within the company. This would also be beneficial to the overall growth of the economy.

6.2.2 Encouraging pay transparency:

The encouragement of pay transparency is a relevant policy for addressing the pay gap based on all three papers. Pay transparency refers to openly sharing information about employee compensation, including salaries, bonuses, and other benefits, regardless of gender. While gender pay gap reporting can help identify pay disparities between male and female employees, pay transparency can go beyond gender and provide information about pay disparities among other groups, such as racial or ethnic minorities, LGBTQ+ employees, or employees with disabilities. Another potential benefit is that it can help reduce glass ceiling and sticky floor effects. Making compensation plans clearer from the start and in job postings makes it challenging to give different pay based on gender and race.

In the first paper, for instance, by making the pay structure more transparent, it is easier to identify and spot discriminatory practices. For example, if experience and education levels are equal and still a pay gap exists, it might be a sign of discrimination. Of course, the company can take it one step further and employ its methodology in what it values, such as hours of work, experience or any other factor to understand in detail why the wage gap exists. Later it can present salaries based on these variables that it values, thereby reducing the gap by making the pay structure more transparent.

In the second paper, we can observe the potential benefits of this policy. By encouraging and being transparent about pay transparency, the companies are held accountable for any gender pay disparities. Also, based on pay transparency, women can negotiate for fair wages.

Pay transparency can also be necessary when facing another potential pandemic like Covid-19. As the paper points out, during Covid-19, women reduced working hours much more than men. Pay transparency can help ensure that women are not disadvantaged when it comes to this and are paid their pro-rata rate appropriately.

Overall, encouraging pay transparency is a policy that can help address the gender pay gap across various contexts. Increasing transparency around pay structures can help identify and address discrimination, support negotiation for equal pay, and hold companies accountable for making progress towards gender pay equality.

6.2.3 Flexible working arrangements (Government or employer sponsored):

Another possible policy consideration is a flexible working arrangement that can help resolve the gender pay gap by reducing the impact of caring responsibilities for women and allowing women to have more balance between family and work life. This solution is also applicable to all three papers.

In the thesis, the neo-classical theory is mentioned as unable to solve this dilemma. Hence, the thesis proposes that the government promote flexible working arrangements, either through government or employer sponsorship to reduce the gender pay gap. Essentially, all jobs that can be done through flexible working arrangements should be enforced to do so by the government. This will allow more women (and men) to enter and remain in the workforce. By offering these options, women can work and manage family responsibilities much more effectively, which allows them to progress in their careers without potential interruptions, which have been shown to decrease earnings.

In the first paper, for instance, flexible working arrangements can aid women with managing caring responsibilities, which can help them to stay in the workforce and progress in their careers. This will ultimately reduce the time required for women to take off work and hence reduce the gender pay gap. By providing flexible work arrangements such as part-time work, job sharing, or flexible hours, employers can support employees who have family obligations such as caring for children or elderly parents. This can help ensure that women have the same opportunities as men to progress in their careers and reduce the gap due to differences in experience and seniority.

The second paper on the IO model also shows that flexible working is hugely relevant as it allows employers to retain women and reduce staff turnover, making it possible for women to match male wages. Additionally, flexible working can aid women coming to previously male-dominated fields such as STEM by offering a balance between work and family. Finally, in the paper, this can reduce the gender pay gap by having more women in the labour force doing higher-level jobs as they do not need to take as much time off as they do right now. This also can increase the pool of skilled women workers available to employers, helping boost the economy.

The Covid-19 paper discusses issues around women and childcare responsibilities. Many studies show that women take on more caregiving roles, such as caring for children and taking care of ill family members, limiting their ability to pursue work full-time. This often leads to women reducing their working hours (as happened during Covid-19) or stopping work altogether. If employers through government enforcement are forced to aid and provide flexible working, this can assist women in continued work. Secondly, in the context of the pandemic, flexible working can help mitigate the disproportionate impact on women's jobs. By offering flexible work arrangements, employers can provide more options for employees with additional caregiving responsibilities due to school closures or the need to care for sick family members.

Hence, flexible working can effectively address the gender pay gap as it can benefit women and society. In all three papers, the theme of flexible working as a solution to address the gender pay gap emerges. Encouraging employers to offer flexible work arrangements can help reduce the gap caused by differences in family responsibilities and increase the participation of women in the labour force. Furthermore, flexible working can help mitigate the impact of external factors such as pandemics on women's jobs. Thus, flexible working can be helpful in a multifaceted approach to addressing the gender pay gap.

6.3 Discussion

This discussion chapter summarises the thesis and re-iterates the main findings and aims. The chapter also provides the main contributions of this study to the literature. Lastly, it also discusses the limitations of this research along with its possible future extensions.

The thesis is divided into five main chapters. The five chapters are related to each other by the common thread of gender discrimination which is at the heart of the thesis. Although different in style, approach and methodology, the underlying aim of the chapters is the same. That is to do research that identifies areas of inequalities and ultimately aids in removing them. That is also the motivation of the thesis, to call attention to issues of discrimination in the labour market. The thesis is an attempt to do so through empirical work (Chapter 3, 4 & 5) backed up by theoretical foundation (Chapter 1 & 2).

The thesis novelty can be mainly found in the empirical applications of the analysis of gender discrimination in the labour market by the use of novel data and methodologies. The thesis adds to the literature in different ways. Chapter 3 adds to the literature by expanding the understanding of gender wage discrimination in highly educated labour markets with a high level of data granularity. Specifically, the paper adds to the understanding of presence of glass ceiling and sticky floors for the educated labour market. At the same time, the paper provides greater granularity in determining how the effect of discrimination changes along the income distribution. The thesis uses the novel multi regional input-output model for the UK to analyse wage discrimination scenarios in Chapter 4 using an underexplored methodology (Ghosh). Meanwhile, Chapter 5 takes a look at the early days of Covid-19 in UK (April, 2020) and applies the theories learned in Chapter 1 and 2 to analyse the gendered effect of the pandemic.

The first empirical chapter, i.e. "The gender pay gap for higher education graduates in the United Kingdom – An Oaxaca-Blinder decomposition approach", interrogates the gender pay gap for individuals who obtained at least a graduate degree in the UK. The paper analyses a homogenous group (higher educated people defined by completing university or equivalent) and looks at the gender pay gap in nine income different quartiles. This is done in order to reduce the heterogeneity of the entire labour market and follows examples of previous work that primarily focus on just the graduate gap. (Simpson et al., 2004; Smith, 2019).

The paper tries to answer some key questions about the graduate pay gap. First, what is the gender pay gap at the graduate level in the UK and has it changed over time? Advancing the same question the paper asks, can the wage gap be attributed to differences in returns linked to individual characteristics or can it only be explained by discrimination? Lastly, the paper looks for the existence of potential glass ceilings and sticky floors across the wage distribution.

In order to answer these questions, the paper uses an Oaxaca-Blinder decomposition using nine income quartiles. The data used comes from three waves of The United Kingdom Understanding Society Survey[29]: wave 1 (covering the period of 2009-2010), wave 5 (covering the period of 2014-2015) and wave 9 (covering the period of 2018-2019). *Overall, there is a wage gap* for both highly educated individuals and the entire UK market. The wage gap varies (both in adjusted and un-adjusted terms) based on the taxonomy of higher education.

The study shows that the overall graduate pay gap in the UK was between 0.370 logs to 0.381 logs, depending on how higher education is defined. This is less than the overall gap

[29] https://www.understandingsociety.ac.uk/

found in the paper for the entire UK labour market, which was 0.412 logs. However, even* though the total wage gap is significantly more for the overall UK market, more of it can be attributed to the explained component (64.56%). This means that the entire UK population has more of a total unadjusted pay gap as compared to the highly educated population. However, when we divide the pay gap for the entire population, *more of it can be explained by our independent variables.*

The discrimination portion of the wage gap showed a wide range depending on how higher education was defined. *Discrimination ranged from 34% to 41%.* Although further education after bachelor's, including masters/PhD, did lower the overall wage gap compared to just graduates, it also increased discrimination, from 34% for the just graduate group to 37% for the group that included masters/PhD.

Looking at the time component of the paper, we find mixed results. From Wave 1 to Wave 5, the overall wage gap increased by 14.5% for highly educated individuals. However, when continuing the timeline from wave 5 to wave 9, the wage gap went down by 3.8%. Our findings suggest that the discriminating component of the wage gap has been on a steady rise. For wave 1 it was 38%; for wave 5 it was 39%, and it continued to increase for the latest wave analysed (wave 9) to 41%. One possible reason for this is that the total raw unadjusted gap is lower for highly educated individuals. Hence, the issue of discrimination in highly educated individuals does not receive the merit and importance that it deserves. However, according to our study, even though the unadjusted wage gap is less of a problem for highly educated individuals, the problem of discrimination remains.

Lastly, the paper looked for the presence of *sticky floors* and *glass ceilings* in the highly educated worker group. The “glass ceiling” refers to an invisible barrier for women preventing them from moving up beyond a certain level in the hierarchy. “Sticky floors” can be considered opposites of the glass ceiling and refer to a wide income gap between men and women at the bottom of the distribution. We found no evidence of sticky floors. However, evidence of the glass ceiling was found no matter how education was interpreted. As we moved up the income quartile, the discrimination component increased, and the effect of characteristics (our explained component) decreased. Furthermore, the overall gap is higher in lower income quartiles, though most of it can be explained by characteristics.

Looking at the time component at nine income quartiles, we discover that there is no presence of a sticky floor and little presence of a glass ceiling in wave 1 (2000-2010). However, there is a clear development of the glass ceiling as we move up the waves from wave 5 (2014-

2015) to wave 9 (2018-2019). Although *there is no evidence of a sticky floor for all three waves, at the lower ends of the distribution*, most of the wage gap can be explained by characteristics (even though there is more of a wage gap at the lower levels).

Chapter 3 further adds to the literature by identifying that the results can change depending on how graduates are defined. The paper also adds to the literature by analysing the graduate pay gap by different definitions at nine income quartiles. Finally, the paper considers the history of OB decomposition for the graduate pay gap and observes how it has evolved using nine income quartiles.

The limitations of the paper revolve around the variables used. One of the variables of industry or occupational could be added to improve the paper. Another variable that could be added is the graduate's study subject, as income might depend not just on education level but also the type of education one receives. Another augmentation in the paper could be to increase the number of observations, working with secure data access. The Covid-19 pandemic did not allow the analysis at this level for this paper (Appendix 1 – Role of Covid explains further). Further research can be conducted by incorporating the graduate's study subject and the industry the graduate is employed in.

The second empirical chapter takes the foundational work built in the first chapter for Oaxaca-Blinder decomposition and extends it to calculate a world where there is no discrimination. The motivation of the research stems from converting a lot of theory that highlights economic growth and removing discrimination to actual empirics. The second empirical chapter ("What would happen if female wages became equal to male ones? A Socio-Economic Impact Multi-Regional Input-Output Model (SEIM-UK) application- A methodological case for a Ghoshian approach") interrogates the question of *what would happen if female wages became equal to men?* The paper finds a positive relationship between removing discrimination and economic growth. The paper finds increased gross value added in several regions and sectors as a result of removing discrimination in just one sector or region. Along with economic growth, the paper finds increased job creation because of removing discrimination.

The input-output model from SEIM-UK (created by City-REDI) and the Input-Output model (ONS) are used to answer the question. The models use data from 2016 for consistency and comparison. The paper can be divided into two parts. The first part deals with scenarios of complete equality. In these scenarios, it is assumed that female wages become equal to male wages in London. A second sectoral scenario is created in which female wages are assumed to be equal to male wages in the Professional, scientific, and technical activities sectors. The reason for selecting the location and sector is the total compensation. The sector and region contained the largest compensation based on the analysis and therefore were chosen.

In the second part, the paper uses the Oaxaca-Blinder decomposition to calculate the remuneration of workers as per their productivity level. After the remuneration amounts are calculated, the paper uses an aggregated version of the Socio-Economic Impact Model (SEIM-UK) (Input-Output) to model scenarios. Finally, the results are compared to the national ONS version of the input-output model for robustness and comparison purposes.

We create two types of scenarios. One in which male and female wages become equal. Second in which productivity differences are considered and just the amount calculated through Oaxaca-Blinder decomposition for discrimination is increased for females. These are more realistic scenarios. We find that scenarios in which male compensation became equal to female compensation performed better than in non-discriminatory scenarios. The range of output increase due to removing discrimination in the labour force ranged from 0.08 % to 0.98%.

For the most realistic scenarios, where productivity differences are adjusted, we have an output increase of 0.15% in our regional scenario, and 0.11% increase in our sectoral scenario. Job increase (in the number of people added to employment), measured by just the SEIM-UK model, *had a range of 0.14% increase 42,720 to 0.94% increase 282,347*. Comparing the IO model with the SEIM-UK model, we observed that overall output increases were higher for the SEIM-UK model than for the IO model. Of the 30 sectors in the model, 22 showed a larger increase in SEIM-UK compared to the IO model. This means that we got higher results for output when using SEIM model versus the IO model. Explanation of this is difficult since MRIO provides greater regional depth whereas greater sectoral depth is provided by IO (ONS) model.

The paper is novel in many ways. First, using female wages instead of female labour force participation (FLFP) to approximate an increase in GDP is novel and is rarely used. In the literature, the usage of minimum wage increases is observed (Lechman & Kaur, 2015; Tsani et al., 2013; Yıldırım & Akinci, 2020)**.** The paper is also novel due to the model it uses. The paper uses the multi-regional UK Socio-Economic Impact Model (SEIM-UK). The SEIM-UK is a multi-regional input-output model for the UK that for the first time provides the ability to conduct an input-output regional analysis at the NUTS 2 level including the four UK nations. The paper is also novel as it compares (by aggregating SIC codes) two input-output models for sectoral scenarios (SEIM-UK and ONS IO). This provides a comparison between the models and the eventual results alongside robustness.

One of the chapter's contributions is technical, it uses the Ghoshian inverse matrix rather than the usual Leontief. The hypothetical and paper provide a use-case of the Ghoshian under-utilised potential and argues that the Ghoshian serves as a good use case for our hypothetical. Addressing the issue of no-increasing Value-added in other sectors, further research is proposed in which value-added subsequently increases based on initial changes.

The third chapter arose because of circumstances of Covid-19 during the thesis (see Appendix 1). The third empirical chapter analyses the Covid-19 effects on UK labour market discrimination. Its main research question focuses on "*How did Covid-19 affect males and females differently*?". The paper also explores *"who faced economic adversity during the Covid-19 pandemic?"* To analyse these research questions, the paper merges the latest data releases from the UK Household Longitudinal Study Covid-19 (April 2020) and *The UK Understanding Society Covid-19* waves (wave 9 which corresponds to 2018-2019).

In contrast to much of the literature, we did not find evidence that females were more likely to face economic adversity in the UK. Labour market variables were the essential characteristics in determining economic adversity. We found young people with low incomes to have the most probability of facing economic adversity. The lowest likelihood of economic adversity was found in the 45 to 54 age group. The marginal effect shows that 45- to 54-year-old had 0.143 percentage points less probability of economic hardship than our reference group(age 16-24).

Being in a key sector was the highest contributing factor to an individual being safe from economic adversity. The probability of economic hardship is reduced by 0.305 (Model 3), 0.303 (Model 3A), and 0.311 (Model 3B) percentage points as compared to not being a key worker. Having a degree had a negative and significant relation with facing economic adversity. However, we also found that having a degree, being self-employed, and working remotely are economic safety factors.

Our study re-emphasised the narrative that being a key worker and having the ability to work remotely were the main reasons for being safe from economic adversity. This means that sectors and occupations one was working in were far more crucial factors than any other in terms of the probability of facing economic adversity. The study adds to the novel and ever-growing literature of Covid-19. The study is novel in its approach (taking a gendered perspective of economic adversity in UK) and uses (relatively) recent data to analyse the impact of Covid-19 on gender in the UK. The study is limited because it analysed just the early part of Covid-19 (April 2020); (this reflects data availability at the time of the analysis).

However, Covid-19 policies and opening/ closing of sectors might yield completely different results if another period of Covid-19 is compared. Therefore, one of the extensions to the research could be the comparison between the early reaction to Covid-19 (April 2020) to one year afterwards (April 2021).

Besides the specific limitations of each chapter, there were a number of concerns that are related more generally to the approach that requires discussion. A significant limitation is the way that discrimination is defined in each of the chapters. In all the chapters labour market is considered the basis for discrimination. For example, discrimination based on productivity differences, being laid off, and being furloughed are defined as discrimination. This, however, is a microscopic view of discrimination and does not cover many aspects of it. In fact discrimination can and does happen in many ways. For example, there is discrimination in hiring, racism, housing and sexism.

Another limitation of the study is that it solely focuses on gender discrimination. In many ways, the research undertaken in the above chapters can also be carried out through an ethnic and racial lens. As discussed in the earlier chapters, many theories of discrimination apply to both gender and ethnic discrimination.

In chapter 3, the thesis finds that despite obtaining higher education, women still suffer an element of discrimination. For future research purposes, this can be investigated with larger sample size and more income quartiles. The thesis also found evidence of glass ceiling which seems to be a sticky phenomenon. It was found despite women receiving higher levels of education at a rate greater than men. The thesis found that how you define highly educated can change the discrimination amount found. This means that future researchers must be careful of what is included in higher education.

In chapter 4, the thesis found increased economic growth due to removing discrimination. Due to using the input-output model, the thesis was able to observe in which regions and by how much economic growth increased as a result of removing discrimination. In the future, this can be expanded to an even smaller regional level (NUTS 2 from NUTS 1). The thesis also found increased job creation in different sectors and regions, a result that is influenced heavily by no decrease in labour demanded. Future research needs to consider the possibility of decreased labour due to increased costs.

In chapter 5, the thesis found no evidence of gender discrimination in the early days of Covid-19 (April, 2020) when it came to being furloughed and/or laid off from work. Hence, the paper makes a case for taste of discrimination which suggests that people are prejudiced against a specific group (in this case, women). The case is made on the basis that no discrimination was found when decisions were made in "panic" due to the early uncertain, unknown and varying conditions that followed the closure of businesses in Covid-19. It would be interesting to conduct the research using different survey data from the early stages of Covid-19 and have the study replicated for different countries.

There are many other routes for future research that can be taken based on the empirical papers. One obvious route is the re-evaluation of the Ghosh model (as presented and discussed in chapter 4). Another route is an expansion on Chapter 3, where rather than taking snapshots of time (wave 1, wave 5 and wave 9), a time series analysis is taken. For Chapter 5 of the thesis, a possible expansion is comparing the early periods of Covid-19 (which the current research does) with the later stages. This will provide a much better understanding of immediate effect versus a more calculated effect where some of Becker's theory of taste-based discrimination might develop. Comparison with other EU based research would be an interesting undertaking for all three of the chapters.

6.3.1 Common themes and synergies:

The papers in the thesis highlight the importance of using a diverse and multi-dimensional approach to solving the issue of the gender pay gap. The papers are linked together by the theme of the gender pay gap, which is still a persistent issue in the UK labour market. The first paper shows how even for those with similar academic backgrounds, there is a gender pay gap.

The research adds to the literature by expanding the understanding of gender wage discrimination in highly educated labour markets with a high level of data granularity. Specifically, the paper adds to the knowledge of the presence of glass ceilings and sticky floors in the educated labour market. At the same time, the paper provides greater granularity in determining how the effect of discrimination changes along the income distribution.

The paper hence aids in identifying the factors that contribute to the gender pay gap and proposes policy interventions to address it. This also links with other papers shedding light on the gender pay gap, demonstrating how it is not simply a matter of education or discrimination. Instead, it is a multifaceted and complex issue that requires nuanced quantitative methodologies to measure and address it. This suggests that the solution must be much more comprehensive and address systemic and individual factors.

The second paper shows the positive effect of reducing the gender pay gap on the economy. This, again, is another dimension of the gender pay gap. Where in the first paper, we are identifying the gender pay gap and in the second paper, we are showing the potential benefits of removing it. The paper adds to the literature in many ways, specifically in using the new multi-regional SEIM model. The biggest addition to the literature is revisiting the use of the Ghosh model, specifically when under-utilized potential or discrimination effects (as in this case) are involved. The paper makes an argument for the use of Ghosh to be incorporated when analysing changes in value-added such as seen with the compensation of employees in the paper. The paper also proposes a new method to balance the resulting output of the Ghosh model. This has massive ramifications for the literature as it allows changes to value added in the input-output model by using Ghosh. This can also aid in policy by making it easier to calculate the effects of removing barriers for women and different under-performing ethnic groups.

The third paper examines the impact of external factors, such as the Covid-19 pandemic, on women's employment. The paper adds to the theoretical literature by supporting Becker's theory through its findings. The study adds to the novel and ever-growing literature on Covid-19. It also looks at how the labour market can be disproportionately affected, given the occupational segmentation that exists between men and women. It highlights the point made earlier that addressing the gender pay gap requires a broader social understanding than just individual factors.

In conclusion, the papers highlight the need for a multi-faceted approach to resolve the issue of the gender pay gap. This will require the collaboration of stakeholders including workers, employers and policymakers to address the individual and societal challenges contributing to the wage gap. This could include policy recommendations proposed in the thesis earlier to promote gender equality and diversity in the workplace. The thesis also serves to contribute to bringing awareness and further understanding to the issue of the gender pay gap and how work and issues of care are interrelated. The papers also highlight how issues of the gender pay gap are intertwined with broader economic and social problems. This might include measures proposed such as pay transparency, flexible working arrangements and making policy that makes publishing gender pay gap stats for middle-sized companies. These policies can help tackle both systemic and induvial factors that contribute to the gender pay gap.

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Appendix 1: Role of Covid-19 : Explanation of third empirical chapter

During my PhD, Covid-19 happened and disrupted a major portion of my studies. I had applied for secure data access from ONS and completed my training in London by September 2019. The purpose of obtaining secure data access was to get the following datasets.

SN 7989 Annual Respondents Database X, 1998-2014: Secure Access

SN 6689 Annual Survey of Hours and Earnings, 1997-2016: Secure Access

SN 6727 Quarterly Labour Force Survey, 1992-2016: Secure Access

SN 6721 Annual Population Survey, 2004-2016: Secure Access

SN 6676 Understanding Society: Waves 1-6, 2009-2015: Secure Access

This would have allowed for much greater insight for one of my empirical chapters, "Gender pay gap for graduates in the UK – An OB decomposition approach at nine income quartiles," as it would have allowed for a far greater number of observations. However, since I went back to Pakistan during Covid-19, I could not complete the ONS accreditation. Therefore, I ended up using the publicly available Understanding Society datasets.

The second way Covid-19 impacted my thesis is my work on the input-output paper. As part of my funding from City-REDI, I planned to work with the input-output model and provide possible extensions. My supervisors and I discussed many possibilities, including expanding on the input-output chapter and creating a possible computer-generated equilibrium model (CGE) model. This would have required me to work with the model's creators in the office. However, this was not possible under the circumstances, and as I was not present in the UK, this greatly hindered my progress.

Instead of being despondent about the circumstances, my supervisors and I decided on a new chapter for my thesis. Since I was already working on the gender pay gap in the UK, I decided to focus on determinants of job loss in Covid-19 (in the context of males and females). I used a logit model to find and answer what were determinants of economic adversity in the early days of Covid-19. I focused on different dimensions of labour market during Covid-19 (especially differentiating gender where possible). I consider this chapter to be one of my greatest assets. The chapter shows my ability to work with the latest data in my field. It also shows my ability to work extremely fast and develop new ideas.

Appendix 2: Analysis of key determinants

In his seminal paper, Oaxaca (1973) identifies as key determinants: education, part of a labour union, self-employment, are education; this is measured by years of schooling (both quadratic and linear term). Dummy variable for, if the worker is in a union or not. Dummy variable for private and government sector plus additional dummy variable for self-employed. Occupation dummy variables, health problems dummy variable (dummy = 1 if the person reports health problems and cannot adequately work. Full time or part-time dummy variable (here 35 hours is used as a cutoff point, and the base category is taken as a part-time work). Marital status with options of divorced, widowed, spouse present, spouse absent and never married as a base group. Last migrated (number of years) (this is included both as a linear and quadratic term). Urban area size again a dummy variable with the standard metropolitan statistical measurement as a benchmark for this. There are multiple options provided for this (area greater than 250,000, for example). A dummy variable for regions (North, South, East, West with South as a reference group). A dummy variable for an urban or rural area. The size of the actual discriminated amount found will rely on the selection of these control variables by the researcher.

Blinder (1973) used education, vocational training, occupation and family history as the main variables. The family history variable in Blinders case involves a father's education, parent's income and place where the individual was brought up. He discovered that these variables were of the utmost importance in explaining the white-black pay gap. He argued that even if the black and white fathers had similar education, blacks generally gained less due to that as compared to whites. Cotton (1988) used education, work experience, married, urban residence, region, industry worker (divided into nine components) as his main variables. He found that the average rate of return of education for whites was higher than blacks. He also observed that wage-experience profile of whites was far superior to blacks. He estimated that about 52% of the differential was due to the skill gap between the two groups.

Christie & Michael (2001) used educational attainment, the field of study, location, marital status, industry, occupation, number of hours worked along with age as her primary variables. She found that educational attainment differences had a low effect on the explained component in 1999 for Canada. She discovered that the inclusion of occupational/industrial dummies dramatically changed the results. The explained component falls by half when these are not added into the model. Brooke et al., (2003) used education, experience, part-time, married, children as their main variables. They found that females working in the private sector in both countries (Germany and UK) faced large underpayments as compared to the public sector.

Swaffield (2000) used occupation, labour work, education and skill occupations in his study on Britain. He used data from 1991-1997 British household survey and observed labour market attitude along with these variables. He added variables like aspiration towards work and motivation towards work (measured through qualitative questions) such as "Having a full-time job is the best way for a woman to be an independent woman?" (Swaffield, 2000, p. 14) to gauge women's attitude towards work. This he found had a significant impact on female wage. The attitude was measured on a Likert scale.

Ejaz (2016) using Pakistan social living measurement data (2004-2009) used age, age 2, married, location, employment, Organization and sector of work as her main variables. She found that the major differences in Pakistan arose from different sectoral work that men and women do. In all these cases, the selection amongst these variables also shows the attitude of the researcher about discrimination in the labour market (Oaxaca, 1973).

The usual data in these analyses is household or individual data. These type of data sets just look at one side of the equation. Whereas firm-level data is ignored (Groshen, 1991), despite market outcomes being determined by both firms and employees. This is an important distinction since we can see from the theoretical understanding built that most discrimination is based on matching employers and employees (Becker, 1971)

Holzer and Neumark (2000) argue that employer behaviour is of primary importance in determining the pay gap. They argue that studying employee behaviour can result in two useful additional information. One, the data can help us in understanding the demand side from which discrimination arises. Secondly, the specific hypothesis can be formulated when the employer's behaviour towards gender and race is observed. Groshen (1991) builds on this and argues that five distinct measures could cause the wage differential from the point of view of the employer. 1) Employers are sorting the workers by ability 2) Compensating differentials (for different workers) 3) Asymmetric information cost yields in variation in wages 4) Wages for certain employers are higher than others in the market place 5) Workers have a claim to rent. All these scenarios are likely and can cause wage differentials. The incorporation of linking both employ side data and employee side data to explain the pay gap is a recent phenomenon with Abowd et al., (1999); Goux and Maurin (1999) pioneering this strand of work. Both works analysed a longitudinal sample of over one million French workers. Their studies found a strong effect of firms in explaining pay difference.

Appendix 3: Demographic descriptive statistics for BG1, BG5 and BG9

Appendix 3a of our thesis illustrates the samples of broad graduates (BG) for waves 1,5, and 9. *The UK Understanding Society* dataset also provides a significant time element to the study as interesting patterns can be seen in the data over time. Our sample is mainly 32 to 49 years old, accounting for 57.1% of individuals in wave 1, 55.4% in wave 5 and 53.6% in wave 9. The largest ethnic group remains British (white), followed by Indian, other white background and Pakistani groups.

Looking at Appendix 3a for education, we see a clear trend of individuals opting for more higher education, with 28.7% choosing MSc and PhD in wave 1, 31.8% in wave 5 and 32.4% in wave 9, respectively. Whereas individuals are now more inclined towards higher education, marriage stats are up, going from 56.4% in BG1 to 58.2% in BG9. Before reading into these statistics, one must practice caution since they represent a small sample of highly educated people. They are not represented of the overall population but selected individuals who have achieved BSc degrees (or equivalent). There were also slight substantial differences in the waves regarding the number of children. Individuals with more than three children diminish from 5.1% in wave 1 to 4.1% in wave 9. These statistics point towards a trend, a decrease in the number of children and proclivity towards higher education. This trend is also captured by the literature that focuses on educated people (Lemieux, 2014).

Appendix 3 a: Descriptive characteristics Wave 1, Wave 5 and, Wave 9

	Broad Graduate Wave 1 (BG1)			Broad Graduate Wave 5 (BG5)			Broad Graduate Wave 9 (BG9)		
	Male	female	Total	Male	female	Total	Male	female	Total
Number of Observations	4042	5258	9300	3110	4376	7486	2576	3624	6200
Age									
16-29 years old	21.90%	21.90%	21.90%	17.80%	20.50%	19.40%	17.00%	18.10%	17.60%
30-39 years old	32.20%	31.30%	31.70%	28.50%	27.10%	27.70%	25.90%	26.10%	26.00%
40-49 years old	24.70%	26.00%	25.40%	27.70%	27.70%	27.70%	28.80%	26.70%	27.60%
50-59 years old	15.90%	17.00%	16.50%	18.70%	19.90%	19.40%	21.10%	23.00%	22.20%
60+ Years	5.30%	3.80%	4.50%	7.30%	4.80%	5.80%	7.20%	6.10%	6.60%
Ethnicity (Selected)									
British/English/Scottish/Welsh/northern Irish (white)	64.10%	71.20%	68.10%	72.70%	75.10%	74.10%	71.90%	72.70%	72.30%
Indian (asian or asian British)	8.60%	4.70%	6.40%	6.30%	3.80%	4.80%	7.10%	4.10%	5.40%
any other white background (white)	5.10%	5.80%	5.50%	3.20%	4.30%	3.80%	3.80%	4.60%	4.30%
Pakistani (asian or asian British)	4.10%	1.50%	2.60%	2.90%	1.50%	2.10%	3.30%	2.20%	2.70%
African (black or black British)	4.90%	4.20%	4.50%	3.40%	3.20%	3.30%	3.00%	3.70%	3.40%
Education									
Masters/PHD	34.20%	24.50%	28.70%	37.30%	28.00%	31.80%	36.70%	29.40%	32.40%
Bachelors	43.50%	42.70%	43.00%	41.00%	41.40%	41.20%	41.60%	42.50%	42.10%
Other degree equal Bachelors	22.30%	32.90%	28.30%	21.70%	30.60%	26.90%	21.70%	28.10%	25.40%
Legal Marital Status									
Single	33.50%	32.10%	32.70%	31.40%	33.10%	32.40%	29.70%	31.70%	30.90%
Married	59.80%	53.80%	56.40%	61.30%	53.20%	56.50%	62.90%	54.90%	58.20%
Divorced	4.30%	9.40%	7.20%	4.60%	9.90%	7.70%	4.20%	8.70%	6.80%
Number of Children									
0	62.00%	59.60%	60.60%	60.60%	59.70%	60.10%	59.70%	61.20%	60.60%
1	16.00%	19.50%	17.90%	14.40%	18.90%	17.00%	16.00%	16.70%	16.40%
2	16.20%	16.50%	16.30%	18.20%	17.10%	17.60%	19.50%	18.60%	19.00%
3+	5.90%	4.50%	5.10%	6.80%	4.30%	5.30%	4.70%	3.60%	4.10%

Appendix 4: Labour Market Characteristics Wave 1, Wave 5, Wave 9

Continuing the labour market analysis for our BG1, BG5 and BG9 sub-samples with Appendix 4 a (where we are essentially trying to grasp the time element amongst graduates), we observe a steady rise in wages over the years. As is expected, the average pay per month increases over time. The average pay in wave 1 is 2,370 pounds per month, 2,464 pounds per month in wave 5, while in wave 9 arrived at 2,716 pounds per month. Observing the number of hours, we can analyse that the number of hours remained constant for all our samples. The highest value for working hours was 33.99 in wave 9. The number of hours worked per week was lowest in wave 5 (although not much of a difference from our other groups) at 33.79. The analysis for full and part-time employees also shares a similar pattern as the number of hours usually worked per week. It ranges from a very high of 81.7% in BG9 to a low of 79.8% in wave 1.

Surprisingly, organizational size for waves 1, 5 and 9 shows no change during the years. The proportion is nicely balanced with individuals working for small companies and large companies. However, one interesting trend to note is individuals in ultra-large organisations (500+ workers). This group shows a steady increase going from 25% in wave 1 to 26.3% in wave 5 and 27.9% in wave 9. Finally, analyzing organization type, we discern a nice balance in wave 1 with individuals working more in private firms, whereas this sees a slight increase of 52.5% in wave 5 and 52.6% in wave 9.

Appendix 4 a:Labour Market Characteristics Wave 1, Wave 5, Wave 9

	Broad Graduate Wave 1 (BG1)			**Broad Graduate Wave 5 (BG5)**			**Broad Graduate Wave 9 (BG9)**		
	male	female	Total	Male	female	Total	Male	female	Total
Number of Observations	4042	5258	9300	3110	4376	7486	2576	3624	6200
usual gross pay per month: current job									
Mean	2833.01	2014.64	2370.32	3018.72	2070.35	2464.34	3308.56	2295.85	2716.62
No. of hours normally worked per week									
Mean	36.84	31.69	33.93	37.2	31.36	33.79	37.28	31.65	33.99
Full or part-time employee									
FT employee	89.00%	72.70%	79.80%	90.90%	72.50%	80.10%	92.50%	74.10%	81.70%
PT employee	11.00%	27.30%	20.20%	9.10%	27.50%	19.90%	7.50%	25.90%	18.30%
Organisation Size									
1	24.90%	26.70%	25.90%	24.20%	26.30%	25.40%	21.70%	25.20%	23.70%
2	24.10%	28.50%	26.60%	22.80%	27.60%	25.60%	23.80%	27.00%	25.70%
3	25.40%	20.20%	22.50%	25.20%	21.00%	22.80%	25.10%	21.10%	22.70%
4	25.60%	24.60%	25.00%	27.80%	25.20%	26.30%	29.40%	26.80%	27.90%
Organisation Type									
Private firm or business, a limited company	63.40%	40.50%	50.40%	65.10%	43.40%	52.50%	66.70%	42.60%	52.60%
other type of organisation	36.60%	59.50%	49.60%	34.90%	56.60%	47.50%	33.30%	57.40%	47.40%

Appendix 5: All worker data – set wave 9

Blinder-Oaxaca decomposition			Number of obs	=	11119	
Model	=	linear	Model = All Worker Data-set Wave 9			
# of obs 1	=	4890	# of obs 2	=	6229	
Lnwage	Coef.	Std. Err.	Z	P>|z|	[95% Conf.	Interval]
Overall						
Male	7.73	0.00	775.01	0	7.70	7.75
Female	7.32	0.00	781.07	0	7.30	7.33
difference	0.41	0.01	30.11	0	0.39	0.44
Explained	0.27	0.01	23.59	0	0.24	0.29
unexplained	0.15	0.01	14.17	0	0.13	0.17
Explained						
Age	0.01	0.02	0.58	0.561	0.02	0.04
agesquared	-0.01	0.01	-0.5	0.614	0.03	0.02
working hour	0.18	0.01	20.75	0.000	0.16	0.19
Parttime	0.08	0.01	14.84	0.000	0.07	0.08
Private	0.00	0.00	0.94	0.347	0.00	0.05
London	-0.00	0.00	-0.15	0.884	0.00	0.00
married	0.01	0.00	5.49	0.000	0.00	0.09
children	0.00	0.00	0.56	0.573	0.00	0.00
organi_2	-0.00	0.00	-3.35	0.001	0.00	0.00
organi_3	0.01	0.00	5.4	0.000	0.01	0.01
organi_4	0.00	0.00	1.96	0.05	7.58E-06	0.01
edu_1	0.01	0.00	3.02	0.003	0.00	0.02
edu_2	-0.01	0.00	-3.47	0.001	0.02	0.00
edu_3	-0.01	0.00	-6.47	0.000	0.01	0.01
edu_4	0.00	0.00	0.81	0.416	0.00	0.00
unexplained						
age	0.68	0.27	2.54	0.011	0.15	1.20
agesquared	-0.35	0.15	-2.4	0.016	0.64	0.06
working hour	-0.52	0.07	-7.69	0	-0.66	0.39
parttime	-0.07	0.01	-7.67	0	0.08	0.05
private	0.04	0.01	3.06	0.002	0.01	0.07
London	-0.00	0.00	-1.17	0.242	0.01	0.00
married	0.02	0.012	1.88	0.06	0.00	0.05
children	0.01	0.01	1.05	0.293	0.01	0.03
organi_2	0.01	0.01	1.23	0.217	0.00	0.02
organi_3	0.00	0.01	0.19	0.848	0.01	0.01
organi_4	0.01	0.01	1.29	0.196	0.00	0.02
edu_1	-0.01	0.01	-2.03	0.042	0.02	-0.00
edu_2	-0.01	0.01	-1.67	0.096	0.02	0.00
edu_3	-0.00	0.00	-0.26	0.797	0.01	0.00
edu_4	-0.00	0.00	-0.1	0.919	0.01	0.01
_cons	_cons	_cons	_cons	_cons	_cons	_cons

Appendix 6: OB decomposition Just Graduate wave 9

Blinder-Oaxaca decomposition	Number of obs = 2613
Model = linear	Model = Just Graduate 9
# of obs 1 = 1072	# of obs 2 = 1541

Lnwage	Coef.	Std. Err.	Z	P>|z|	[95% Conf.	Interval]
overall						
group_1	7.94	0.02	407.77	0	7.91	7.98
group_2	7.58	0.02	462.48	0	7.54	7.61
difference	0.37	0.03	14.52	0	0.32	0.42
explained	0.25	0.02	12.97	0	0.21	0.28
unexplained	0.12	0.02	6.01	0	0.08	0.16
explained						
age	0.11	0.04	2.66	0.008	0.03	0.19
agesquared	-0.09	0.04	-2.48	0.013	-0.16	-0.02
working hour	0.12	0.013	8.64	0	0.09	0.14
parttime	0.07	0.009	7.58	0	0.05	0.09
private	0.011	0.005	2.15	0.032	0.00	0.02
London	0.001	0.002	0.57	0.571	-0.00	0.01
married	0.014	0.004	3.86	0	0.00	0.02
children	-0.0001	0.001	-0.16	0.869	-0.00	0.00
organi_2	-0.006	0.003	-2.11	0.034	-0.01	-0.00
organi_3	0.007	0.003	1.88	0.06	-0.00	0.013
organi_4	0.014	0.01	2.35	0.019	0.002	0.025
unexplained						
age	-0.10	0.61	-0.17	0.866	-1.29	1.086
agesquared	0.098	0.32	0.3	0.763	-0.54	0.73
working hour	-0.34	0.14	-2.36	0.018	-0.62	-0.06
parttime	-0.03	0.013	-2.04	0.042	-0.051	-0.00
private	0.106	0.02	4.59	0	0.061	0.11
London	-0.01	0.01	-1.13	0.26	-0.027	0.01
married	0.023	0.03	0.71	0.479	-0.041	0.09
children	0.04	0.02	1.87	0.062	-0.002	0.07
organi_2	-0.00	0.02	-0.27	0.787	-0.03	0.03
organi_3	-0.02	0.02	-1.21	0.225	-0.05	0.01
organi_4	0.02	0.02	1.17	0.244	-0.01	0.05
_cons	0.34	0.32	1.08	0.279	-0.28	0.962

Appendix 7: OB decomposition Masters/PhD wave 9

Blinder-Oaxaca decomposition			Number of obs = 4624			
Model = linear			Model = Masters PhD 9			
# of obs 1 = 2018			# of obs 2 = 2606			
Lnwage	Coef.	Std.	Err.	z	P>|z|	[95% Conf. Interval]
Overall						
group_1	7.99	0.015	548.76	0	7.961	8.018
group_2	7.64	0.013	585.47	0	7.615	7.667
Difference	0.35	0.0195	17.83	0	0.310	0.387
Explained	0.22	0.014	15.56	0	0.191	0.246
Unexplained	0.13	0.016	8.09	0	0.099	0.162
Explained						
Age	0.10	0.03	3.23	0.001	0.038	0.157
Agesquared	-0.09	0.027	-3.21	0.001	-0.14	-0.034
Working hour	0.113	0.01	11.37	0	0.093	0.132
Parttime	0.063	0.01	9.35	0	0.049	0.076
private	0.006	0.004	1.65	0.099	-0.0012	0.014
London	0.002	0.002	0.94	0.346	-0.002	0.006
married	0.012	0.003	4.75	0	0.007	0.017
children	-0.00	0.00	-0.38	0.706	-0.00	0.000
organi_2	-0.005	0.002	-2.51	0.012	-0.01	-0.001
organi_3	0.01	0.003	2.67	0.007	0.00	0.013
organi_4	0.01	0.005	2.22	0.026	0.001	0.019
unexplained						
age	0.45	0.54	0.84	0.39	-0.60	1.515
agesquared	-0.231	0.288	-0.8	0.42	-0.79	0.33
working hour	-0.391	0.108	-3.63	0	-0.60	-0.18
parttime	-0.025	0.010	-2.5	0.013	-0.04	-0.01
private	0.052	0.017	3.02	0.003	0.018	0.086
London	-0.01	0.007	-1.35	0.17	-0.02	0.004
married	0.014	0.024	0.58	0.55	-0.03	0.061
children	0.02	0.02	1.6	0.11	-0.01	0.054
organi_2	0.01	0.01	0.69	0.48	-0.01	0.030
organi_3	0.003	0.012	0.22	0.82	-0.02	0.025
organi_4	0.03	0.01	2.02	0.04	0.001	0.057
_cons	0.20	0.27	0.74	0.46	-0.33	0.73

Appendix 8: OB decomposition Broad Graduate 1

Blinder-Oaxaca decomposition Number of obs = 9300

Model = linear Model = Broad Graduate 1
# of obs 1 = 4042 # of obs 2 = 5258

Lnwage	Coef.	Std.	Err.	z	P>|z|	[95% Conf. Interval]
overall						
group_1	7.727	0.012	645.03	0	7.703	7.750
group_2	7.381	0.011	697.8	0	7.360	7.402
difference	0.346	0.0121	21.64	0	0.3145	0.377
explained	0.213	0.012	17.63	0	0.1889	0.236
unexplained	0.133	0.013	10.43	0	0.108	0.158
explained						
age	0.008	0.02	0.42	0.675	-0.031	0.047
agesquared	-0.014	0.02	-0.79	0.431	-0.049	0.021
working hour	0.141	0.01	14.95	0	0.122	0.159
parttime	0.073	0.01	11.93	0	0.061	0.084
private	-0.014	0.003	-4.83	0	-0.02	-0.008
London	0.005	0.001	4.72	0	0.003	0.008
married	0.004	0.001	3.71	0	0.002	0.006
children	3.78E-05	0.000	0.11	0.914	-0.001	0.001
organi_2	-0.007	0.002	-4.26	0	-0.01	-0.004
organi_3	0.0127	0.002	5.45	0	0.008	0.017
organi_4	0.004	0.003	1.18	0.236	-0.0023	0.009
unexplained						
age	0.267	0.346	0.77	0.44	-0.41	0.945
agesquared	0.015	0.179	0.08	0.933	-0.336	0.366
working hour	-0.728	0.098	-7.41	0	-0.9205	-0.535
parttime	-0.098	0.012	-8.08	0	-0.123	-0.074
private	0.105	0.013	7.83	0	0.079	0.131
London	-0.013	0.006	-2.22	0.027	-0.025	-0.002
married	-0.020	0.016	-1.22	0.222	-0.052	0.012
children	0.022	0.0119	1.87	0.061	-0.001	0.045
organi_2	0.007	0.009	0.87	0.385	-0.009	0.024
organi_3	0.002	0.008	0.28	0.777	-0.013	0.017
organi_4	0.009	0.009	0.99	0.324	-0.009	0.027
_cons	0.565	0.1897	2.98	0.003	0.193	0.936

Appendix 9: OB decomposition Broad Graduate 5

Blinder-Oaxaca decomposition	Number of obs = 7486

Model = linear
# of obs 1 = 3110

Model = Broad Graduate 5
# of obs 2 = 4376

Lnwage	Coef.	Std.	Err.	z	P>|z|	[95% Conf. Interval]
overall						
group_1	7.81	0.01	616.28	0	7.79	7.84
group_2	7.42	0.01	669.7	0	7.40	7.44
difference	0.40	0.02	23.53	0	0.36	0.43
explained	0.24	0.01	18.34	0	0.23	0.27
unexplained	0.15	0.01	11.4	0	0.13	0.18
explained						
age	0.07	0.02	2.9	0.00	0.02	0.12
agesquared	-0.07	0.02	-3.14	0.00	-0.1	-0.03
working hour	0.15	0.01	14.41	0	0.13	0.17
parttime	0.08	0.01	12.6	0	0.07	0.10
private	-0.01	0.00	-3.94	0	-0.02	-0.01
London	0.00	0.00	1.82	0.07	-0.00	0.00
married	0.01	0.00	5.24	0	0.01	0.01
children	3.50E-06	0.00	0.02	0.98	-0.00	0.00
organi_2	-0.01	0.00	-4.11	0	-0.01	-0.00
organi_3	0.01	0.00	4.04	0	0.00	0.01
organi_4	0.01	0.00	2.49	0.013	0.00	0.02
unexplained						
age	0.25	0.39	0.64	0.521	-0.51	1.00
agesquared	0.00	0.21	0.02	0.988	-0.40	0.41
working hour	-0.65	0.10	-6.81	0	-0.84	-0.46
parttime	-0.07	0.01	-6.14	0	-0.09	-0.05
private	0.09	0.01	6.21	0	0.06	0.12
London	0.00	0.01	0.5	0.619	-0.01	0.01
married	0.04	0.02	2.1	0.036	0.00	0.07
children	0.02	0.01	1.66	0.097	-0.00	0.04
organi_2	0.02	0.01	2.13	0.033	0.00	0.04
organi_3	0.00	0.01	0.35	0.724	-0.01	0.02
organi_4	0.03	0.01	2.98	0.003	0.01	0.05
_cons	0.42	0.212	2.03	0.042	0.02	0.83

Appendix 10: OB decomposition Broad Graduate 9

Blinder-Oaxaca decomposition				Number of obs = 6200		
Model = Linear # of obs 1 = 2576				Model = Broad Graduate 9 # of obs 2 = 3624		
Lnwage	Coef.	Std.	Err.	z	P>|z|	[95% Conf. Interval]
overall						
group_1	7.930	0.013	614.71	0	7.905	7.956
group_2	7.549	0.011	678.19	0	7.527	7.571
difference	0.381	0.017	22.38	0	0.348	0.415
explained	0.225	0.012	17.98	0	0.20	0.249
unexplained	0.157	0.014	11.23	0	0.129	0.184
explained						
age	0.024	0.024	1.01	0.314	-0.023	0.0708
agesquared	-0.0215	0.022	-0.99	0.32	-0.064	0.021
working hour	0.130	0.009	13.84	0	0.112	0.149
parttime	0.065	0.006	10.85	0	0.054	0.077
private	0.001	0.003	0.32	0.746	-0.005	0.007
London	0.0009	0.002	0.58	0.559	-0.002	0.004
married	0.010	0.002	5.08	0	0.006	0.014
children	-3.1E-05	0.000	-0.13	0.894	-0.00	0.000
organi_2	-0.00425	0.002	-2.63	0.009	-0.007	-0.001
organi_3	0.009	0.003	3.51	0	0.004	0.014
organi_4	0.009	0.004	2.22	0.027	0.001	0.017
unexplained						
age	0.651	0.441	1.48	0.139	-0.212	1.515
agesquared	-0.301	0.239	-1.26	0.208	-0.769	0.167
working hour	-0.474	0.095	-4.99	0	-0.66	-0.288
parttime	-0.035	0.009	-3.81	0	-0.05	-0.017
private	0.0568	0.015	3.7	0	0.027	0.087
London	-0.008	0.006	-1.36	0.172	-0.019	0.003
married	0.005	0.020	0.29	0.774	-0.03	0.044
children	0.026	0.013	2.07	0.039	0.001	0.052
organi_2	0.004	0.010	0.45	0.651	-0.015	0.023
organi_3	-0.002	0.009	-0.24	0.81	-0.021	0.016
organi_4	0.017	0.011	1.52	0.127	-0.005	0.040
_cons	0.214	0.221	0.97	0.332	-0.219	0.648

Appendix 11: Quantile regression for all worker data-set

Decomposition of differences in distribution using quantile regression

Model = All Worker Data-set

Total number of observations 11119 No. of quantile regressions estimated 100

No. of observations women 6229 No. of observations men 4890

	quantile	fitted_1	fitted_X1C0	fitted_0	total_diff~l	characteri~s	coefficients	se_total_d~l	se_charact~s	se_coeffic~s
r1	0.100	6.922	6.820	6.349	0.573	0.471	0.102	0.023	0.016	0.015
r2	0.200	7.267	7.186	6.738	0.528	0.447	0.081	0.011	0.011	0.011
r3	0.300	7.461	7.364	7.014	0.447	0.350	0.097	0.010	0.012	0.009
r4	0.400	7.621	7.506	7.220	0.401	0.286	0.116	0.010	0.013	0.007
r5	0.500	7.772	7.640	7.389	0.382	0.251	0.131	0.010	0.012	0.005
r6	0.600	7.926	7.780	7.550	0.376	0.231	0.146	0.010	0.011	0.004
r7	0.700	8.090	7.931	7.718	0.372	0.213	0.159	0.009	0.010	0.004
r8	0.800	8.279	8.108	7.915	0.364	0.193	0.171	0.008	0.010	0.006
r9	0.900	8.540	8.352	8.175	0.364	0.177	0.188	0.008	0.014	0.013

Note: The variance has been estimated by bootstrapping the results 100 times, Standard Error (se),

Appendix 12: Quantile regression for Just Graduate (Wave 9)

Decomposition of differences in distribution using quantile regression

Model = Just Graduate 9

Total number of observations 2613 No. of quantile regressions estimated 100

No. of observations women 1541 No. of observations men 1072

	quantile	fitted_1	fitted_X1C0	fitted_0	total_diff~l	characteri~s	coefficients	se_total_d~l	se_charact~s	se_coeffic~s
r1	0.100	7.220	7.126	6.728	0.492	0.398	0.095	0.036	0.041	0.034
r2	0.200	7.507	7.400	7.109	0.398	0.291	0.107	0.030	0.027	0.022
r3	0.300	7.699	7.565	7.334	0.365	0.231	0.134	0.027	0.024	0.013
r4	0.400	7.855	7.701	7.501	0.355	0.200	0.154	0.022	0.025	0.011
r5	0.500	7.994	7.831	7.643	0.351	0.188	0.164	0.018	0.022	0.011
r6	0.600	8.131	7.962	7.783	0.349	0.180	0.169	0.017	0.018	0.011
r7	0.700	8.274	8.099	7.931	0.343	0.168	0.175	0.018	0.016	0.011
r8	0.800	8.444	8.248	8.090	0.354	0.158	0.195	0.022	0.017	0.013
r9	0.900	8.671	8.462	8.297	0.374	0.165	0.209	0.021	0.024	0.020

Note: The variance has been estimated by bootstrapping the results 100 times, Standard Error (se),

Appendix 13: Quantile regression for Master/PhD (Wave 9)

Decomposition of differences in distribution using quantile regression

Model = Masters/PhD 9
Total number of observations 4624 No. of quantile regressions estimated 100
No. of observations women 2606 No. of observations men 2018

	quantile	fitted_1	fitted_X1C0	fitted_0	total_diff~l	characteri~s	coefficients	se_total_d~l	se_charact~s	se_coeffic~s
r1	0.100	7.246	7.152	6.805	0.441	0.346	0.095	0.020	0.018	0.028
r2	0.200	7.548	7.439	7.170	0.378	0.269	0.109	0.015	0.014	0.018
r3	0.300	7.741	7.616	7.392	0.349	0.224	0.125	0.015	0.013	0.014
r4	0.400	7.900	7.761	7.560	0.340	0.201	0.140	0.014	0.014	0.012
r5	0.500	8.043	7.895	7.707	0.336	0.187	0.148	0.013	0.015	0.011
r6	0.600	8.182	8.030	7.851	0.331	0.179	0.152	0.012	0.017	0.011
r7	0.700	8.330	8.169	7.999	0.331	0.170	0.161	0.012	0.019	0.012
r8	0.800	8.504	8.327	8.163	0.342	0.164	0.177	0.014	0.021	0.014
r9	0.900	8.739	8.548	8.382	0.357	0.167	0.190	0.015	0.026	0.017

Note: The variance has been estimated by bootstrapping the results 100 times, Standard Error (se),

Appendix 14: Quantile regression for Broad Graduate (Wave 1)

Decomposition of differences in distribution using quantile regression

Model = Broad Graduate 1
Total number of observations 9300 No. of quantile regressions estimated 100
No. of observations women 5258 No. of observations men 4042

	quantile	fitted_1	fitted_X1C0	fitted_0	total_diff~l	characteri~s	coefficients	se_total_d~l	se_charact~s	se_coeffic~s
r1	0.100	6.807	6.750	6.410	0.397	0.340	0.057	0.010	0.017	0.020
r2	0.200	7.242	7.127	6.852	0.390	0.275	0.115	0.010	0.013	0.014
r3	0.300	7.495	7.331	7.118	0.377	0.213	0.163	0.008	0.010	0.012
r4	0.400	7.678	7.492	7.311	0.368	0.181	0.186	0.008	0.008	0.010
r5	0.500	7.832	7.640	7.474	0.358	0.166	0.192	0.008	0.008	0.009
r6	0.600	7.975	7.788	7.631	0.345	0.157	0.187	0.008	0.008	0.007
r7	0.700	8.123	7.944	7.790	0.333	0.154	0.179	0.010	0.009	0.008
r8	0.800	8.296	8.122	7.971	0.324	0.151	0.173	0.011	0.010	0.010
r9	0.900	8.540	8.365	8.207	0.333	0.158	0.175	0.014	0.013	0.014

Note: The variance has been estimated by bootstrapping the results 100 times, Standard Error (se),

Appendix 15: Quantile regression for Broad Graduate (Wave 5)

Decomposition of differences in distribution using quantile regression

Model = Broad Graduate 5

Total number of observations	7486	No. of quantile regressions estimated	100
No. of observations women	4376	No. of observations men	3110

	quantile	fitted_1	fitted_X1C0	fitted_0	total_diff~l	characteri~s	coefficients	se_total_d~l	se_charact~s	se_coeffic~s
r1	0.100	6.989	6.856	6.462	0.527	0.394	0.134	0.027	0.025	0.021
r2	0.200	7.345	7.202	6.884	0.460	0.318	0.142	0.016	0.016	0.016
r3	0.300	7.558	7.405	7.138	0.420	0.267	0.153	0.013	0.014	0.012
r4	0.400	7.732	7.569	7.328	0.404	0.242	0.162	0.012	0.014	0.011
r5	0.500	7.885	7.718	7.496	0.389	0.222	0.166	0.011	0.013	0.010
r6	0.600	8.034	7.862	7.657	0.377	0.206	0.171	0.011	0.013	0.009
r7	0.700	8.184	8.010	7.822	0.362	0.188	0.174	0.012	0.013	0.009
r8	0.800	8.360	8.173	8.001	0.359	0.172	0.187	0.014	0.014	0.009
r9	0.900	8.610	8.408	8.232	0.378	0.176	0.202	0.016	0.019	0.012

Note: The variance has been estimated by bootstrapping the results 100 times, Standard Error (se),

Appendix 16: Quantile regression for Broad Graduate (Wave 9)

Decomposition of differences in distribution using quantile regression

Model = Broad Graduate 9

Total number of observations	6200	No. of quantile regressions estimated	100
No. of observations women	3624	No. of observations men	2576

	quantile	fitted_1	fitted_X1C0	fitted_0	total_diff~l	characteri~s	coefficients	se_total_d~l	se_charact~s	se_coeffic~s
r1	0.100	7.171	7.072	6.687	0.484	0.385	0.098	0.024	0.021	0.022
r2	0.200	7.476	7.357	7.055	0.421	0.302	0.119	0.015	0.014	0.017
r3	0.300	7.672	7.533	7.285	0.387	0.248	0.139	0.013	0.013	0.014
r4	0.400	7.836	7.677	7.459	0.376	0.217	0.159	0.013	0.012	0.012
r5	0.500	7.984	7.811	7.613	0.372	0.198	0.173	0.013	0.013	0.011
r6	0.600	8.129	7.947	7.760	0.369	0.187	0.181	0.012	0.014	0.011
r7	0.700	8.277	8.091	7.915	0.362	0.176	0.185	0.013	0.014	0.012
r8	0.800	8.450	8.252	8.087	0.363	0.164	0.198	0.014	0.015	0.012
r9	0.900	8.688	8.474	8.310	0.378	0.164	0.214	0.015	0.018	0.014

Note: The variance has been estimated by bootstrapping the results 100 times, Standard Error (se),

Appendix 17: Origin and subsequent models of Fontana and Wood (2000)

One of the first people to disaggregate the labour market by gender were Fontana and Wood (2000). They included gender component by leisure activity and work in households for analyzing effects of trade liberalization (using CGE models). Leisure activity and work can be thought of as a new sector in their model. This was done by including time element in the social accounting matrix (SAM). It showed how much time households (which were disaggregated by gender) were spending on various tasks: In this case it was market work and non-market work (leisure time). Fontana and Wood (2000) discuss the technical issues of making such a model especially of incorporating leisure time in the CGE. Their study assumed low levels (elasticity) of substitution between female and male labour especially in the household production sector. Their simulation provided insight into the effects of trade policies on gender.

After this study, Fontana (2001) extended the social accounting matrix framework to include more market related activities for an analysis of trade policy in Bangladesh. Fontana extended the model by adding labour categories differentiated by gender and the level of education in the households. The main difference of this paper as compared to the last paper lies in the households. Here the members of households produce social reproduction as per their education. The study finds that effects on trade differ by households when education is considered. Extending further upon this work a similar study by Fontana (2002) was done for Zambia. This served as a good benchmark for comparison with the previous study on Bangladesh. They found that affects varied greatly by country and affects were mainly influenced by the key parameter which is elasticity of substitution. The larger the elasticity of substitution they found, the more negative impact of a reduction in garment manufacturing on women. This was found to be true for both countries. However, results varied in magnitude. In the case of Bangladesh, the reduction in tariffs on manufactured imports caused less employment increase and overall gains for women than compared to Zambia. The opposite was found to be true in the case of agricultural exports. For agricultural exports more benefits were accrued by Zambian women than Bangladeshi women.

Fontana (2004) specifically highlights differences in labour market characteristics, resource allocation and socio-cultural norms for trade expansion for gender in different countries. Her work suggests that liberalization of trade (less tariffs) has more value in labour abundant countries like Bangladesh rather than a country abundant in resource like Zambia. The conclusion of these studies is that results vary significantly when household leisure and production are measured as opposed to when these non-market activities are not considered. The impact is different for both women's wage and employment under the measured extended CGE. Similar results were found by Fofana, et al (2003) about the impact of liberalization of trade on women and men when household participation was considered. Prior to this, most social accounting Matrix`s were extended by disaggregating labour by gender or by disaggregating head of household (Sangita and Anushree, 2003).

Sangita and Anushree (2003) conduct a study that disaggregates the economy by female intensive informal sectors and by make intensive formal sectors. After running the simulation, they find that reduction in tariff has a negative effect on women's earning in the informal sector. So, the parameters chosen by the researcher become of utmost importance as economic reforms are dependent not just on household type and education level. They argue that including the informal sector can have great impact on results.

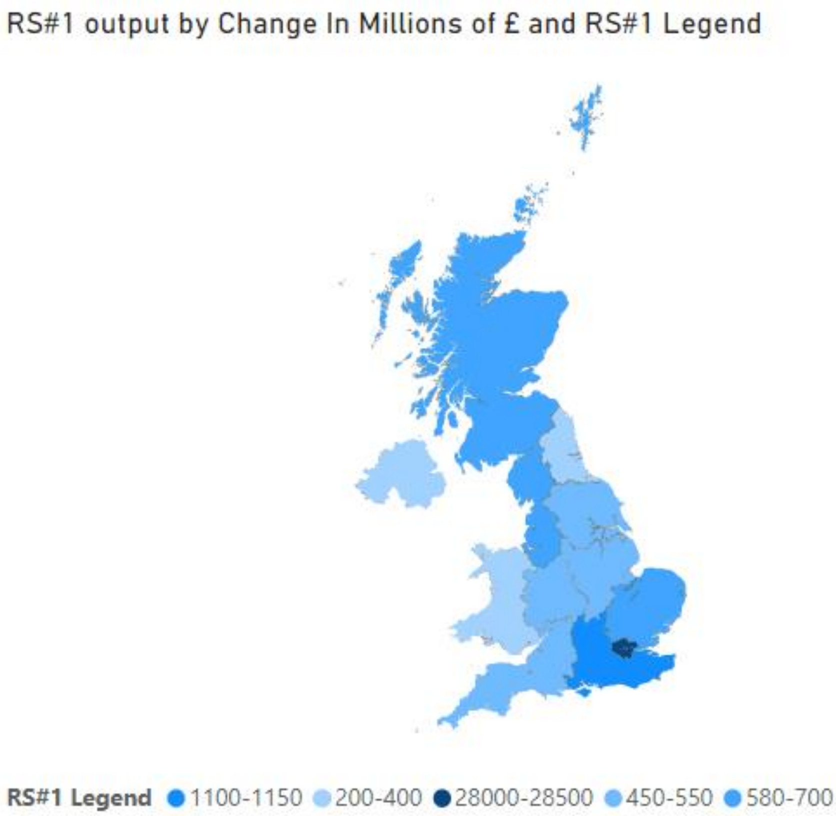
In the studies mentioned above governmental consumption and investment (in final demand) are both assumed to be fixed at a base level. Along with this, current account is also assumed to be fixed. Results therefore are driven by varying socio-economic structures of countries rather than behavior patterns of consumers and households. The studies mentioned above point to the fact that despite women's increase in participation, gender division within the households has remained unequal. The studies show that level of education is also a key component of gender allocation of time. The results in studies by Fontana reveal that differences are greater for lower educated, less earning females as compared to highly educated females. The results differed as mentioned above in both countries and differ by continents (as we will discuss later). The higher the level of elasticity of substitution, the more the increase in labour force participation for women with little to no education. The effect was also marginally higher for secondary educated women as compared to highly educated women.

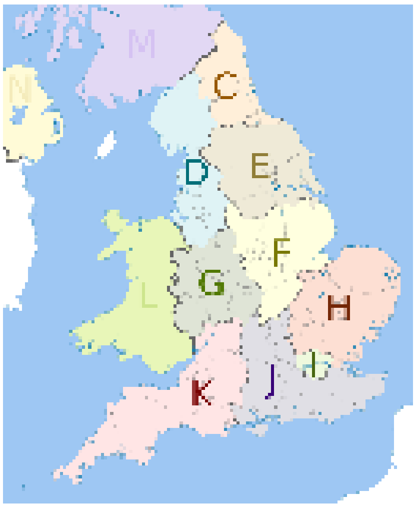
Schaffer and Stahmer (2006) have also done large amounts of work on gender specific input-output table studies. They extended the input-output framework by identifying men's and women's contribution to gross domestic product. Gunluk and Sensen (2011) further extended the framework by studying the impact of sectors on male and female employment in Turkey (2011). Petrongolo and Olivetti (2014) identified key forces using a multi-sectoral approach within and between industries that affect gender and skill to find evidence of differences in wages and hours between the genders. Another interesting study was conducted by (Aslamawi et al., 2014) who looked at the labour issues differences between genders.

Appendix 18: List of data used to convert and disaggregate gender compensation

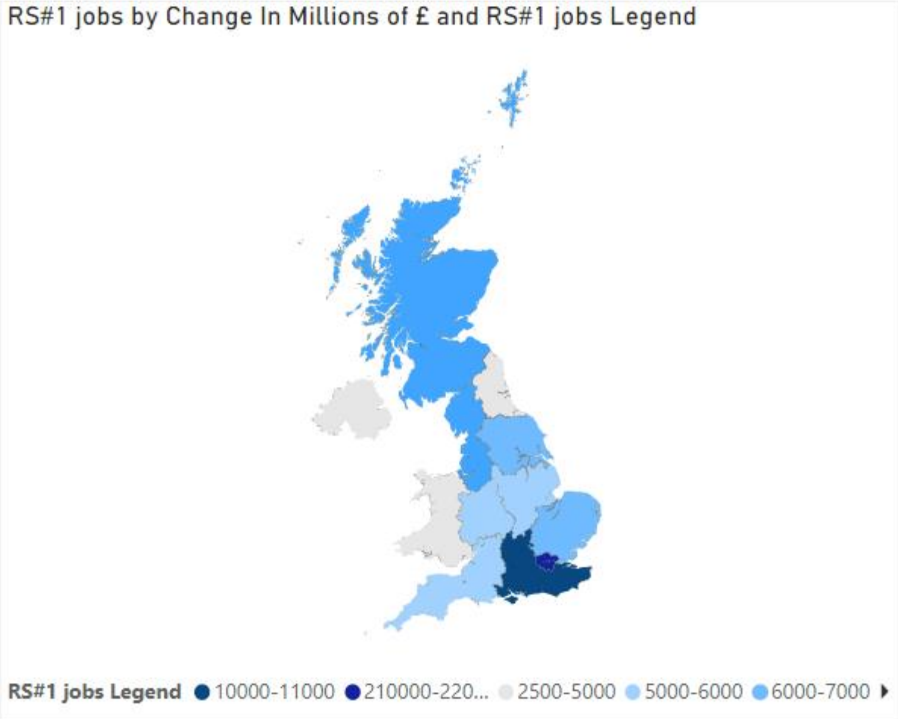
- SEIM-UK NUTS 2 – *City-REDI Institute*
- R Package. "ioanalysis" Authors (John Wade, Ignacio Sarmiento-Barbieri) (https://sites.google.com/view/jjpwade/r-packages/ioanalysis)
- Sic07 Work Region Industry (2) SIC2007 Table 5.12 Gender pay gap 2016 – Office for National Statistics (https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/datasets/regionbyindustry2digitsicashetable5)

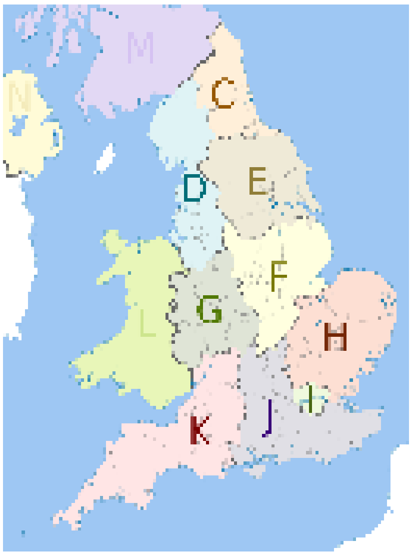
Appendix 19:RS#1 Output



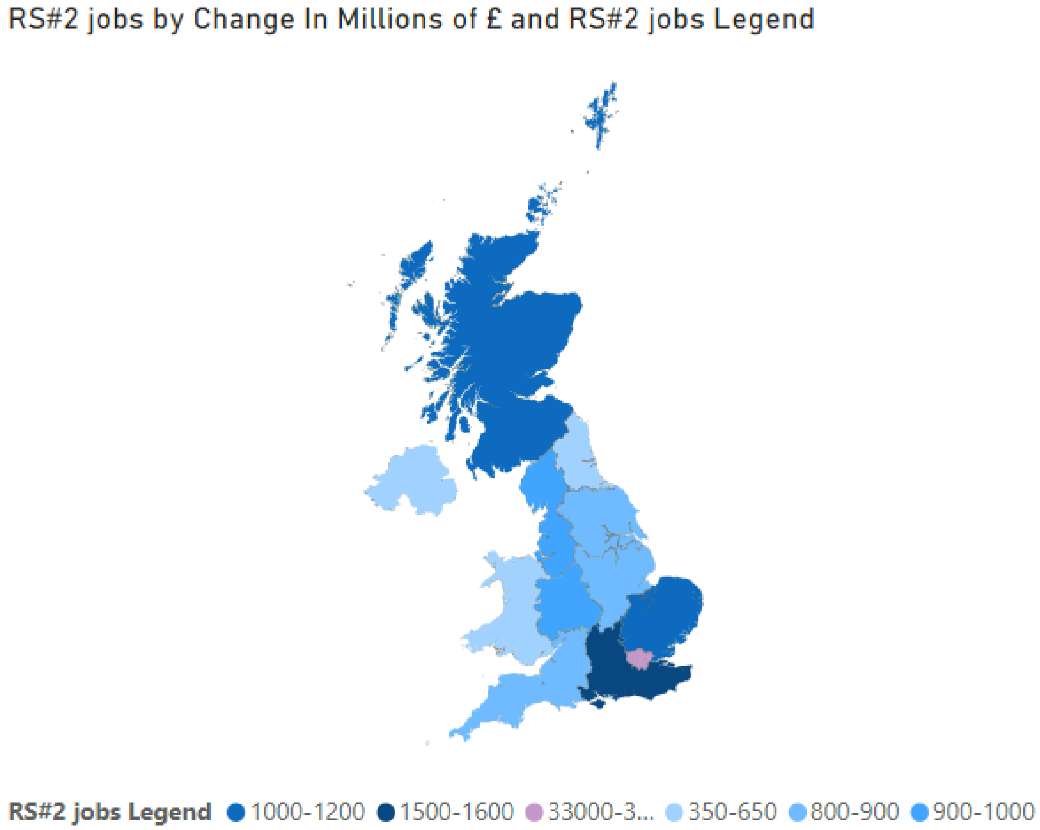


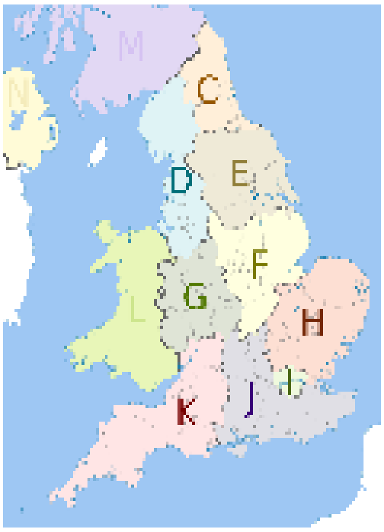
Appendix 20: RS# 1 Jobs





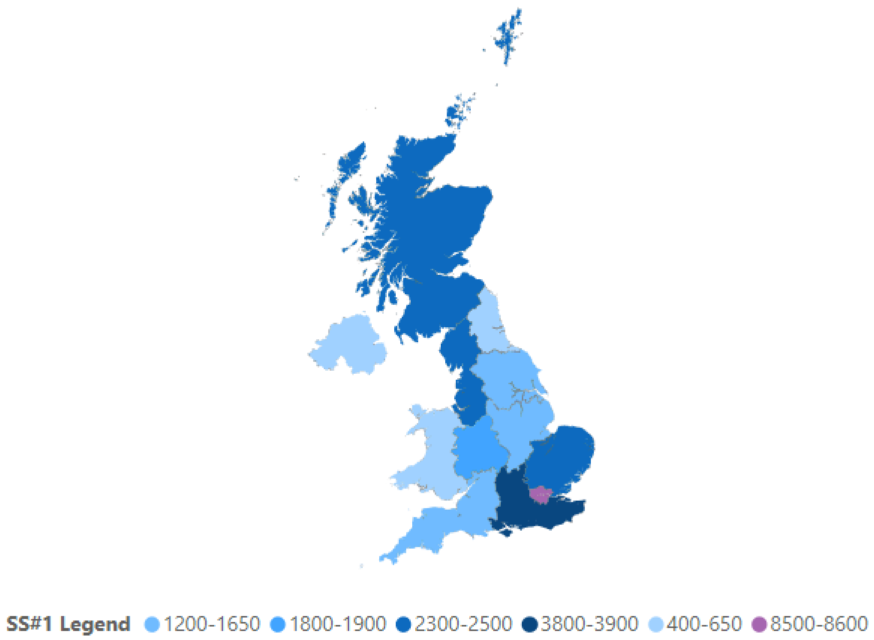
Appendix 21: RS# 2 Jobs

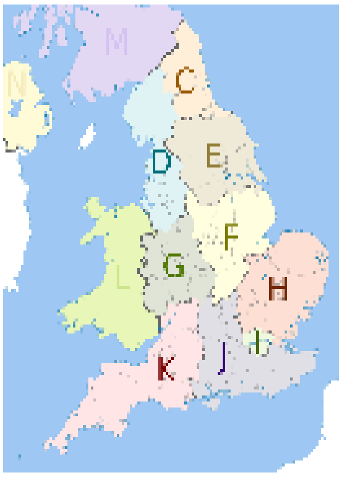




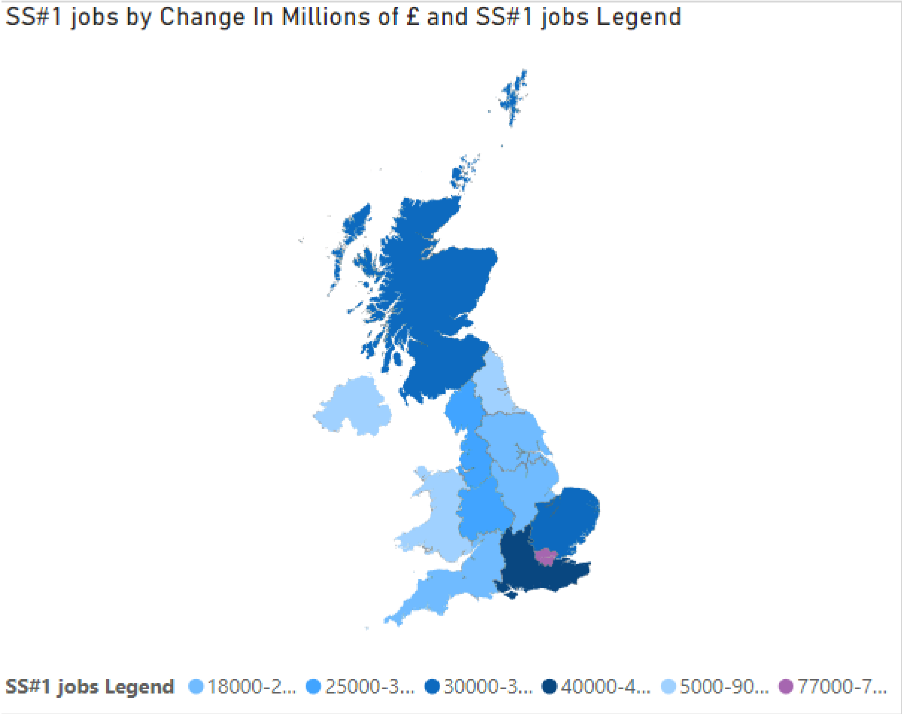
Appendix 22: SS#1 Output

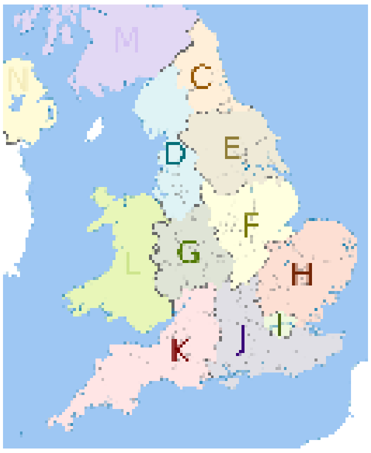
SS#1 output by Change In Millions of £ and SS#1 Legend



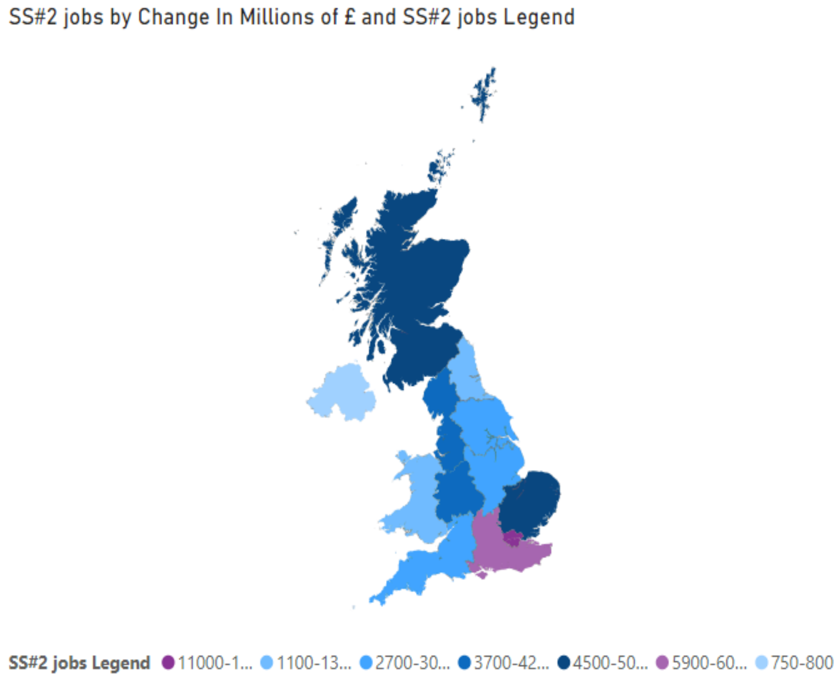


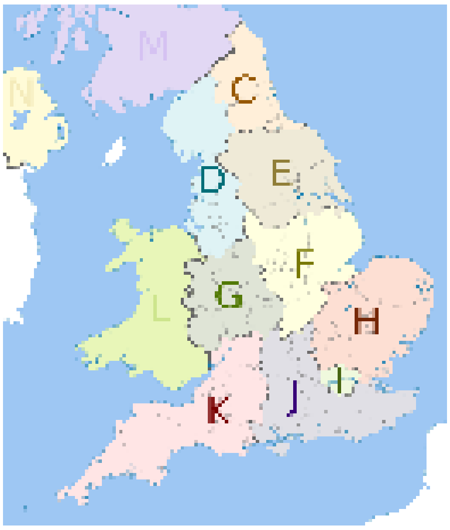
Appendix 23:SS# 1 Jobs





Appendix 24: SS#2 Jobs





Appendix 25:Conversion of IO model ONS to SEIM-UK based on sectors (using SIC codes)

Code_30	Sector (SEIM-UK)	Sectors Combined/Conversion (ONS)		
A	Agriculture, forestry, and fishing	Products of agriculture, hunting and related services	Products of forestry, logging and related services	Fish and other fishing products; aquaculture products; support services to fishing
B	Mining and quarrying	Mining and quarrying		
CA	Manufacture of food, beverages and tobacco	Food products, beverages and tobacco products		
CB	Manufacture of textiles, wearing apparel and leather	Textiles, wearing apparel and leather products		
CC	Manufacture of wood and paper products and printing	Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials	Paper and paper products	Printing and recording services
CD-CF	Manufacture of petroleum, chemicals and pharmaceuticals	Coke and refined petroleum products	Chemicals and chemical products	Basic pharmaceutical products and pharmaceutical preparations
CG	Manufacture of rubber, plastic and non-metallic minerals	Rubber and plastics products	Other non-metallic mineral products	
CH	Manufacture of basic and fabricated metal products	Basic metals	Fabricated metal products, except machinery and equipment	

CI	Manufacture of computer, electronic and optical products	Computer, electronic and optical products				
CJ	Manufacture of electrical equipment	Electrical equipment				
CK	Manufacture of machinery and equipment	Machinery and equipment n.e.c.				
CL	Manufacture of transport equipment	Motor vehicles, trailers and semi-trailers	Other transport equipment			
CM	Other manufacturing, repair and installation	Furniture; other manufactured goods	Repair and installation services of machinery and equipment			
D	Electricity, gas, steam and air-conditioning supply	Electricity, gas, steam and air-conditioning				
E	Water supply; sewerage and waste management	Natural water; water treatment and supply services	Sewerage; waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services			
F	Construction	Constructions and construction works				
G	Wholesale and retail trade; repair of motor vehicles	Wholesale and retail trade and repair services of motor vehicles and motorcycles	Wholesale trade services, except of motor vehicles and motorcycles	Retail trade services, except of motor vehicles and motorcycles		
H	Transportation and storage	Land transport services and transport services via pipelines	Water transport services	Air transport services	Warehousing and support services for transportation	Postal and courier services
I	Accommodation and food service activities	Accommodation and food services	Publishing services			

J	Information and communication	Motion picture, video and television programme production services, sound recording and music publishing; programming and broadcasting services	Telecommunications services	Computer programming, consultancy and related services; information services		
K	Financial and insurance activities	Financial services, except insurance and pension funding	Insurance, reinsurance and pension funding services, except compulsory social security	Services auxiliary to financial services and insurance services		
L	Real estate activities	Real estate services excluding imputed rents	Imputed rents of owner-occupied dwellings			
M	Professional, scientific and technical activities	Legal and accounting services; services of head offices; management consulting services	Architectural and engineering services; technical testing and analysis services	Scientific research and development services	Advertising and market research services	Other professional, scientific and technical services; veterinary services
N	Administrative and support service activities	Rental and leasing services	Employment services	Travel agency, tour operator and other reservation services and related services	Security and investigation services; services to buildings and landscape; office administrative, office support and other business support services	
O	Public administration and defence; compulsory social security	Public administration and defence services; compulsory social security services				
P	Education	Education services				
Q	Human health and social work activities	Human health services	Social work services			

R	Arts, entertainment and recreation	Creative, arts and entertainment services; library, archive, museum and other cultural services; gambling and betting services	Sporting services and amusement and recreation services	
S	Other service activities	Services furnished by membership organisations	Repair services of computers and personal and household goods	Other personal services
T	Activities of households	Services of households as employers; undifferentiated goods and services produced by households for own use		

Appendix 26: Sectoral results (change in millions of pounds by the 30 sectors including ONS model)

Code	Sector name	*RS#1 output*	*RS#1 jobs*	*RS#2 output*	*RS#2 jobs*	*SS#1 output*	*SS#1 jobs*	*SS#2 output*	*SS#2 jobs*	*SS#1 output (IO)*	*SS#2 output (IO)*
s1	Agriculture, forestry and fishing	33.81	198.32	5.13	30.07	36.01	217.21	5.26	31.70	71.47	10.46
s2	Mining and quarrying	26.57	55.16	3.97	8.30	15.54	48.77	2.26	7.10	73.63	10.78
s3	Manufacture of food, beverages and tobacco	217.18	944.05	33.29	144.13	131.67	744.92	19.24	108.89	293.39	42.93
s4	Manufacture of textiles, wearing apparel and leather	136.74	214.47	20.23	31.92	79.83	197.67	11.68	28.94	23.37	3.42
s5	Manufacture of wood and paper products and printing	149.14	767.22	22.68	116.54	123.25	683.40	18.02	99.95	39.92	5.84
s6	Manufacture of petroleum, chemicals and pharmaceuticals	155.85	163.77	23.46	24.71	197.20	254.13	28.85	37.18	151.69	22.20
s7	Manufacture of rubber, plastic and non-metallic minerals	157.43	507.04	23.90	76.96	115.14	398.74	16.84	58.33	65.36	9.56
s8	Manufacture of basic and fabricated metal products	98.40	459.69	14.57	68.31	48.12	277.88	7.04	40.63	56.01	8.19
s9	Manufacture of computer, electronic and optical products	87.68	149.29	12.95	22.41	52.14	143.01	7.62	20.91	49.68	7.27

s10	Manufacture of electrical equipment	89.64	159.26	13.29	23.93	49.18	131.84	7.19	19.28	29.04	4.25
s11	Manufacture of machinery and equipment	80.84	218.42	12.26	33.08	107.11	308.77	15.66	45.14	48.99	7.17
s12	Manufacture of transport equipment	268.95	622.69	40.80	94.27	529.39	1409.29	77.45	206.24	171.31	25.07
s13	Other manufacturing, repair and installation	139.14	609.42	21.22	92.79	147.21	692.64	21.51	101.25	82.76	12.11
s14	Electricity, gas, steam and air-conditioning supply	125.44	215.72	19.26	33.05	88.59	176.56	12.94	25.79	447.00	65.37
s15	Water supply; sewerage and waste management	11.02	47.80	-2.82	-10.97	246.84	1003.22	36.07	146.65	68.36	10.00
s16	Construction	1217.27	7232.59	185.53	1101.59	242.58	1833.03	35.45	267.87	648.24	94.85
s17	Wholesale and retail trade; repair of motor vehicles	3170.18	35462.38	483.14	5399.93	2106.56	26781.13	308.00	3915.24	983.18	143.86
s18	Transportation and storage	1326.55	8619.02	203.09	1315.19	834.24	6585.48	121.93	962.70	256.93	37.59
s19	Accommodation and food service activities	936.83	16335.43	143.06	2489.21	544.67	10519.31	79.59	1537.36	385.52	56.41
s20	Information and communication	3104.24	16526.17	477.22	2538.14	1035.37	6439.25	151.35	941.22	658.09	96.30
s21	Financial and insurance activities	7341.94	22062.21	1086.15	3265.02	1635.41	5810.72	238.83	848.71	1083.06	158.48
s22	Real estate activities	1349.33	1895.42	203.76	286.16	560.69	849.51	81.95	124.16	530.69	77.65
s23	Professional, scientific and technical activities	6251.47	70298.95	942.38	10596.19	14676.14	202622.68	2145.02	29616.64	11124.17	1627.92

s24	Administrative and support service activities	414.22	3237.17	63.90	498.04	252.88	2602.62	36.96	380.46	399.69	58.48
s25	Public administration and defence; compulsory social security	1262.25	10486.40	194.48	1614.45	1192.22	10634.54	174.14	1553.01	403.23	59.00
s26	Education	1725.29	26050.78	264.00	3983.43	526.61	10102.61	76.98	1477.07	198.65	29.07
s27	Human health and social work activities	2730.63	42286.03	411.18	6365.56	1116.16	20170.74	163.10	2947.50	452.86	66.26
s28	Arts, entertainment and recreation	912.97	8369.39	134.79	1238.79	179.79	2423.50	26.28	354.13	210.73	30.83
s29	Other service activities	816.54	8152.48	124.14	1239.18	264.10	2884.65	38.60	421.57	99.80	14.60
s30	Activities of households	-67.03	0.00	-11.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Appendix 27: Model 1

Model 1

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Male	.111	.054	4.230	1	.040	1.117
	25-34	-.246	.098	6.320	1	.012	.782
	35-44	-.698	.101	47.953	1	.000	.498
	45-54	-.809	.098	67.639	1	.000	.445
	55+	-.684	.095	51.370	1	.000	.504
	Degree	-.807	.070	131.789	1	.000	.446
	A levels	-.166	.074	5.105	1	.024	.847
	Other qualification	.288	.112	6.614	1	.010	1.333
	No qualification	.059	.172	.117	1	.732	1.061
	Constant	-.283	.093	9.255	1	.002	.753

Nagelkerke (R Square): 0.065

N: 7969

Chi-Square: p< .000

Appendix 28: Model 2

Model 2

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Male	.098	.067	2.130	1	.144	1.103
	25-34	.091	.118	.599	1	.439	1.096
	35-44	-.064	.122	.279	1	.597	.938
	45-54	-.112	.119	.877	1	.349	.894
	55+	-.003	.115	.001	1	.978	.997
	Degree	-.595	.086	47.738	1	.000	.552
	A levels	-.089	.088	1.018	1	.313	.915
	Other qualification	.191	.137	1.944	1	.163	1.210
	No qualification	.048	.208	.053	1	.817	1.049
	Self-Employed	-3.039	.163	346.900	1	.000	.048
	Employed & Self-Employed	-.152	.174	.764	1	.382	.859
	Working hours	.003	.003	1.407	1	.236	1.003
	Fixed Salary	-.786	.072	119.088	1	.000	.456
	Temporary	-.271	.124	4.786	1	.029	.762
	middle income	-.373	.079	22.262	1	.000	.688
	High income 3001-4500	-.959	.160	35.897	1	.000	.383
	elite income 4500+	-.949	.244	15.141	1	.000	.387
	Key worker	-2.644	.081	1066.187	1	.000	.071
	Telecommute	-.756	.081	86.093	1	.000	.469
	Constant	.886	.135	43.346	1	.000	2.426

Nagelkerke (R Square): 0.387

N: 7969

Chi-Square: p< .000

Appendix 29 Model 3 A

Model 3 A

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Male	-.139	.095	2.112	1	.146	.870
	25-34	-.099	.143	.482	1	.487	.906
	35-44	-.298	.149	4.031	1	.045	.742
	45-54	-.272	.145	3.542	1	.060	.762
	55+	-.064	.143	.202	1	.653	.938
	Degree	-.476	.098	23.824	1	.000	.621
	A levels	-.038	.097	.155	1	.693	.962
	Other qualification	.220	.151	2.128	1	.145	1.247
	No qualification	-.324	.250	1.686	1	.194	.723
	Self-Employed	-2.671	.203	173.900	1	.000	.069
	Employed & Self-Employed	.207	.191	1.177	1	.278	1.230
	Working hours	-.002	.003	.435	1	.510	.998
	Fixed Salary	-.543	.082	43.415	1	.000	.581
	Temporary	-.037	.134	.078	1	.780	.963
	middle income	-.536	.131	16.746	1	.000	.585
	High income 3001-4500	-1.129	.181	38.821	1	.000	.323
	elite income 4500+	-1.375	.301	20.912	1	.000	.253
	Key worker	-2.509	.088	807.222	1	.000	.081
	Telecommute	-.716	.092	60.471	1	.000	.489
	1 is private, 0 other	.926	.089	107.731	1	.000	2.525
	MANAGERS, DIRECTORS AND SENIOR OFFICIALS	-.355	.164	4.669	1	.031	.701
	PROFESSIONAL OCCUPATIONS	-.975	.191	26.001	1	.000	.377
	ASSOCIATE PROFESSIONAL AND TECHNICAL OCCUPATIONS	-.576	.168	11.824	1	.001	.562
	ADMINISTRATIVE AND SECRETARIAL OCCUPATIONS	-.697	.171	16.669	1	.000	.498

	SKILLED TRADES OCCUPATIONS	-.343	.172	3.996	1	.046	.710
	CARINGLEISURE AND OTHER SERVICE OCCUPATIONS	-.619	.188	10.872	1	.001	.538
	SALES AND CUSTOMER SERVICE OCCUPATIONS	-.580	.180	10.421	1	.001	.560
	ELEMENTARY OCCUPATIONS	-.370	.165	5.054	1	.025	.691
	middleman	.341	.155	4.806	1	.028	1.406
	Constant	.866	.242	12.849	1	.000	2.378

Nagelkerke (R Square): 0.419

N: 7028

Chi-Square: p< .000

Appendix 30 Model 3 B

Model 3B

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	25-34	-.372	.216	2.964	1	.085	.690
	35-44	-.692	.225	9.446	1	.002	.500
	45-54	-.446	.221	4.083	1	.043	.640
	55+	-.466	.216	4.638	1	.031	.627
	Degree	-.615	.139	19.602	1	.000	.541
	A levels	.203	.133	2.333	1	.127	1.225
	Other qualification	.211	.201	1.102	1	.294	1.235
	No qualification	.010	.354	.001	1	.978	1.010
	Self-Employed	-2.696	.267	101.945	1	.000	.067
	Employed & Self-Employed	.083	.263	.100	1	.752	1.086
	Working hours	-.011	.005	4.648	1	.031	.990
	Fixed Salary	-.452	.117	15.062	1	.000	.636
	Temporary	-.220	.204	1.164	1	.281	.802
	middle income	-.118	.117	1.011	1	.315	.889
	High income 3001-4500	-.947	.216	19.169	1	.000	.388
	elite income 4500+	-1.141	.344	11.022	1	.001	.320
	Key worker	-2.415	.124	380.216	1	.000	.089
	Telecommute	-.610	.128	22.857	1	.000	.543
	1 is private, 0 other	.972	.138	49.585	1	.000	2.644
	MANAGERS, DIRECTORS AND SENIOR OFFICIALS	-.627	.191	10.793	1	.001	.534
	PROFESSIONAL OCCUPATIONS	-1.284	.231	30.803	1	.000	.277
	ASSOCIATE PROFESSIONAL AND TECHNICAL OCCUPATIONS	-.780	.201	15.012	1	.000	.458
	ADMINISTRATIVE AND SECRETARIAL OCCUPATIONS	-.825	.236	12.209	1	.000	.438
	SKILLED TRADES OCCUPATIONS	-.571	.181	9.912	1	.002	.565

CARINGLEISURE AND OTHER SERVICE OCCUPATIONS	-.711	.314	5.126	1	.024	.491
SALES AND CUSTOMER SERVICE OCCUPATIONS	-.763	.239	10.172	1	.001	.466
ELEMENTARY OCCUPATIONS	-.526	.191	7.558	1	.006	.591
Constant	1.323	.350	14.270	1	.000	3.756

Nagelkerke (R Square): 0.420

N: 3525

Chi-Square: p< .000

Appendix 31 Model 3 C

Model 3C

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	25-34	.018	.201	.008	1	.928	1.018
	35-44	.001	.206	.000	1	.996	1.001
	45-54	-.218	.199	1.202	1	.273	.804
	55+	.185	.198	.871	1	.351	1.203
	Degree	-.339	.141	5.761	1	.016	.713
	A levels	-.298	.148	4.067	1	.044	.743
	Other qualification	.271	.239	1.293	1	.256	1.312
	No qualification	-.633	.360	3.080	1	.079	.531
	Self-Employed	-2.635	.321	67.589	1	.000	.072
	Employed & Self-Employed	.455	.283	2.577	1	.108	1.576
	Working hours	.008	.005	2.613	1	.106	1.008
	Fixed Salary	-.725	.121	35.816	1	.000	.484
	Temporary	.073	.181	.161	1	.688	1.076
	middle income	-.715	.146	24.065	1	.000	.489
	High income 3001-4500	-1.396	.356	15.344	1	.000	.247
	elite income 4500+	-1.739	.682	6.508	1	.011	.176
	Key worker	-2.718	.132	425.430	1	.000	.066
	Telecommute	-.920	.138	44.107	1	.000	.399
	1 is private, 0 other	.912	.121	56.849	1	.000	2.490
	MANAGERS, DIRECTORS AND SENIOR OFFICIALS	1.088	.426	6.538	1	.011	2.969
	PROFESSIONAL OCCUPATIONS	.583	.454	1.648	1	.199	1.791
	ASSOCIATE PROFESSIONAL AND TECHNICAL OCCUPATIONS	.755	.423	3.175	1	.075	2.127
	ADMINISTRATIVE AND SECRETARIAL OCCUPATIONS	.592	.414	2.047	1	.153	1.808
	SKILLED TRADES OCCUPATIONS	1.088	.549	3.923	1	.048	2.969

CARINGLEISURE AND OTHER SERVICE OCCUPATIONS	.604	.422	2.047	1	.153	1.830
SALES AND CUSTOMER SERVICE OCCUPATIONS	.766	.424	3.268	1	.071	2.151
ELEMENTARY OCCUPATIONS	.902	.423	4.547	1	.033	2.465
Constant	-.639	.476	1.806	1	.179	.528

Nagelkerke (R Square): 0.437

N: 3502

Chi-Square: $p < .000$

Appendix 32 SOC 2000

Current job: SOC 2000, condensed			
Missing	2.3	Administrative occupations: government and related organisations	1.1
inapplicable	9.2	Administrative occupations: finance	2.5
Refusal	0.2	Administrative occupations: records	1.7
don't know	0.0	Administrative occupations: communications	0.2
Corporate managers and senior officials	0.3	Administrative occupations: general	2.6
Production managers	1.4	Secretarial and related occupations	1.8
Functional managers	4.0	Agricultural trades	0.9
Quality and customer care managers	0.5	Metal forming, welding and related trades	0.2
Financial institution and office managers	1.3	Metal machining, fitting and instrument making trades	1.2
Managers in distribution, storage and retailing	1.6	Vehicle trades	0.6
Protective service officers	0.1	Electrical trades	1.6
Health and social services managers	0.5	Construction trades	1.1
Managers in farming, horticulture, forestry and services	0.1	Building trades	0.4
Managers and proprietors in hospitality and leisure services	0.8	Textiles and garments trades	0.1
Managers and proprietors in other service industries	3.1	Printing trades	0.1
Science professionals	0.4	Food preparation trades	0.8
Engineering professionals	1.0	Skilled trades nec	0.2
Information and communication technology professionals	1.6	Healthcare and related personal services	3.6

Health professionals	1.1	Childcare and related personal services	3.1
Teaching professionals	4.8	Animal care services	0.2
Research professionals	0.5	Leisure and travel service occupations	0.8
Legal professionals	0.5	Hairdressers and related occupations	0.4
Business and statistical professionals	0.8	Housekeeping occupations	0.4
Architects, town planners, surveyors	0.4	Personal services occupations nec	0.1
Public service professionals	0.8	Sales assistants and retail cashiers	4.4
Librarians and related professionals	0.1	Sales related occupations	0.4
Science and engineering technicians	1.0	Customer service occupations	1.6
Draughts persons and building inspectors	0.2	Process operatives	0.4
It service delivery occupations	1.0	Plant and machine operatives	0.6
Health associate professionals	2.8	Assemblers and routine operatives	1.1
Therapists	0.7	Construction operatives	0.4
Social welfare associate professionals	0.9	Transport drivers and operatives	2.5
Protective service occupations	0.9	Mobile machine drivers and operatives	0.2
Artistic and literary occupations	0.6	Elementary agricultural occupations	0.1
Design associate professionals	0.6	Elementary construction occupations	0.3
Media associate professionals	0.6	Elementary process plant occupations	0.5
Sports and fitness occupations	0.3	Elementary goods storage occupations	1.1
Transport associate professionals	0.2	Elementary administration occupations	0.5
Legal associate professionals	0.2	Elementary personal services occupations	3.0

Business and finance associate professionals	2.3	Elementary cleaning occupations	1.5
Sales and related associate professionals	1.3	Elementary security occupations	1.7
Conservation associate professionals	0.1	Elementary sales occupations	0.6
Public service and other associate professionals	1.6	Total	100.0