University of Sussex

A University of Sussex PhD thesis

Available online via Sussex Research Online:

http://sro.sussex.ac.uk/

This thesis is protected by copyright which belongs to the author.

This thesis cannot be reproduced or quoted extensively from without first obtaining permission in writing from the Author

The content must not be changed in any way or sold commercially in any format or medium without the formal permission of the Author

When referring to this work, full bibliographic details including the author, title, awarding institution and date of the thesis must be given

Please visit Sussex Research Online for more information and further details

Three Essays on Productivity, Regional Wage Disparities, and the Public Sector Pay Gap in Great Britain in a Period of Economic Shocks

Bridget Chifundo Kauma

Submitted for the Degree of Doctor of Philosophy in Economics
University of Sussex
August 2022

DECLARATION

I hereby declare that this thesis has not been and will not be submitted in whole or in part to another University for the award of any other degree. I also hereby declare that this thesis is my independent work.

Signature:

Bridget Kauma

University of Sussex

Bridget Chifundo Kauma

Doctor of Philosophy in Economics
Three Essays on Productivity, Regional Wage Disparities, and the Public Sector Pay Gap in Great Britain in a Period of Economic Shocks
Summary

The thesis re-visits three themes relating in turn to the UK productivity puzzle, regional wage disparities, and the public sector wage premium. The second chapter employs a decomposition analysis linking micro- to macro-level outcomes to examine whether the 2008 financial crisis exerted an effect on UK productivity. The research utilizes the HMRC VAT returns panel and reveals that the financial crisis had a disproportionate effect on both labour and total factor productivity. A key finding is that the *within*-firm allocation of resources is pro-cyclical and a significant driver of productivity dynamics at the macro level over this period.

The third chapter provides a detailed econometric-based descriptive analysis of local wage disparities for men in Great Britain. The analysis employs the Annual Survey of Hours and Earnings (ASHE) dataset to examine how regional disparities at the Travel to Work Area (TTWA) level are evolving and whether the financial crisis is implicated in this evolution. The key conclusion drawn from the analysis is that the disparity in wage differentials across TTWAs narrowed over the period of analysis, with the downward trend evident before, and not given any impetus by, the financial crisis. However, despite the contraction in regional wage disparity, there remains strong persistence in the rank ordering of regional wages. In addition, the analysis reveals that even with falling wage inequality across TTWAs, the inequality within TTWAs has increased over time with some indication of wage polarization emerging within local labour markets.

Using the ASHE dataset over the period 2002 to 2019, the fourth chapter investigates if either the financial crisis or the subsequent austerity programme introduced by the coalition and subsequent Conservative governments impacted the public sector wage premium for men in Great Britain across the unconditional pay distribution. The empirical analysis suggests some degree of stability in the public sector pay premium over time and across the distribution, with neither the financial crisis nor the austerity programme found to impact the magnitude of the public sector wage premium for men.

ACKNOWLEDGEMENTS

The path towards this thesis has been circuitous. I am immensely indebted to the special people who challenged, supported, and stuck with me along the way. I am forever grateful to God: without His grace and faithfulness this work would neither have commenced nor been completed, I say 'Ebenezer'. I owe my most profound gratitude to my two supervisors, Professor Barry Reilly and Professor Giordano Mion, who have guided me through the process. Carrying out the research in unprecedented times seemed like a tall order, but their expertise, constant encouragement, guidance, and support gave me the energy to face each day in research and for that, I am truly grateful. I thank Professor Rebecca Riley for the extensive comments she provided to my chapter on productivity under the RES mentoring programme.

There are so many people I would like to thank. Without the love and support of my family and friends, I could not have accomplished this thesis. A big thank you to my husband, Zakeyu Kauma, for the endless amount of support, love, and encouragement to complete my academic journey, and to my daughters, Joy and Janella, for routing for me all the way. You are an amazing support system. Enormous gratitude to my parents, Wynn and Susan Chalira, for the love and support through and through. I would like to thank all my PhD colleagues, with whom I have shared moments of deep anxiety but also of big excitement. Their presence was very important in a process that is often felt as tremendously solitary. A warm word for my colleagues and great friends Amina Micah and Hannah Sam, who always managed to make me feel special and with whom I have made some of my best memories on the PhD journey.

Finally, I would like to acknowledge the Economics Department at the University of Sussex for providing me with a doctoral scholarship, without which this work could never have begun.

Chapter 2 contains statistical data from HMRC that is Crown Copyright. The research datasets used may not exactly reproduce HMRC aggregates. The use of HMRC statistical data in this work does not imply the endorsement of HMRC in relation to the interpretation or analysis of the information.

Chapters 3 and 4 contain statistical data from the Office for National Statistics (ONS) which are Crown copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the ONS statistical data does not imply the endorsement of the ONS in relation to the interpretation or analysis of the data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

DEDICATION

To my husband Zakeyu Dan and my daughters Joy Mandisa and Janella Gloria Seira, whose endless love, support, encouragement, and constant prayer has made this and so much more possible.

Contents

List of Figures

List of Tables

Chapter 1: Introduction

This thesis is comprised of three connected but independent empirical chapters that focus on a period of great volatility in the UK economy. A key theme across all three chapters is the role played by the financial crisis on several different aspects of economic activity. Chapter 2 explores the impact of the crisis on productivity growth in the UK. Chapter 3 focuses on the evolution of regional wage disparities at the ‘Travel to Work Area’ (TTWA) level and the extent to which it has been affected by the financial crisis. Chapter 4 focuses on whether or not both the financial crisis and the austerity programme subsequently implemented exerted an impact on the public sector wage gap for men in Britain both at the mean and across the unconditional wage distribution. Overall, the empirical research in this thesis is best interpreted as providing econometrically descriptive insights on these topics rather than causal effects.

The thesis is organized as follows. Chapter 2 presents a productivity decomposition analysis delineated across a number of different time periods spanning the banking crisis. Chapter 3 investigates the extent to which the financial crisis affected regional wage disparities for men based on TTWAs. Chapter 4 presents evidence of the impact of the financial crisis and austerity on the public sector wage gap in the UK. Chapter 5 offers some concluding remarks on the thesis

The financial crisis that originated at the end of 2007 in the United States (US) subprime credit market led to a liquidity crisis in the short-term money markets (Fosberg ,2012). It was concentrated on the secondary and subprime mortgage markets in the US. According to the Deutsche Bank, (2010) other countries outside the US experienced different exposures and suffered different consequences to the financial crisis. The UK stands out as being amongst those countries most exposed and took a long time to recover experiencing substantial long-term effects. According to the ONS (2018), since 1992 the size of the UK economy, measured by adding up the value of all the goods and services produced in the country, grew every quarter. But between April to June 2008, it began to contract. The economy contracted for five successive quarters. Two or more consecutive quarters of falling gross domestic product (GDP) is commonly called a recession. Figure 1.1 below plots quarterly UK GDP since the first quarter of 1993 to the first quarter of 2018.

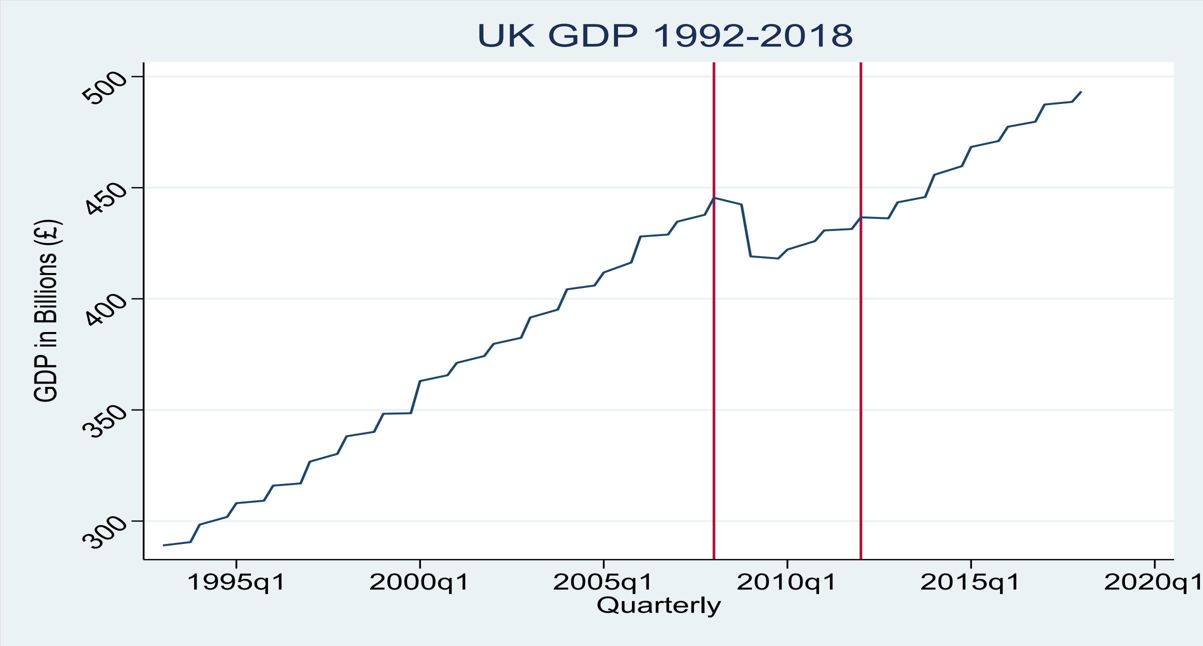

Figure 1.1: UK Gross Domestic Product (GDP) per quarter (in £ Billion)

Source: Author's calculations from the ONS (2018) dataset.

As the economy shrank, there was also an increase in the unemployment rate. However, in contrast to previous recessions, the 2008 crisis was not accompanied by a sharp rise in unemployment (Pryce, 2015). Figure 1.2 shows that employment has been increasing over the period of the analysis. The period of the recession was characterized by a modest drop in employment of around 3% between 2008 to 2010. By 2013, employment had recovered, and surpassed pre-recession levels with growth positive again. The evidence provided in Figure 1.2 confirms that relative to output the UK labour market suffered less and recovered more rapidly from the financial crisis.

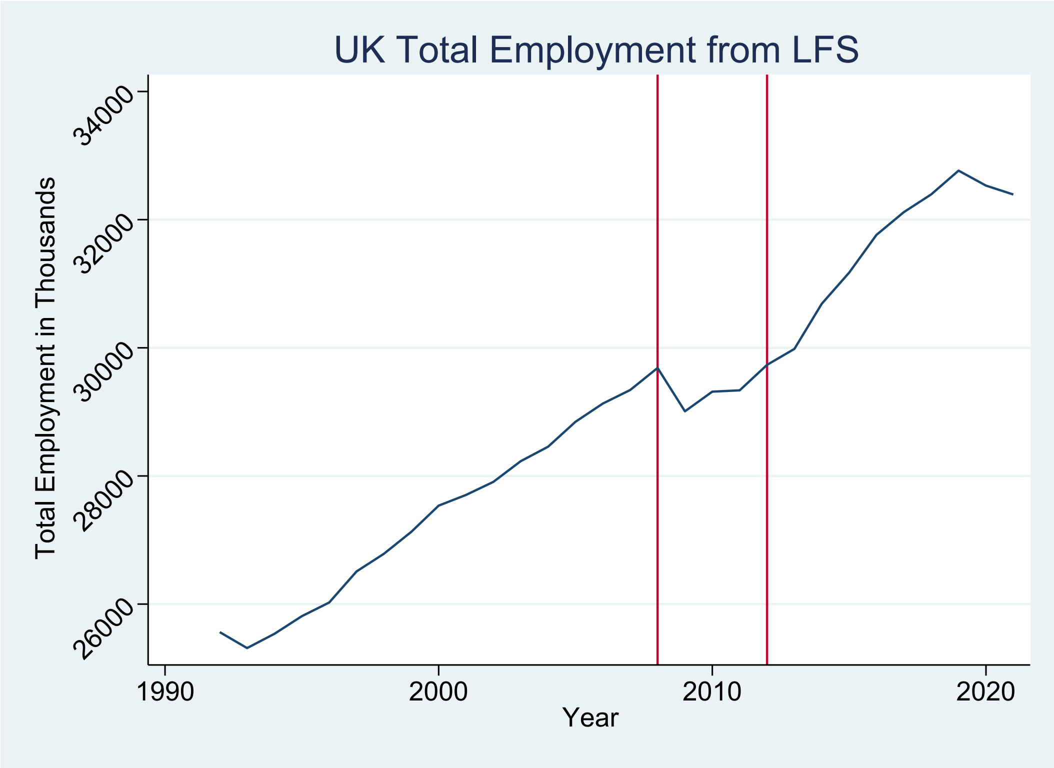

Figure 1.2: UK Total Employment (in Thousands)

Source: Author's calculations from the ONS (2018) dataset.

By the end of 2011, almost 2.7 million people were unemployed and actively looking for work. The quarterly unemployment rate reached 8.4%, the highest rate since 1995. Unemployment had returned to its pre-downturn rate by the end of 2015, and since then it has continued to fall – reaching a record low of 4.3% in the third quarter of 2017 before rising slightly by the end of the year.

One way to measure the strength of the economy is by examining productivity measured as output per unit of input. In Chapter 2 , the empirical focus is centred around the ongoing debate on aggregate productivity growth in the UK. Total Factor Productivity (TFP) and Labour Productivity (LP) measures are constructed using data drawn from the HM Revenue and Customs (HMRC) Value Added Tax (VAT) returns panel, the Business Structure Database (BSD) and the Financial Analysis Made Easy (FAME) datasets for the period 2002 to 2016. Year-on-year decomposition analysis and decompositions for selected periods are conducted to explain and document the sources of change in aggregate productivity growth for non-financial private sector firms.

It is acknowledged that this is not the only paper that provides evidence on productivity growth in the UK in the wake of the financial crisis. The novel contribution of Chapter 2, however, is its use of longitudinal administrative data. These provide access to almost the entire population or universe of private sector firms in the UK, approximately one million firms per year with inevitably a greater coverage of the small and medium enterprises (SMEs). This ensures that the analysis undertaken in this chapter has some value-added over the existing literature that generally relies on the Annual Business Survey (ABS) or the Annual Respondents Database (ARD) survey which selectively covers around 60,000 firms a year, the majority of which are large firms. The analysis also contributes to the current literature through its explicit use of a micro-level to a macro-level approach for the decomposition methodology. This allows the drivers of aggregate productivity growth over time and their corresponding magnitudes to be determined.

The empirical results reveal that the financial crisis adversely affected both the TFP and LP measures. However, in the post-crisis period, TFP appears to have been affected less negatively than LP. The empirical evidence derived from the decomposition analysis suggests that the within-firm restructuring is the main driver of the changes in both TFP and LP growth across all the relevant time periods. There seems to be contrasting aggregate productivity growth between the non-financial services and the manufacturing sectors. In particular, the non-financial services sector has been affected more adversely by the financial crisis, compared to the manufacturing sector, although the non-financial services sector has shown a more rapid recovery in the post-crisis period. In contrast, manufacturing sector productivity has failed to rebound to its pre-crisis levels.

The research in Chapter 2 also provides some insights into the comparative evolution of TFP and LP. Both measures exhibit largely similar trends, as reflected in the decomposition analysis, and confirm that labour hoarding was a key behavioural response by firms to the financial crisis. However, although the economics literature tends to consider use of TFP as more desirable, it is more complex to compute, and its estimation requires invoking more assumptions compared to LP. This can undermine confidence in its use as a measure of productivity and underscores the importance of using both measures of productivity to provide complementary evidence. This enables more effective insights into how productivity has evolved since the financial crisis and whether its evolution is more rooted in labour or other inputs.

All regions and nations within the UK have been affected by recession, but there has been some variation, typically strengthening existing differences (UKCES, 2015). Chapter 3 explores the evolution of regional wage disparities in the labour market for male workers at the TTWA level both during and after the financial crisis. The analysis uses the Annual Survey of Hours and Earnings (ASHE) data. The empirical approach uses mean analysis and the Recentred Influence Functions (RIF) at selected quantiles in conjunction with the Gini coefficient to inform the evolution of wage dispersion. The use of inter-quantile percentile gaps provides a precise indication of whether wage inequality is driven by changes at the top or the bottom end of the wage distribution. The empirical analysis provides evidence that the persistence in regional wage structure rankings was robust to the shock of the financial crisis. However, it documents a trend towards convergence in regional wage disparities over time, which actually persisted throughout the financial crisis. In other words, ceteris paribus, average regional labour market wage disparities have been narrowing reasonably steadily since the start of the 21st century, and this trend was not disrupted or affected by the financial crisis.

In regard to the evolution of wage dispersion within TTWA labour markets, the chapter reveals that wage inequality within local labour markets has been increasing and that the most pronounced wage inequality within TTWAs is at the top end of the distribution. The empirical evidence also suggests the emergence of wage polarization within local labour markets. The empirical results demonstrate that there is some convergence in the degree of intra-labour market wage inequality across regions, although its persistence is weaker relative to that of regional wage disparities.

The third and final empirical chapter (Chapter 4) revisits the debate on the size and evolution of the public sector wage gap in Great Britain. In this chapter, the analysis incorporates the effects of the financial crisis and includes an investigation of the impact of the UK government's post-crisis austerity programme on the public sector pay gap. Of major interest is whether the financial crisis and/or the fiscal consolidation measures adopted in the aftermath of the crisis exerted a discernible impact on the public sector wage gap. This chapter augments the literature by decomposing the wage structure at the mean and across the pay distribution to provide deeper policy insights. Several methodologies are used including a pooled regression model, the standard Oaxaca (1973) and Blinder (1973) decompositions, and Firpo et al.'s (2018) re-weighting methodology which is situated explicitly within a Recentred Influence Function (RIF) framework.

The preferred empirical methodology for chapter 4 is the re-weighted RIF. The role of re-weighting is to provide a more credible counterfactual. Rather than mechanically comparing public and private sector employees, the methodology re-weights the distribution of the characteristics of public sector workers to reflect the distribution of these characteristics for private sector workers.

The main finding from the analysis is that before the financial crisis, the public sector pay gap exhibited substantial stability across most points of the wage distribution. In general, public-sector workers, particularly those at the bottom end of the distribution, were reasonably well protected from the more adverse effects of the financial crisis compared to private sector workers. In contrast, the public sector wage gap at the top end of the distribution was adversely affected by the financial crisis. However, the empirical analysis of the austerity period tentatively suggests that public sector workers at the top end of the distribution regained the losses incurred during the crisis.

Each of the substantive empirical chapters in this thesis is self-contained consisting of a set of research questions and details the context within which the analysis is undertaken. Likewise, it provides a detailed description of the empirical methodology applied and the data sources used for the applied work. The final chapter 5 provides conclusions and brings together all three chapters in light of the common theme explored in the thesis. In addition, it discusses the limitations of the current analysis, provides some implications for policy, and sets out an agenda for future research across the three themes explored in this thesis.

Chapter 2: The Impact of the Financial Crisis on Two Measures of UK Productivity

‘Productivity isn’t everything, but in the long run it is almost everything’.

Paul Krugman (1994, p.204)

2.1 Introduction

In the current economic environment, many advanced economies are struggling with the problems of low productivity and poor prospects for potential growth combined with high debt within a fairly constrained fiscal and monetary policy space. This has led to renewed interest in the study of productivity and a search for policies to boost output (Dias *et al.*, 2016). Productivity growth is considered to be one of the major factors contributing to overall economic growth and, therefore, to well-being. It has attracted much research interest. For instance, Total Factor Productivity (TFP) analysis can be traced back to the seminal paper by Solow (1957). Increased availability of firm level data now allows estimation of productivity at the level of the individual establishment (Bartelsman and Doms, 2000). Existing empirical findings vary widely in terms of the importance of the contribution of firm level micro-drivers to aggregate productivity growth in the UK.

Despite the UK’s favourable business environment according to its ranking in the World Bank Doing Business Index,[1] its productivity performance has deteriorated relative to many other developed economies since the financial crisis. According to ONS (2016) using GDP per hour worked, UK productivity grew by an annual average of 1.9 percent between 1997 and 2007, the fastest growth of all G7 countries. The UK experienced relatively strong productivity growth up to 2007. However, UK GDP per hour worked grew only grew by an annual average of 0.7 percent between 2007 and 2019. Over the past decade, Labour Productivity (LP) growth has slowed in both the UK and the other G7 countries, although this slowdown has been more pronounced in the UK. For instance, output per hour in the G7 excluding the UK was 18% above that of the UK in 2014. Output per worker in the UK ranked sixth out of the G7 countries only performing better than Italy.

During the economic downturn, the UK’s productivity gap of about 14% was about twice as large as the gap for the rest of the G7. UK productivity growth fell more sharply than in other G7 countries and was weaker during the subsequent seven years. Some other

[1] For doing business rankings see World Bank (2013)

countries experienced a slowdown in growth. For example, growth in Germany began slowing in 2004. However, Italy experienced relatively slow growth between 1997 and 2016. Comparing average productivity growth rates since 2007, the UK ranks lower compared to the USA (38% above), Germany (25%) and France (20%) (see ONS,2016).

Drawing on a comprehensive firm level longitudinal set of administrative data, the analysis in this chapter identifies the sources of aggregate TFP and LP growth at the micro level. This chapter uses Her Majesty's Revenue and Customs (HMRC) and Business Structural Database (BSD) data that allow analysis of aggregate firm productivity growth for nearly a million firms per year. The analysis of granular longitudinal data provides deeper and sharper insights into levels and growth of aggregate UK TFP and LP. Disney *et al.* (2003) suggest that hard evidence on firm entries and exits (external restructuring) is scarce since it requires representative longitudinal data on surviving, entering and exiting firms. The well-known and more commonly used Annual Respondents Database (ARD) or the Annual Business Survey (ABS) dataset includes only 60,000 firms per year whereas HMRC data cover the entire firm population. Additionally, the VAT Returns panel also boasts a greater coverage of Small and Medium Enterprise (SMEs) firms and this allows us to provide evidence on the productivity that includes these SMEs, a subset generally absent from the extant literature. Much of what is known invariably relates to the productivity of large firms that are the dominant group in the ARD/ABS. However, this coverage comes at a cost, in that information on individual firms is limited. For instance, HMRC data do not permit the construction of a firm level measure of capital stock and thus TFP estimates are not computable. Therefore, this chapter also uses the Bureau van Dijk (BvD) Financial Analysis Made Easy (FAME)[2] data that provide information on fixed assets (capital stock) for the universe of firms operating in the UK required to make returns to Companies House. Merging this information with the fairly rich longitudinal VAT Returns panel and BSD datasets allows us to derive estimates of TFP.

In addition to using a novel micro-level administrative dataset that includes around one million firms per year, this research also contributes to the existing literature by employing a micro to macro approach. This allows aggregation of firm-level productivity to obtain an overall UK productivity measure, using the formula devised by Foster *et al.* (2001). Specifically, the chapter measures the level and growth of UK firm TFP and LP and provide a detailed account of the contribution of the various micro components

[2] The BvD FAME data are based on Companies House data on the population of UK firms. The FAME dataset is part of the global AMADEUS database.

linking individual to aggregate productivity growth. The analysis is restricted to private non-financial firms in the UK economy. More generally, this research contributes to work that links macro-productivity growth to firm level determinants, before, during and after the financial crisis. The main research question addresses how UK TFP and LP have evolved at the micro level, during and beyond the period of the 2008 financial crisis. The aim of the research is to demonstrate descriptively how the effect of the financial crisis on productivity at the micro level also affected aggregate growth using both measures of productivity (TFP and LP) in the UK during this period.

The labour productivity measure (constructed as Gross Value Added (GVA) per worker over time) is calculated for the period prior to and after the financial crisis, using the BSD and VAT returns panel data. In contrast to how LP is calculated, computation of TFP requires estimation of a production function. This is undertaken at the two-digit industry level over the entire study period (2006-2016) using firm level fixed effects estimation in conjunction with data drawn from these three data sources. In order to address the problem of endogeneity inherent in the estimation of production functions for TFP, the Wooldridge (2009) Instrumental Variable (IV) strategy, which derives TFP as a residual, is adopted.

The aggregate (macro) TFP and LP metrics are then decomposed into their firm level micro components using the method outlined in Foster *et al*. (2001) (hereafter, FHK method). The FHK approach decomposes productivity into the contributions made by several attributes related to the economic environment, including *within*-firm productivity growth, reallocation of market shares and firm entry and exit. This chapter provides a detailed analysis of the changes to the micro drivers of TFP and LP and maps them to the changes in aggregate productivity growth. The chapter also discusses changes to mark-ups over the period of the financial crisis, which is measured as price over marginal cost. This measure is considered to provide insights on firm-level profitability that appears to be pro-cyclical and rising in the post-crisis period.

The empirical results obtained are suggestive of a sizeable pro-cyclical contribution of *within*-firm restructuring to the level and growth of both aggregate TFP and LP; this is particularly evident during the financial crisis period. It can also be inferred that the misallocation of resources from firms that became more productive to those that became less productive was a key feature of the UK market prior to the crisis and was not given impetus or slowed down by the financial crisis. Therefore, the weakness in the performance of both TFP and LP in the aftermath of the financial crisis appears to be associated with an efficiency issue within establishments and not necessarily the misallocation of resources across businesses. The evidence also suggests that both TFP and LP were disproportionately affected by the financial crisis. However, aggregate TFP growth rebounded quickly after the financial crisis, whereas the growth in aggregate LP has consistently failed to pick up during the period under analysis. This seems to suggest that the UK productivity puzzle is related to a continued weakness in LP compared to TFP. The discussion above raises important questions about the appropriate measure of productivity to focus down on from a policy viewpoint.

A more granular disaggregation of the sample between manufacturing and non-financial services sectors (NFS) suggests that the *within* firm variation is continuing to drive growth in aggregate productivity. However, the financial crisis seems to have had a disproportionate effect on both LP and TFP in the services relative to the manufacturing sector. In turn, this suggests weak LP and TFP in the manufacturing sector, and a relatively weaker LP and more robust TFP growth in the non-financial services sectors. This might, in part, reflect the failure to account for intangible capital,[3] which comprises the bulk of the output from the services sector (O'Brien, 2018). Exploring this possibility is beyond the scope of the present research but would constitute a fruitful research agenda for the future.

This chapter is organized as follows: Section 2.2 briefly outlines the research context; Section 2.3 reviews the related empirical literature; Section 2.4 discusses the contributions of this research; Sections 2.5 and 2.6 describe the data used in the analysis and the empirical methodology employed. Section 2.7 presents the main results and Section 2.8 concludes the chapter by discussing some of the limitations of this research and suggesting future research directions.

2.2 Context to the Evolution of UK Productivity

UK productivity growth has been comparable to most G7 countries however, since 2008, the UK experienced a sizeable contraction in GDP relative to most other industrialized economies, and a correspondingly slow recovery. Aggregate productivity growth has not returned to pre-crisis levels. In previous recessions, any productivity losses were

[3] Intangible capital refers to non-physical or financial assets. This includes assets such as software, reputation and branding, design and R&D; these contribute to the long-term accumulation of the firm's knowledge capital. These assets complement physical (tangible) capital, such as buildings, equipment and machinery, which drives economic growth O'Brien, (2018). Note that during and after the recession, intangible investment fell by less than tangible investment. In 2008-09 tangible investment fell sharply whilst although intangible investment does fall it is nowhere near as steeply. Part of the effect in the case of tangibles may be due to the sharp increase that took place from around 2004-05, part of which may have been an 'Olympic effect' from associated infrastructure investment (see Goodridge et al.,2016).

recovered quickly with employment cut back faster than the deterioration in output. However, unlike previous recessions, the 2008 crisis was not accompanied by a sharp rise in unemployment (Pryce, 2015). The increase in employment over a period of sustained output fall makes the 2008 financial crisis distinct to the previous recessions where both output and employment were falling.

Historically, productivity has exhibited an upward trend over time: more goods and services have been produced per hour worked or per worker. This has allowed living standards to rise. Economies are subject to cyclical booms and busts, and it is not unusual for productivity to fall, as happened in the 2008-2009 economic downturn.[4] What is unusual is the flat lining of productivity since 2010 over a lengthy period (Haldane, 2014).

Figure 2.1 plots the standardized employment[5] weighted UK aggregate LP and TFP since 2006. Value added per worker fell by about 5% between 2006 and 2008 with most of the contraction occurring in 2008. Figure 2.1 shows that TFP grew by 4% over the same period. Both TFP and LP declined at the onset of the financial crisis. However, in the post-crisis period, aggregate TFP picked up and even surpassed its pre-crisis level, although the post-crisis period exhibits a weak recovery in LP relative to the pre-crisis period. This is unprecedented in the post-war era and is described as the ‘productivity puzzle’. The productivity puzzle has dominated public debate and policy discourse since the late 2010s. The Office for National Statistical Office (ONS) estimates that had pre-2008 aggregate productivity growth continued, aggregate productivity would have been 20% higher than the level reported at the end of 2017.[6] Wages and living standards would also be higher.

[4] An overview of the UK productivity puzzle is provided in ONS (2015).
[5] Both TFP and LP are weighted by the share of firm employment. Appendix Table 2.1A shows that some 77% of the firms in the sample are classified as micro firms. Weights are applied to correctly reflect the population structure since some firms are over-represented, potentially biasing outputs.
[6] For a discussion of the UK Productivity Puzzle see ONS (2018).

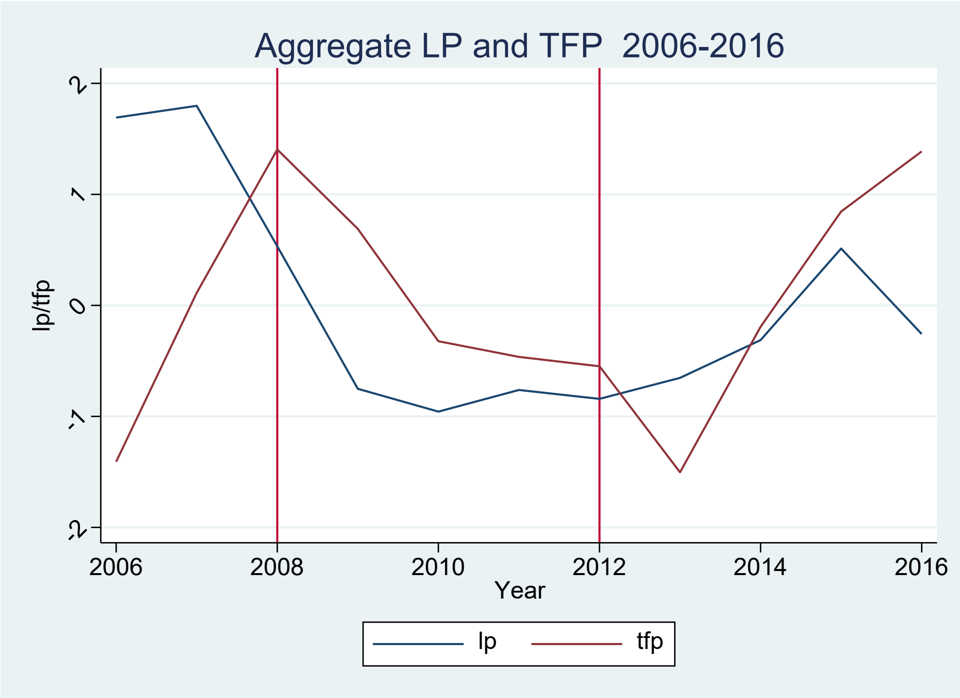

Figure 2. 1: Standardized Total Factor Productivity and Gross Value Added per worker for the UK: 2006-2016

Notes: The two vertical red lines delineate the period of the financial crisis

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets,

Barnett et al.(2014a) and Pessoa and Van Reenen (2014) provide an excellent summary of the various explanations for the productivity slowdown to date. These explanations are also broadly characterised into four main hypotheses including the fact that the weakness in productivity is cyclical, reflecting lower factor utilisation due to weak demand conditions, and is likely to be temporary in nature. This first hypothesis suggests that the weakness in productivityis more cyclical in nature and driven principally by weak demand conditions. The mechanism at work here is that firms are unable or unwilling to dispose of capital or lay off workers, either because of minimum staffing levels required to keep the business going, or because they believe the weakness in demand to be temporary. However, since the onset of the recent financial crisis, productivity growth has been weaker than one would have expected given its normal cyclical relationship with GDP, particularly since 2010. Growth rates in output per hour have been persistently weaker than GDP , reflecting strong employment growth over the past few years. Based on business survey data, Barnett et al. (2014a) exclude the possibility of a cyclical explanation for the fall in productivity, finding little evidence of spare capacity and a demand shortfall. Therefore, cyclical factors alone are unlikely to explain the productivity puzzle fully.

The second hypothesis suggests that other factors are slowing growth in either the amount of capital per worker or TFP, leading to a more persistent effect on the level of productivity. For this reason, the weakness in productivity is likely to persist for some time, as the underlying factors behind it may have disrupted the capacity of the economy to supply goods and services, through underinvestment or the inefficient allocation of resources. There are several mechanisms associated with the recent financial crisis that may have caused this to occur. These include impaired access to finance for companies and heightened uncertainty with respect to the macroeconomic environment. This may have dissuaded firms wishing to invest in profitable projects from doing so, impeding growth in the amount of capital per worker. Tight credit conditions may also have slowed the investment in, and introduction of, new innovations.Furthermore, the crisis may have led to impediments in the movement of capital and labour towards their most productive uses, again slowing growth in productivity.

The third hypothesis is that the low levels of productivity could be due to the over-estimation of past productivity resulting from employment and output measurement issues. If, in the past, productivity was over estimated, these lower figures now reflect a return to normal. Oulton and Sebastiá-Barriel (2013) argue that between 4% and 16% of the productivity shortfall is due to measurement issues. However, investigating the role of measurement issues is not easy since the data are not sufficient to construct a longitudinal capital stock series. Some studies argue that it is possible that a large part of the productivity loss is permanent, and that the UK will be on a much lower long term trend growth path for the foreseeable future as a consequence of the financial crisis (see Pessoa and Van Reenen(2014),Pryce (2015)).

The UK labour market has been characterized as one facilitating a labour hoarding phenomenon. In order to avoid the costs of firing and then re-hiring, firms retained their workers as output fell during the recession. However, the increase in labour market hiring rates during recovery periods (Barnett *et al.,* 2014a), might challenge this explanation. The UK labour market has also experienced increased flexibility with the decline in unionization. Hence, labour hoarding is likely to be only a partial explanation for the productivity puzzle (see Du and Bonner, 2016).

Figure 2.2 shows that employment[7] has been increasing over the period of analysis. The period of the recession was characterized by a sharp drop in employment of around 3%, from 2008 up to 2010. By 2013, employment had recovered, and surpassed pre-

[7] Employment includes firms that are registered for VAT and PAYE and excludes self-employed individuals whether in a partnership or sole traders as well as firms that operate below the VAT threshold.

recession levels with growth positive again. The evidence provided in Figure 2.2 confirms that the UK labour market suffered less and recovered more rapidly from the financial crisis. In addition, the right-hand side of the figure depicts the evolution of output during the study period. Between 2006 and 2009, output fell by 5%. Between 2009 and 2013 output reached below pre-crisis levels and seemed to be plateauing at the end of the study period. In contrast, total employment appears to be on a steady upward trajectory.

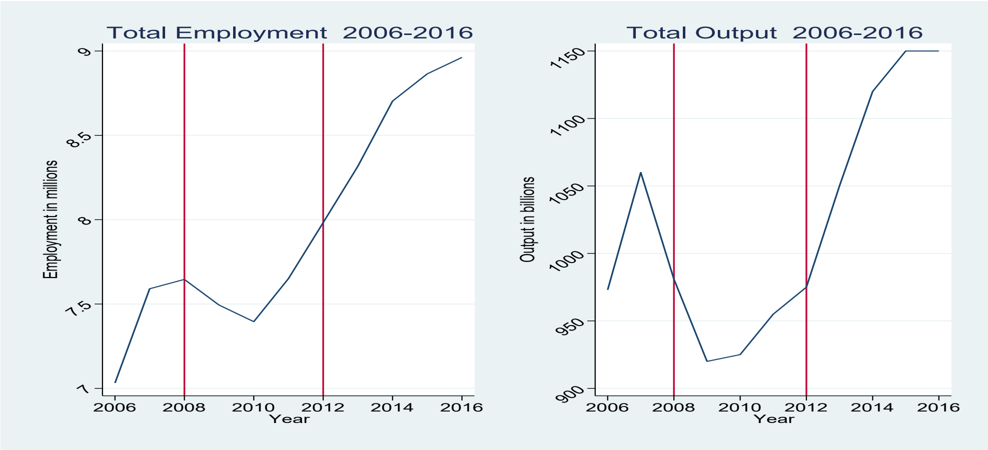

Figure 2. 2: Total Employment (in Millions) and Output (in billions): 2006-2016

Notes: The left (right) hand side is the total Employment (Output). The two vertical red lines delineate the period of the financial crisis

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Pessoa and Van Reenen (2014) argue that 'capital shallowing' (i.e., the fall in the capital-labour ratio) might be the main reason for the fall in GDP per worker because productivity growth depends on the technology level and the capital-labour ratio. Figure 2.3 shows a general downward trend in the capital-labour ratio at both the aggregate and sectoral levels. Across the two sectors identified, the capital-labour ratio is lower for manufacturing than for services. Potentially, this might be due to the inclusion of housing stock in the services sector. In national accounts, the value added of the real estate sector includes actual and imputed (for owner-occupiers) rents for the provision of housing and the associated capital is the housing stock. Consequently, this activity is highly capital-intensive. In the post-crisis period, the capital-labour ratio flattens and is less pronounced in the manufacturing sector. There is a sharp decline in the capital-labour ratio in the services sector, which seems to persist into the post-crisis period. During this period, it rises slightly but flattens towards the end of the data period. The magnitude differs but the direction of travel is fairly similar and points to a falling capital-labour ratio over time.

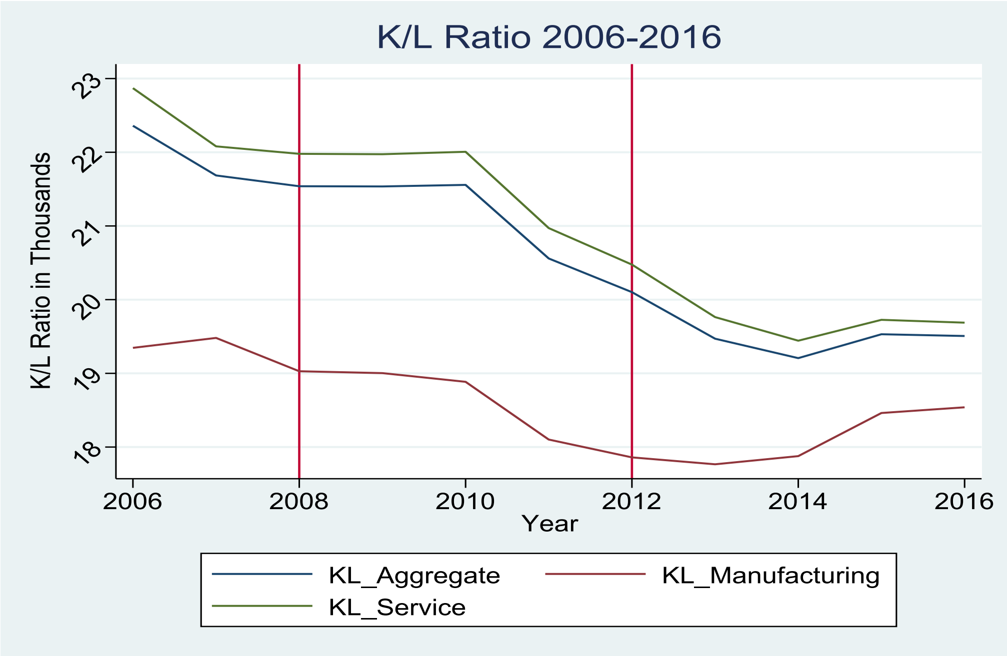

Figure 2. 3: Capital Labour Ratio (in Thousands): 2006-2016

Notes: the two vertical red lines delineate the period of the financial crisis

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Due to both the current political landscape and some specific features of the economy, productivity is a top priority for the UK government. The coalition government entered office with a deficit equivalent to 5 per cent of national income and a commitment to substantial additional spending cuts (see Crawford and Johnson, 2015). Implementing these additional cuts proved challenging. This compounded with Brexit, international trade, both within and outside the EU, cannot be expected to be a major source of GDP growth in either the short or medium term. Therefore, government objectives related to, for example, increasing the standard of living of UK citizens in the face of spending cuts, reducing the debt to GDP ratio and releasing more resources for public services in distress (such as the NHS) can only be met, if at all, by an increase in UK productivity. Economists agree that productivity improvement is a source of sustainable long-term economic growth which can deliver on material well-being and improvements in living standards.

Economic theory suggests that less efficient firms are forced either to become more efficient or to exit the market. Resource misallocation refers to a situation where capital and labour are poorly distributed so that less productive firms receive a larger share of capital and labour than justified by their level of productivity. Some argue that the misallocation of resources to small and unproductive firms could account for the fall in UK productivity. For instance, Barnett *et al.* (2014a) claim that in the wake of the financial crisis, capital movements have been inhibited by an impaired financial sector that is more tolerant of low-productive firms but shows risk-aversion to funding new projects. This may also be reducing the exits of less productive firms and derailing the entry of potentially productive firms.

In addition, Emmerson *et al.* (2013) proposed that the flexibility in the labour market means that adjustments through wages (rather than just employment) are more likely. They claim that lower real wages have played a part in allowing firms to continue to employ workers even while producing less. This has had a dampening effect on aggregate LP. The issue of misallocation is the subject of continuing debate, with some studies (see Oulton, 2016; Oulton and Wallis, 2015) showing that during the crisis, there was an increase in the use of capital per hour worked. Emmerson *et al.* (2013) report that firms hire both high-skilled and low-skilled labour. Riley *et al.* (2014) suggest that the weakness in LP after the financial crisis might be associated with an efficiency problem in establishments rather than the misallocation of resources among businesses. However, Barnett *et al.* (2014a) claim that this theory is able to explain less than a third of the productivity gap.

There would appear to be several explanations for the UK productivity puzzle. There is a large stream of work suggesting that within-firm changes are responsible for the trend in the aggregate productivity growth. Riley *et al.* (2014) argue that a key driver of the UK's aggregate productivity changes is *within*-firm variation. This *within*-firm component depends on changes in the efficiency and intensity of input use in production among the surviving firms. Several other studies (see Bernard *et al.,* 2006; Mayer *et al.,* 2014) try to quantify the relative contributions of the *within* and *between* effects, by decomposing aggregate productivity growth into terms that reflect these separate effects. The present chapter contributes to this literature stream by providing a synopsis of what occurred at the micro-level in the pre-financial crisis, crisis and post-crisis periods, and underpins developments in UK aggregate TFP and LP growth using a longitudinal administrative dataset.

The implications of the decline and slow recovery of productivity growth apply not just to the short term; they will have an impact on long run LP even if productivity growth returns to pre-crisis levels (Oulton and Sebastiá-Barriel, 2013). Understanding the productivity puzzle has attracted huge interest among policymakers and researchers. There is currently no consensus about what explains the stagnation in UK productivity growth or, therefore, what policy measures might revive it. Several studies offer logical and clear expositions of this puzzle; some of these are discussed in the literature review in Section 2.3.

2.3 Literature Review

The origins of TFP analysis can be traced back to Solow's (1957) seminal paper. Since then, there has been a surge in both the theoretical and empirical studies of TFP. This renewed interest has been driven by the increasing availability of firm-level data that allows estimation of TFP at the level of the individual establishment (e.g., Bartelsman and Doms, 2000).

Disney *et al.* (2003) provide one of the more influential analyses of productivity growth in UK manufacturing during the period 1980-92. This study used the then newly available ARD panel of establishments drawn from the Census of Production. The authors decompose productivity growth into the parts attributable to growth within surviving establishments and firms that experienced external restructuring; this includes the net effects of entry, exit and changes in the market shares of the survivors. Disney *et al*. (2003) employ three alternative decomposition methods to calculate labour and TFP growth.

The first decomposition method employed was proposed by Bailey, Hulten and Campbell (BHC) (1992). It considers aggregate sectoral productivity growth as a weighted average of firm-level productivity growth between two periods. One problem with this decomposition is that entering firms always increase productivity while exiting firms always decrease it. This is because it ignores the different productivity levels between continuing, entering and exiting firms. The second developed by Griliches and Regev (1995) overcomes the problem with Bailey *et al* (1992) by comparing productivity of each group of firms with a reference level of productivity. Nevertheless, it can be argued that this method does not correctly measure the impact of firm entry and exit on overall productivity growth because the reference productivity includes the entering and exiting firms' productivity. This could lead to an under(over) estimation of the impact of entering and exiting firm productivity with their shares. The final method was proposed by Foster, Haltiwanger and Kirzan (FHK) (2001) and measures productivity growth relative to the initial period. This method has a fifth term capturing changes in both productivity and firm market share. This is of interest in this chapter and is extensively discussed in the empirical methodology sections. It should be noted that all three methods yield biased measures of the contributions of entrants and exiters due to inappropriate reference productivity and sharing the common weights with the surviving firms. The results are consistent across the three methods of decomposition though the magnitudes may vary. Disney *et al* (1993) show that over the period 1980-92 external restructuring accounted for around 50% of LP growth and 90% of TFP growth. The key driver in aggregate productivity growth across all three decomposition methodologies was the *within* firm component.

Harris and Moffat (2011) exploit ARD data for the period 1997 to 2008 at plant level and conclude that the reallocation of output shares towards highly productive industries, and the opening of productive plants, explain most of the productivity growth during that period. Broadbent (2012) argued that the misallocation of production factors could account for the fall in UK productivity and there is some evidence suggesting that these capital misallocation forces strengthened in the recession.

Martin and Rowthorn (2012) use the LFS from 1979-2011. They note the significant rise in unemployment and the fall in the employment rate (defined as the number of employees as a proportion of the working age population) during the recession. This suggests underutilization of human resources. It may well be that, even in their formally measured hours, labour is not being used to its full potential when at work. This 'labour hoarding' means that firms do not reduce employment by as much as expected because they anticipate a later pick-up in demand and want to avoid the costs of re-hiring laid-off workers (e.g., if they have firm-specific human capital). This is the usual explanation for productivity being pro-cyclical in nature (see Bernanke and Parkinson, 1990).

Many economists have tried to rationalize the 'productivity puzzle' but a full explanation remains elusive. Three of the many explanations are: i) measurement issues, including mismeasurement of output, lower trend productivity in the mining and extraction sector and the finance sector; ii) cyclical issues, including uncertain lower levels of measured capacity or factor utilization and other factors reflecting changing demand conditions; iii) more persistent factors include reduced investment in physical and intangible capital and impaired resource allocation, unusually high firm survival rates, higher numbers of people working beyond normal retirement age as a result of population demographics and pension changes, and a stronger preference among firms for labour inputs given low pay growth (see discussion on Barnett et al, (2014a), Pessoa and Van Reenen(2014), Pryce(2015)). While these and other factors may be relevant, none is able to completely explain the weaknesses inherent in productivity growth.

Barnett *et al.* (2014a) summarize estimates of the contribution made by each of the possible explanations for the UK productivity puzzle, grouping perceived weakness in productivity growth into cyclical explanations related to demand conditions, and more persistent causes related to the financial crisis. They compare these two groups[8] and estimate the shortfall in productivity relative to a continuation of their pre-crisis trends. They utilize the ARD data for the period 2005-2011.They reveal that, although these different explanations account for a large part of the measured discrepancy, there is a wide margin of uncertainty surrounding each of these factors that leaves a significant proportion of the puzzle unexplained.

Barnett *et al*. (2014a) also show that during the initial phases of the recession, firms appear to have acted flexibly by retaining labour and lowering levels of factor-utilization in response to weak demand conditions. Other cyclical explanations, such as having to work harder to win new business, are also likely to have played a significant role. However, the protracted weakness in productivity and the strong employment growth after the financial crisis (beyond 2011), suggest that there are other factors that are likely to be having a more persistent impact on aggregate productivity growth. These factors are likely to emerge in the form of reduced investment in both physical and intangible capital, such as innovation, and impaired resource allocation from low to high productive usages.

Pessoa and Van Reenen (2014) argue that at the eve of the financial crisis, the UK had overtaken France and Germany and made inroads into the productivity lead of the US. Some of this was due to labour market improvements and rising employment rates, but a good part of it was due to an improvement in productivity growth. The authors summarize a number of the explanations that emerged for the UK productivity puzzle. It is possible that a large part of the productivity loss will be permanent and/or that the UK will be on a much lower trend growth path for the foreseeable future. In addition to falls in real wages, the authors claim that other factors may have depressed the capital-labour ratio. For instance, the increase in the cost of capital for Small and Medium Sized Enterprises (SMEs) is even higher (Armstrong *et al.,* 2013).

Modern theories of heterogeneous firms emphasize that much of the aggregate productivity growth is caused by the reallocation of capital from less productive to more productive firms (see Pessoa and Van Reenen, 2014). A given aggregate quantity of capital may be allocated in different ways across firms with different levels of efficiency. Allocating too much capital to inefficient firms will diminish aggregate productivity. This

[8] Barnett et al (2014a) further summarise the explanations into two. They bundle (i)and (iii) of the three known factors into one explanation which they call ‘other factors’

has been shown to be of first-order importance when considering aggregate productivity differences across countries (see Hsieh and Klenow, 2007).

Pessoa and Van Reenen (2013) further argue that one possible reason for poor productivity is low growth in the effective capital-labour ratio. They hypothesize that this occurred due to a fall in real wages relative to the cost of capital as a result of the financial crisis. They simulate various changes in the capital-labour ratio and, after accounting for these changes, note that the evolution of TFP appears similar to its evolution in earlier severe recessions. Pessoa and Van Reenen (2013) most striking result is the existence of a widespread weakness in TFP *within* firms, highlighting the importance of the *within* firm term for explaining weak productivity. Pessoa and Van Reenen (2014) also find that the positive correlation between surviving firms' employment growth and their relative productivity ranking broke down after 2007-08. As expected, an adverse credit supply shock caused inefficiencies in resource allocation across firms.

Barnett *et al.* (2014b) employ the decomposition analysis method, popularized by Baily *et al.* (2001), using firm-level data from the ABS and Inter-Departmental Business Register (IDBR) datasets to understand why LP in the UK has been exceptionally weak since the 2007-08 financial crisis. They found that *within*-firm productivity growth tends to be pro-cyclical and drives the changes in aggregate productivity growth. Furthermore, they conclude that the reallocation among firms (in terms of both labour mobility and firm entry and exit) contributed significantly to aggregate productivity growth before the crisis, but that its contribution fell substantially after the financial crisis. In addition, they conclude that the lack of labour shedding, combined with a low firm exit rate, is also indicative of low levels of resource reallocation between firms and sectors.

Riley *et al.* (2015) exploit the UK ARD to examine the dynamics of LP growth among British businesses during the period 2007-2013 and compare it to LP growth in the pre-recession years 1998-2007. They focus on the extent to which inefficiencies in resource allocation across businesses explain the weakness in UK LP in the aftermath of the global financial crisis. They also use information on firms' investment expenditure to construct measures of capital stock and TFP. Specifically, they document how the weak productivity growth in the UK between 2007 and 2013 can be accounted for by shifts in productivity within firms, and by changes in the composition of the business population, respectively.

The findings in Riley *et al.* (2015) indicate that the weakness in the *within* firm term of TFP is widespread. They found that the positive correlation between surviving firms' employment growth and their relative productivity rankings broke down after 2007-08. They attribute this to inefficiencies in resource allocation across firms. Indeed, during the years 2008-09, this shift was most apparent in sectors with many small and bank dependent businesses. Subsequently, the contribution of external reallocation (i.e. the net effect of firm entry and exit) and changes in market shares of surviving firms to aggregate productivity growth in 2010-13 was smaller than in previous years. They employed the productivity growth decomposition, as proposed originally by Diewert and Fox (2017), to isolate the contributions to aggregate productivity performance of business restructuring and productivity growth within firms and found a systemic TFP weakness within firms.

In addition, the authors provide regression-based evidence on the link between firm growth and productivity and draw comparisons with the recession in the 1990s. They found that the greater part of the LP weakness since the crisis, which occurred *within*-firms, was associated with declines in measured TFP growth relative to its trend. After an initial sharp drop, productivity growth *within*-firms rebounded slightly, but not sufficiently to return productivity to its pre-crisis levels. Therefore, *within*-firm productivity weakness was pervasive across groups of firms and differed by level of bank dependent financing across small and large firms, and across industry sectors.

The authors conclude that inefficiencies in resource allocation have contributed to stagnation in UK productivity growth over the period 2008-13. Initially, these inefficiencies may have been associated with contraction in the credit supply, but there is no clear evidence showing why these effects persisted. More importantly, the authors found that, for example, widespread uncertainty and general demand weakness (caused, perhaps, by the financial crisis), coupled with flexible wages were a likely major explanation of UK productivity growth stagnation.

It should be noted that both Riley *et al.* (2015) and Barnett *et al.* (2014b) attribute the fall in productivity post-recession to *within*-sector and *within*-firm factors. The implication is that neither bank forbearance nor the lack of a cleansing effect due to problems in the banking sector were major contributors to low productivity growth after 2008.

Harris and Moffat (2017) employ ARD panel data for the period 1997-2012 to investigate some of the explanations adduced for the UK productivity puzzle. They show that, based on (weighted) mean values, average productivity levels (both LP and TFP) in market-based economies declined significantly post-2008, and did not recover. They conclude that the loss in productivity is likely due to permanent rather than cyclical factors. In the case of LP, they found evidence that both the manufacturing and service sectors experienced substantial and sustained decline post-2007. However, in the case of TFP, they found no evidence of a ‘productivity puzzle’ in manufacturing since the entire post-2008 decline is accounted for by services. While the surviving plants in both sectors experienced substantial falls in TFP, this effect was offset by the contribution of net entrants to manufacturing. The fall in TFP was confined to small (especially the smallest) firms, which are particularly prevalent in the services sector.

Goodridge *et al.* (2018) revisited the UK productivity puzzle using new data on outputs and inputs to clarify the role of output mismeasurement, input growth and industry effects. They employ several sources of data including the Goodridge *et al.* (2013) dataset and the ONS industry dataset (excluding real estate, public administration and defence, health and education services). Data on capital services are from Oulton and Wallis (2015). They also use ONS data on nominal investment and asset prices and historic series to estimate UK capital stock and capital services growth since the 1950s. Data on labour inputs are from the ONS release on Quality-Adjusted Labour Input. They apply growth accounting techniques to explain away the productivity gap. Before the 2008 financial crisis, value-added per hour worked (a measure of labour productivity) grew in the UK relatively quickly, at 2.64% p.a. (2000–7). The level of UK productivity in 2011 is shown to be 13 percentage points below what it would have been had GVA per hour continued to grow at a rate of 2.64% per annum. Goodridge *et al.* (2018) conclude that the inclusion of labour quality deepens rather than explains the ‘productivity puzzle’. However, like Barnett *et al*. (2014a), their analysis is limited to the period up to 2011. They also use industry-level data reconstructed from the ARD/ABS, so their analysis includes an average of 60,000 firms per year.

2.4 The Contributions of this Chapter

This chapter builds on existing work in this area and attempts to provide a comprehensive analysis of firm level TFP and LP across the UK economy. The chapter extends the work done by Disney *et al.* (2003), Barnet *et al*.(2014b), Riley *et al.* (2015), Harris and Moffat (2017) and others, by examining the whole firm population rather than a sample of firms in the ARD. In addition, the chapter analyses changes in firm mark-ups over the crisis and post-crisis periods. The study explores the sources of the weaknesses in aggregate TFP and LP for all private NFS firms in the UK prior to and then after the financial crisis. Aggregate TFP and LP is decomposed into its micro drivers before, during and after the 2008 financial crisis. The aim is to identify nuances in firm level productivity, and then link it to aggregate productivity at the macro level in the periods prior to and after the financial crisis.

One of the novelties of the current work is its micro to macro approach; this allows the aggregation of firm-level productivity growth into UK overall productivity growth using formulae developed in the literature (e.g., see Foster *et al.,* 2001). Another novelty is using the VAT returns panel, FAME and BSD data that affords the analysis a large pool of data to undertake a more direct and comprehensive account of the salient features of the economic environment (market power)[9] to estimate aggregate productivity growth. The longitudinal database used includes around one million firms per year over the period 2006 to 2016, and allows identification of entry, exit and survival. Since it is based on the population of firms registered for VAT in the UK, this is the most comprehensive UK firm-level dataset available for analysis. Furthermore, and as already noted, the dataset has a greater coverage of SMEs, a category of businesses that is not well represented in the traditional ARD/ABS datasets.

In addition, the chapter explores how firm entry and exit have contributed to aggregate productivity growth in the UK. The entry and exit components reflect the gains in productivity arising from the entry of more productive firms and the exit of less productive ones. The evidence in the literature (e.g., Baily *et al.,* 1992; Haltiwanger, 1997) suggests that net entry contributes disproportionately to productivity growth. This disproportionate contribution is associated with less productive plants being displaced (exiting) by more productive new entrants. These new entrants tend to be less productive than the surviving incumbents, but exhibit substantial productivity growth, reflecting both a selection effect (less productive firms exit) and a learning effect.

There continues to be a lack of consensus on the correlation between changes in firm productivity and changes in market share as a driver of aggregate productivity growth. The way that highly productive firms gain market share and less productive firms either lose market share or go out of business is thought to be a crucial driver of productivity gains. Foster *et al.* (2001) and Baily *et al.* (2001) find resource reallocation to be a key driver of aggregate productivity in the US case. Disney *et al.* (2003) analyse labour and TFP growth in British manufacturing from 1980 to 1992 and reached similar conclusions for the British case. They found that external restructuring (i.e., the net effect of firm entry and exit and changes in the market shares of surviving firms) accounts for around 50% of establishment labour productivity growth and 80-95% of establishment TFP growth.

[9] The FHK like other productivity decomposition methodologies weights individual firm productivity using a measure of market power like employment or output

However, Broadbent (2012) argues that the correlation between changes in market shares and changes in productivity have had no significant influence on the level of aggregate productivity growth in the UK. Therefore, the chapter investigates whether or not resource reallocation in the UK contributes to changes in aggregate TFP and LP growth.

Another contribution of this chapter is its identification of the role of mark-ups in determining aggregate productivity growth. Specifically, the descriptive analysis undertaken in this chapter investigates whether the financial crisis has altered firm level productivity growth and how this has affected aggregate macro level TFP and LP. Specifically, three research questions are addressed:

1. Has the financial crisis altered firm survival, entry and exit in the UK and how has this affected both aggregate TFP and LP growth?
2. Has the financial crisis altered resource reallocation across firms in the UK and has this contributed to changes in aggregate TFP and LP growth?
3. What is the role of firm mark-ups in determining aggregate productivity growth in the pre-crisis and post-crisis periods?

2.5 Data and Descriptive Statistics

2.5.1 Data

The analysis in this chapter covers the period 2006-2016 and provides insights into productivity growth across the pre-crisis and post-crisis periods. The data required to decompose firm-level LP and TFP revenue into its constituent parts are drawn from three data sources: ONS BSD, VAT returns panel data from HMRC, and BvD FAME data. All datasets are accessible from the HMRC datalab and all relate to the April to March financial years.

The BSD sampling frame is the IDBR, an administrative database that captures information from VAT returns and employer Pay As You Earn (PAYE) tax and social security records, and ONS business surveys such as the Business Register and Employment Survey (BRES) and the Annual Business Survey (ABS). The population of firms is stratified by Standard Industrial Classification (UK SIC 2007 and UK SIC 2003) activities at the 4-digit level. The BSD contains 2.6 million (3 million +inactive) businesses in all sectors of the UK economy, accounting for approximately 99% of economic activity (ONS, 2006). Since the main two tax sources have thresholds, very small businesses operating below these will, in most cases, not be included. The purpose of the BSD is to provide researchers with a version of the IDBR that reflects a wide variety of firm demographics.

The unit of analysis of the BSD is an 'employer enterprise'; this is a business with at least one employee (since an employee can work for more than one firm summing over firms produces an estimate of jobs rather than employment), which is referred to as an enterprise.

The strength of the BSD is its near universal coverage of all firms in the UK. The BSD[10] data are divided into 'enterprises' and 'local units'. The longitudinal datasets for the enterprise and local unit versions of the BSD, are created by linking together successive annual (taken every March) snapshots of the IDBR. An enterprise is the overall business organization, while a local unit is a 'plant', such as a factory, shop, branch, etc. The dataset contains information on turnover, indicative employment, industry sector, ownership structure, postcode, an entity's legal status and age.

The core variables used for the decomposition analysis of TFP and LP include GVA, employment, sales revenue, intermediate inputs, employment and total fixed assets. The IDBR lacks information on GVA; however, this can be derived after merging with the VAT returns panel. The VAT returns panel contains information submitted by all registered VAT taxpayers detailing turnover, purchases, and VAT payable or repayable. In order to preserve confidentiality of the firm-level information, HMRC assigns a unique anonymous identifier to each firm. FAME data provide reliable information on firm-level capital stock.

The FAME database contains information on public and private companies registered at Companies House in the UK and Northern Ireland. The database provides information on 3.8 million companies with up to 10 years of history, detailed corporate structures and the corporate family, shareholders and subsidiaries. These data are collected from various sources including the national official bodies responsible for collecting company accounts data. The data are compiled and organized by BvD in a consistent format and following strict guidelines.

---

[10]The register contains records of over 2 million businesses from all sectors of the economy. It excludes organizations generating annual turnover below the VAT threshold (£61,000 in 2006, £82,000 in 2016) and/or organizations that do not use PAYE to pay their employees. Salaries of £100 per week and over must be paid via PAYE. A business may be included if it pays a salary of over £100 per week to an employee but does not generate sufficient revenue to be registered for VAT, and *vice-versa*. Therefore, the sample necessarily excludes small firms.

The VAT returns panel provides information on sales revenues and the cost of goods and services inputs, and this allows us to measure GVA at the firm-level for the whole population of VAT registered firms (over 2 million per year). TFP is estimated as a residual using Wooldridge's (2009) Two Stage Least Squares (2SLS) estimation technique. In contrast, LP is measured as GVA per worker. The merged VAT-BSD-FAME panel data allow us to compute GVA per worker and TFP at the firm level. The analysis is undertaken for firms at the 4-digit SIC 2007 activity level as registered for VAT.

The issue encountered when merging the three datasets was that one enterprise could be linked to multiple VAT unique identifiers. VAT Registration Numbers (VRN) are issued to successful applicants for registration for VAT. Similarly, a particular VRN can apply to multiple enterprises owned by a single entity. To deal with this issue, these units are aggregated into one unit, to which is assigned total employment, input and output across the various units in each year. FAME data were matched to VAT returns data using the VRNs derived from a table provided by HMRC. Although the data are a population of firms, a perfect match among the three datasets was not obtained. In 2004 and 2005, only 74% of matches were identified, while in 2006-2016, 99% matches were achieved. For this reason, the years 2004 and 2005 were excluded from the analysis.

Since the focus of the analysis is understanding productivity growth due to the financial crisis, all financial services sector firms (SIC 64-67) are removed from the dataset. Also excluded are public sector organizations (SIC 84-88 and SIC 35-39), Agriculture and Mining (SIC 01-09 and SIC 97-99). The dataset contained outliers at the top end of the distribution at the 99.75th percentile. Therefore, the top 0.25% of the data is trimmed leading to a reduction of 2,300 firms a year on average. Only those firms that employed at least one person and that have information on output are included. The merged datasets enabled descriptive and decomposition analysis of UK productivity levels and their changes. Material inputs and producer price indices (available from ONS, 2019, 2019b,2019c) are used to deflate firm-level intermediates and outputs. These were constructed at the 2, 3 and 4 digit SIC 2007 levels. Capital stock deflators were constructed from the ONS dataset on capital stocks and fixed capital consumption.[11] In order to explore whether the financial crisis had differentiated impacts at sectoral level, the industries were disaggregated into manufacturing (section C) and NFS (sections F, G, H, I, J, L, M, N and R, S, T, U).

[11] Divide the current price estimates of gross capital stock (1.2.1) by the chain-volume measures estimates (1.2.2) at https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/datasets/capitalstocksconsumptionoffixedcapital

TFP is estimated at the SIC 2007 level for each 2-digit industry for the years 2006-2016. The first step was the estimation of Cobb-Douglas production functions for each 2-digit industry.[12] The Ordinary Least Squares (OLS) and Wooldridge TFP regression estimates[13] are reported in Appendix Tables 2. A1 and 2.A2.

TFP estimation of a standard production function inevitably encounters endogeneity issues because the firm observes and takes decisions based on productivity shocks that are unobservable to the econometrician. However, the econometrician observes firm decisions (investments) that do not impact on current productivity and that, under certain conditions, can be used to proxy for productivity shocks. A proxy variable approach developed in Wooldridge (2009) (see methodology section) is employed, to tackle the issue of unobservable productivity shocks. TFP is obtained as a residual of three inputs (capital, labour and materials), using a Cobb-Douglas production function, where output is measured by revenue and the coefficients are estimated following Wooldridge (2009).[14] Section3.6 outlines the procedure for the estimation of TFP.

2.5.2 Variable Description

Table 2.1 presents the variables used for the analysis. A key variable is employment and is used to create weights that provide a measure of market share for each individual firm. Using total outputs and total inputs, GVA is calculated. This is used to generate firm-level LP, which is measured as GVA per worker.

From the FAME dataset, the value of fixed assets is used to measure capital stock. For each firm, year-on-year changes in the stock of tangible fixed assets is measured; this captures the net effect of gross investment, disposals and the depreciation of assets. In the present analysis this is referred to as (net) investment.

[12] The analysis also excluded firm-year observations with non-positive capital-labour ratio values or values greater than 1 million, or with materials share greater than 1 or equal to 0 and LP greater than 1.2 million or less than or equal to 1,000. A small trimming procedure is applied (top and bottom 0.5%) based on the distribution of the following three ratios: capital labour ratio, LP, materials share. 2-digit industries with less than 1,000 observations as follows; SIC10, 11, 12 and Sic 19, 20, 21, and SIC 32 and 34, and finally SIC 90 and 9 are aggregated giving a total of 59 2-digit industries.

[13] The regression results exhibit a low value for the estimated coefficient of capital stock. This is not uncommon in the literature and possibly reflects a measurement issue inherent in the capital stock data, since the measure is based on gross investment data.

[14] Overall, there seems to be evidence of slightly decreasing returns to scale in the estimates obtained.

Table 2. 1: Description of Variables

Variable Name	Description
Employee (worker)	Standard ILO definition consists of an employee as a unit of a worker irrespective of the number of hours worked within a business, reported in the BSD.
Employment	Employee including proprietors and owners of firms.
Total Outputs/Revenue	Total value (tax exclusive) of all supplies made during the period measured in billions of Pounds (£)
Total Inputs/Intermediates/materials	Total value (tax exclusive) of all purchases during the period measured in billion Pounds (£).
Gross Value Added	GVA at basic prices, calculated as total outputs minus total intermediates measure in billion Pounds (£)
Labour Productivity (LP)	Gross Value Added per Employee (worker)
Capital	Plant and Machinery that a firm owns and uses in its operations to generate income. Calculated from the value of fixed assets in FAME.
Total Factor Productivity (TFP)	A residual obtained from the regression of Output on Materials, Capital and Labour.

2.5.3 Descriptive Statistics[15]

Table 2.2 presents the number of firms, total and average output, and average employment per firm. For the period of analysis, there are between 372,729 (2006) and 493,897 (2016) firms. A significant slump in the sample size from 404,183 in 2007 to 398,265 in 2009 for the period of the financial crisis is observed. In the pre-crisis period, the average number of firm 'hirings' was almost 19 in 2006 and fell by half a percent between 2006 and 2007. For the most part and, as already shown in the context section, average employment was fairly stable in the pre-crisis and post-crisis periods. On average, over the entire period, employment fell by only 3.82%.[16] Relative to employment in the same period, output was quite volatile. This would seem to support the idea of labour hoarding in the post-crisis period, as employment did not fall significantly and, when it did, it rebounded fairly rapidly.

[15] Since the analysis employs a universe of firms to obtain the population parameters, standard errors are not estimated.
[16] The increase in the number of firms might reflect both a real increase in the actual number of firms in the UK economy and the improved capacity of HMRC to capture firms.

Table 2.2 presents descriptive statistics for the main variables used to analyse the period from 2006 to 2016. An increase in overall employment of about 27% is observed. However, as already noted, average employment per firm fell by about 4% during the same period. The capital-labour ratio fell by close to 13%. This shows that over the study period, most firms became labour rather than capital intensive. GVA per worker fell by about 9% over the same period. This is against a backdrop of both falling output and persistent but steady average employment growth over the period. However, output per worker increased by 8.76% between 2006 and 2016. Relative to labour productivity, TFP grew by only about 4% between 2006 and 2016. Over the relevant period, firm 'mark-ups' grew by over 3%.

Table 2. 2 : Descriptive Statistics

Variables	**Year**	
	2006	**2016**
Total Employment (Millions)	7.03	8.96
Total Output (£billion)	7.97	11.5
Capital Labour ratio ('000)	23.43	20.29
Labour Productivity (value added/Worker in £'000)	47.37	42.96
Output/Worker (£'000)	113.34	128.14
Log Total Factor Productivity	3.36	3.50
Mark up	2.36	2.40

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.3 summarizes the size distribution of the firms in the sample. Most firms employ an average of four people and are classified as micro firms.[17] About 0.67% of the firms are classified as large; they have the highest capital labour ratio, but lower LP relative to micro firms. Micro firms seem to be more productive measured by both TFP and LP. Appendix Table 2. A3 presents an annual breakdown of the firm size distribution. Note the disproportionate effect of the financial crisis on the population of firms across firm sizes with micro firms being affected more and more immediately, while the effect on the other firm sizes was more lagged. However, the financial crisis did not alter the firm size distribution since the fall in employment was minimal and fairly transitory and picked up in subsequent periods.

[17] Firm employment size distribution is; micro <=10, small >10-25, medium small, >25-50, medium >50-250 and large >250.

Table 2. 3: Firm Size Distribution - Full Sample

Size	TFP	Mark-up	LP	K/L	Average Employment	Total observations
Micro	4.03	2.52	52.56	20	4	4,156,851
Small	3.52	1.57	42.87	19.24	15	638,145
Medium small	3.49	1.59	43.59	22.37	31	412,407
Medium	3.54	1.78	45.31	29.66	98	198,404
Large	3.51	2.01	47.76	40.02	1208	36,314

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

An analysis of productivity growth requires two time periods (data points) at firm level, namely t-k and t. These two time periods allow us to categorize firms as either survivors (existing in both periods or entrants existing at time t but not at time t-k), and exiting firms (existing at time t-k, but not at time t). Table 2.4 presents the total numbers and composition of firms in the periods t and t-k. During 2006 to 2016, there was a total of 703,152 firms - 372,729 firms in 2006 and 493,897 firms in 2016. Among these, 163,474 are survivors. Survivor firms account for around one-third of firms in 2016 and 44% in 2006. There is a disproportionate replacement of exiters by entrants. The number of entrants is higher than the number of exiters in these data. There were 330,423 new entrants in 2016, and 209,255 exiters in the same year.

Table 2. 4: Total and Composition of Firms Between 2006 and 2016

Type of Firm	Year			
	2006	**Percentage**	**2016**	**Percentage**
Total	372,729		493,897	
Survivors	163,474	44%	163,474	33%
Entrants			330,423	67%
Exiters	209,255	56%		

Notes: Output is deflated by 2-digit ONS SIC2007 industry-level PP Indices. Physical capital is deflated by Capital stock deflators

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Appendix Table 2.A3 reports that about 76% of firms in both 2006 and 2016, and in the other years, were micro firms employing 10 or fewer employees. Over the years, less than 1% of firms are classified as large. For this reason, all outputs are weighted by employment share. Table 2.5 shows that, when firms are split between those in operation over the whole period and those that entered or exited, surviving firms experienced significant falls in all measures except employment. On average, employment in surviving firms increased between 2006 and 2016. Average employment size per entrant firm is eleven, whereas for survivors it is nearly three times that number. This shows that in 2016 there were many entrants that were more productive and smaller in size relative to survivors. Also, in 2016, entrants were more productive than survivors, while survivors were more productive than exiters in 2006. Value added per worker was lower in 2016 for both survivors and entrants compared to the corresponding values for survivors and exiters in 2006. This shows that the process of entry raises aggregate productivity growth, although the productivity advantage from entering over exiting firms is smaller. TFP is higher for entrants relative to survivor firms. It is interesting that exiting firms exhibit both high 'mark-ups' and high TFP relative to surviving firms. However, survivors outperform exiters on the other three measures (see Table 2.5). The productivity disadvantage based on use of relatively little capital and intermediate inputs is offset by the much higher TFP of entering plants relative to survivors.

Table 2. 5: Levels of Productivity for Survivors, Entrants and Exiters in 2006 and 2016

Variable	2006-2016			
	Survivors (2006)	Survivors (2016)	Entrants (2016)	Exiters (2006)
Employment	25	32	11	14
Output per Worker(£'000)	150.45	120.70	125.41	128.80
Capital-Labour ratio	23,800	22,864	17,864	21,236
Value Added per worker (£'000)	61.19	45.78	51.54	56.53
Log TFP	3.77	3.72	3.95	4.14
Mark-up	1.86	1.77	2.71	2.74

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.6[18] presents yearly entry and exit rates and the difference between them. In the pre-crisis period, entry was about 7 percentage points higher than exit rates. However, at the start of the financial crisis, there was a drop in entry rates while exit rates soared. The financial crisis may have inhibited potentially high productive firms from entering the business environment, while simultaneously increasing the exit of low productive firms.

[18] This may be due to the restrictions applied for the purposes of the analysis, including merging the data with BSD and FAME datasets, and may not necessarily reflect entry and exit rates for the entire population of VAT registered firms.

As the crisis progressed, exit rates fell but entry exhibited some degree of volatility. This shows that less productive firms were shielded from exiting. In the post-crisis period both entry and exit rates fell, suggesting the presence of an increasing fraction of firms in the sample with lower average productivity.

Table 2. 6: Churn Rate

Period	Entry (in %)	Exit (in %)	Difference in percentage points
2006-2007	20.4	13.7	6.7
2007-2008	**15.4**	**16.2**	**-0.8**
2008-2009	**15.2**	**15.6**	**-0.4**
2009-2010	16.2	14.7	1.5
2010-2011	16.8	14.0	2.7
2011-2012	16.0	13.8	2.3
2012-2013	**17.1**	**12.9**	**4.2**
2013-2014	16.3	12.7	3.6
2014-2015	15.9	12.9	3.0
2015-2016	15.3	14.3	1.0

Notes: The Churn rate are somewhat different (mainly higher) than HMRC's published statistics on VAT registrations and deregistrations as a proportion of the live trader population. This is because the VAT registered population has been restricted for the purpose of the analysis

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets.

Table 2.7 shows the dispersion in productivity levels across firm size distribution. There seems to be wide and persistent variation in productivity based on differences between the log of productivity for firms in the 90th and 10th percentiles and firms in the 50th and 10th percentiles. Column 2 shows that a firm in the top 10% of the productivity distribution produces almost 12 times more output with the same measured units of labour compared to a firm in the bottom 10% of the productivity distribution. This gap grew between 2006 and 2016. However, for the log of TFP, the gap narrows. The gap between the 50th and 10th percentile for LP fell between 2006 and 2016, in line with the log of TFP. The 'mark-up' gap between the 90th and 10th percentile varies across the firm size distribution, narrowing slightly between 2006 and 2016 and between the 50th and 10th percentiles of the firm size distribution.

The average coefficient of variation is the standard deviation divided by the mean. The coefficient of variation reveals relatively little variation in TFP with an increase from 0.396 in 2006 to 0.405 in 2016. This also applies to LP, although the pattern is different. There is an extremely large variation, with a coefficient of variation of 1.194 in 2006 converging to 1.173 in 2016. On the other hand, the 'mark-up' shows more variation across firms over time at 2.181 in 2006 and 2.299 in 2016.

Table 2. 7: Variation of Productivity & Mark-ups by Firm Size Distributions

Variable	90^{th}-10^{th}		50^{th}-10^{th}		Coefficient of Variation	
	2006	2016	2006	2016	2006	2016
Log Labour Productivity	2.5057	2.6735	1.3527	1.2882	1.1944	1.1726
Log TFP	4.4498	4.3530	1.8694	1.7997	0.3961	0.4045
Mark-up	2.8171	2.6735	0.4706	0.4412	2.1810	2.2989

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

2.6 Methodology

In addition to describing the productivity growth decomposition methodology that is used for the empirical analysis this section outlines the procedure for the calculation of both TFP and LP.

2.6.1 Estimating TFP

As Solow (1957) demonstrates, TFP is fundamentally a residual, being that part of output growth that is not explained by input growth. In order to estimate production functions using firm-level panel data, Olley and Pakes (1996) demonstrate that, under certain assumptions including the assumption that productivity of firm *i* in time *t* (Ω_{it}) is seen by the firm but not by the econometrician implying that inputs are correlated with the realization of the productivity shock i.e., firms do not observe the shock Ω_{it} until time *t*, the distribution p(Ω_{it+1}| Ω_{it})) defines what they know about the distribution of future productivity shocks; labour is chosen at t and is a non-dynamic input, the choice of labour at time *t* does not impact future profits while period *t* capital stock of the firm is determined at *t-1*; investment is a function of the state variables capital, productivity shock. Labour is a non-dynamic variable, so it does not enter the investment function, it is chosen at time *t*. This precludes the possibility of any unobserved heterogeneity across firms in adjustment costs of capital, in demand or labour market conditions, or additional unobservables entering other parts of the production function. This assumption allows us to invert the investment decision to recover the unobservable time-varying productivity as a residual of the production function. Building on this, Levinsohn and Petrin (2000) propose a modification to the Olley-Pakes (OP) approach to address the problem of lumpy investment. Levinsohn and Petrin (LP) suggest using intermediate inputs to proxy for unobserved productivity. They make some assumptions that allow productivity to be written as a function of capital inputs and intermediate inputs (such as materials and electricity). Similar to Olley and Pakes (1996), they propose a two-step estimation method to consistently estimate the coefficients of the variable inputs and capital inputs. Wooldridge (2009) proposed a framework for estimating the two-stage OP and LP procedures in one step. The Wooldridge (2009) 2SLS is a modification of the LP estimator.

To account for sector heterogeneity, the following production function is estimated for each 2-digit industry sector:

$$y_{it} = \alpha_i + \beta_1 m_{it} + \beta_2 l_{it} + \beta_3 k_{it} + f(m_{it}) + g(k_{it}) + \pi_t + e_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots..[2.1]$$

where f(·) and g(·) are higher order polynomial terms in *m* and *k* respectively andπ_t are year dummies the subscripts *i* referees to each two-digit industry (using sic2007) while *t* is time period in years. The polynomials are included to capture the functional form of the unobservable productivity function since actual productivity is unobservable. The polynomial provides consistent estimates of the unobservable productivity.

Given the potential endogeneity of materials and labour, they are instrumented using the lagged values (of order 2) of materials, labour and capital, while their cross-products are used as additional regressors. The Hansen J test of over-identifying restrictions is used to test for validity of the instruments (see Baum *et al.*, 2003). The TFP measure is then computed as follows:

$$TFP_{it} = y_{it} - (\hat{\beta}_1 m_{it} + \hat{\beta}_2 l_{it} + \hat{\beta}_3 k_{it}) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..[2.2]$$

where m_{it} and l_{it} are instrumented using the lagged values of materials.

2.6.2 Calculating Labour Productivity

The firm level LP is the GVA of firm *i* at time *t* (GVA_{it}) per worker *i* at time *t* (l_{it}) and is expressed as;

$$\varphi_{it} = \frac{GVA_{it}}{l_{it}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.[2.3]$$

2.6.3 Productivity Growth Decomposition

The decomposition method proposed by Foster *et al.* (2001) is used to decompose changes in aggregate productivity into the contributions of entering and exiting plants, and the contribution of continuing plants. Aggregate productivity is calculated as the share-weighted mean of firm-level productivity. Both year-on-year as well as period-on-period changes (for the periods preceding, during and after the financial crisis) in LP and TFP is undertaken. FHK defines the aggregate productivity level in year t, Φ_t, as follows:

$$\Phi_t = \sum_i \theta_{it}\varphi_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [2.4]$$

where θ_i is the share of employment of firm *i* at time *t*, representing the firm's market share in period *t*; Φ_t and φ_{it} are the aggregate and firm-level productivity of firm *i* in period *t* (in this analysis, $\varphi_{it,}\ \Phi_t$ represent firm level and aggregate level TFP and LP) respectively. Using equation [2.4], the rate of aggregate productivity growth in the economy is given by $\Delta\Phi_t = \Phi_2 - \Phi_1$. The contribution to aggregate productivity growth of each firm is classified based on the firm's activity status:

(i) existing firm (active in both periods (i.e., surviving);

(ii) entering firm (active only in period 2);

(iii) exiting firm (active only in period 1).

Using this categorization, the FHK method decomposes aggregate productivity growth into five components - the *within*, *between*, *covariance* or *cross-term*, *entry* and *exit,* as follows:

$$\Delta\Phi_t = \underbrace{\textstyle\sum_{i\in S}\theta_{it-k}\Delta\varphi_{it}}_{Within} + \underbrace{\textstyle\sum_{i\in S}\Delta\theta_{it}(\varphi_{it-k}-\Phi_{t-k})}_{Between} + \underbrace{\textstyle\sum_{i\in S}\Delta\theta_{it}\Delta\varphi_{it}}_{Covariance}$$

$$+\underbrace{\sum_{i\in E}\theta_{it}(\varphi_{it}-\Phi_{t-k})}_{Entry} - \underbrace{\sum_{i\in X}\theta_{it-k}(\varphi_{it-k}-\Phi_{t-k})}_{Exit} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ldots [2.5]$$

where S is a set of indexes for surviving firms; E is a set of indexes for entry firms; X is a set of indexes for exiting firms. In equation [2.5], the first, second and third terms are the contribution from existing firms; the fourth term is the contribution from entrant firms; and the fifth term is the contribution from exiting firms. Δ is the change over the *k*-year interval between the first (*t*–*k*) and last (*t*) years; θ_{it} is the employment market share of firm *i*; and Φ_{t-k} is the aggregate (employment weighted average) productivity level of the industry in the first year (*t*–*k*).

The components of the FHK decomposition are defined as follows:

- The *within*-firm term measures the average change in firm productivity holding market shares constant at the base year (t-k) structure, in order to distinguish average productivity growth from composition effects. This term reflects both firm restructuring and mis-measured price and quality changes. It denotes counterfactual aggregate productivity growth if the individual firm share is held constant. Disney *et al*. (2003) also label the *within* effect as internal restructuring.
- The *between*-firm component reflects changing shares, adjusted for initial year aggregate productivity. It captures the reallocation of market shares between surviving firms, adjusted for initial year aggregate productivity (weighted by the initial shares). The term is positive only if the firms that gain market share are also those firms with above-initial period aggregate productivity. The term is negative if the firms that are downsizing are the more productive firms.
- The *covariance* term captures covariance between changes in market share and changes in productivity amongst surviving firms. It is also described as the 'cross' effect. A positive (negative) covariance implies that firms that have become more productive during the period are also gaining (losing) market shares. Therefore, covariance reflects resource allocation efficiency (see Olley and Pakes, 1996). If resources are allocated efficiently, more productive firms should acquire more resources and have higher market shares, resulting in a high covariance. A negative covariance term is consistent with the idea that downsizing may be

productivity enhancing. According to Bartelsman *et al.* (2013), the covariance measure is a robust theoretical and empirical measure to assess the effect of misallocation of resources or market distortions.

- *Entry* is the sum of the differences between each entering firm's productivity and the initial productivity in the industry weighted by the market share of each entrant firm. The contribution of entrants is positive only if entering firms' productivity exceeds the period t-k industry aggregate productivity for all active firms.
- *Exit* is the sum of the differences between each exiting firm's productivity and the initial productivity in the industry, weighted by the market share of each exiting firm. The contribution of exiters is negative if exiting firm aggregate productivity exceeds the period t-k industry aggregate productivity for all active firms.

The FHK method uses the first year's values for a continuing firm's market share (θ_{it-k}), productivity level (φ_{it-k}) and level of average aggregate productivity (Φ_{t-k}). A potential problem from use of this method is that, in the presence of measurement error in assessing market shares and relative productivity levels in the base year, the correlation between changes in productivity and changes in market share may be spurious, which will affect the *within*- and *between*-firm effects.

The FHK method has been criticized for not completely removing bias since it uses inappropriate reference productivities (including entrant and exiter productivity in the reference productivity) to estimate the contributions of entering and exiting firms (Melitz and Polanec, 2015). The weights used for exiters and entrants are based on the overall initial period market shares of the surviving firms. Therefore, use of inappropriate weights exacerbates the bias. The FHK conflates the contributions of different groups of firms (entering, exiting, and surviving). Therefore, it could potentially yield upward biased measures of the entrants' and exiters' contributions due to the use of both an inappropriate reference productivity and common weights with surviving firm (see Melitz and Polanec, 2015).

FHK emphasizes two important features that distinguish it from other methods. First, the decomposition treats surviving, entering and exiting firms in an integrated manner. Second, it separates *within* and *between* components from *cross* or *covariance* terms. Most alternative decomposition methods omit the *covariance* term and, therefore, contain only four terms. The fact that both the *within* and *between* components partly reflect the *covariance* component is the main disadvantage of these methods. Although the first and the second terms are still defined as *within* and *between* components, they partly reflect the *covariance* term. In this context, the FHK method investigates the *within*, *between*, *covariance*, firm *entry* and *exit* components in more depth and so provides a richer understanding of the micro level components that drive aggregate productivity growth.

2.6.4 Markups

The mark-ups are calculated as price over marginal cost. Since both price and marginal cost are not observable at the firm level they are obtained as the ratio of the coefficient of the log of input (materials) to the revenue share of materials (i.e., materials/revenue) for each two-digit Industry as follows;

Markup=$\widehat{\beta_1}$(materials/revenue)$_i$ $\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ldots$ [2.6]

where $\widehat{\beta_1}$ is the coefficient of the log of materials from equation 2.1 and *i* is each two-digit Industry.

2.7 Empirical Results

This subsection starts by undertaking a decomposition of aggregate LP growth. The TFP obtained as a residual from the estimation of the Cobb-Douglas production function is also decomposed. The results for the coefficients of the production function are reported in Appendix Table 2.A1. The production function regression results reveal that most industries exhibit constant returns to scale. This result is robust to using Wooldridge's (2009) proxy variables or the OLS[19] fixed effects techniques. The null hypothesis that the instruments are valid for all industries, cannot be rejected using the Hansen J test for over-identifying restrictions for 52 of the 59 2-digit Industries. This confirms that most of the 2-digit industries, with the exception of a small number (SIC13, 14,15,26, 30, 50 and 95), meet the orthogonality of the instruments condition. The models yield plausible results and provide a good fit to the data.

Both LP and TFP are decomposed as shown in equation [2.6]. The decomposition for the manufacturing and NFS sectors is also presented separately. The full sample results are provided first and as a robustness check, the analysis is also undertaken for firms that generate a revenue of £100,000 or more in a year. This is a robustness check that

[19] Table 2.A1 reports results using the OLS estimation as in Riley *et al.* (2015, 2018) using the formula $TFP_i = Yi /(Ki^{(1-\alpha L)} L_i^{\alpha L})$, where α_L is the industry average labour share on average over the relevant period. Y is GVA, K is the estimated capital stock and L is labour. The magnitude of the coefficients obtained from the two methods is shown in Appendix Tables 2. A1 and 2.A2 are fairly similar.

attempts to simulate the type of sample characteristically used in studies that exploit the ARD(x)/ABS data. These data are only representative of large firms hence the use of the revenue threshold of £100,000 per annum for the purpose of this simulation.

2.7.1 Firm-Level Results Obtained Using the FHK Decomposition Method

The analysis in this chapter is mainly descriptive and covers the sample of entering, exiting and continuing firms during the study period. Using the FHK methodology, year-on-year changes in the level of aggregate productivity are characterized. However, the sources of its fluctuations are unknown. Aggregate productivity changes could be due to a general shift in the productivity distribution that affects all firms, or, at least, each firm category, equally. Alternatively, it could be due to changes in an incumbent firm's internal restructuring, reallocation of market shares, entry or exit, or a firm transitioning from one category to another. These decompositions allow us to understand what causes both TFP and LP growth. This chapter aims to investigate the micro drivers as mediated through these five channels of the peaks and troughs in aggregate TFP and LP growth between given time period intervals.

First, TFP and measure firm LP growth and decompose this growth across industries are estimated. The aim is to analyse the contributions of *within*-firm improvement, *between*, *cross*-firm reallocation, firm entry and exit to aggregate TFP and LP growth. Firms are classified at the 4-digit 2007 SIC, with industry aggregated at the 2-digit level. Using this strategy of firm identification, the productivity growth decomposition for the UK over the period 2006 to 2016, using the FHK method is implemented.

2.7.2 Decomposition Results for Labour Productivity[20]

Table 2.8 presents the real normalized[21] ratios and growth rates based on year-on-year changes in aggregate productivity for the set of non-financial private sector firms during the period 2006 to 2016. Column 7 presents the change in aggregate productivity over each period. During the period analysed, productivity fell by 9.3%. The *within* and *covariance* terms of survivor firms and the process of *entry* exerted a dampening effect on productivity. *Covariance*, which represents resource misallocation, accounts for most of the fall in LP. However, this is attenuated by the positive *between*-firm productivity

[20] Appendix to this chapter presents the decomposition results for labour productivity using BSD and VAT returns data. Although the merging with FAME data reduces the number of firms in the sample, the results for LP remain comparable despite being fairly sensitive to sample size changes.

[21] In following previous studies' (Disney, 2003; Riley *et al.,* 2014) the analysis in this chapter, normalizes ratios with decomposition shares adding to 100%. The original decompositions results are presented in Appendix Tables 2.A4, 2.A5 and 2.A6.

component. Firm *entry* had an overall negative effect on productivity, while exiting firms enhanced productivity. This is in line with the findings in Barnett *et al*. (2014b) and Riley *et al.* (2014), whose studies reveal that entering (exiting) plants had a negative (positive) effect on LP growth post-2007. However, the disproportional positive impact of exits failed to outweigh the negative impact of firm entry over the period of the analysis. Overall, this is evidence that LP growth deteriorated over the study period. The decomposition analysis is then undertaken on aa year-on-year basis to identify the performance of LP growth across individual years.

Table 2. 8: Labour Productivity Decomposition Between 2002 and 2016

	Surviving Firms					
Period	**Within**	**Between**	**Covariance**	**Entering**	**Exiting**	**Change in LP**
2006-2016	-0.0329	0.1106	-0.1517	-0.0329	-0.0138	-0.0931

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.9 presents the results for the year-on-year decomposition of aggregate LP growth. The estimates suggest that between 2006-2007 (pre-financial crisis), internal restructuring within surviving firms accounted for most of the growth in aggregate LP. The fall in the reallocation of resources across firms offset this positive contribution and LP grew by 0.5%. This shows that, before the financial crisis, LP growth in the UK was positive, but somewhat weak given the modest reallocation of resources across firms.

During the 2007-2008 period, LP fell sharply by 6%. This was attributable to the deteriorating *within*-industry term coupled with continued weakness in the reallocation of resources across industry. Over this period both the *within* and *across* firm terms were negative, leading to a massive contraction in LP growth. However, relative to the previous period, the reallocation of resources did not worsen; it remained negative, but stable. The contribution of net firm entry was also negative during this period. *Within*-firm restructuring and reallocation were at their poorest level during the peak of the financial crisis (2008-2009) period. Both deteriorated, resulting in a record low for aggregate LP growth. This seems to have been the biggest annual decline and was due to the depth of the financial crisis in that year.

In the aftermath of the financial crisis, the *within*-industry effect rebounded (2009-2010) relative to the previous period; this resulted in slightly improved productivity, although aggregate productivity growth remained negative. The contribution from resource reallocations across firms also fell, providing further evidence of weaknesses in resources allocation that crippled productivity growth and recovery during this period. In

2010-2011 the *within*-firm term improved and was accompanied by positive LP growth. However, this was short-lived and, in the subsequent period, the *within* term deteriorated and aggregate LP fell. In the next period, from the onset of the post-crisis period 2012-2013, there were improvements in the *within* term and a slight rise in aggregate LP. The period 2014-2015 saw a positive and record growth in aggregate LP due to an improvement in the *within*-firm growth term. In 2015-2016, the *within*-firm components worsened and LP growth weakened.

The changes in LP growth appear to have been driven by changes to the internal restructuring *within* as well as *across* surviving firms. These two effects worked either to reinforce the weak LP growth or to counteract each other. Changes in the *within*-firm and *covariance* terms drove movements in LP over time. In some periods, despite an improvement in the *within*-firm term, negative *covariance* dampened LP growth. Clearly, restructuring *within*-firms is an important driver of aggregate LP growth. This finding is in line with Riley *et al.* (2014) who suggest that productivity growth *within* continuing firms was the predominant source of aggregate TFP growth during the 2000 to 2010 period. Coupled with resource misallocation across firms, this led to Barnett *et al*.'s (2014b) evidence of firm level 'labour hoarding'. Using ONS firm-level data, Barnett and colleagues show that aggregate movements in employment can be linked to individual firm-level behaviour at different points in the cycle. Productivity growth is associated with restructuring and downsizing rather than with expansion.

It should be noted that the misallocation of resources (*covariance* term) has always been a weakness in the UK economy, in both the pre-financial and post-financial crisis periods; it fell to record low levels during the period of the financial crisis. Although the *covariance* component has remained negative across each period, it has been improving in recent years (2014-2016) relative to both the crisis and early post-crisis years. *Within*-firm restructuring was disproportionately altered by the financial crisis and this clearly affected growth in aggregate LP during the crisis and post-crisis periods. There was a cyclical movement of the *within*-firm component and aggregate LP growth. It could be said that the financial crisis highlighted the impact of *within*-firm restructuring on aggregate LP growth.

Productivity growth has been erratic. In the periods when *within*-firm restructuring was negative, aggregate LP growth also turned negative. Arguably, if the *within*-firm term improves, overall LP growth should also improve. Appendix Tables 2.A7 to 2.A9 provide detailed decompositions of LP for firms with revenue of £100,000 or over. The decomposition results are consistent when this revenue threshold is applied. *Within*-firm restructuring coupled with the misallocation of resources continues to drive movements in aggregate LP growth. The difference between the two terms is that the *within*-firm restructuring seems to have been weakened by the financial crisis while *covariance* seems to have been weak even before the outbreak of the financial crisis.

The estimated contributions of *entry* and *exit* to productivity growth are relatively small. Low productivity exiters make a positive contribution to aggregate productivity growth while entering firms contribute positively to LP growth over the years. This is confirmed by the raw data that show that entering firms have higher LP relative to incumbents. Overall, market selection seems to have been significant for the evolution of aggregate LP growth. The contribution of entry is higher than the contribution made by *exit* rates. The exit of low productivity firms would appear to make a very modest contribution to growth in aggregate productivity. The structure of the *between* term seems to have been unaffected by the financial crisis and has generally remained positive in both the pre-crisis and post-crisis periods.

Table 2. 9: Year on Year Labour Productivity Decomposition

Period	Surviving Firms			Entering	Exiting	Change in LP
	Within	Between	Covariance			
2006-2007	0.0147	0.0453	-0.0569	0.0046	0.0026	0.0051
2007-2008	-0.0529	0.0519	-0.0599	-0.0016	-0.0023	-0.0601
2008-2009	**-0.0587**	**0.0503**	**-0.0713**	**0.0067**	**-0.0081**	**-0.0649**
2009-2010	-0.0061	-0.0253	-0.0381	0.0059	-0.0026	-0.0111
2010-2011	0.0128	0.0469	-0.0595	0.0014	-0.0091	0.0107
2011-2012	-0.0045	0.0392	-0.0527	0.0054	-0.0083	-0.0043
2012-2013	0.0112	0.0300	-0.0423	0.0071	-0.0044	0.0103
2013-2014	0.0381	0.0319	-0.0437	-0.0014	0.0066	0.0183
2014-2015	**0.0347**	**0.0286**	**-0.0375**	**0.0055**	**-0.0123**	**0.0436**
2015-2016	-0.0092	0.0227	-0.0322	-0.0090	0.0114	-0.0390

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.10 presents the LP decomposition for the three periods: pre-crisis (2006-2007), crisis (2008-2012) and recovery (2013-2016). With the exception of the *covariance* term, all the sub-components enhanced growth in aggregate productivity in the pre-crisis period. The *within*-firm term worsened during the period of the crisis and coupled with *entry* of less productive firms and poor reallocation of resources across firms, aggregate LP showed negative growth in this period. This supports the idea that the financial crisis altered the *within*-firm restructuring term, which then worked to weaken aggregate LP growth. In the recovery period, *covariance* and *entry* of low productive firms dampened growth in aggregate LP, but this was counterbalanced by a positive *within*-firm term. The *exit* of productive firms in the post-crisis period had a modest effect on LP growth. Overall, LP growth was positive in the pre-crisis period and negative in the crisis period. There is evidence that the financial crisis had a disproportionate effect on the *within* term, which grew at an average 0.5% per year in the post-crisis period.

Table 2. 10: Pre-Crisis, Crisis and Post Crisis Labour Productivity Decomposition

	Surviving Firms					
Period	**Within**	**Between**	**Covariance**	**Entering**	**Exiting**	**Change in LP**
2006-2007	0.0147	0.0453	-0.0569	0.0046	0.0026	0.0051
2008-2012	-0.0487	0.0994	-0.1347	-0.0083	-0.0228	-0.0695
2013-2016	0.0499	0.0467	-0.0640	-0.0075	0.0039	0.0213

Source: Author’s own calculations based on HMRC-VAT, BSD and FAME datasets

2.7.3 Decomposition Results for Total Factor Productivity

The results for the TFP decomposition in Table 2.11 highlight the importance of reallocation for increased productivity growth. During 2006 to 2016, TFP grew by 14%, although it was slowed by the covariance term that captured a reduced reallocation of resources across firms. The entry of new firms accounts for all of the growth in aggregate TFP over the period of analysis. The role of entry in explaining aggregate TFP growth is discussed in Disney *et al.* (2003), who studied a large sample of UK manufacturing firms and found that external restructuring (entry and exit) accounted for 80%-90% of TFP growth during the period 1980-1992. Unlike LP growth, TFP growth was positive during the period of analysis.

Table 2. 11: Total Factor Productivity Decomposition Between 2006 and 2016

	Surviving Firms					
Period	**Within**	**Between**	**Covariance**	**Entering**	**Exiting**	**Change in TFP**
2006-2016	0.0107	0.0430	-0.0145	0.1355	0.0393	0.1353

Source: Author’s own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.12 shows that although TFP growth remained positive, before the onset of the financial crisis it had started to fall gradually. During the period 2006-2007, aggregate TFP increased by 7% per annum, due, almost entirely, to the contribution made by the *entry* of more productive firms to the business environment. This positive effect was attenuated by decreasing *within* and *covariance* terms. The onset of the financial crisis (2007-2008) witnessed a one percentage point weakening in TFP, due mostly to weaker net *entry*. The fall in TFP was modest during this period and can be attributed to the sizable positive contribution of the *within*-firm term, which effectively cushioned TFP from further decreases. This effect was strengthened further by a modest positive contribution from the *between* and *covariance* terms.

In the 2008-2009 period, deteriorating *within* and *cross* terms, coupled with weak *net entry*, worsened aggregate TFP growth; both net *entry* and *within*-firm terms seem to have been impaired by the financial crisis and were driving changes in aggregate TFP growth. This negative trend reached a record high in the subsequent period (2009-2010) with the *within* term showing its lowest value during this period. In contrast, improved net *entry* during this period appears to have acted as a shock absorber against a further decline in aggregate TFP growth.

In the TFP decomposition relative to the LP decomposition, the magnitude of the *cross* term is fairly small. This might imply that shifts in the share of labour are less negatively correlated to shifts in TFP compared to LP. This might be taken to imply that large firms were downsizing in terms of labour (but not capital stock) and were increasing their LP based largely on capital deepening and not necessarily TFP. This suggests that firms that increase their (labour) productivity exhibit a reduced share of labour input *within* an industry.

Between 2010 and 2011, *covariance* was positive, suggesting that market shares move towards firms that have become more productive. However, this was not enough to offset the negative effect of the *within* term since although aggregate TFP growth improved relative to the preceding period, it remained negative. During this period, TFP was driven by *within*-firm restructuring. This also applies to the next period (2011-2012), with the net *entry* term deteriorating during this period. Although the within term was negative, it improved by 0.86% relative to the previous period. This translates into an improvement in aggregate TFP growth (relative to the 2010-2011 period) despite remaining negative.

The negative growth in aggregate TFP during the 2012-2013 period is attributable largely to *within*-firm changes combined with a negative net *entry* contribution. The improvement in the *covariance* term outweighed the negative contribution of the *within* and net *entry* terms. This TFP-enhancing process of resource reallocation was driven mostly by labour moving to firms with low levels of capital deepening and, therefore, high levels of TFP.

The start of the post-crisis period (2013-2014) witnessed a great improvement in aggregate TFP growth driven by the mechanisms of restructuring *within* continuing firms and dampened by weakness in the *covariance* component (firms that were less productive gained market share). This indicates that firms who were downsizing rather than expanding reaped the productivity gains. The positive effect on growth of aggregate TFP can be accounted for by improvements in the *within*-firm restructuring term. The positive fluctuations in the *between* term over the years are too small in magnitude to counteract any movements in the *within* and net *entry* terms and their subsequent impact on aggregate TFP growth.

In the 2014-2015 period, aggregate TFP growth fell slightly and levelled off at around 5%. The *within*-firm share, although positive, fell considerably, relative to the previous period. Therefore, TFP would have dropped slightly less had resources not moved away from firms whose productivity increased, towards firms whose productivity fell during this period (*covariance* term). Net firm *entry* accounts for about half of the increase in aggregate TFP during this period.

In the 2015-2016 period, aggregate TFP experienced a drop. Net *entry* was crucial for enhancing productivity during this period, while the reallocation of shares somewhat stifled TFP growth. The *within* term fell relative to the previous period. Overall, the evidence shows that the role of net *entry* was more prominent in the pre-crisis and recovery periods, whereas *within*-firm restructuring seems to have been important during the period of the financial crisis. The disproportionate effect of the financial crisis on the *within*-firm term seems to have driven changes in aggregate TFP growth.

Table 2. 12: Year on Year Total Factor Productivity Decomposition

	Surviving Firms					
Period	Within	Between	Covariance	Entering	Exiting	Change in TFP
2006-2007	-0.0072	0.0188	-0.0020	0.0806	0.0167	0.0736
2007-2008	**0.0431**	**0.0191**	**0.0002**	**0.0063**	**0.0062**	**0.0625**
2008-2009	-0.0183	0.0070	-0.0076	-0.0054	0.0103	-0.0346
2009-2010	-0.0679	0.0037	-0.0034	0.0123	-0.0062	-0.0490
2010-2011	-0.0204	0.0080	0.0009	0.0112	0.0067	-0.0068
2011-2012	-0.0118	0.0052	-0.0014	0.0001	0.0198	-0.0041
2012-2013	-0.0476	0.0091	0.0030	0.0128	0.0235	-0.0462
2013-2014	0.0617	0.0161	-0.0070	0.0203	0.0277	0.0634
2014-2015	0.0208	0.0075	-0.0036	0.0241	-0.0014	0.0503
2015-2016	0.0124	0.0051	-0.0044	0.0296	0.0165	0.0262

Source: Author’s own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.13 shows the change in TFP over the three periods - pre-crisis, crisis and post-crisis. In the pre-crisis period (2006-2007), aggregate TFP grew by 7%, driven mostly by the net *entry* term. During the crisis (2008-2012), TFP fell sharply and there was a simultaneous worsening of the *within*-firm term. The *covariance* term weakened further and there was a sharp decline in the net *entry* term. This fall in TFP during the 2008-2012 period is consistent with the findings in Goodridge *et al,* (2018).

Table 2. 13: Pre-Crisis, Crisis and Post Crisis Total Factor Productivity Decomposition

	Surviving Firms					
Period	Within	Between	Covariance	Entering	Exiting	Change in TFP
2006-2007	-0.0072	0.0188	-0.0020	0.0806	0.0167	0.0736
2008-2012	-0.0890	0.0139	-0.0117	-0.0011	0.0066	-0.0945
2013-2016	0.0977	0.0247	-0.0107	0.0544	0.0261	0.1399

Source: Author’s own calculations based on HMRC-VAT, BSD and FAME datasets

In the post-crisis period (2013-2016), aggregate TFP growth rebounded. Clearly, changes in the *within*-firm term and net *entry* had a huge impact on changes in aggregate TFP. Appendix Tables 2.A10 to 2.A12 show that the pattern of aggregate TFP growth was consistent, even for firms with annual revenues of £100,000 or more.

2.7.4 Growth of Aggregate Labour Productivity and Total Factor Productivity

Combining the results for the LP and TFP decompositions with the above evidence suggests that incumbent firms increased their LP by substituting capital for labour (capital deepening) or by exiting the market, but not necessarily by achieving a marked improvement in the overall efficiency of their production processes. In contrast, new entrants had a more optimal combination of factor inputs and new technologies, which resulted in faster TFP growth. Both the LP and TFP decompositions suggest that the process of resource reallocation towards less productive surviving firms was underway even before the financial crisis.

The deterioration in TFP growth was lagging relative to LP growth. At the onset of the crisis, TFP exhibited a modest deterioration but as the crisis progressed, it declined sharply. Overall, the changes in aggregate TFP growth indicate that *within*-firm restructuring is as important for aggregate TFP growth as it is for aggregate LP growth. The role of net *entry* is less important for LP growth compared to TFP growth. Most of the changes can be explained by surviving firms (i.e., movements at the intensive margin). The extensive margin (entries and exits) plays a limited role in all sub-periods. In addition to being smaller, the contributions of entry and exits are typically minimal. New firms tend to be smaller, but more productive than incumbents, leading to a positive contribution from entry. Exiting firms are less productive than surviving firms, with the result that the contribution of exits is also positive. This pattern applies particularly to LP and is relevant to a lesser extent for TFP.

Overall, there was a modest fall in TFP relative to the change in LP. Appendix Table 2.A13 shows that if TFP is not weighted by firm size, a 2% decline in TFP during the period analysed is observed. This is consistent with evidence based on micro-data (e.g., Harris and Moffat, 2019; Field and Franklin, 2013). Harris and Moffat (2019) show that when grouping plants by size of their (real) output, the post-2008 decline in TFP is confined to smaller (especially the smallest) plants and does not affect plants with a sales revenue of over £714,000 per year (in 2000 prices). Therefore, using the LP measure shows that productivity has continued to decline while TFP portrays a recovery post-financial crisis.

Figure 2.4 shows that, for all the firms in the sample, aggregate TFP growth stagnated or declined during the period 2008-2009 to 2013-2014. This was followed by periods of positive growth. Aggregate LP weakened in the pre-crisis period and continued to fall up to 2009 with a slight rebound between 2009 and 2010. It then worsened in 2011-2012 and 2012-2013. Nevertheless, the decomposition of aggregate labour and TFP growth into *within*, *between*, *covariance*, *entry* and *exit* terms provides a better understanding of the source of these movements in aggregate productivity growth. The oscillations in TFP and LP trends at the macroeconomic level are corroborated by firm level data at the micro-level. Central here is the role of *within*-firm restructuring in driving changes to aggregate TFP and LP growth.

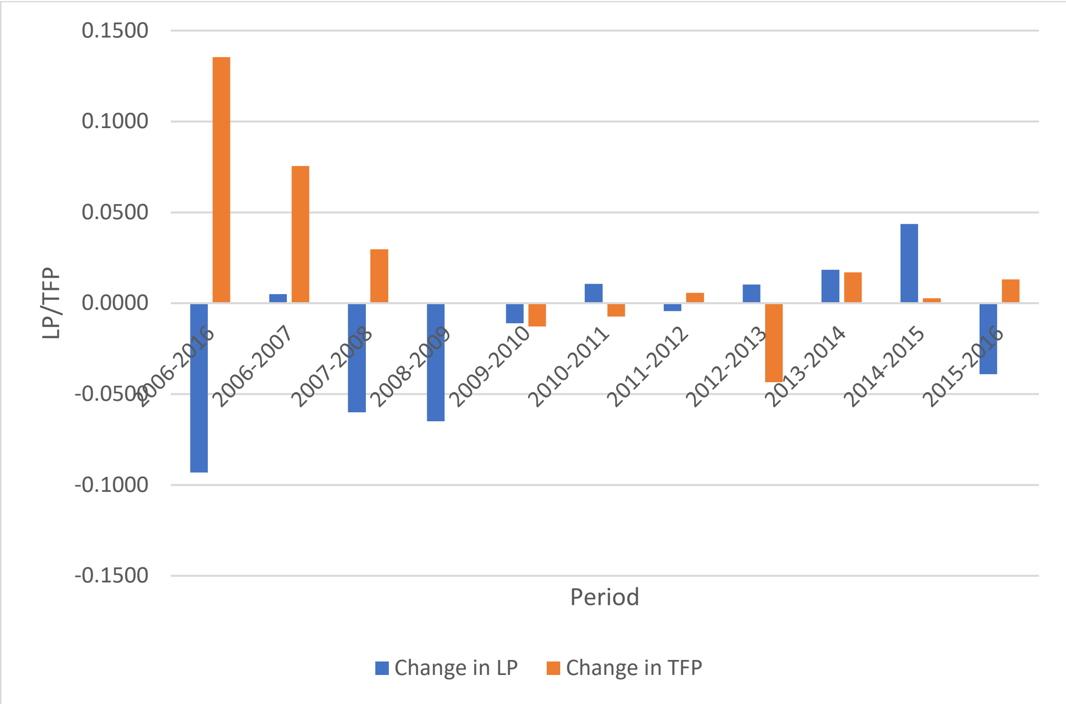

Figure 2. 4: Aggregate Year on Year Total Factor Productivity and Labour Productivity Growth

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Figure 2.5 plots the changes in TFP and LP for firms with revenue of £100,000 or more per annum. Note that the pattern of fall for both TFP and LP changes is generally similar. However, at the onset of the financial crisis (2007-2008 and 2008-2009) these firms experienced significant falls in TFP. Among all firms, TFP bounced back, but LP remained relatively weak.

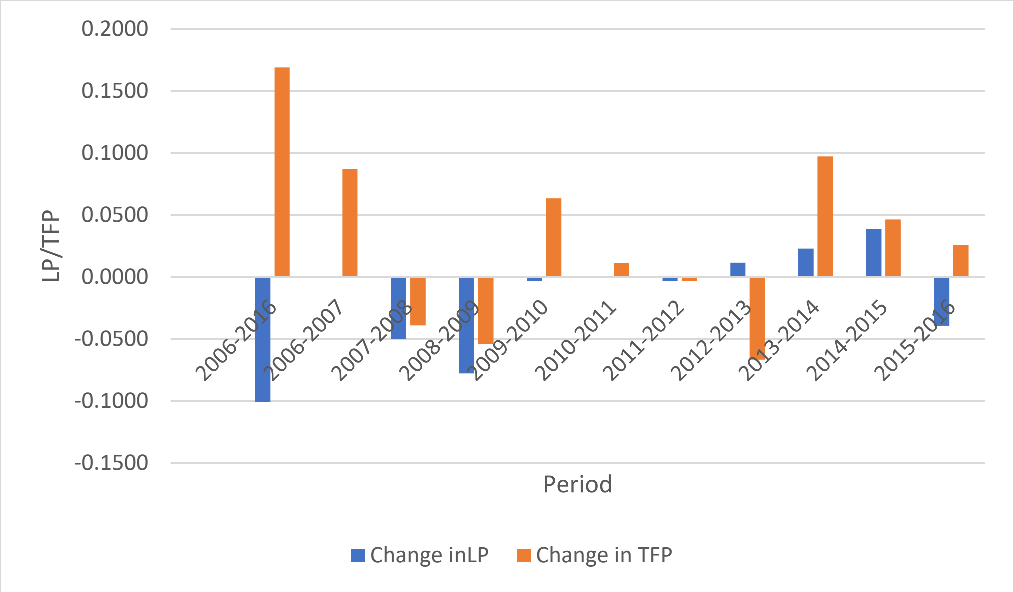

Figure 2. 5: Aggregate Year on Year Total Factor Productivity and Labour Productivity Growth for Firms With £100,000 Revenue

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

2.7.5 Productivity Differences in Manufacturing and Non-Financial Services

The structure of the UK economy has changed over time with a rising share of NFS in total output (Kierzenkowski *et al.,* 2018) and a decreasing relative size of the manufacturing sector. Therefore, a sectoral level decomposition is undertaken to establish whether the impact of the crisis on these two sectors is different from the impact on the aggregate economy. TFP and LP growth are disaggregated at the sectoral level, focusing on the manufacturing and NFS sectors.

2.7.6 Growth in Aggregate Labour Productivity in the Manufacturing and Non-Financial Services

Tables 2.14 shows that the 2008-09 recession had a heterogeneous effect on the NFS and manufacturing sectors. In the manufacturing sector, LP growth fell by 1% with the onset of the financial crisis (2007-2008) relative to the pre-crisis period (2006-2007). A further worsening of the *within*-firm term led to a record (8%) drop in sectoral LP at the peak of the financial crisis (2008-2009). However, improvements in the *within* term post-crisis, translated into positive growth in manufacturing sector LP. At the dawn of the recovery period (2012-2013), manufacturing sector LP rose based on an improved contribution of net *entry* coupled with a strong *within* term. Kierzenkowski *et al.* (2018)

hypothesize that weak corporate restructuring and greater substitution of labour for capital held back productivity gains in the manufacturing sector.

Table 2. 14: Year on Year Labour Productivity Decomposition for the Manufacturing Sector

Period	Surviving Firms			Entering	Exiting	Change in LP
	Within	Between	Covariance			
2006-2007	0.0054	0.0167	-0.0243	0.0510	0.0331	0.0156
2007-2008	-0.0061	0.0272	-0.0256	0.0068	-0.0009	0.0032
2008-2009	**-0.0733**	**0.0287**	**-0.0326**	**-0.0093**	**-0.0083**	**-0.0782**
2009-2010	0.0764	0.0164	-0.0235	0.0061	0.0091	0.0662
2010-2011	0.0070	0.0192	-0.0246	-0.0018	-0.0071	0.0069
2011-2012	0.0444	0.0185	-0.0268	-0.0012	0.0097	0.0252
2012-2013	0.0230	0.0106	-0.0172	0.0328	0.0059	0.0434
2013-2014	0.0030	0.0115	-0.0120	0.0071	0.0008	0.0088
2014-2015	**-0.0152**	**0.0064**	**-0.0145**	**0.0047**	**0.0096**	**-0.0281**
2015-2016	**0.0165**	**0.0085**	**-0.0125**	**-0.0084**	**0.0232**	**-0.0191**

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

The response was different in the NFS sector. Table 2.15 shows that LP growth deteriorated considerably to negative levels (8%) at the start of the financial crisis (2007-2008). The fall in aggregate LP in this sector was sharper compared to the more gradual fall in the manufacturing sector. The fall in aggregate LP was due, in part, to a worsening *within* term. During the crisis period, LP improved slightly, but remained negative due to a fairly volatile *within* term. However, during the recovery period, NFS productivity increased, but did not regain pre-crisis growth. The *within* firm term remained erratic but improved slightly in the post-crisis period. NFS LP remained weak.

Table 2. 15: Year on Year Labour Productivity Decomposition for the Non-Financial Services Sector

Period	Surviving Firms			Entering	Exiting	Change in LP
	Within	Between	Covariance			
2006-2007	0.0221	0.0529	-0.0660	-0.0016	0.0021	0.0052
2007-2008	**-0.0662**	**0.0568**	**-0.0653**	**-0.0016**	**-0.0006**	**-0.0756**
2008-2009	**-0.0539**	**0.0547**	**-0.0788**	**0.0127**	**-0.0055**	**-0.0599**
2009-2010	**-0.0279**	**0.0276**	**-0.0417**	**0.0123**	**0.0037**	**-0.0334**
2010-2011	0.0033	0.0576	-0.0719	0.0285	0.0031	0.0144
2011-2012	**-0.0223**	**0.0454**	**-0.0583**	**0.0144**	**-0.0133**	**-0.0075**
2012-2013	0.0069	0.0343	-0.0478	0.0155	0.0062	0.0027
2013-2014	0.0485	0.0379	-0.0524	0.0008	0.0133	0.0215
2014-2015	0.0471	0.0349	-0.0437	0.0177	-0.0093	0.0652
2015-2016	**-0.0184**	**0.0248**	**-0.0350**	**-0.0072**	**0.0046**	**-0.0405**

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

The evidence points to a heterogeneous effect of the financial crisis on these two sectors, although the *within*-firm variation was the driver of changes in aggregate LP growth in these two sectors. In both sectors there is evidence of pro-cyclical net *entry*, improving (weakening) as sectoral aggregate productivity improved (weakened). Sectoral aggregate LP growth was relatively higher in manufacturing compared to NFS, although still negative and well below pre-crisis growth rates in both sectors.

2.7.7 Growth in Aggregate Total Factor Productivity in the Manufacturing and Non-Financial Services

Table 2.16 reports year-on-year decompositions for sectoral TFP growth. In the manufacturing sector, TFP growth fell at the onset of the crisis and became volatile. The *within* term was the main driver of TFP growth in the manufacturing sector. TFP in this sector remained somewhat volatile, picking up in the post-crisis period, but remaining well below pre-crisis levels. The effect of the deterioration in the net *entry* term has had a more pronounced effect on TFP growth in this sector in both the crisis and post-crisis periods.

Table 2. 16: Year on Year Total Factor Productivity Decomposition for the Manufacturing Sector

Period	Surviving Firms			Entering	Exiting	Change in TFP
	Within	Between	Covariance			
2006-2007	-0.0150	0.0097	-0.0007	0.0415	-0.0401	0.0755
2007-2008	-0.0013	0.0128	-0.0012	-0.0056	-0.0251	0.0297
2008-2009	-0.0136	0.0057	-0.0019	-0.0168	-0.0269	0.0003
2009-2010	**0.0137**	**-0.0071**	**-0.0009**	**-0.0261**	**-0.0076**	**-0.0128**
2010-2011	**0.0042**	**0.0002**	**-0.0008**	**-0.0347**	**-0.0239**	**-0.0073**
2011-2012	-0.0046	0.0028	-0.0014	-0.0275	-0.0365	0.0058
2012-2013	**0.0041**	**0.0004**	**0.0004**	**-0.0155**	**0.0328**	**-0.0434**
2013-2014	0.0060	-0.0005	-0.0006	-0.0002	-0.0124	0.0170
2014-2015	0.0049	-0.0031	-0.0006	-0.0011	-0.0026	0.0026
2015-2016	0.0046	-0.0023	-0.0005	-0.0100	-0.0211	0.0130

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.17 shows that relative to the manufacturing sector, TFP growth in the NFS sector did not begin to fall until well into the financial crisis. At the start of the post-crisis period, it recovered to outstrip its pre-crisis levels, but fell below pre-crisis levels at the end of the period. The *within*-firm restructuring term appears to have driven the changes in sectoral productivity.

Table 2. 17: Year on Year Total Factor Productivity Decomposition for the Non-Financial Services Sector

Period	Surviving Firms			Entering	Exiting	Change in TFP
	Within	Between	Covariance			
2006-2007	-0.0151	0.0211	-0.0025	0.0815	0.0453	0.0397
2007-2008	0.0440	0.0164	0.0009	0.0184	0.0178	0.0620
2008-2009	**-0.0047**	**-0.0004**	**-0.0063**	**-0.0064**	**0.0295**	**-0.0472**
2009-2010	**-0.0845**	**0.0029**	**-0.0048**	**0.0203**	**-0.0031**	**-0.0631**
2010-2011	**-0.0199**	**0.0045**	**0.0003**	**0.0205**	**0.0147**	**-0.0094**
2011-2012	**0.0044**	**0.0045**	**-0.0015**	**0.0077**	**0.0318**	**-0.0167**
2012-2013	**-0.0586**	**0.0090**	**0.0071**	**0.0306**	**0.0349**	**-0.0468**
2013-2014	0.0721	0.0194	-0.0084	0.0278	0.0372	0.0737
2014-2015	0.0251	0.0087	-0.0044	0.0261	0.0015	0.0539
2015-2016	-0.0080	0.0019	0.0013	0.0433	0.0179	0.0204

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Overall, the evidence reveals that in the NFS and manufacturing sectors, in terms of both TFP and LP growth, both were affected adversely by the financial crisis. In the post-crisis period, aggregate LP and TFP in both sectors failed to rebound to pre-crisis growth levels and sectoral LP continued to deteriorate in the post-crisis period. TFP growth picked up in this period but remained below pre-crisis levels of growth. Therefore, the impact of the financial crisis shock on *within*-firm restructuring weakened both sectoral LP and TFP growth. Resource misallocation was in place prior to the financial crisis and persisted in the post-crisis period. Overall, the financial crisis seems to have neither changed its trend nor given it momentum.

2.7.8 Mark-Ups and Aggregate Productivity Growth

Figure 2.6 depicts the weighted and unweighted mark-ups for all firms, and for firms with revenues of £100,000 or over in a year. Both weighted and unweighted mark-ups follow similar trends, particularly in the post-crisis period. The mark-ups started falling with the onset of the financial crisis and continued to fall considerably during the period of the crisis.

In the case of the unweighted mark-ups (the majority of the firms in the dataset are classified as small), evidence was found of a decline in price margins over marginal costs during the period of the financial crisis. Taken together with the observed weak firm entry and rising exit rates during this period, this provides compelling evidence of rising costs of inputs; this raised marginal costs (particularly for small firms) but changed output prices little. This worked to reduce firm profits and, hence, mark-ups.

In the post-crisis period, there is a rise in mark-ups. This might suggest a return to profitability for firms in the sample data. The trend is steeper when weighted, but the direction of travel is upwards in both cases. Since output price levels were more stable in the post-crisis period, it can be conjectured that firms increased mark-ups by reducing their marginal costs through downsizing or reducing output. Overall, mark-ups increased in the period after the crisis, implying that mark-ups are pro-cyclical with respect to changes in productivity. Periods of higher mark-up are also characterized by high aggregate productivity growth.

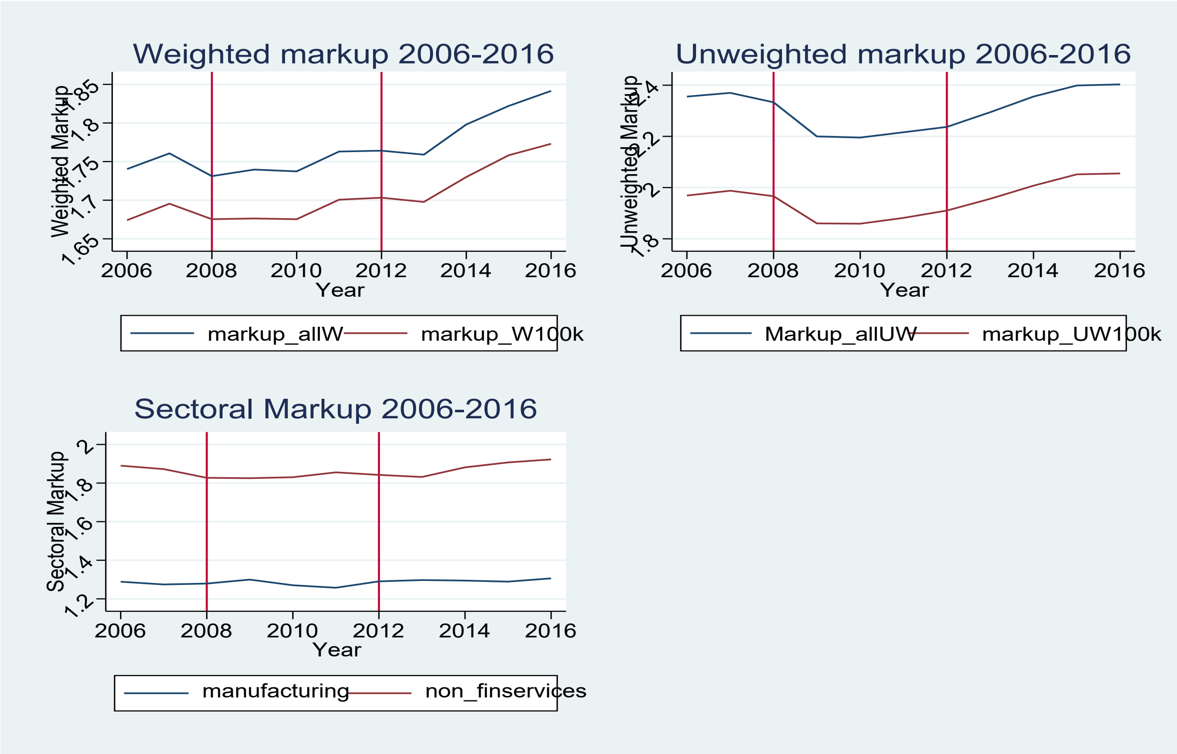

Figure 2. 6: Firm Mark-ups

Notes: Mark-up refers to price over marginal cost; on the left panel is all firms in the sample while on the right it is firms that earn a revenue of £100,000 and above. The vertical red lines delineate the period of the financial crisis.

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets;

At the sectoral level, mark-ups are generally higher in the NFS sector. In the pre-crisis period, mark-ups fell by 9% in this sector compared to only 1% in the manufacturing sector. During the crisis period, mark-ups were more resilient in the NFS sector and continued to grow, whereas they fluctuated in the manufacturing sector. In the post-crisis period, there was a sharp rise in NFS mark-ups, resulting in a rise in profits after the financial crisis. In the manufacturing sector, this increase was more modest.

This chapter is interested in the existence of heterogeneity in mark-ups across the different firm groups in the sample. Therefore, Figure 2.7 shows that there is a degree of heterogeneity in the mark-ups across different firms. For instance, entrants exhibit high mark-ups in all other periods except the one immediately prior to the onset of the crisis. In the later periods, they show evidence of some convergence with incumbents. It seems that the overall structure of mark-ups was resilient to the financial crisis shock and, particularly, in the case of the newer firms.

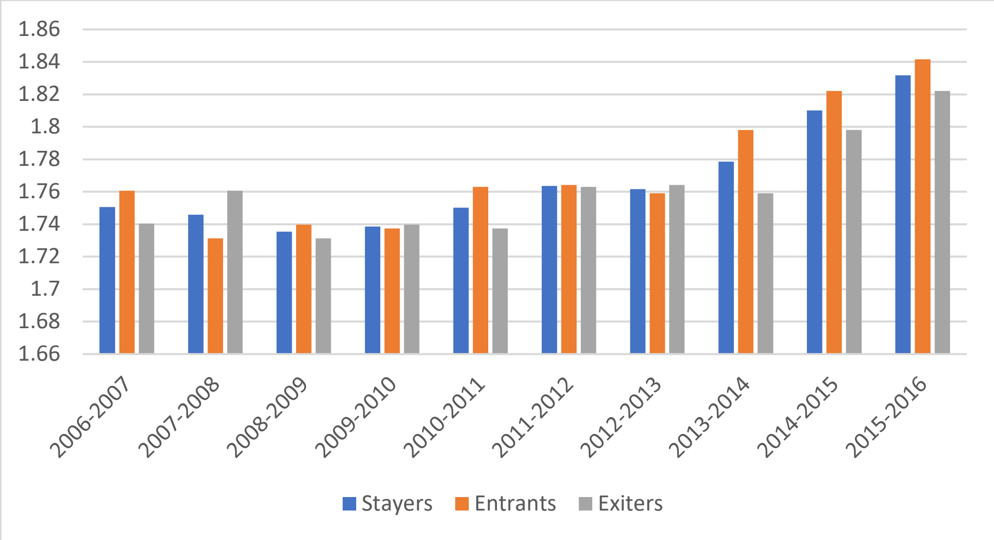

Figure 2. 7: Distribution of Mark-ups by Entrants, Exiters and Incumbent Firms (weighted by employment)

Notes: Mark-up refers to price over marginal cost across different firm categories

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets;

2.8 Summary and Conclusions

This chapter uses the VAT returns data and BSD micro panel data for private NFS firms, to try to identify the source of the UK productivity puzzle over the period 2006-2016. These data were exploited to show how the financial crisis affected productivity at the micro level and its effect on growth in aggregate LP and TFP at the macro level. The analysis is based on the decomposition method proposed by Foster *et al.* (2001); this allowed us to measure the contributions of continuing firms and entry-exit turnover to aggregate productivity growth. The main conclusion, based on the evidence presented in this chapter, is that aggregate productivity growth of both labour and TFP declined significantly post-2008, but that the decline in TFP was more modest relative to the decline in LP.

The implication for policy is that it is important to know which measure of productivity to use. Focusing only on LP could overstate productivity losses while a focus on TFP could understate the weak productivity growth. However, although the estimation of TFP is considered a semi-parametric method, it is still highly parameterized and involves stronger assumptions in its computation compared to the estimation of LP. Therefore, a great degree of care and caution should be exercised in the choice of productivity metric used to inform policy.

Nevertheless, in the case of both TFP and LP, the decompositions are in agreement that the productivity growth of incumbent firms was the most significant source of aggregate productivity growth. The contribution of this component, in most cases, accounts for more than 50% of the variation in both LP and TFP. In the pre-crisis period, this term was positive. However, in the post-crisis period the pattern changed and it became negative. There appears to be a significant *within*-firm productivity decline that seems to be pro-cyclical. This suggests that the financial crisis had a disproportionate negative effect on *within*-firm restructuring, resulting in a fall in aggregate productivity growth. The results are in agreement with previous research documented earlier in the literature review section. A potential area for future research would be to use this rich dataset to implement alternative decomposition methodologies in order to determine if the results are robust to this finding. Furthermore, like most previous studies in the literature, the current chapter utilized revenue-based TFP. Given the increasing availability of more granular datasets detailed at the product level like PRODCOM, it would be worth exploring the use of quantity-based TFP measures.

In addition, the results are suggestive of the existence of an inherent weakness in the allocation of resources across firms in the UK economy, a weakness that has not declined over time. The evidence would suggest that the misallocation of resources was a feature of the British economy even before the financial crisis. However, unlike the *within*-firm component, the contribution of *covariance* was mostly unaffected by the financial crisis. Therefore, one attention of policy-makers is to focus on designing interventions including supporting and encouraging through targeted tax breaks firm-specific training to improve resource allocation within and across firms. This may help enhance aggregate productivity growth in the future. This underscores the importance of setting a framework for the proper functioning of market-driven intra-firm and inter-firm resource reallocations in preference to pursuing traditional industrial policies aimed at supporting the better performing firms or sectors only.

Furthermore, the research provides evidence that productivity growth in the non-financial services' sector was more adversely affected at the start of the crisis relative to the manufacturing sector. In the post-crisis period, however, this sector rebounded eventually surpassing its pre-crisis growth rates. In contrast, manufacturing productivity growth has remained somewhat subdued since the end of the crisis. This result may be due to the failure to account for a confounding variable such as intangible capital, which has increasingly become more important in the services sector. There is an indication that the UK economy has undergone a structural transition into a knowledge economy in which intangibles act as a significant driver of firm-level productivity. In this regard, future research may exploit the emerging data on intangible capital available in the FAME dataset to explore explicitly the role of intangible capital in explaining aggregate productivity growth.

Mark-ups appear to be pro-cyclical and fell greatly during the period of the financial crisis. Firms that entered during this period had very low mark-ups relative to incumbents and exiting firms, while incumbents survived by reducing their mark-ups given their falling productivity. In the post-crisis period, however, there seems to be evidence of mark-ups returning to profitability.

3.1 Appendix

Table 2.A1: Ordinary Least Squares Regression Estimates

2 Digit-SIC	SIC Description	Log Materials	Log Labour	Log Capital	Observations	R-squared
10	Manufacture of food products, beverages & tobacco Products	0.8049***(0.0018)	0.1506***(0.0016)	0.0328***(0.0011)	34,214	0.9986
13	Manufacture of textiles	0.7497***(0.0032)	0.2256***(0.0036)	0.0244***(0.0010)	17,348	0.9974
14	Manufacture of wearing apparel	0.7530***(0.0044)	0.2076***(0.0045)	0.0159***(0.0021)	12,858	0.9889
15	Manufacture of leather and related products	0.8014***(0.0030)	0.1625***(0.0028)	0.0275***(0.0015)	7,164	0.9985
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	0.7393***(0.0018)	0.2177***(0.0019)	0.0181***(0.0006)	30,100	0.9983
17	Manufacture of paper and paper products	0.7712***(0.0024)	0.1841***(0.0022)	0.0293***(0.0010)	16,580	0.9987
18	Printing and reproduction of recorded media	0.7180***(0.0021)	0.2386***(0.0018)	0.0252***(0.0008)	58,234	0.9953
19	Manufacture of coke and refined petroleum products, chemicals and chemical products & basic pharmaceutical products and pharmaceutical preparations	0.7864***(0.0025)	0.1595***(0.0023)	0.0294***(0.0012)	21,666	0.9983
22	Manufacture of rubber and plastic products	0.7521***(0.0015)	0.2027***(0.0014)	0.0300***(0.0006)	53,789	0.9985

23	Manufacture of other non-metallic mineral products	0.7429***(0.0027)	0.2097***(0.0028)	0.0276***(0.0011)	19,140	0.9978
24	Manufacture of basic metals	0.7946***(0.0031)	0.1570***(0.0030)	0.0223***(0.0013)	10,079	0.9987
25	Manufacture of fabricated metal products, except machinery and equipment	0.6745***(0.0012)	0.2652***(0.0012)	0.0347***(0.0004)	133,386	0.9969
26	Manufacture of computer, electronic and optical products	0.7220***(0.0025)	0.2271***(0.0024)	0.0277***(0.0008)	34,110	0.9968
27	Manufacture of electrical equipment	0.7513***(0.0027)	0.2011***(0.0026)	0.0253***(0.0009)	17,101	0.9981
28	Manufacture of machinery and equipment n.e.c.	0.7089***(0.0013)	0.2369***(0.0013)	0.0322***(0.0005)	68,506	0.9976
29	Manufacture of motor vehicles, trailers and semi-trailers	0.7548***(0.0020)	0.2022***(0.0019)	0.0312***(0.0008)	22,621	0.9988
30	Manufacture of other transport equipment	0.6927***(0.0097)	0.2714***(0.0099)	0.0302***(0.0027)	6,824	0.9937
31	Manufacture of furniture	0.7667***(0.0015)	0.2025***(0.0015)	0.0215***(0.0005)	30,484	0.9989
32	Other manufacturing	0.7470***(0.0021)	0.2096***(0.0021)	0.0312***(0.0007)	36,999	0.9971
33	Repair and installation of machinery and equipment	0.6680***(0.0030)	0.2829***(0.0028)	0.0330***(0.0012)	31,791	0.9927
41	Construction of buildings	0.7171***(0.0011)	0.1863***(0.0012)	0.0363***(0.0005)	163,423	0.9904
42	Civil engineering	0.6872***(0.0018)	0.2173***(0.0020)	0.0348***(0.0009)	84,186	0.9893
43	Specialized construction activities	0.6786***(0.0006)	0.2292***(0.0006)	0.0478***(0.0003)	589,566	0.9896
45	Wholesale and retail trade and repair of motor vehicles and motorcycles	0.7643***(0.0009)	0.1673***(0.0008)	0.0289***(0.0004)	280,693	0.9933
46	Wholesale trade, except of motor vehicles and motorcycles	0.8086***(0.0008)	0.1481***(0.0007)	0.0187***(0.0003)	366,824	0.9958

47	Retail trade, except of motor vehicles and motorcycles	0.8097***(0.0006)	0.1420***(0.0005)	0.0201***(0.0002)	438,719	0.9964
49	Land transport and transport via pipelines	0.6958***(0.0017)	0.2439***(0.0013)	0.0307***(0.0009)	109,603	0.9937
50	Water transport	0.7870***(0.0012)	0.1711***(0.0014)	0.0256***(0.0006)	36,014	0.9965
51	Air transport	0.8214***(0.0009)	0.1484***(0.0009)	0.0229***(0.0004)	76,434	0.9972
52	Warehousing and support activities for transportation	0.7595***(0.0013)	0.1815***(0.0011)	0.0253***(0.0005)	118,315	0.9943
53	Postal and courier activities	0.6658***(0.0038)	0.2343***(0.0044)	0.0502***(0.0022)	17,255	0.9871
55	Accommodation	0.7417***(0.0019)	0.1550***(0.0012)	0.0369***(0.0006)	82,635	0.9941
56	Food and beverage service activities	0.7602***(0.0011)	0.1697***(0.0007)	0.0290***(0.0003)	249,611	0.9944
58	Publishing activities	0.5667***(0.0037)	0.3597***(0.0039)	0.0321***(0.0015)	32,111	0.9824
59	Motion picture, video and television programme production, sound recording and music publishing activities	0.5574***(0.0026)	0.3043***(0.0031)	0.0485***(0.0015)	48,164	0.9659
60	Programming and broadcasting activities	0.6790***(0.0032)	0.2241***(0.0028)	0.0359***(0.0016)	18,276	0.992
61	Telecommunications	0.6207***(0.0050)	0.2995***(0.0056)	0.0423***(0.0023)	16,511	0.9805
62	Computer programming, consultancy and related activities	0.3665***(0.0015)	0.5186***(0.0022)	0.0459***(0.0010)	286,043	0.9456
63	Information service activities	0.6052***(0.0031)	0.3131***(0.0031)	0.0254***(0.0015)	21,245	0.9825
68	Real estate activities	0.5660***(0.0021)	0.3389***(0.0022)	0.0363***(0.0005)	103,852	0.9808
69	Legal and accounting activities	0.4726***(0.0020)	0.4309***(0.0022)	0.0602***(0.0007)	88,562	0.9856
70	Activities of head offices; management consultancy activities	0.4658***(0.0012)	0.3978***(0.0016)	0.0344***(0.0005)	271,484	0.9604

71	Architectural and engineering activities; technical testing and analysis	0.4406***(0.0016)	0.4480***(0.0020)	0.0376***(0.0008)	209,486	0.9651
72	Scientific research and development	0.3840***(0.0021)	0.4832***(0.0035)	0.0470***(0.0015)	66,957	0.9492
73	Advertising and market research	0.6265***(0.0024)	0.3099***(0.0026)	0.0291***(0.0011)	59,844	0.9849
74	Other professional, scientific and technical activities	0.5116***(0.0011)	0.3691***(0.0010)	0.0395***(0.0005)	263,586	0.9683
75	Veterinary activities	0.6141***(0.0099)	0.2740***(0.0079)	0.0388***(0.0035)	9,161	0.9865
77	Rental and leasing activities	0.6857***(0.0027)	0.2335***(0.0020)	0.0538***(0.0013)	53,370	0.9912
78	Employment activities	0.5636***(0.0017)	0.3480***(0.0017)	0.0551***(0.0011)	73,917	0.9845
79	Travel agency, tour operator and other reservation service and related activities	0.6669***(0.0022)	0.2695***(0.0030)	0.0145***(0.0012)	21,270	0.9916
80	Security and investigation activities	0.5438***(0.0032)	0.3915***(0.0025)	0.0270***(0.0015)	27,618	0.9832
81	Services to buildings and landscape activities	0.5901***(0.0021)	0.3199***(0.0010)	0.0431***(0.0010)	76,091	0.9877
82	Office administrative, office support and other business support activities	0.6013***(0.0017)	0.3080***(0.0017)	0.0285***(0.0008)	121,368	0.9797
90	Creative, arts and entertainment activities & Libraries, archives, museums and other cultural activities	0.6024***(0.0028)	0.2082***(0.0028)	0.0292***(0.0012)	48,731	0.974
92	Gambling and betting activities	0.6729***(0.0029)	0.2064***(0.0028)	0.0121***(0.0012)	24,282	0.982

93	Sports activities and amusement and recreation activities	0.6576***(0.0023)	0.2243***(0.0017)	0.0189***(0.0008)	74,410	0.9788
94	Activities of membership organizations	0.7558***(0.0044)	0.2115***(0.0036)	-0.0113***(0.0013)	11,556	0.9909
95	Repair of computers and personal and household goods	0.6335***(0.0051)	0.3051***(0.0046)	0.0399***(0.0019)	15,173	0.9858
96	Other personal service activities	0.6367***(0.0016)	0.2498***(0.0013)	0.0267***(0.0007)	131,064	0.9799

Notes: Ceteris paribus Cobb-Douglas Production function estimates based on estimation of regression model [2.1]. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Year effect dummies included, but not reported.

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.A2: Wooldridge 2SLS Regression Estimates

2 Digit-SIC	Log Materials	Log Labour	Log Capital	Hansen test (stat)	Observations	R-squared
10	0.8604***(0.0168)	0.1457***(0.0020)	0.0189***(0.0030)	22.248	24,413	0.9987
13	**0.7359***(0.0205)**	**0.2304***(0.0045)**	**0.0252***(0.0023)**	**1.394**	**13,886**	**0.9977**
14	**0.9176***(0.0957)**	**0.1937***(0.0063)**	**-0.0011(0.0099)**	**1.272**	**9,379**	**0.9867**
15	**0.8461***(0.0616)**	**0.1805***(0.0078)**	**0.0220***(0.0061)**	**0.566**	**1,931**	**0.9982**
16	0.7465***(0.0074)	0.2199***(0.0024)	0.0124***(0.0015)	10.889	23,656	0.9986
17	0.7878***(0.0131)	0.1777***(0.0034)	0.0248***(0.0024)	7.87	10,875	0.9989
18	0.7339***(0.0095)	0.2373***(0.0023)	0.0230***(0.0017)	21.729	44,747	0.9963
19	0.9182***(0.0408)	0.1433***(0.0036)	0.0143***(0.0043)	6.647	11,372	0.9981
22	0.8062***(0.0145)	0.1995***(0.0026)	0.0217***(0.0019)	8.318	31,341	0.9987
23	0.7528***(0.0111)	0.2070***(0.0031)	0.0213***(0.0022)	9.756	15,508	0.9983
24	0.8196***(0.0193)	0.1625***(0.0040)	0.0123***(0.0036)	6.441	5,994	0.999
25	0.6841***(0.0042)	0.2633***(0.0014)	0.0302***(0.0009)	4.753	105,899	0.9975
26	**0.7478***(0.0124)**	**0.2133***(0.0027)**	**0.0232***(0.0018)**	**1.173**	**25,357**	**0.9976**
27	0.7773***(0.0122)	0.1990***(0.0028)	0.0189***(0.0017)	3.448	13,190	0.9985
28	0.7372***(0.0072)	0.2257***(0.0020)	0.0239***(0.0012)	6.529	37,719	0.9981
29	0.7984***(0.0191)	0.1911***(0.0041)	0.0224***(0.0026)	4.018	9,906	0.999
30	**0.6927***(0.0544)**	**0.2478***(0.0145)**	**0.0411***(0.0080)**	**1.436**	**3,963**	**0.9958**
31	0.7767***(0.0081)	0.2084***(0.0023)	0.0174***(0.0012)	4.214	17,764	0.9991
32	0.7674***(0.0108)	0.2034***(0.0028)	0.0260***(0.0015)	17.668	23,233	0.9974
33	0.7173***(0.0166)	0.2572***(0.0038)	0.0214***(0.0026)	6	18,922	0.9948
41	0.7049***(0.0059)	0.1819***(0.0020)	0.0334***(0.0012)	105.205	101,055	0.9921
42	0.6925***(0.0077)	0.1938***(0.0025)	0.0309***(0.0018)	14.411	62,519	0.9922
43	0.6921***(0.0029)	0.2210***(0.0009)	0.0378***(0.0006)	137.778	410,589	0.9915
45	0.8879***(0.0158)	0.1459***(0.0014)	0.0153***(0.0015)	13.659	140,701	0.9942
46	0.8596***(0.0084)	0.1474***(0.0009)	0.0125***(0.0007)	48.056	264,302	0.9965
47	0.8358***(0.0078)	0.1430***(0.0006)	0.0186***(0.0007)	74.566	293,527	0.9971

49	0.7484***(0.0082)	0.2366***(0.0018)	0.0200***(0.0021)	58.441	79,715	0.9944
50	**0.7322***(0.0416)**	**0.2031***(0.0084)**	**0.0195***(0.0047)**	**0.608**	**2,781**	**0.9955**
51	**0.8092***(0.0433)**	**0.1548***(0.0069)**	**0.0160***(0.0042)**	**1.237**	**1,457**	**0.9982**
52	0.7824***(0.0141)	0.1836***(0.0028)	0.0201***(0.0018)	11.327	36,076	0.9949
53	0.7051***(0.0503)	0.2104***(0.0061)	0.0346***(0.0073)	2.309	8,940	0.9903
55	0.8099***(0.0121)	0.1443***(0.0021)	0.0266***(0.0025)	6.892	34,461	0.9957
56	0.8257***(0.0082)	0.1575***(0.0011)	0.0213***(0.0011)	15.22	157,551	0.9963
58	0.5998***(0.0205)	0.3293***(0.0050)	0.0266***(0.0027)	7.609	23,050	0.9873
59	0.6488***(0.0141)	0.2285***(0.0040)	0.0322***(0.0036)	9.946	27,990	0.9756
60	0.7143***(0.0532)	0.1930***(0.0143)	0.0283***(0.0077)	5.377	2,017	0.9928
61	0.6290***(0.0482)	0.2687***(0.0074)	0.0263***(0.0059)	5.092	8,278	0.9896
62	0.4321***(0.0069)	0.4179***(0.0029)	0.0319***(0.0014)	37.954	181,486	0.9675
63	0.7646***(0.0738)	0.2971***(0.0089)	0.0077(0.0095)	6.924	7,257	0.9828
68	0.5677***(0.0082)	0.3459***(0.0035)	0.0329***(0.0012)	47.682	68,570	0.9833
69	0.5164***(0.0095)	0.4273***(0.0032)	0.0541***(0.0014)	112.975	58,837	0.9867
70	0.5073***(0.0064)	0.3349***(0.0025)	0.0302***(0.0012)	8.156	140,977	0.9749
71	0.4750***(0.0064)	0.3916***(0.0025)	0.0330***(0.0017)	79.623	138,162	0.9772
72	0.7353***(0.0596)	0.3338***(0.0103)	0.0029(0.0087)	4.27	5,849	0.9824
73	0.7137***(0.0178)	0.2682***(0.0031)	0.0164***(0.0024)	2.637	38,687	0.9897
74	0.6244***(0.0115)	0.3044***(0.0029)	0.0316***(0.0021)	51.485	69,935	0.9767
75	0.6695***(0.0736)	0.2548***(0.0089)	0.0392***(0.0077)	6.662	5,863	0.9916
77	0.7168***(0.0105)	0.2264***(0.0026)	0.0356***(0.0032)	12.456	39,722	0.9924
78	0.6960***(0.0233)	0.3471***(0.0023)	0.0431***(0.0030)	61.652	49,141	0.9802
79	0.6682***(0.0230)	0.2566***(0.0034)	0.0222***(0.0030)	4.097	13,447	0.9933
80	0.5521***(0.0262)	0.4018***(0.0035)	0.0303***(0.0050)	19.046	14,089	0.9836
81	0.6139***(0.0082)	0.3159***(0.0013)	0.0333***(0.0021)	76.826	49,437	0.9906
82	0.6520***(0.0108)	0.2746***(0.0021)	0.0236***(0.0017)	6.892	86,469	0.9846
90	0.6579***(0.0122)	0.1532***(0.0035)	0.0246***(0.0025)	36.071	29,611	0.9799
92	0.7623***(0.0367)	0.1724***(0.0065)	0.0251***(0.0092)	3.983	2,815	0.9951

93	0.7605***(0.0211)	0.1902***(0.0026)	0.0114***(0.0032)	12.304	32,248	0.9892
94	0.7362***(0.0309)	0.1933***(0.0057)	-0.0011(0.0028)	13.019	7,874	0.9946
95	**0.7159***(0.0347)**	**0.2750***(0.0053)**	**0.0251***(0.0039)**	**1.731**	**10,262**	**0.9905**
96	0.6757***(0.0093)	0.2382***(0.0014)	0.0207***(0.0016)	25.72	84,967	0.9858

Notes: Wooldridge 2SLS Cobb-Douglas Production function estimates based on estimation of regression model [2.1], Robust Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1, The test for the over-identifying restrictions is based on Hansen's J-test. 2-digit SIC names are as defined in Appendix Table2.A1 above. Year effect dummies included, but not reported.

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.A3: Annual Firm Size Distribution (by Employment)

Size/Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Total observations
Micro	286,375	314,132	307,776	305,123	314,249	321,775	324,869	341,091	353,929	368,736	372,610	4,156,851
Small	41,595	43,769	45,117	46,144	45,243	49,562	53,317	56,676	59,889	59,944	60,199	638,145
Medium small	28,494	29,388	30,226	29,772	28,831	29,793	33,190	34,794	37,113	37,918	39,186	412,407
Medium	13,725	14,292	14,400	14,616	14,448	14,906	15,732	16,366	17,368	18,192	18,547	198,404
Large	2,540	2,602	2,647	2,610	2,654	2,722	2,889	2,988	3,137	3,258	3,355	36,314

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.A4: FHK Labour Productivity Decomposition for all Firms in the Sample Between 2006 and 2016

	Surviving Firms					Change				
Period	**Within**	**Between**	**Covariance**	**Entering**	**Exiting**	**in LP**	**Stayer**	**Entrant**	**Exiter**	**Observations**
2006-2016	-1556.70	5239.45	-7186.87	-1560.29	-652.72	-4411.68	163474	330423	209255	703152

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.A5: Year on Year FHK Labour Productivity Decomposition for all Firms in the Sample

Period	Surviving Firms			Entering	Exiting	Change in LP	Stayer	Entrant	Exiter	Observations
	Within	Between	Covariance							
2006-2007	696.96	2144.68	-2695.65	217.50	123.81	239.68	308506	95677	64223	468406
2007-2008	-2517.62	2471.27	-2852.03	-74.15	-110.14	-2862.39	326826	73340	77357	477523
2008-2009	-2624.38	2248.70	-3191.55	297.58	-364.02	-2905.62	326745	71520	73421	471686
2009-2010	-253.37	1056.64	-1626.39	247.72	-110.06	-465.34	328655	76770	69610	475035
2010-2011	531.25	1939.26	-2461.58	56.25	-375.96	441.14	337108	81650	68317	487075
2011-2012	-188.69	1641.05	-2205.06	225.28	-346.21	-181.21	350053	79944	68705	498702
2012-2013	464.43	1248.75	-1762.77	295.78	-181.66	427.84	363167	88748	66830	518745
2013-2014	1603.66	1341.91	-1837.01	-58.77	279.57	770.22	383308	88128	68607	540043
2014-2015	1487.87	1223.14	-1608.02	235.26	-528.67	1866.92	399062	88986	72374	560422
2015-2016	-409.29	1016.74	-1437.37	-403.67	509.32	-1742.91	405568	88329	82480	576377

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.A6: Pre-Crisis, Crisis and Post Crisis Period FHK Labour Productivity Decomposition for all Firms in the Sample

Period	Surviving Firms			Entering	Exiting	Change in LP	Stayer	Entrant	Exiter	Observations
	Within	Between	Covariance							
2006-2007	696.96	2144.68	-2695.65	217.50	123.81	239.68	308506	95677	64223	468406
2008-2012	-2179.23	4447.18	-6025.56	-371.84	-1018.42	-3111.03	255927	174070	144239	574236
2013-2016	2099.31	1966.05	-2691.73	-316.97	162.43	894.22	323145	170752	128770	622667

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.A7: Labour Productivity Growth Over the Study Period for Firms with Revenue of £100,000 and Above

Period	Surviving Firms			Entering	Exiting	Change in LP	Stayer	Entrant	Exiter	Observations
	Within	Between	Covariance							
2006-2016	-1,523	5,294	-7,524	-1,888	-686	-4954.63	141,605	274,928	169,492	586,025

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.A8: Year on Year Labour Productivity Decomposition for Firms with Revenue of £100,000 and Above

Period	Surviving Firms			Entering	Exiting	Change in LP	Stayer	Entrant	Exiter	Observations
	Within	Between	Covariance							
2006-2007	700.41	2092.96	-2711.86	200.91	242.63	39.80	256816	80674	54281	391771
2007-2008	-2599.61	2579.00	-2987.48	-268.97	-834.12	-2442.94	269151	62018	68339	399508
2008-2009	-2662.28	2237.76	-3226.69	10.90	-15.78	-3624.54	264549	58984	66620	390153
2009-2010	-206.95	1116.98	-1653.88	565.79	-35.68	-142.39	266329	66069	57204	389602
2010-2011	515.35	1974.15	-2502.37	-276.90	-257.01	-32.77	275329	68906	57069	401304
2011-2012	-163.81	1611.03	-2220.45	308.20	-320.00	-145.04	286853	67350	57382	411585
2012-2013	497.89	1223.18	-1782.01	456.01	-96.80	491.87	299415	74376	54788	428579
2013-2014	1708.31	1287.17	-1876.03	-125.32	5.08	989.04	318045	75793	55746	449584
2014-2015	1452.62	1258.66	-1623.06	420.10	-208.65	1716.97	333963	76381	59875	470219
2015-2016	-627.65	1003.81	-1462.65	-470.14	248.01	-1804.64	341453	75080	68891	485424

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.A9: Pre-Crisis, Crisis and Post Crisis Period FHK Labour Productivity Decomposition for Firms with Revenue of £100,000 and above

Period	Surviving Firms			Entering	Exiting	Change in LP	Stayer	Entrant	Exiter	Observations
	Within	Between	Covariance							
2006-2007	700.41	2092.96	-2711.86	200.91	242.63	39.80	256816	80674	54281	391,771
2008-2012	-2282.15	4328.71	-5978.77	-591.42	-578.89	-3944.73	212408	141795	118761	472,964
2013-2016	1910.71	2039.38	-2782.28	-183.22	83.21	901.37	272196	144337	101595	518,128

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.A10: Total Factor Productivity Growth Over the Study Period for Firms with Revenue of £100,000 and above

Period	Surviving Firms			Entering	Exiting	Change in TFP
	Within	Between	Covariance			
2006-2016	0.0034	0.0434	-0.0022	0.1616	0.0369	0.1692

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.A11: Year on Year Total Factor Productivity Decomposition for Firms with Revenue of 100,000 and Above

Period	Surviving Firms			Entering	Exiting	Change in TFP
	Within	Between	Covariance			
2006-2007	-0.0111	0.0164	0.0024	0.1130	0.0333	0.0873
2007-2008	-0.0677	0.0181	-0.0029	0.0117	-0.0017	-0.0390
2008-2009	-0.0224	0.0113	-0.0050	0.0003	0.0381	-0.0539
2009-2010	0.0501	0.0023	0.0017	0.0246	0.0153	0.0634
2010-2011	-0.0041	0.0057	-0.00003	0.01538	0.0055	0.0115
2011-2012	0.0032	0.0052	-0.0010	0.0082	0.0190	-0.0033
2012-2013	-0.0802	0.0111	0.0056	0.0152	0.0184	-0.0667
2013-2014	0.0926	0.0125	-0.0056	0.02536	0.0275	0.0974
2014-2015	0.0194	0.0097	-0.0042	0.0260	0.0044	0.0465
2015-2016	0.0092	0.0031	-0.0009	0.0326	0.0181	0.0260

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.A12: Pre-Crisis, Crisis and Post Crisis Period FHK Total Factor Productivity Decomposition for Firms with Revenue of 100,000 and Above

Period	Surviving Firms			Entering	Exiting	Change in TFP
	Within	Between	Covariance			
2006-2007	-0.0111	0.0164	0.0024	0.1130	0.0333	0.0873
2008-2012	0.0287	0.0139	-0.0005	0.0175	0.0419	0.0177
2013-2016	0.1297	0.0262	-0.0149	0.0643	0.0355	0.1698

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Table 2.A 13: Unweighted Annual Aggregate Total Factor Productivity and Labour Productivity for the Sample period

Year	TFP	LP
2006	3.9752	58575.53
2007	3.9940	58653.24
2008	3.9657	52616.61
2009	3.8923	47953.96
2010	3.9104	49510.31
2011	3.8921	46700.12
2012	3.8770	46127.65
2013	3.8763	46717.73
2014	3.8790	48507.38
2015	3.8878	51527.64
2016	3.8769	49630.22

Source: Author's own calculations based on HMRC-VAT, BSD and FAME datasets

Chapter 3: An Empirical Analysis of Local Area Wage Disparities for Men in Great Britain

3.2 Introduction

Wage inequality in the UK grew rapidly over the 40-year period from 1970 to 2010. However, in the ten years between 2010 and 2020, the UK experienced a narrowing of wage inequality.[22] Between 1970 and 2010, the UK was considered the most unequal among the developed economies with regard to wages (Bell and Van Reenen, 2010). Overall wage inequality and inequalities in both the upper and lower parts of the distribution all grew sharply during this period. Despite efforts to address the problems this posed, regional disparities in wages have also remained large and persistent.

Labour-market earnings comprise a major part of household income, and this has implications for the overall distribution of income and household well-being. In the debate around rising wage inequality in the UK, the role of spatial disparities is often neglected. This chapter provides an updated and comprehensive analysis of the spatial distribution of log hourly wages at the level of Travel to Work Areas (TTWAs)[23] in Britain. The chapter employs both standard mean regression analysis and Recentred Influence Function (RIF)-based procedures to measure disparities in TTWA wage differentials relative to the national average. This analysis is undertaken in order to assess, among other things, the impact that the global financial crisis has had on area-level wage differentials and their dispersion. During the financial crisis, output contracted by more than 6% over six successive quarters between 2008-Q1 and 2009-Q2.[24] The structure and magnitude of these disparities over time is explored and further investigate whether agglomeration economies can explain observed differences in the level and distribution of earnings across TTWAs.

Recent studies on wage inequality in Europe reveal the existence of greater heterogeneity in the degree of income and wage inequality across countries. European Union Statistics on Income and Living Conditions (EU-SILC) data confirm diverging trends in wage inequality across Europe. Inequality continues to rise in some countries, particularly the UK, but also to some extent in Greece and Portugal. In the formerly centrally planned economies of Hungary

---

[22]For a discussion of UK Wage inequality see Herz, B., and Van Rens, T (2020).

[23] TTWAs are a geography derived to reflect self-contained labour market areas in which 75% of the people both live and work there.

[24] ONS (2018) provides a comprehensive discussion the beginning of the recession and how the UK economy has performed 10 years on.

and Poland it has been steadily decreasing since the middle of the 2000s (see Galego and Pereira, 2014). Fernandez-Macias *et al.* (2015) report that the overall extent of wage inequality in the EU has been below that in the US. However, it is evident that, within the EU, there are disparities in earnings inequality across countries. UK hourly wage inequality is higher than observed in Germany, Spain and France (see Fernandez-Macias *et al.,* 2015). Machin (2011) observe that the UK experienced a decreasing trend in wage inequality up to 2008 but in the wake of the financial crisis suffered a subsequent reversal, which was more acute than that experienced in France, for instance. In Germany, wage inequality increased consistently at a declining rate between 2004 and 2011 but plateaued immediately after 2008. Machin (2011) further argues that UK wage inequality is significantly higher than it was some 30 years ago. In common with the US, wage inequality for men in the UK has continued to rise with the $90^{th}/50^{th}$ percentile wage ratio steadily increasing, and at a higher rate in the UK than in the US (see Autor *et al.,* 2008; Lindley and Machin, 2014). However, the $50^{th}/10^{th}$ percentile ratio has remained either constant or has declined. Of course, the movement in aggregate wage differentials in the UK hides important differences in the wage differentials and degree of dispersion that occurs *within* and *across* regions and localities in the UK.

Several theories have been proposed to explain the observed changes in wage inequality. The stylized fact of an empirical association between wages and productivity is consistent with traditional microeconomic theory and the idea that wages at the micro-economic level are related closely to marginal productivities. In the long run, at the macro level, the real pay of workers tends to follow labour productivity. However, in recent years, there have been concerns that this relationship has broken down and that pay has become decoupled from productivity and is therefore growing much more slowly.

Pessoa and Van Reenen (2013) report that UK trends in decoupling appear different from those in the US in some respects. Using 1972-2010 data, the authors find that (unlike in the US) average employee compensation in the UK rose at a similar rate to labour productivity. However, like the US, the median wages of employees have risen much more slowly than labour productivity. Teichgräber and Van Reenen (2021) did not find a 'net decoupling', defined as the difference between labour productivity growth and mean hourly employee compensation when both series are deflated by GDP, of labour productivity and employee compensation during the period 1981 to 2019. However, they provide evidence of substantial 'overall decoupling' (defined as the difference between labour productivity growth - deflated by the GDP deflator - and median hourly employee wages - deflated by the CPI) of labour productivity and employee median wages. Their results reveal that most of the divergence (60%) can be explained by an increase in wage inequality that drove a large wedge between the mean and median wages.

The empirical evidence presented in Chapter 2 of this thesis suggests that the UK productivity puzzle is largely related to the evolution of labour productivity. Chapter 3 builds on this finding and provides evidence showing how wage disparities evolved in the pre-crisis and post-crisis periods. In a sub-theme, it is explored whether agglomeration economies enhance local labour productivity as proxied by wages. There is a consensus among urban and regional economists about the importance of agglomeration economies for defining regional productivity and economic growth. Therefore, it might be that regional variation in agglomeration economies explains some of the variation in regional pay structures. Also, given the current Conservative government's concern over regional disparities, deeper insights into agglomeration effects could provide scope for the design of regional industrial policy that would influence the distribution of spatial economic activity.

A number of studies of the UK economy, including Machin and Van Reenen (2008), Gibbons *et al.* (2010) and Machin (2011), analyse regional wage disparities at the NUTS 3[25] level. This is a more aggregated level than the granular approach proposed in this chapter. Aggregate wage differentials at the NUTS 3 level can be misleading in terms of the magnitude and nature of the persistence in wage differentials across regions within the UK. This suggests that, even when local area inequality and/or wage effects are below the national average, there may be within-regional variations in the inequality in the wage distribution. A more disaggregated approach, such as that employed in this chapter, might more accurately capture the degree of heterogeneity in the evolution of wage inequality, both within and across areas. Gibbons *et al.* (2010) argue that earnings disparities across regions in Britain are pronounced and very persistent. These disparities among different areas are a cause for concern because, potentially, they imply differences in living standards and economic welfare. From a policy perspective, it is important to know the magnitude and extent of the disparities in wage levels across regions within Britain. The regional variation in wages in the UK are known to be sizeable and larger than those prevailing in other western European countries (see Zymek and Jones, 2020). This suggests that there may be barriers or constraints related to the functioning of UK local labour markets that are impeding or preventing convergence in regional wages. These disparities may reflect the interactions among area-specific effects and the sorting of

[25] The NUTS area classification for the UK generally comprises current national administrative and electoral areas, although in Scotland some NUTS areas comprise whole and/or parts of Local Enterprise Regions. There are 139 such regions including 5 in Northern Ireland (ONS Postcode Directory, 2016).

individuals across regions. For example, as noted by Overman and Gibbons (2011), individuals can trade-off wages with respect to both living costs and amenities and move locality in response. However, if area effects are persistent, individual mobility may be constrained.

Regional wage inequality has become an important item on the policy-making agenda at both the national and regional level, with the current Conservative government emphasizing the importance of a ‘levelling up’ agenda. At the time of undertaking the research in this chapter, neither the objectives specific to this agenda nor the policies designed to achieve these objectives had been clearly articulated or defined. However, a recently published White Paper presented to Parliament by the Secretary of State for Levelling Up, Housing and Communities set out 12 national missions or policy objectives that the government would implement as part of the levelling up agenda, with a target of achieving them by 2030 (Department for Levelling Up, Housing and Communities, 2022). The policy objectives of interest to the current research relate to those that the UK government intends to pursue to ensure that pay, employment, and productivity grow everywhere, and that the disparities between the top and worst-performing areas narrow. This is defined as Mission 1 in the government’s recently released White Paper.

The magnitude and persistence of regional wage disparities are a key concern in this context. Although the primary aim of the analysis in this chapter is to examine the impact of the financial crisis along different dimensions of regional wage inequality, it is extremely timely given the collective challenges posed for different areas of the country by Brexit, the current Covid-19 pandemic, and the ‘levelling up’ agenda. For instance, it can be argued that the outbreak of Covid-19 has increased remote working and this may provide an opportunity to reduce the pull of the highest-paid regions and increase economic opportunities for the more peripheral regions in the country. Ultimately, therefore, the effect of the pandemic may be to reduce geographic wage inequalities. This means that this thesis chapter, in addition to its primary objective of analysing the impact of the financial crisis, might provide a detailed benchmarking of the within-regional and between-regional distribution of wages in Britain at a fine level of disaggregation for the period immediately prior to the Brexit withdrawal agreement and the onset of the pandemic. Subsequent work could extend this framework to determine whether either Brexit or the pandemic has exerted a persistent effect on regional wage inequality. The work in this chapter could also provide a benchmark to assess any government policies introduced to serve its ‘levelling up’ agenda.

The empirical approach exploits individual-level Annual Survey of Hours and Earnings (ASHE) data for 2002 to 2018. Mean regression analysis is used initially to investigate the magnitude of the deviation in area-level wages from the national average over time. RIF-based techniques are used to enable estimation of both unconditional quantile and Gini regression models that explore the factors influencing the wage dispersion within TTWAs during that time period.

The results provide strong evidence that the trend of a narrowing in regional wage differentials preceded the financial crisis, and this trend continued in the post-crisis period. There is no discernible evidence that the financial crisis either gave this process impetus or slowed it down. In one sense, the trend is actually consistent with a 'levelling up' agenda. However, there is strong persistence in rank order of regional wages. Therefore, despite falling regional wage disparities, TTWAs that paid high (low) wages in the pre-crisis period continued to do so in the post-crisis period. This has implications for the design of policy to narrow regional wage differentials. The Government is committed to embarking on a 'levelling up' agenda to improve livelihoods and opportunities in all parts of the UK. However, if such a substantial economic shock as the financial crisis failed to alter these wage disparities in a meaningful way, any policy interventions designed to lower wage disparities across regions will need to be radical and extremely potent. This particular conclusion finds resonance in the work of Overmann (2022) who argues that for the levelling up strategy to work, countering the economic forces behind the UK's spatial disparities requires addressing multiple barriers and exploiting differing approaches. The level of funds committed so far do not appear to be proportionate to the scale of this policy objective.

Additionally, there is also evidence from this research that although interregional wage inequality is falling, the persistence in the inter-TTWA wage dispersion is weaker than that exhibited by the wage differentials and appears subject to change over time. There is clear evidence of rising within TTWA wage inequality despite falling wage inequality across TTWAs. Effectively, this has resulted in the convergence of highly unequal labour markets. This points to the need for a 'levelling up' agenda designed to focus on disparities within and not just across regions.

It can be observed, also, that the nature of the relationship between the disparity in wage levels across TTWAs in Britain and their dispersion within TTWAs, switched from being negative to being positive after the crisis. This switch is attributed to the increased inequality at the top end of the wage distribution (90^{th}-50^{th}) relative to the bottom end of the distribution (50^{th}-10^{th}), where inequality has been reducing. This is tentative evidence of the emergence of wage polarization in the British labour market, a phenomenon that requires the development of a future research agenda beyond the scope of the current work. Finally, Chapter 3 provides evidence that agglomeration factors, particularly based on urbanization (congestion) compared to localization economies, explain some of the observed spatial differences in the level and distribution of earnings across TTWAs.

The chapter is organized as follows: Section 3.2 reviews the related empirical literature and discusses the contributions of the current study to that literature in more detail. Section 3.3 outlines the research context and Section 3.4 describes the data used for the analysis. Section 3.5 discusses the empirical methodology and Section 3.6 presents the main results. Section 3.7 concludes the chapter with a discussion of some limitations of the study and suggestions for a future research agenda.

3.3 Literature Review

There is a substantial literature on the evolution of wage inequality across developed economies (Moretti, 2010; Combes *et al.,* 2012) and evidence of regional wage disparities within countries. Redding and Venables (2004) point to the importance of understanding the part played by geography in shaping the evolution of the cross-country earnings distribution. Most countries appear to prefer ‘place-based policies’, aimed at reducing growth in regional wage disparities (Kline and Moretti, 2014). The high wage disparities that exist between the northern and southern parts of England are referred to as the north-south divide. This phenomenon is not unique to the UK. Schran (2019) documents the uneven spatial distribution of aggregate wage growth in Germany. Although wages in southern German local labour markets rose by up to 0.28 log points, they increased only modestly or even declined in the northern areas of the country. Autor *et al.* (2013) discuss the effect of international trade on regional wage differentials in the USA between 1990 and 2007. Lindley and Machin (2014) investigate spatial variation in the college wage premium across US states between 1980 and 2010 and report that increased relative demand for high-skilled labour is higher in those states with higher levels of R&D spending. Complementing their finding, Senftleben-König and Wielandt (2014), who study Germany, for the period 1975 to 2008 document substantial differences in both the evolution of wage inequality within and across space, and the degree to which regions are exposed to technology.

In contrast to other major European economies that experienced falling earnings inequality over the 1990s, such as France, Germany, Italy and Spain (see Machin, 1996), Great Britain witnessed a sharp rise in its regional earnings inequality during the 1980s and 1990s. However, the literature focuses extensively on wage inequality at the national level and neglects the evolution of regional wage inequality. Machin (1996) discusses the shifts in the anatomy of the wage distribution focusing on between group and within group changes in inequality. The author measures wage inequality based on the ratio between the 90th and 10th wage percentile. The analysis reveals that inequality has risen along several dimensions. By comparing different groups of workers, the research also reveals large increases in the wage differentials within particular worker groups (e.g., high versus low educated workers, white versus blue collar workers, old versus young workers). Machin (1996) concludes that workers with certain attributes have done much better than those lacking those particular attributes. However, the study found substantial inequality of wages among workers within these groups. It seems that, regardless of how the data are sliced to define groups, within-group wage equality has risen. Machin (1996) argues that a combination of factors including worker attributes, changing nature of work, changing human resource strategies and management styles and the influence of labour market institutions in wage setting (unionization) are all implicated in the rise in wage inequality that occurred in Britain in the period analysed (1979-1993). However, the author does not compute the magnitude of the effects associated with these different factors, and the period of analysis does not include an economic crisis comparable to the 2008 great recession.

In contrast, Duranton and Monastiriotis (2002) investigate regional inequalities and their evolution by examining regional labour market earnings. The data are from the Family Expenditure Survey (FES) and the General Household Survey (GHS) and cover the period 1982-1997. They employ the standard approach proposed by Mincer (1974) and regress individual log wages for full-time employees on gender, education, labour force experience and its quadratic. Each regression includes the full set of the regional dummy variables. Since individuals cannot be identified and followed over time, a separate cross-section analysis is undertaken for each year. This allows for the coefficients to vary across regions and time. Therefore, a constant regional wage fixed effect is obtained for each region-year combination. Duranton and Monastiriotis (2002) employ this approach and find evidence of rapid convergence across regions in the determinants of individual wages (i.e., regional fixed-effects, gender gaps and returns to education and experience). However, data on average regional earnings point to a worsening in UK regional inequalities and a rise in the north-south gap (or divide). Education accounts for most of the discrepancy between aggregate divergence and disaggregated convergence. Rising inequalities between skilled and unskilled workers, combined with an uneven spatial distribution of human capital, amplifies these aggregate regional inequalities. In addition, rising average education attainment in London and the southeast relative to the rest of the country contributed to a widening in regional wage inequalities. These findings have potentially important implications since they suggest that the fortunes of UK regions are determined primarily by their skill composition and by the fact that comparably qualified individuals are likely to secure similar wages across different UK regions. However, their study considers the disparity in regional wage effects and does not investigate regional wage inequality explicitly.

Taylor (2006) explored male wage inequality in the UK across industries and regions over a 15-year period from 1981 to 1995. The author employs the New Earnings Survey (NES) data but augmented by other datasets. The empirical analysis controls for heterogeneity of observable worker characteristics across the population, at both the industry and regional levels, to assess the ability of the dominant themes in the literature to predict within-group wage inequality (*viz*., technology, globalization, female participation, immigration, shifts in the supply of relative education across cohorts and falling unionization). The author also considers the trend in within-group wage inequality across industries and regions using the two-stage approach suggested by Bernard and Jensen (2000). The novelty of Taylor's study is its focus on rising residual (or unexplained) wage inequality. The study concludes that there is strong evidence of rising residual wage inequality in the data. However, this can be explained, in part, by the degree of heterogeneity in inequality across industries and regions.

Taylor (2006) also provides evidence of a north-south divide in the UK. The biggest impact on within-region wage inequality in the north is the growth in international trade followed by the impact of changing female participation rates. In contrast in the south, the role of female participation is the dominant cause of within-regional wage inequality. Taylor (2006) notes that a comprehensive explanation of the changes in wage inequality would need to account not only for changes in the returns to observable skills but also to the large changes in the within-group wage inequality. However, the study only considers within differences for individual characteristics such as age, gender and education, and does not focus on within regional wage inequality.

Earnings inequality can stem from inequalities within or between regions. Although several studies highlight inequality between and within regions (see Dickey, 2007; Brewer *et al.*, 2009; Lee *et al.,* 2016; Walsh and Whyte, 2018; Schran, 2019), there is little empirical research that focuses on the impact of the 2008 financial crisis on the evolution of earnings inequality both within and across regions. This is particularly relevant to any investigation of regional earnings inequality in Great Britain over the more recent period. In particular, the financial crisis has deepened the contraction in productivity as noted in the previous chapter, and this exhibits a strong regional dimension. This, in turn, has affected wages due to the intimate relationship between wages and productivity.

Dickey (2007) suggests that almost all of the inequality in wages during the 1980s and 1990s was within regions. The author uses NES data and conditional quantile regression techniques to investigate factors that have influenced regional earnings inequality over time and at different points along the conditional regional earnings distributions. The sample includes full-time male and female employees aged between 16 and 65 years. The study investigates the causes of rising inequality within the regional earnings distributions, but mostly ignores inter-regional differences in these wages. Dickey (2007) examines the changes that took place in the regional earnings distributions in Great Britain over the period 1976 to 1995. Dickey estimated cross-sectional conditional quantile regressions for six broad regions of Great Britain: Greater London, the rest of the south, the Midlands, the north, Wales and Scotland for four separate years (*viz*., 1976, 1980, 1991, and 1995). The study identifies returns to education, experience, occupational category, age, collective agreement, gender and regional migration as factors that have contributed to the rise in within-region inequality. Dickey then examines whether the forces shaping inequality within each region differ, and whether these differences occur at selected points in the regional wage distributions. The use of conditional quantile regressions may not provide an adequate basis for interrogating within-region inequality since the estimated quantiles are determined by the variables included in the specification. This problem is overcome with use of an unconditional quantile regression model (see Firpo *et al.,* 2009), which is one of the empirical approaches adopted in this chapter.

Rice *et al.* (2006) investigated regional variations in earnings per worker using NES data for the NUTS 3 sub-regions of Great Britain over the period 1998 to 2001, with the four years of data averaged to remove any year-to-year volatility. The chapter addresses two key issues relevant to the analysis in the current chapter. First, it explores the extent to which regional inequalities are a consequence of the variation in job quality as distinct from variation in the productivity of a given type of job. Second, it decomposes average earnings in each area into a productivity index and an occupational composition index. The authors report that about two-thirds of the spatial variance in earnings is attributable to variations in productivity. It should be noted that the two indices are positively correlated, so there is a tendency for high productivity areas also to benefit from a larger share of jobs in high-paying occupations.

Bell *et al*. (2007) investigate the public-private sector spatial wage variation and its evolution across areas through time within the UK. The authors exploit NES, Labour Force Survey (LFS) and British Household Panel Survey (BHPS) data for the period 1994-2001. Their empirical analysis uses a Mincerian equation and employs Standardized Spatial Wage Differentials (SSWD)[26] and conditional quantile regression techniques. The authors conclude from their analysis that public sector labour markets are only around 40% as responsive as private sector labour markets to area differences in amenities and costs. For example, in high-cost low-amenity areas, such as the southeast of England, the public sector underpays relative to the private sector; this creates problems for public sector recruitment in these areas and, therefore, the provision of public services. It can be deduced from their analysis that private sector jobs in the southeast of England exhibit sizeable wage premia relative to similar jobs elsewhere. This finding also emphasizes the distinct nature of the public compared to the private sector wage-setting mechanism in the UK, and its implications for both intra- and inter-region wage inequalities. An aspect of this issue is explored in more detail in the final empirical chapter of this thesis.

Brewer *et al.* (2009) use gross earnings (i.e., before taxes) at the individual level to account for changes in earnings inequality between 1968 and 2007 (inclusive). They exploit the Households Below Average Incomes data (created by the Department for Work and Pensions), to provide annual snapshots of Britain's income distribution. The study uses three different methods to analyse changes in inequality, decomposing changes by income source, population sub-group and an array of other factors including age, ethnic group, health and education.

The empirical results in Brewer *et al.* (2009) reveal that, similar to household income inequality, earnings inequality between regions accounts for a very small (but growing) fraction of aggregate inequality relative to within-regional earnings inequality. One striking difference between income and earnings inequality is the relative position of London. Income inequality is highest for London in almost every year since 1968, while earnings inequality was lowest in London for most of the time period covered by the analysis. However, earnings inequality has increased substantially in London since 1990; this has led to London 'catching up' with respect to the inequality prevailing in other regions. However, the southeast suffers from both high household income inequality and high earnings inequality. Whereas most regions have seen declining earnings inequality since the start of the new century, the level of inequality in the southeast has remained at more or less the same level. Overall, the authors conclude that changes in inequality within regions account for almost all the movement in overall inequality

[26] Brief description is provided in the empirical methodology section.

over time. Fluctuating inequality between regions accounts for a tiny fraction of the changes witnessed over the last 40 or so years.

Stewart (2011) conducted a descriptive statistical analysis of the differences in inequality and inequality growth between regions and between economic sectors during the period 1997-2008. The study uses NES and ASHE data. The author focuses on the $90^{th}/10^{th}$, $90^{th}/50^{th}$ and the $50^{th}/10^{th}$ percentile ratios of wages for full-time workers in different regions and concludes that inequality has grown faster in London than in other regions. The southeast and East Anglia exhibit intermediate inequality growth trajectories; this is lower than that reported for London but higher than in the rest of Britain. The change in inequality in the rest of Britain is numerically small and insignificantly different from zero. The growth in national inequality over the period 1997-2008 has been driven principally by London - and the financial services sector in particular. The study disaggregates the country into four regions (*viz*., East Anglia, London, the southeast, and the rest of Great Britain).

A more granular city level approach often provides a deeper insight into the disparities that exist within and not just across regions. This prompted Lee *et al.* (2016) to investigate the patterns of wage inequality in 60 British cities. The city boundaries in their study are the TTWAs defined using the 2001 census boundaries. The authors employ the ASHE dataset to determine which cities are the most unequal and to assess the main determinants of inequality. They also use the $90^{th}/10^{th}$, $90^{th}/50^{th}$, $50^{th}/10^{th}$ percentile ratios to capture the dispersion in wages. Their results reveal a distinct geography of wage inequality. The most unequal cities tend to be the more affluent cities generally located in parts of the greater southeast of England. A central determinant of these patterns is the geography of highly skilled workers. For this reason, the authors conclude that the geography of urban wage inequality reflects the geography of affluence more generally. Their study focuses only on inequality across cities, which potentially masks the extent of within city wage inequality.

Walsh and Whyte (2018) exploit earnings data from the UK Office for National Statistics (ONS) ASHE dataset to explore trends in earnings and income inequalities in the UK between 1997 and 2016. The data cover all four UK nations and the 11 largest cities in Scotland and England, defined by their current local authority boundaries; these include Glasgow, Edinburgh, Aberdeen and Dundee in Scotland and Liverpool, Manchester, Birmingham, Leeds, Sheffield, Bristol and London in England. The principal measures of inequality they employ are the relative wage gap (defined as the 90^{th} percentile divided by the 10^{th}), the absolute gap (the 90^{th}

percentile minus the 10th), and the slope[27] of the regression line across percentiles. The authors conclude that between 1997 and 2016, absolute inequalities in earnings widened considerably in Scotland and in other parts of the UK. Relative inequalities widened up to around 2011, but then decreased to levels comparable to those observed in 1997. However, there are differences between the scale of, and the trends in, inequalities in earnings between full-time and part-time employment. In addition, the authors note that, across cities, absolute and relative earnings inequalities are higher in Edinburgh and, particularly, Aberdeen, compared to Glasgow. Although London has the widest absolute gap across the earnings distribution, in a relative sense, inequality has been, and remains, widest in Aberdeen. This finding is linked to its importance as a North Sea oil processing city.

Agrawal and Phillips (2020) postulate that earnings in London are between 33% and 50% higher than the UK average, and that Wales has the lowest productivity and earnings - approximately 15% below the UK average and around 40% below London. They provide evidence that in the south of England, within-region inequalities are even larger than between-region inequalities. For example, median full-time earnings were 53% above the UK average in Kensington and Chelsea (west London) and 3% below the UK average in Barking and Dagenham (east London). In the east and southeast of England, median full-time earnings are much higher in well-to-do commuter areas, such as Brentwood and south Buckinghamshire, than in areas farther from London such as north Norfolk and Hastings where they are respectively 16% and 19% below the UK median. This is despite their being in ‘high-wage’ regions.

Rice and Venables (2021) explore the impact of adverse economic shocks in the 1970s. They exploit UK Local Authority District (LAD) data to investigate the impact of the large and rapid fall in the share of the secondary sector in national output in the UK, which fell from 40% to 30% in the 15 years between 1966 and 1981. They argue that had the classical convergence forces been at work, we would expect to observe a negative relationship between the size of the shock to employment rates in the LADs and subsequent growth of employment. The authors found no such relationship. Two-thirds of the LADs with the highest rates of deprivation in 2015 had experienced large negative shocks some 40 years earlier. They also found that, on average, the places that experienced negative shocks were not drawn from atypical starting

[27] The authors estimate the linear relationship by regressing gross pay at each percentile on the percentile ranking over time. The authors use the slope of this relationship to represent the scale of absolute inequalities across the distribution and plot this over time. The results of this exercise are confirmed using the two alternative measures (absolute and relative inequalities).

points. This demonstrates that fairly prosperous areas can succumb to adverse shocks and endure a difficult recovery.

The above review of the extant literature on wage inequality in the UK strongly emphasizes a regional dimension. An important feature of UK wage inequality is that, as noted in Lee *et al.* (2013), it is rather heterogeneous across the country. In other words, the degree of inequality is larger in some compared to other regions. This can be explained largely by the dominance in the UK labour market of London and the financial services industry. The emphasis in the regional labour economics literature is generally on the differences in average wages across regions or areas. The current research focuses on the persistence of the average regional wage differential and regional wage inequality over time. Specifically, this chapter investigates the degree of persistence in both regional wage differentials and regional wage inequality and examine the extent to which this persistence has weakened (or not) since the financial crisis.

The research in this chapter, builds on the literature on regional inequality in Britain and focuses on how both within-regional and between-regional wage disparities among men have changed and evolved across the period 2002-2018. This focus allows an investigation of how the distribution of earnings within and between British regions has been affected by the 2008 financial crisis. The analysis is undertaken at the TTWA level, which provides a finer geographical level than the level of aggregated regions. The latter can hide significant variations within these larger areas. Dickey (2007) observes that most studies of regional inequality focus either on aggregate variables, such as unemployment differentials, per capita income or per capita GDP at the regional level, or use more disaggregated micro-data to highlight cross-regional variations. Few studies to date have focussed explicitly on wage inequality within regions. To the author's knowledge, the current chapter provides the first empirical analysis to focus on the effect of the 2008 financial crisis on both the within and between regional pay structures at the TTWA level.

3.4 The Contributions of this Chapter

The literature review motivates the objectives of the research in this chapter. It examines how, if at all, the financial crisis affected regional wage differentials and their dispersion across TTWAs. It provides a descriptive analysis of the evolution of the structure of regional wage disparities and inequality, both before and after the 2008 financial crisis. It addresses the following research questions:

1. What is the magnitude of average wage disparity across TTWAs in Britain and has its persistence changed over the last 20 or so years, with a particular emphasis on the impact of the financial crisis?
2. What is the structure, magnitude and persistence of the disparities in the wage dispersion across TTWAs in Britain over the last 20 or so years, and how have these been impacted by the financial crisis?
3. What is the nature of the relationship between wage levels in TTWAs in Britain and their dispersion, and has this changed over time but particularly after the financial crisis?
4. Do agglomeration economies explain observed differences in the level and distribution of earnings across TTWAs, and have such relationships been affected by the financial crisis?

3.5 Data

This chapter follows the literature by studying a sample of male workers in order to avoid concerns about the (potentially unobservable) drivers of labour force participation and mobility of female workers. However, it is acknowledged that in the more recent years of the analysis female labour market participation rates have risen[28], there remain issues around the peculiarities of the female selection process. Given that the analysis covers the period 2002 to 2018 with female participation still an issue in the earlier part of the data, the analysis is therefore, restricted to male workers. The data are obtained from the Great Britain ASHE.[29] This dataset has been exploited by several scholars, including D'Costa and Overman (2014) and Gibbons *et al.* (2010) to conduct similar research, as already discussed in the literature review. The analysis covers the period 2002-2018. ASHE is maintained by the ONS and is based on a 1% sample of employees in the Inland Revenue Pay as You Earn (PAYE) register for February and April (ONS, 2012).

ASHE provides individual-level information such as home and work postcodes. The sample includes employees whose National Insurance numbers end in two specific digits, which have not changed since 1975. ASHE therefore provides individual level data, allowing observation of workers for multiple years. The sample is replenished as workers exit the PAYE system (e.g., through retirement or transitioning to self-employment) and new workers enter (e.g., school-leavers). The major advantage of the ASHE data is that earnings information is based

---

[28] Women's' participation was 66.3% in 2002 and rose to 72.1 % in 2022, see ONS(2022).
[29] Access to the NI ASHE dataset is obtained separately through NISRA

on payroll information and therefore represents more reliable data than obtained from employee surveys (such as the LFS). As a revolving panel, ASHE has a potential attrition problem that could compromise the effectiveness of its synthetic cohort panel design. Since there is a reasonable sample size for each year, cross-sectional log wages regression models are fitted separately for each of these years, for both the mean and for selected quantiles using unconditional quantile regressions. Therefore, the analysis in this chapter, does not exploit the panel dimension of these data.[30]

The data provide detailed information on individual earnings, including basic pay, overtime pay, and basic and overtime hours worked. This analysis includes males aged between 16-65 years, who report information for their main job and who have not been identified as having incurred loss of pay in the reference period, through absence, employment starting in the current period, or short time working, and who are identified as receiving an adult rate of pay (i.e., the analysis excludes trainees and apprentices). The ONS apply this filter to their annually published results for UK 'Patterns of Pay' using ASHE data.

The analysis exploits basic hourly wages to measure earnings that, therefore, excludes overtime pay and bonuses. The basic pay is used because it is comparable given every worker receives this compared to overtime which is only received by a selection of workers. This renders comparisons across workers and over time more meaningful.[31] The data also include information on other individual characteristics, such as occupation, industry, and whether the job is in the private or public sector, worker age and gender, and whether the worker is in a full-time or a part-time job and/or in temporary/permanent employment. Some modest trimming is performed based on excluding the top and bottom 1% of the basic hours and basic pay per week, to purge the sample of extreme outliers that could potentially skew the point estimates at the mean in particular. A disadvantage of ASHE data is that they do not contain explicit information on certain characteristics. Ritchie *et al.* (2014) emphasize that the ASHE dataset provides limited coverage of information on personal characteristics including education. They contend that in most studies using ASHE data that occupation proxies for education. The standard occupation category tends to be correlated with individual education level. Following D'Costa and Overman (2014) and Kaplanis (2010) the analysis undertaken in this chapter

[30] In the absence of longitudinal weights on ASHE, there is a greater risk that analysis over a longer time period could be biased due to sample attrition (ONS,2016).
[31] The failure to account for overtime for those workers for whom overtime is not only a substantial component of their wage, but also a usual component too is a constraint to the present analysis.

includes a set of 2-digit standard occupation controls in the log wage equation in order to proxy for an individual's education level.

individuals with either more than 100 or less than 1 basic hour worked are excluded to avoid potential measurement error and erroneous inclusion of overtime in the 'usual hours of work' response. The survey defines basic hours as the normal number of the worker's weekly working hours (excluding overtime and meal breaks). Hourly wage rates are derived by dividing weekly basic earnings, exclusive of overtime, by the number of basic weekly paid hours worked; this provides the outcome variable for the basic hourly wage.[32] Those observations with missing records for personal identifiers, basic hours, basic wages, or hourly wage rates are excluded. The dependent variable is the logarithm of the individual basic hourly wage (defined here as ln (W)).

The empirical analysis is undertaken at the individual level, with the regional dimension captured by the individual's TTWA. The TTWAs do not correspond to administrative boundaries but capture the *de facto* boundaries to local labour markets based on commuting patterns recorded in the census data. Essentially, they are based on areas where at least 75% of those working in a TTWA live in that same TTWA. The advantage of using TTWAs as the geographical unit of regional interest is that they comprise relatively small spatial units, enabling identification of phenomena that might be unobservable at a higher geographical level, such as the NUTS 3 level. The TTWA boundaries are non-overlapping and cover the whole of the UK. Over time there has been a consistent pattern of a reduction in the number of TTWAs: more people tend to commute longer distances to work, leading to an increase in the average size of TTWAs in terms of geographical area and population, and a consequent decrease in the number of TTWAs. In 1991 there were 308 TTWAs covering the UK, in 2001 there were 243 TTWAs, and in 2011 a further reduction to 228 TTWAs within order address the changing boundaries overtime the UK Data Services provides a conversion table that maps all postcodes to the current TTWAs. This is used in the current analysis. All TTWAs with less than five (5) observations in each cross-section[33] are excluded. Table 3.1 presents a description of the variables used in the first stage of the analysis.

---

[32] The ASHE dataset provides pay, measured as basic weekly earnings, both with and without overtime. To avoid any distortions caused by the inclusion of overtime, the analysis is restricted to the basic weekly earnings variable. This analysis in this chapter follows most studies, including Dickey (2007), Rice *et al. (*2006), and Lee *et al.* (2016) using hourly wages.

[33] In the empirical analysis, following data cleaning the lowest possible cell size of a TTWA is 5. To comply with the Datalab threshold rule TTWAs with a cell size of 10 and below are not shown.

Table 3. 1: Variable Names and Description for Primary Analysis

Variable	Description
ln (W)	This is the dependent variable and is the log of basic nominal hourly wages.
age	This is the age of the individual at the time of the survey expressed in years
age_sq	This is the square of the age variable
ind	This variable provides the information to construct 85 dummies representing the 2-digit standard industrial classification. One dummy is dropped and used as a reference category.
occ	This variable provides the information to construct 25 two-digit occupation categories. One category is dropped in the estimation as a reference category.
Size_1	The dummy takes the value of 1 if an employee is working in a firm that employs less than or equal to 10 people.
Size_2	The dummy takes the value of 1 if an employee is working in a firm that employs more than 10 people but less or equal to 50.
Size_3	The dummy takes the value of 1 if an employee is working in a firm that employs more than 50 people but less or equal to 250.
size_4	The dummy takes the value of 1 if an employee is working in a firm that employs more than 250 people.
tenure_1	A piece-wise linear spline[34] for less than 5 years working.
tenure_2	A piece-wise linear spline of between 5 and 10 years working
tenure_3	A piece-wise linear spline of more than 10 years working.
Public	A dummy variable that takes the value of 1 if an individual is in a public sector job and 0 otherwise
Permanent	A dummy variable that takes the value of 1 if an individual is in permanent employment and 0 otherwise

[34] A linear 'spline' is a function constructed piecewise. The thresholds where the functions meet are known as knots and the set of piece-wise linear splines allow the estimated effect of the relevant variable on the outcome measure to differ.

Tables 3.2 and 3.3 present the summary statistics for the variables used in the analysis for selected years. There is a change in the sample size between 2002 and 2018. This is because the variable '*empstat*', which captures employee start dates, was not well reported in 2002 and earlier years and, therefore, dropping these observations reduces the sample size substantially. This variable is used to create the three employment tenure splines[35] used in the econometric analysis. Table 3.2 shows that the mean nominal log wage increased steadily over the years. In the pre-crisis period (2002 to 2007), nominal mean wages grew by about 14%, and between 2012 and 2018, over the post-crisis period by 9%. In the sample period (2002-2018), nominal average wages grew by about 29% and the standard deviation fell by about 0.02 log points. In real terms, this suggests a modest fall in the dispersion of male log wages over this time period. The Gini coefficient also shows that the wage dispersion contracted in the post-crisis period. The estimate reveals that inequality narrowed between 2002 and 2018 with lower inequality in the post-crisis period relative to the pre-crisis period, and even lower in 2018. The next thing is to look at the 90^{th}-50^{th} and the 90^{th}-10^{th} percentile wage gaps, it can be observed that the gaps increased over the relevant years. The raw data are suggestive that the fall in wage inequality was due to a narrowing of the gap between the 50^{th} and the 10^{th} percentiles of the wage distribution, as reflected in a reduction in the wage gap between the 50^{th} and 10^{th} percentiles of the wage distribution.

Table 3. 2: Summary Statistics for Outcome Variables

	2002		**2007**		**2012**		**2018**	
Statistic	**Mean**	**Std Dev.**	**Mean**	**Std Dev.**	**Mean**	**Std Dev.**	**Mean**	**Std Dev.**
$\overline{\ln(W)}$	2.34	0.49	2.48	0.50	2.53	0.49	2.62	0.47
90^{th}- 50^{th}	0.72	n/a	0.76	n/a	0.75	n/a	0.76	n/a
50^{th}- 10^{th}	0.58	n/a	0.55	n/a	0.55	n/a	0.46	n/a
90^{th}-10^{th}	1.31	n/a	1.31	n/a	1.30	n/a	1.22	n/a
Gini	0.2846 (0.00095)		0.2920 (0.00103)		0.2893 (0.00074)		0.2807 (0.00086)	
N	35,167		45,155		59,365		66,120	

Notes: The standard errors for the Gini coefficient are reported in parentheses.

Source: Author's calculations from the ONS ASHE dataset

[35] A linear 'spline' is a function constructed piecewise. The thresholds where the functions meet are known as knots and the set of piece-wise linear splines allow the estimated effect of the relevant variable on the outcome measure to differ

Table 3.3 provides summary statistics for the explanatory variables used in the individual-level wage regression analysis. This provides a comparison of the initial and final year of the data and changes that have happened during the entire period under study. Note that the average age of a sample employee is around 41 and 42 years in 2002 and 2018 respectively. Note also that a large proportion of the firms in each year employ more than 250 people (66% in 2002 and 61% in 2018). Among the other firm sizes, employment increased in 2018 relative to 2002. Almost all employed workers are in permanent employment, although the percentage in full time jobs fell from 97% in 2002 to 88% in 2018. Over the sample years, the percentage of men working in the public sector fell from 28% in 2002 to 20% in the post-crisis period.

Table 3. 3: Summary Statistics for Independent Variables

Year	**2002**		**2018**	
Variable	**Mean**	**Std Dev.**	**Mean**	**Std Dev.**
Age	42.00	10.6326	41.00	12.3045
size1	0.0665	0.2491	0.0912	0.2880
size2	0.1305	0.3369	0.1428	0.3498
size3	0.1423	0.3493	0.1577	0.3645
size4	0.6607	0.4735	0.6082	0.4881
tenure_1	4.3045	1.1872	3.6553	1.6081
tenure_2	2.7005	2.3142	1.9656	2.2915
tenure_3	4.3107	6.9443	2.7861	6.0954
public	0.2790	0.4485	0.2006	0.4005
permanent	0.9848	0.1225	0.9940	0.0774
fulltime	0.9664	0.1801	0.8835	0.3209

Source: Author's calculations from the ONS ASHE dataset

3.6 The Context

The empirical analysis is conducted in the context of a number of economic developments in the UK over the sample period. Figure 3.1 plots nominal hourly wages for men[36] and shows

[36] Appendix Figures 3.A1, 3.A2 and 3.A3 plot respective real wages for all TTWAs, for London only and for non-London. The average inflation rate between 2002 and 2018, measured by the CPI, is 2.48% per annum (see Appendix Table 3.A1). Therefore, although the nominal wage grew in real terms, the real wage rate fell, with the result that, in both nominal and real terms, the 10th percentile showed more rapid growth. However, it should be noted, also, that the basket of goods used to predict price levels, might differ along the wage distribution; average CPI, therefore, may fail to pick up these differences across different wage percentiles.

that the average nominal hourly wage grew by almost 30% between 2002 and 2018. In the period prior to the financial crisis (i.e., between 2002 and 2007), a sharp increase of about 14% is observed. This is the sub-period that experienced the most significant wage growth. During the crisis period (2008-2012) nominal wages increased slightly, growing by a more modest 1.5%. In the post-crisis period (2013-2018) nominal wages started to recover and rose by about 8%. Costa and Machin (2017) argue that the modest wage recovery that began in 2014 was subsequently eroded by two factors: (i) higher price inflation as a consequence of the sterling depreciation following the vote to leave the EU in the June 2016 referendum; and (ii) nominal wage growth becoming rigid at around 2% on average per annum.

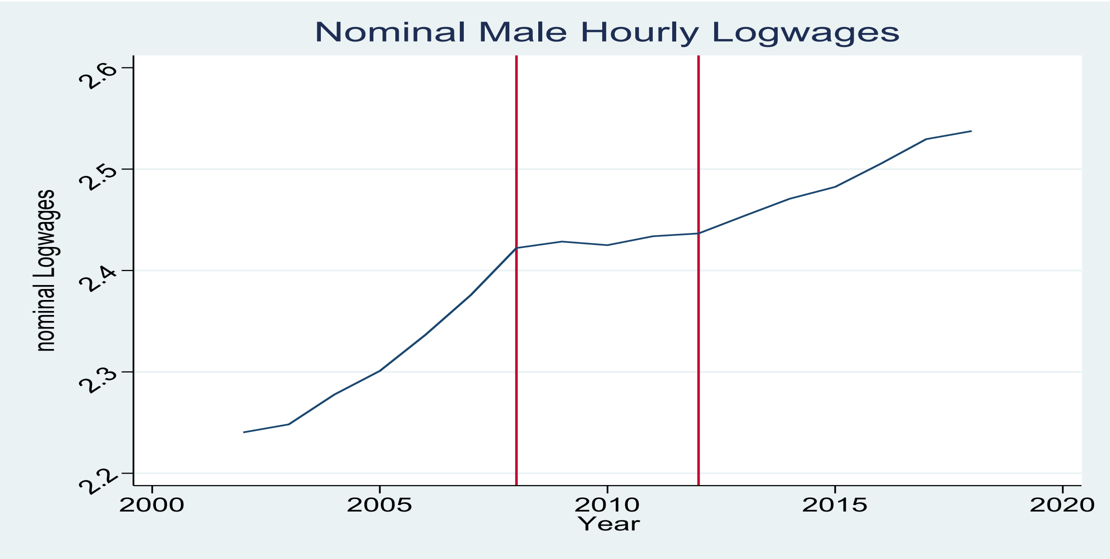

Figure 3. 1: Nominal Male Log Wages

Notes: the vertical lines delineate the period of the financial crisis.

Source: Author calculations from the ONS ASHE dataset.

Due to the dominance of the financial services sector in the London TTWA, this local labour market receives special attention. A closer look at the evolution of nominal hourly wages for London reveals that, somewhat unexpectedly, this local economy proved less resilient during the period after the financial crisis relative to the rest of Britain. Figure 3.2 suggests that, between 2002 and 2018, nominal log hourly wages in London grew by 24%. During the financial crisis, nominal log wages in London fell by about 2% and in the post-crisis period grew by about 7%, a much lower rate than the growth reported for the pre-crisis period. Wage growth in London exhibits a more pronounced decline relative to the rest of Great Britain (i.e., nominal wages fell less in the rest of the TTWAs compared to London). Therefore, on average and as expected,[37] London was affected more adversely by the financial crisis than the rest of Britain. In the pre-crisis period, nominal wages rose sharply, then flattened out during the crisis, and exhibited some recovery but then a flattening out in the post-crisis period.[38]

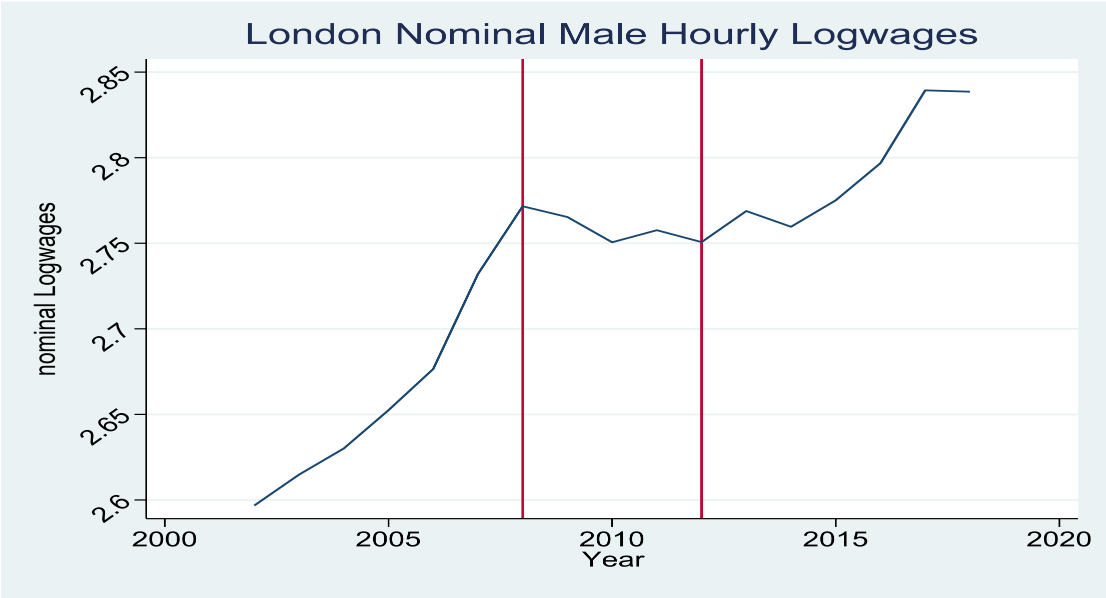

Figure 3. 2: Nominal Male Log Wages (London Only)

Notes: the vertical lines delineate the period of the financial crisis.

Source: Author's calculations from the ONS ASHE dataset.

In regard to other TTWAs, nominal hourly wages grew by 30%, roughly 6 percentage points higher than in London between 2002 and 2018, In addition, during the crisis period (2008-2012) nominal log hourly male wages grew by 1.5% (see Figure 3.3). In the post-financial crisis period (2013-2018), the rest of Britain performed slightly better (8%) than London given the lower contractions in log hourly wages in these areas. The variation in the evolution of wages between London and the rest of Great Britain suggests that regional responses to the financial crisis are characterized by a certain dichotomy. Wages show less of a collapse than in London during the financial crisis but increased less before the crisis. Overall, wages grew more outside London during both the crisis and post-crisis periods.

---

[37] This is because London boasts a substantial presence of the financial sector and the 2008 crisis affected primarily the financial sector as already noted in Chapter 1.

[38] Appendix Figure 3.A2 shows a significant decline in real wages across all periods.

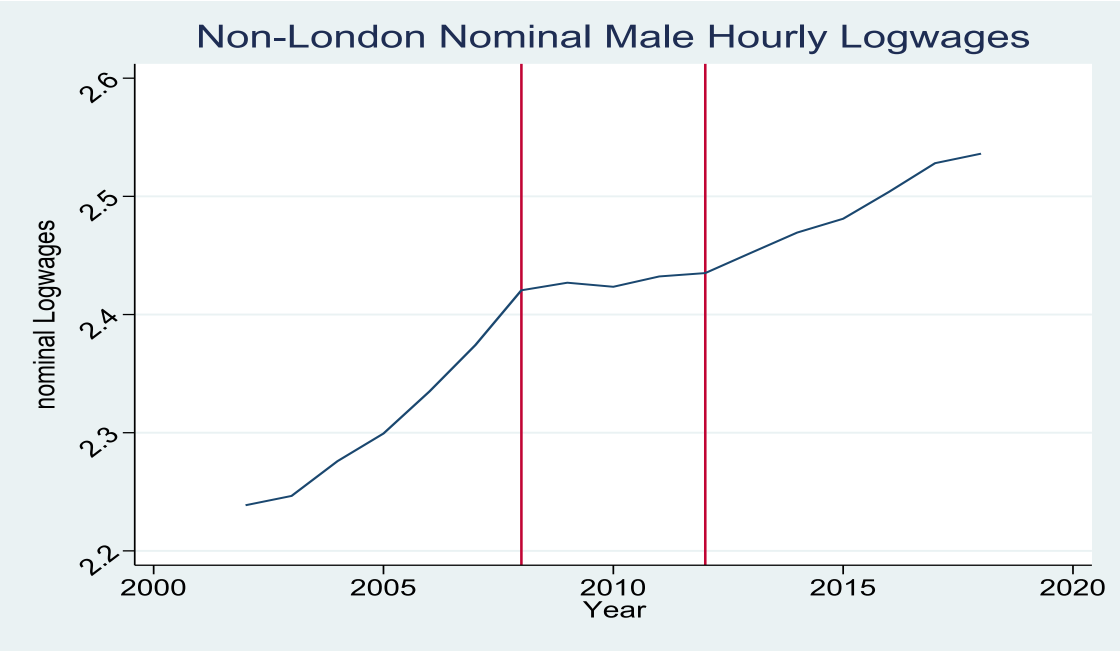

Figure 3. 3: Nominal Male Log Wages for all TTWAs (Except London)

Notes: The vertical lines delineate the period of the financial crisis.

Source: Author's calculations from the ONS ASHE dataset.

The trends in overall wage inequality are depicted in Figure 3.4. The Gini coefficient estimate confirms a narrowing of wage inequality over time across Great Britain. In 2002, the overall Gini was 0.2846 and rose to 0.2893 in 2012; it then contracted to 0.2850 in 2015 and was only 0.2807 by 2018. Labour market wage inequality was rather volatile in the post-crisis period for all TTWAs. In recent years, however, London has seen its overall wage inequality rise sharply relative to the rest of the TTWAs, surpassing pre-crisis levels. The overall Gini for Britain appears to reflect the Gini coefficients for the rest of the TTWAs excluding London. The pattern for London is diverse and the overall national Gini may conceal the extent of diversity across the regions. Overall, wage inequality is highest in London and appears to have risen over time.

Figure 3. 4: Gini for London and Non-London TTWAs

Notes: The vertical lines delineate the period of the financial crisis.

Source: Author's calculations from the ONS ASHE dataset.

Following this the source of change in the wage distribution is explored. It should be noted that although the Gini provides insights into wage disparities, it does not reveal where within the wage distribution such disparities are more evident. For example, detecting increased wage disparity using the Gini suggests that it might be due to the increasing disparity in the gaps between the 90th and the 50th, or the 50th and the 10th, as well as the 90th and the 10th parts of the log wage distribution. Figure 3.5 reveals that the wage quantile gap between the 90th and the 50th increased for London and was more volatile for the rest of the TTWAs (excluding London), both falling and increasing towards the end of the study period. In the post-crisis period, there is generally a narrowing of the gap between the 50th and the 10th percentiles of the wage distribution, both within and outside London. This suggests that the reduction in wage inequality might be due to the growth in wages at the 10th percentile[39] (although the NLW was not introduced until 2016 the NMW had been rising before then) of the wage distribution. However, the reduction in the wage gap was not sufficient in London to counteract the effect of the widening gap between the 90th and the 50th percentiles of the wage distribution. In recent years, London experienced growth at both the top and bottom ends of the wage distribution, as demonstrated by the increasing gap between the 90th and the 10th percentiles. This suggests that while the gap between the 50th and 10th fell in London, the wage gaps between

[39] This is likely to be due to the impact of the minimum wage; however, this is beyond the scope of the current analysis.

the 90^{th} and 10^{th}, and the 90^{th} and 50^{th} increased. This implies that wages grew at both the top and bottom ends of the distribution, but more so at the top end.

Non-London (all TTWAs excluding London) wages seem to have risen only at the bottom end of the distribution, falling at both the median and the top end of the distribution. In the post-crisis period, the reduction in wage inequality can be explained by a steady narrowing of the inequality between the 50^{th} and 10^{th} percentiles, with a more modest increase in inequality between the 90^{th} and 50^{th} percentiles of the wage distributions in the most recent years. Outside London, wages have grown at the bottom end of the distribution relative to both the 90^{th} and 50^{th} percentiles.

Overall, there is some evidence that the wage dispersion is narrowing in Great Britain. The degree of wage inequality across all other regions, excluding London, has narrowed over time. This is mostly due to the reduction in the gap between the 50^{th} and the 10^{th} percentiles. These changes help to explain the overall decline in the wage dispersion as measured by the Gini coefficient. Appendix Figure 3.A4 provides plots of the relative gaps, defined as the 90^{th} percentile divided by the 10^{th} ($90^{th}/10^{th}$), the 90^{th} percentile divided by the 50^{th} ($90^{th}/50^{th}$), and the 50^{th} divided by the 10^{th} ($50^{th}/10^{th}$). As expected, where the absolute gap increases (falls) this is mirrored in the relative measure. These graphs point to visible differences between what happened in the London labour market relative to the rest of Great Britain, across the entire period of study and in the pre-crisis, crisis and post-crisis periods. These spatial variations are evident in both the mean wages and in its dispersion.

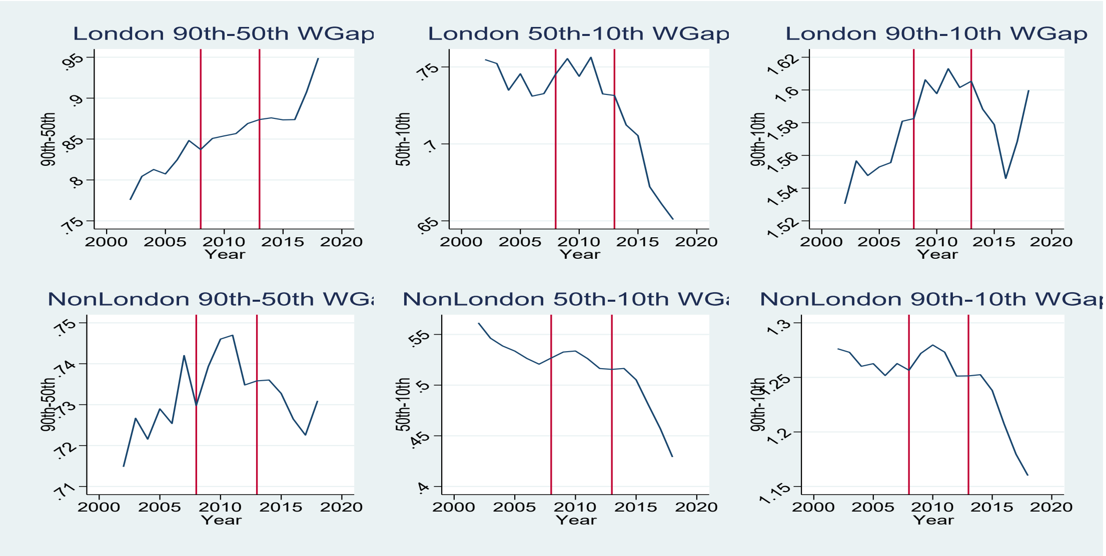

Figure 3. 5: Log Wage Quantile Gaps across the Distribution

Notes: The vertical lines delineate the period of the financial crisis.

Source: Author's calculations from the ONS ASHE dataset.

There is a degree of volatility in the wage gaps across the distribution. The financial crisis, which led to a 6% fall in total output over six quarters between 2008 and 2009,[40] appears to have slowed the trend growth but did not alter its direction. In 2016, the National Living Wage (NLW) was introduced. However, the gap between the 50th and 10th percentiles had already started to contract prior to its introduction. Therefore, the narrowing of the gap in wage inequality cannot be attributed to this policy change. The Institute for Fiscal Studies (IFS)[41] suggests that the households that gained from the new NLW are more evenly spread across the income distribution, with the largest gains in the middle. Furthermore, Manning (2011) suggests that the 50th/10th percentile ratio for hourly earnings (excluding overtime) for all workers was declining gradually before the introduction of the UK national minimum wage. The analysis of the effects of both the minimum wage and the NLW[42] is beyond the scope of this chapter but are a worthy part of an agenda for future research.

[40] See ONS (2018)
[41] See Elming *et al.,* (2015)
[42] The levelling up White Paper proposes that to address the disparities of low pay seen in areas across the country, the UK Government will increase the National Living Wage (Department for Levelling up, Housing and Communities, 2022, p.199).

3.7 Econometric Methodology

In order to derive area wage differentials by TTWAs, a modified approach originally proposed by Krueger and Summers (1988) in the context of industry wage differentials[43] is adopted. This has some similarities with the approach adopted in Bell *et al.* (2007), who used the SSWD method. The SSWD can be used if there are a large number of observations and detailed area identifiers, as in the ASHE dataset, and if the analysis concentrates on the complete sample of employees in each area. SSWDs are simple area-specific dummy variable coefficients, estimated from the standard Mincerian earnings equation. The specification imposes a common set of responses across areas on regressors such as age, education, and tenure. It therefore assumes that the effects of area-compensating differentials are reflected only in the estimates of the area dummy variable coefficients. If the returns to these characteristics are constant across regions, then spatial wage differences across regions should not be influenced by these factors. This equation is usually estimated using least squares and only private sector employees because selection issues are unlikely to affect the relative size of the area dummies. The use of private sector workers assumes that the private sector labour market is competitive and that private sector area differentials adjust to compensate employees for differences between areas, in living costs and amenities. This approach has some significant commonalities with the mean estimator adopted in this study.

The initial specification is an individual-level logged hourly wage regression model for each year containing a set of 2-digit occupation controls (as noted earlier proxying for education), age and its quadratic, a set of 2-digit SIC industry controls, three piece-wise splines in job tenure, controls for public sector employment, contract type and full-time status, and controls for firm size categories (micro, small, medium and large). The TTWA effects capture local labour market disparities and are included as a set of TTWA-specific dummy variables, which Bell *et al.* (2007) described as SSWDs. A cross-sectional log-wage equation for each year is specified as follows:

$$\ln (W_{it}) = \beta_1 \mathrm{age}_{it} + \beta_1 \mathrm{age\_sq}_{it} + \sum_{k=1}^{25} \phi_k \, \mathrm{occ}_{k,it} + \sum_{k=1}^{85} \theta_k \, \mathrm{ind}_{k,it} + \sum_{k=1}^{4} \kappa_k \, \mathrm{size}_{k,it} +$$

$$\lambda_1 \mathrm{tenure\_1}_{it} + \lambda_2 \mathrm{tenure\_2}_{it} + \lambda_3 \mathrm{tenure\_3}_{it} + \psi \mathrm{public}_{it} + \varphi \mathrm{permanent}_{it} + \pi \mathrm{fulltime}_{it} +$$

$$\sum_{k=1}^{g=216} \gamma_k \, \mathrm{Area}_{k,it} + u_{it} \qquad [3.1]$$

[43] Using the dummy variables to denote industries captures structural effects. The chapter acknowledges that, using them for geographical areas will pick up both structural and cost of living differences.

where the dependent variable is the natural logarithm of the hourly nominal wages of individual i, occ_i are the 2-digit occupation controls, ind_i are the 2-digit industry controls, $size_i$ are the firm size dummies, $tenure\_1_i$ to $tenure\_3_i$ capture the job tenure splines for individual i, $public_i$ is a public sector dummy, permanent is a dummy for whether the individual is in a permanent job or not, full-time is a dummy for whether the individual is in full time employment or not, and $Area_i$ is the variable used to construct the 216 TTWA dummies (the key variables of interest here).

In the current application, γ is interpreted as a $k \times 1$ vector of unknown parameters corresponding to the g TTWA dummies included in the specification. The estimated k area wage effects can be examined most meaningfully by normalizing the estimated effects as the deviation from a hypothetical overall sample weighted average. This transformation is appealing in that the estimated differences then are expressed relative to an overall sample average, rather than relative to an arbitrary base group and, therefore, are more readily interpretable. Defining the effect for the k^{th} area as γ_k, the deviation for the k^{th} group (D_k) is expressed as:

$$D_k = \gamma_k - \sum_{j=1}^{g+1} \pi_j \gamma_j \qquad [3.2]$$

where π_j is the sample average proportion (of employment) for the j^{th} area group. The area base group in the estimation attracts a zero coefficient in this exercise. Interpretation of these D_k area effects then is relative to the sample average rather than to an arbitrary base group, which in this empirical application provides more meaningful information.[44]

The standard least-squares regression in equation [3.1] is performed to obtain the estimated coefficient vector γ. Wage differentials are expressed as proportional deviations from the national weighted average, where the weights used are sample employment shares for each TTWA given by π_j expressed in [3.2] above.

D_k are the k area-specific wage differentials. Positive and negative differentials indicate an area respectively above or below the national average. To determine whether the estimates are statistically different from the national average, standard errors are computed using an approach suggested by Zanchi (1998). Defining the vector of estimates of these k deviations

[44] This analysis deviates slightly from what is proposed in Haisken-DeNew and Schmidt (1997) and Zanchi (1998), who omit one of the regional dummies to permit identification of the TTWA effects. Preference is given to estimating the full matrix of TTWAs; this involves dropping the constant term from the estimation.

as $\widehat{\mathbf{D}}$ and the OLS vector of area coefficients as $\hat{\boldsymbol{\gamma}}$, then the corresponding k $\times$ k variance-covariance matrix is denoted as:

$$\text{Var}(\widehat{\mathbf{D}}) = (Z - e\pi')\text{Var}(\hat{\boldsymbol{\gamma}})(Z - e\pi')' \qquad [3.3]$$

where Z is an identity matrix of the order k, e is a k$\times$1 vector of the 1s, and π is a k$\times$1 vector of area employment shares. The sampling variances for these deviations are computed to enable hypothesis testing and construction of confidence intervals.

The analysis further explores, the dispersion in the D_k by computing the standard deviation ($\hat{\sigma}_{\text{TTWA}}$) of wages across the k TTWAs. This standard deviation provides a measure of the dispersion in the deviations from the national mean area effects across TTWAs. This provides some insight into the dispersion in the wage differentials across TTWAs and is often used in the literature to assess the initial degree of wage dispersion within a labour market.

Following Firpo *et al.* (2009), the above analysis at the mean is extended to employing RIFs to estimate a set of unconditional quantile regression models and a Gini-based regression model. This allows us to explore within-regional variation in wages relative to the national average using both inter-quantile differences and the Gini measure.

The point of departure for the development of Firpo *et al.*'s (2009) methodology is the understanding that many common descriptive statistics can be expressed as statistical functionals. A statistical functional is any function of distribution function the outcome variable (conventionally defined as F(·)) that can be expressed as T(F). For example,

Mean: $T(F) = \int y dF(y)$

Variance: $T(F) = \int (y - \mu)^2 dF(y)$

Quantiles: $T(F) = F^{-1}(p)$

For example, assume that in the last expression p=0.5 (i.e., the median), then inverting the distribution function at this probability yields the median value of the outcome variable. The relationships between the probabilities and the quantiles specified above are central to this procedure.

Assuming the statistic is continuously differentiable, the first order directional derivative is known as the Influence Function (IF). The IF provides a framework to assess the influence of either adding or deleting an individual observation (or of data contamination more generally), on the distributional statistic of interest, without the need to re-calculate the statistic. For example, the IF for the population mean μ (i.e., E(w)) is the demeaned value of the outcome variable w – μ, where, in this case, w represents the log wage. Therefore, the IF is centred around 0. If the distributional statistic of interest is added back to the IF, this yields the RIF that is then centred around the statistic of interest (μ in this case) and is not 0.

Assume IF(w;v) is the IF corresponding to an observed outcome variable w, and the distributional statistic is defined as $v(F_w)$. Assume the RIF corresponding to this case is defined as RIF(w;v) where:

$$\mathrm{RIF}(w;\, v) = v(F_w) + \mathrm{IF}(w;\, v) \qquad [3.4]$$

For distributional statistics, such as quantiles, the IF is defined as:

$$\mathrm{IF}(w;\, Q_\tau) = \frac{(\tau - \mathrm{I}[w \leq Q\tau])}{f_w(Q\tau)} \qquad [3.5]$$

where τ is the quantile of interest, I(·) is an indicator function which assumes the value 1 if the expression in parentheses is satisfied, Q_τ is the population quantile of the τ^{th} quantile of the unconditional distribution of w, and $f_w(Q_\tau)$ is the density of the marginal distribution of the outcome variable evaluated at Q_τ. The corresponding RIF is then expressed as:

$$\mathrm{RIF}(w;\, Q_\tau) = Q_\tau + \frac{(\tau - \mathrm{I}[w \leq Q\tau])}{f_w(Q_\tau)} \qquad [3.6]$$

which is generally re-expressed as:

$$\mathrm{RIF}(w;\, Q_\tau) = Q_\tau + \frac{\tau - (1 - \mathrm{I}(w > Q_\tau))}{f_w(Q_\tau)}$$

The Firpo *et al.* (2009) RIF regression model is then defined as:

$$E[\mathrm{RIF}(w;\, Q_\tau) \mid \mathbf{X}] = \mathbf{X}'\boldsymbol{\beta} \qquad [3.7]$$

where the RIF is a dichotomous variable with two values and is assumed here to be a linear function of the covariates originally specified in [3.1] above, but now defined by **X**. This expression can be estimated by Ordinary Least Squares (OLS). Firpo *et al.* (2009) show that an OLS regression provides estimates for **β** that represent the effect of the x covariates on the unconditional τ^{th} quantile of the outcome variable w.

As a prelude to the estimation of equation [3.7] using OLS, the RIF expression [3.6] is computed. This emphasizes a conceptual difference between the conditional and the unconditional quantile regression approach. In the former case, the specification of the covariates determines the quantile (given it is conditional on the covariates contained in the specification); in the latter case the quantile is independent of the covariates used since it is computed pre-regression.

The expression [3.6] is unobserved in practice, so the corresponding sample analogues are used. This requires computing value at the point $\hat{f}(\hat{Q}_\tau)$ using non-parametric kernel density methods (see below). An estimate of the RIF for each observation is then obtained by plugging the density estimates into expression [3.6]. Multiplying the probability by the inverse of the density yields the quantile values of interest in this case.

In summary, the RIF-OLS regression approach involves the following steps:

1. Estimate a linear probability model for being above the quantile of interest (Q_τ). This procedure yields estimated marginal (for continuous variables), and impact (for dummy variables) effects expressed in probability units.
2. Divide these marginal/impact effects by the kernel (probability) density evaluated at the quantile of interest.

This locally inverts the (unconditional) probability effects into their corresponding (unconditional) quantile effects. The estimator of the density for the log wage (w) is obtained using a kernel density estimator. Define $K_w(z)$ as the kernel function and b_w as a positive scalar bandwidth. The kernel density estimator is defined for quantile Q_τ as:

$$\hat{f}_w(\hat{Q}_\tau) = \frac{1}{N \times b_w} \sum_{i=1}^{N} K_w\left(\frac{w_i - \hat{Q}_\tau}{b_w}\right) \qquad [3.8]$$

where $K_w(z)$ can be chosen from a set of kernel densities (e.g., Epanechnikov) and b_w is set in advance. The appropriate weight from the estimated kernel density for local inversion to the relevant quantile are chosen. The estimated scaling factor $\frac{1}{\hat{f}_w(\cdot)}$ is then used to invert the probability effect back to the relevant quantile effect.

The log wage equation, originally specified in [3.1], is re-estimated using the RIF-OLS procedure at the 10th, 50th and 90th percentiles. The RIF is then used to compare the impact that changes in, *inter alia*, the area-level effects have on selected unconditional quantiles of the male log wages across different TTWAs. The RIF methodology is also amenable to estimating inter-quantile regressions based on the 90th-10th, 90th-50th and 50th-10th percentile differences in log wages, which are of potential interest for the study of inequality here. The 90th-50th inter-quantile is constructed simply by subtracting the RIF at the 50th percentile from the RIF at the 90th percentile and running an OLS estimation using this newly constructed RIF differenced variable.

These differences in RIF measures are used to investigate the source of change in the within-regional wage distribution at the various unconditional log wage quantiles using the expression in [3.2]. This allows us to determine the source of changes in area-specific wage inequality over time. Specifically, it will allow us to assess whether changes in the dispersion in wages within TTWAs are driven by changes in the 90th-50th portion of the distribution or in the 50th-10th portion (or both).

Finally, the RIF expression for the Gini coefficient to examine the evolution in the area level dispersion in wages is used. This complements the analysis undertaken using the inter-quantile regressions. Essama-Nssah and Lambert (2011) describe how the RIF concept can be applied to the Gini coefficient. The RIF for the Gini is given by (where W, as before, now represents the non-logged wage):

$$\mathrm{RIF} = (\mathrm{W}; \mathrm{G}) = 2\frac{\mathrm{y}}{\mu}\mathrm{G} + \frac{1-\mathrm{W}}{\mu} + \frac{2}{\mu}\int_0^{\mathrm{w}} \mathrm{F}(\mathrm{z})\mathrm{dz} \qquad [3.9]$$

while the RIF for the Lorenz ordinates is given by:

$$\mathrm{RIF}\ (\mathrm{W};\mathrm{L(p)}) = \begin{cases} \frac{\mathrm{W}-(1-\mathrm{p})\mathrm{qp}}{\mathrm{u}} + \mathrm{L(p)} * \left(1 - \frac{\mathrm{W}}{\mu}\right) & \text{if } \mathrm{W} < \mathrm{qp} \\ \frac{\mathrm{Pqp}}{\mathrm{u}} + \mathrm{L(p)} * \left(1 - \frac{\mathrm{W}}{\mu}\right) & \text{if } \mathrm{W} \geq \mathrm{qp} \end{cases} \qquad [3.10]$$

The Gini RIF is then expressed as a linear function of covariates as follows:

$$\mathrm{E}[\mathrm{RIF}(\mathrm{W}; \mathrm{G}) \mid \mathbf{X}] = \mathbf{X}'\boldsymbol{\beta} \qquad [3.11]$$

3.8 Empirical Results

3.8.1 TTWA Wage Differentials

The analysis undertaken in this chapter for regional wage patterns first focuses on the differences in hourly wages across 216 TTWA local labour markets in Britain. To begin with the wage equation [3.1] (see Appendix Table 3.A2) is fitted to ASHE data. The signs and magnitude of the estimates for the control variables are all consistent[45] with theory and priors, and what has been found in the literature for Great Britain.

Using the estimates obtained by employing the deviation expression [3.2], the top 20 and lowest 20 wage differential areas in the UK across three selected years (*viz*., 2002, 2007 and 2018) are ranked (see Appendix Table 3.A3). On average and *ceteris paribus*, most of the high wage paying areas are in the southern part of the country with many of the lower paying regions concentrated in the north of the country, confirming the existence of the north-south divide[46]. In the aftermath of the financial crisis, the areas that paid a high wage prior to the crisis continued to do so after the crisis. Some areas may have shifted up or down the rankings, but the spatial structure observed does not appear to have altered radically or been impacted by the financial crisis and the subsequent recession. For instance, the town of Reading was a high wage area prior to the financial crisis and remained so in the aftermath of the crisis. This applies also to low wage areas, such as Bridlington, which continued to be low wage area after the financial crisis.

Appendix Figures 3.A5 to 3.A12 plot the wage differentials and their confidence intervals around the mean, for low and high wage areas in the north and the south, for the years 2002, 2007 and 2018. Again, it can be noted that, on average, the areas in the north fall below the national mean wage (i.e., suffer a wage penalty) while those in the south are above the national mean wage and obtain a wage premium relative to the national average. It can be seen that,

---

[45] The coefficients from the regression have the expected signs for instance, larger firms pay a higher wage relative to small and medium sized firms. This is also true for tenure, the longer an employee stays in the same job, the higher their wage compared to newer employees. Furthermore, there seems to be evidence of a public sector pay premium.

[46] The present research follows Dorling (2010) and defines the north as any TTWA within counties north of the old English shires of Gloucestershire, Warwickshire, Leicestershire and Lincolnshire. By constituencies, the north includes and lies to the north of the new parliamentary constituencies of the Forest of Dean on the north bank of the Severn; includes west and Mid-Worcestershire, Redditch, Bromsgrove (and hence all of Birmingham), Meriden, Coventry south and northeast, Warwickshire north, Nuneaton, Bosworth, Loughborough, Rushcliffe, Newark, Bassetlaw, Brigg and Goole, Scunthorpe, Cleethorpes, ending at Great Grimsby and the south bank of the Humber. Scotland and Wales are part of the north. All the other TTWAs that lie below these are in the south.

in some cases, the mean overlaps, but the confidence intervals generally differ. This suggests that the pay differentials in each broadly defined area are likely to be statistically significantly different from each other. Furthermore, it can be noted that the highest wage areas remained highest even after the turbulent economic period of the financial crisis. This, arguably, represents a divide between the quality of life in these regions, although high wages might just reflect the presence of high housing costs and better amenities in local areas.[47] Overall, there appears to be some evidence of a persistent stability in the regional wage structure over time that was not materially altered by the financial crisis.

Figure 3.6 plots the four-year (smoothed) moving average for the standard deviation in wage differentials across TTWAs (based on the square root of expression [3.3]) over the years of the analysis. The reported plot summarizes the overall variability, *ceteris paribus,* in wages across regions during the period of the current analysis. There is variation in regional wage disparity across the 216 areas over the years, ranging from a high of 0.081 log points in 2002, to a low value of 0.056 log points in 2018.[48] This suggests that, during the period under study, dispersion in regional wages contracted by around a third. Figure 3.6 provides evidence that, well before the onset of the financial crisis, wage differentials were already declining substantially. This implies that the financial crisis neither exacerbated nor disrupted this trend. The declining trajectory of regional wage dispersion appears to have been part of an on-going process that pre-dated the financial crisis.

---

[47] It is assumed that the differences in wages and house prices across the regions also potentially capture differences in the quality of life.

[48] The smoothed values of the standard deviation shown in Figure 3.6 are 0.074 in 2002 and 0.56 in 2018.

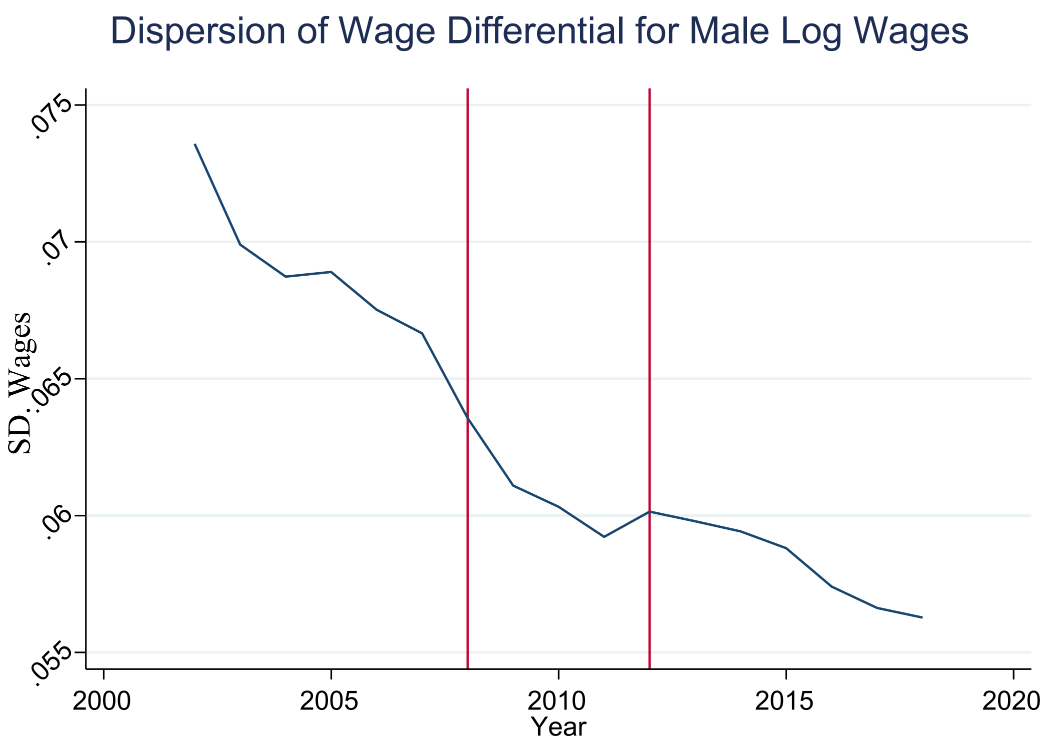

Figure 3. 6: $\mathbf{Standard\ Deviation}(\hat{\boldsymbol{\sigma}}_{\mathbf{TTWA}})$ **for TTWA Wage Differentials for 2002- 2018**

Notes: The vertical lines delineate the period of the financial crisis.

Source: Author's calculations from the ONS ASHE dataset.

Figure 3.7 plots the smoothed four-year moving average deviations in London's hourly wages relative to the weighted national average over the period of the analysis. The graph shows that the wage premia for London were well above the national average during the entire period. However, there is evidence they were steadily declining before the financial crisis and continued to decline up to 2016. This pattern may explain the decline in the dispersion of the regional wage differentials depicted in Figure 3.6. However, there is little evidence that the financial crisis exerted a disproportionate effect on the wage dispersion *within* the London local labour market over the period of this analysis.

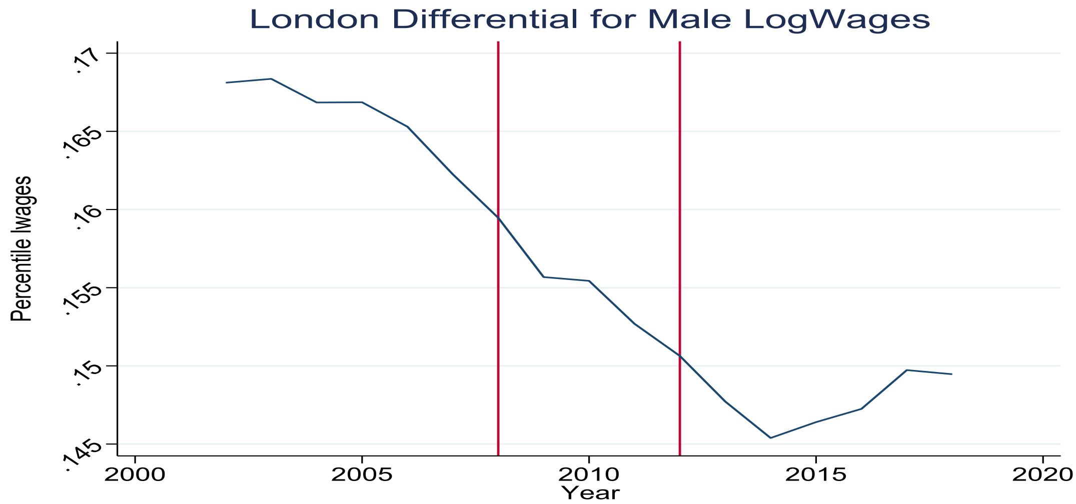

Figure 3. 7: Mean Wage Differentials for London Relative to the National Level

Notes: The vertical lines delineate the period of the financial crisis.

Source: Author calculations from the ONS ASHE dataset.

Figure 3.8 plots the smoothed four-year moving average mean annual wage differential (relative to the national average) for the remaining TTWAs, excluding London. Unlike London, on average, the other TTWAs have experienced a falling wage relative to the national average. The non-London wage differentials are near to the national average and the wage penalty reduced by 0.012 log points over this period. Therefore, the wage differential has been improving steadily and has continued to do so throughout the financial crisis. This is further evidence of a narrowing in the spatial wage disparities across time, a trend that does not seem to have been altered by the incidence or intensity of the financial crisis.

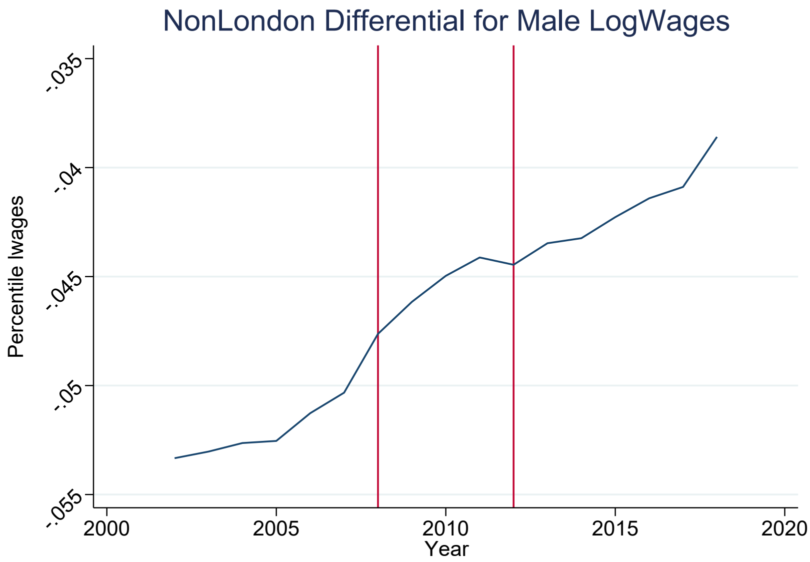

Figure 3. 8: Wage Differentials Relative to the National Mean (excluding London)

Notes: The vertical lines delineate the period of the financial crisis

Source: Author's calculations from the ONS ASHE dataset.

Gibbons *et al.* (2010) suggest that earnings disparities across regions in Britain are pronounced and very persistent, and that isolating London potentially provides a different portrait of pay dispersion. It is possible that there are areas that performed better or worse than London during the financial crisis, and aggregate values might mask these individual nuances within local labour markets. Figure 3.9 plots London's wage differentials against some selected large TTWAs[49] in the UK. Relative to the national average, the wage differential in London is much higher than in other areas. London is the only city that exhibited a positive wage premium throughout the crisis (although it seems to be reducing), whereas the wage penalty in other regions is more stable. Overall, Figure 3.9 confirms that, for a smaller set of cities, rankings are fairly persistent and that the regional pay structure did not alter materially due to the financial crisis – as indicated by the space between the two vertical red lines. Subsequent to the crisis, however, the gap in the relative wage differentials appears to be narrowing, which is consistent with Figure 3.6.

---

[49] The TTWAs are selected on the basis of being large settlements in terms of both population and economic activity. This gives us confidence in the statistical power underpinning the results. The focus in this part of the analysis is large cities (as used in previous studies) because larger cell sizes enable more observations and, therefore, more precise estimates. The English cities of Birmingham, Liverpool, Manchester, Sheffield, Leeds, Bradford and Newcastle, like Glasgow the largest city in Scotland, and Cardiff the capital of Wales, the driving forces of UK industrial power in the Victorian era and, were mostly so, until the middle of the 20th century. London is thus compared to the first four of these large cities.

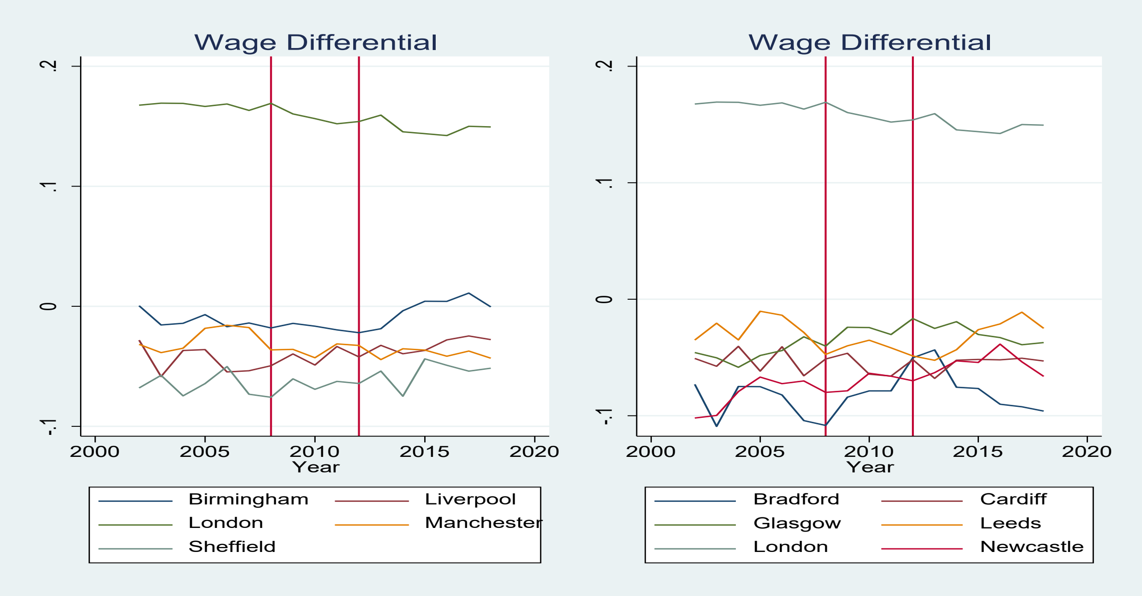

Figure 3. 9: Wage Differentials for London and Selected TTWAs Relative to the National Average

Notes: The vertical lines delineate the period of the financial crisis.

Source: Author's calculations from the ONS ASHE dataset.

Figure 3.10 depicts the scatter diagram of spatial wage differentials over two consecutive periods. There is a strong and positive relationship between the wage differentials across both periods. The rank order of the estimated wage differentials exhibits a high degree of stability over time, as indicated by the fact that the scatter plots fall close to the solid line of best fit. This stability in regional wage differentials over time again suggests that the financial crisis did not exert discernible effects on the spatial wage distribution. Again, the strong and positive correlation conveys the persistence of the wage structure across both time and space. This implies that the TTWAs that paid high wages remained high payers, despite the narrowing of the wage disparities across TTWAs.

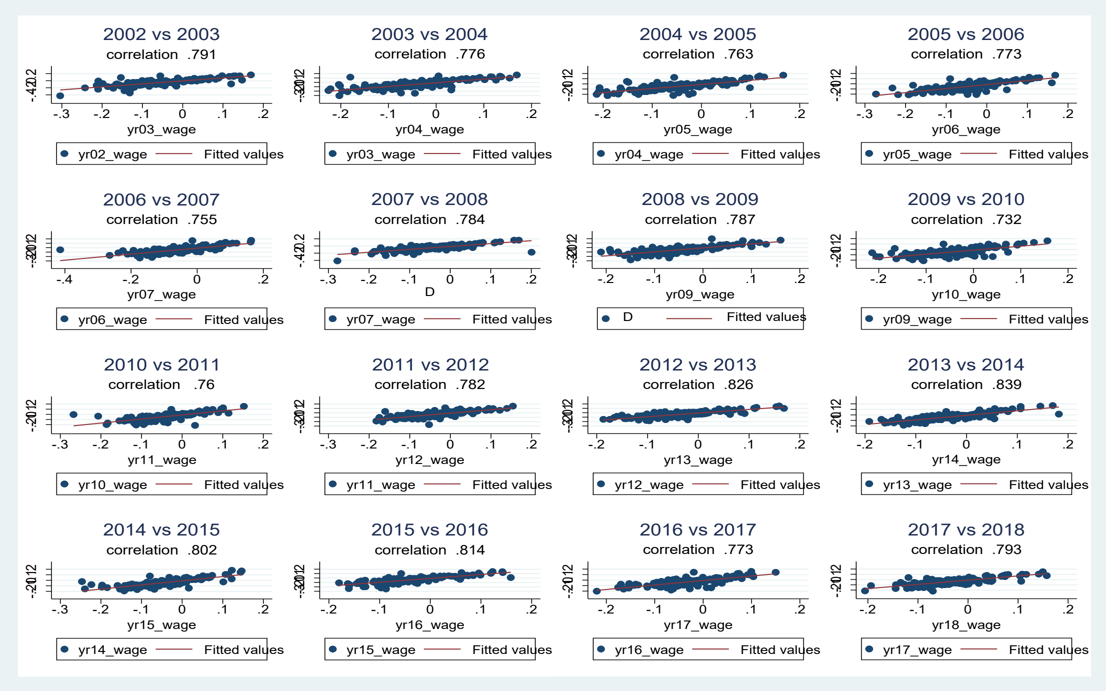

Figure 3. 10: Year on Year Scatter Plot of TTWA Wage Differentials

Source: Author’s calculations from the ONS ASHE dataset

Figure 3.11 presents period-on-period plots of the wage differentials for the study period (2002-2018): the pre-crisis period (2002-2007), the crisis period (2008-2012), and the post-crisis period (2013-2018). It shows a strong positive correlation in the wage differentials across each given period.

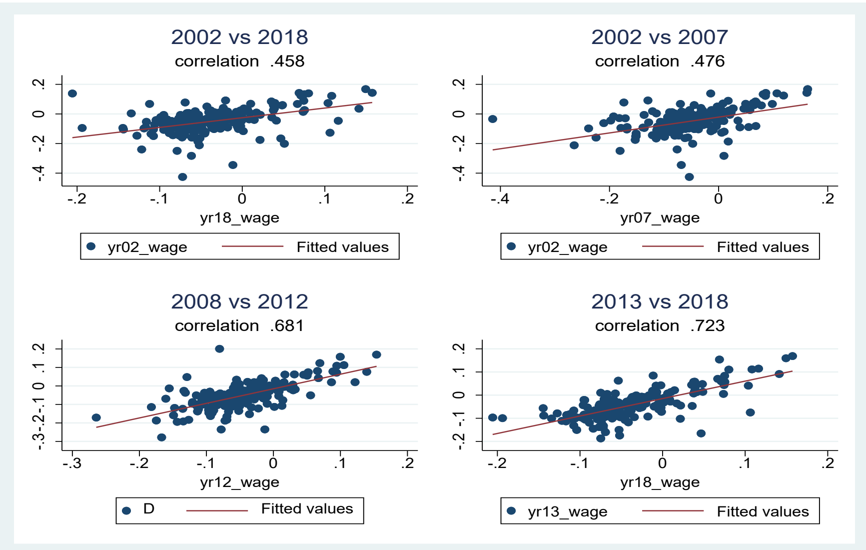

Figure 3. 11: Period on Period Scatter Plot of Wage Differentials

Source: Author’s calculations from the ONS ASHE dataset.

The top panel in Table 3.4 reports the correlations for the log regional wage differentials based on the 216 TTWAs across the four distinct sub-periods. These are the years at the start and at the end of the pre-financial crisis period, the start and the end of the financial crisis, the start and the end of the post financial crisis, and the start and the end of the full period. For all sub-periods, the correlation between the wage differentials is positive and strong. For instance, regions that paid high wages in 2008 continued to do so in 2012, with a correlation of 0.66, while areas where employees received high wages prior to the financial crisis in 2002 continued to do well after the end of the financial crisis. This finding suggests that, even after controlling for a wide variety of individual, industry and geographic characteristics, there are large and persistent correlations in wage differentials across TTWAs over time. The high correlation between the wage differentials suggests the structure of regional wage disparities is stable and highly persistent, also, that it has changed only marginally over time and does not appear to have been disrupted or given impetus by the financial crisis. This descriptive analysis provides suggestive evidence that regional pay disparities were already narrowing in the absence of an intervening shock.

Table 3. 4: Correlation Coefficients of Area Wage Differentials and Dispersion Across Selected Years

Period	**2002 versus 2007 (Pre-Crisis)**	**2008 versus 2012 (Crisis)**	**2013 versus 2018 (post-Crisis)**	**2002 versus 2018**
Wage Differential	0.4977	0.6630	0.6875	0.4837
Wage Dispersion				
Gini Coefficient	0.3668	0.3633	0.2444	0.1522
90^{th} - 50^{th}	0.2968	0.2906	0.3922	0.0801
50^{th} - 10^{th}	0.1235	0.3417	0.3231	0.1317
90^{th} - 10^{th}	0.2440	0.3388	0.3537	0.1208

Notes: First-stage estimations and author's calculation of the Spearman rank correlation coefficient between two periods. Data used: ASHE, 2002-2018. All correlation coefficients are significant at 1% level.

In order to consolidate these findings, Figure 3.12 presents the 'year-on-year' four-year moving averages of the Spearman rank order correlation coefficients for the area wage differentials, over the period 2002-2018. All year-on-year correlation coefficients are high (above 0.7) and statistically significant at the 1% level. The year-on-year correlations in regional wage differentials fluctuate substantially and appear to weaken slightly around the financial crisis;

they pick up again in the aftermath of the financial crisis. However, the correlation coefficients never fall below 0.74, suggesting strong persistence in the rankings of these differentials. This again confirms the high degree of stability in the UK regional wage structure across time. The results suggest that the wage structure appears to follow a pattern that was only modestly (if at all) affected by the shock of the financial crisis. It raises the possibility that the financial crisis may not have been implicated in changes in the structure of wages across regions. These results confirm very strong spatial persistence in the rank order of the wage differentials (i.e., areas that were paying high (low) wages before the financial crisis were still paying high (low) wages post the financial crisis). As noted, the TTWA wage disparities may be picking up both structural and cost of living differences.

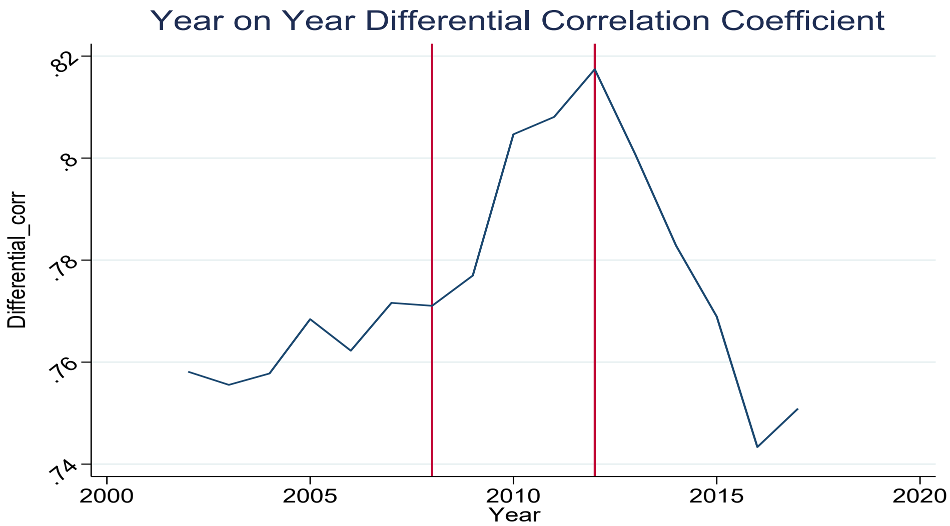

Figure 3. 12: Year-on-Year Correlation Coefficients for Regional Wage Differentials

Notes: The vertical lines delineate the period of the financial

Source: Author's calculations from the ONS ASHE dataset

3.8.2 TTWA Wage Dispersion

The mean-level analysis above examined the disparities in wage differentials across TTWAs before and after the financial crisis. In order to understand whether the financial crisis changed the structure of these wage disparities within TTWAs, the analysis now employs the RIF-based Gini coefficient methodology to examine the evolution in the area level dispersion of wages across time and space. The interest is also in whether the changes in the wage dispersions in TTWAs were driven by changes in the 90^{th}-50^{th} percentiles of the distribution or in the 50^{th}-10^{th} percentiles of the distribution (or a combination of both).

Figure 3.13 plots four-year smoothed moving averages over time for the standard deviation across TTWAs for each year and for each of the three measures of dispersion. They appear to suggest that inequality within TTWAs became less dispersed across the TTWAs over time, certainly for the Gini and the 50th-10th percentile, although at the top end (90th-50th) inequality was more volatile. It might be argued that there has been a degree of convergence in intra-wage dispersion effects over time, reflecting the movement in relative wages. However, based on the correlation coefficients, there seems to have been less persistence in these effects compared to what was found in the relative wage differential.

Figure 3. 13: **Standard Deviation(σ_{TTWA}) for Measures of TTWA Wage Dispersion for 2002- 2018**

Notes: The vertical lines delineate the period of the financial crisis

Source: Author's calculations from the ONS ASHE dataset.

Figure 3.14 plots the wage inequality measures across other areas in the UK relative to London. London's relative within-inequality rose steadily in the pre-crisis period. There is a greater degree of volatility outside London, although there seems to be some evidence that the wage dispersion in London has widened in recent years relative to the national average. A period of stability is observed, followed by a less evident widening of the dispersion of wages in London in more recent years, relative to the national average, and compared to other areas. Most of the changes in overall wage inequality in London appear to have been driven by the percentile gaps across the entire wage distribution (i.e., the 90th-50th, 90th-10th and the 50th-10th), and not by changes in any specific part of the distribution.

In general, there are more disparities across local labour markets, but greater inequality within local labour markets towards the end of the time period. Despite the steady decline in overall wage inequality, within local labour markets inequality rose and is especially pronounced in the London labour market relative to the remaining TTWAs. The 'levelling up' White Paper acknowledges that differences *within* UK regions or cities are larger than differences *between* regions on most performance metrics. The analysis in this chapter confirms that this is the case for wages and shows that there is no evidence of the downward trend in inequality within local labour markets as observed at the aggregate level. Overall, there appears to be evidence of rising inequality *within* TTWAs coincidental with falling inequality across labour markets. London appears to have the most unequal labour market relative to the national TTWAs average. The other areas appear to follow a different trajectory from London. In contrast to the London labour market, where inequality rises at both the top and bottom ends of the distribution, there was a sharp fall in wage inequality in the non-London areas at the 50^{th}-10^{th} segment of the wage distribution and, as a consequence, a more modest fall in the 90^{th}-10^{th} gap. Unlike in London, the rise in intra-TTWA wage inequality within the local labour markets of the other TTWAs (towards the end of the time period) appears to have been driven by the rising gap between only the 90^{th} and 50^{th} percentiles of the wage distribution. The London labour market seems to be characterized by both high relative wage differentials and high relative within dispersion compared to all other TTWAs.

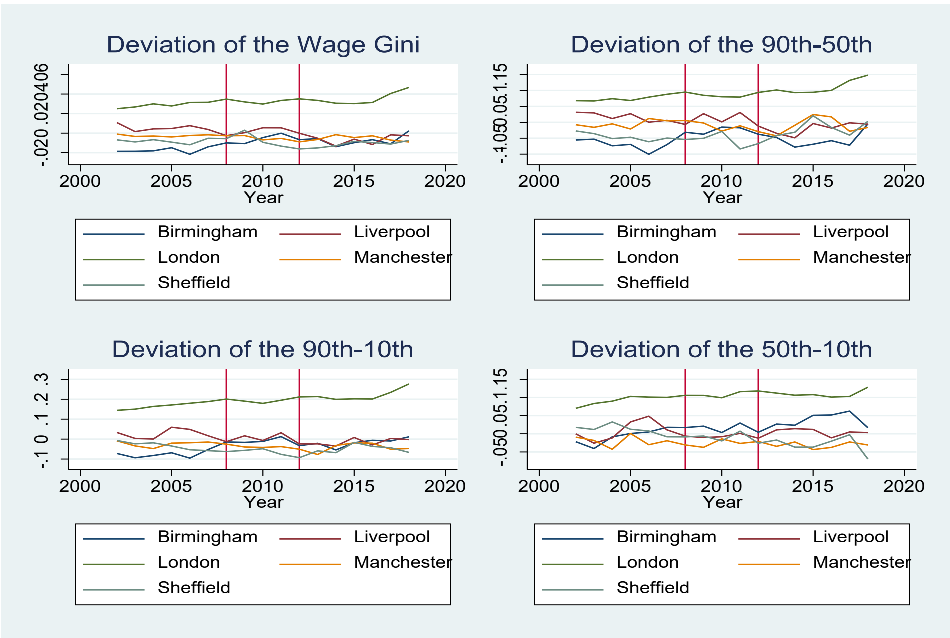

Figure 3. 14: Wage Inequality in London and other TTWAs

Notes: The vertical lines delineate the period of the financial crisis

Source: Author's calculations from the ONS ASHE dataset.

Figure 3.15 is a plot of London relative to five[50] other areas and reveals a broadly similar pattern, with the wage inequality in London again standing out. London appears to have more stable overall wage inequality. There is volatility in the rest of the TTWAs relative to the national average, but this may be due to variations in TTWA cell sizes. The wage gap between the 90th and 50th percentiles rose in London at the onset of the crisis.

In recent years, inequality has fallen in the rest of the TTWAs, but has increased in London. This, again, is driven by the widening gap between the 90th and the 50th percentiles. Overall, the degree of wage dispersion within the London labour market is considerably higher relative to the national average, compared to the degree of inequality within other selected cities. In general, the dispersion for London appears stable, although the degree of dispersion appears to widen in more recent years. In contrast, the evolution of wage disparity in other cities over time is more erratic and appeared more volatile during the financial crisis. Specifically, in London the magnitude of the 90th-50th log wage percentile gap appears to have widened compared to other cities; this is responsible for the overall increase in wage inequality within London.[51]

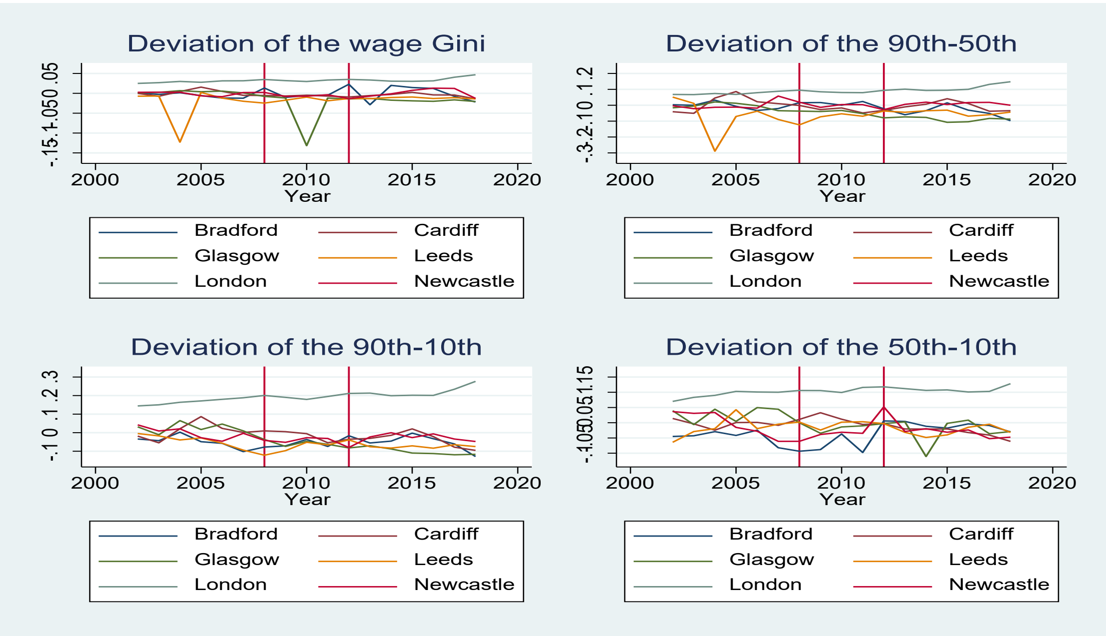

Figure 3. 15: Wage Inequality in London and Other TTWAs

Notes: The vertical lines delineate the period of the financial crisis.

[50] Bradford, Cardiff, Glasgow, Leeds, Newcastle.
[51] There is a reasonable distribution of sample sizes across TTWAs, ruling out any large sample bias problems. This picture is consistent when we isolate London and the larger cities in GB.

Source: Author's calculations from the ONS ASHE dataset.

These findings suggest that the financial crisis is associated with a small effect on overall wage inequality, but no effect on the degree of intra-TTWA wage inequality. Despite a narrowing of the overall Gini, within TTWA inequality widened in the post-crisis period. Overall, there is evidence of a widening of wage dispersion within the London labour market, particularly towards the end of the period under study. Much of this widening was driven by what happened at the 90th-50th percentile and less by the 50th-10th percentiles of the log wage distribution. For the other regions, the position is less clear.

Figure 3.16 reports the year-on-year correlation coefficients for the overall wage dispersion measured by the Gini. It shows a sharp reduction and some volatility in the correlations in 2008, but a recovery after the financial crisis. This is evidence that rank orders are much weaker and more erratic for wage inequality compared to the rank orders for the wage differential, which are stronger and more stable. However, this may be capturing unexplained variability (noise) due to small TTWA cell sizes.

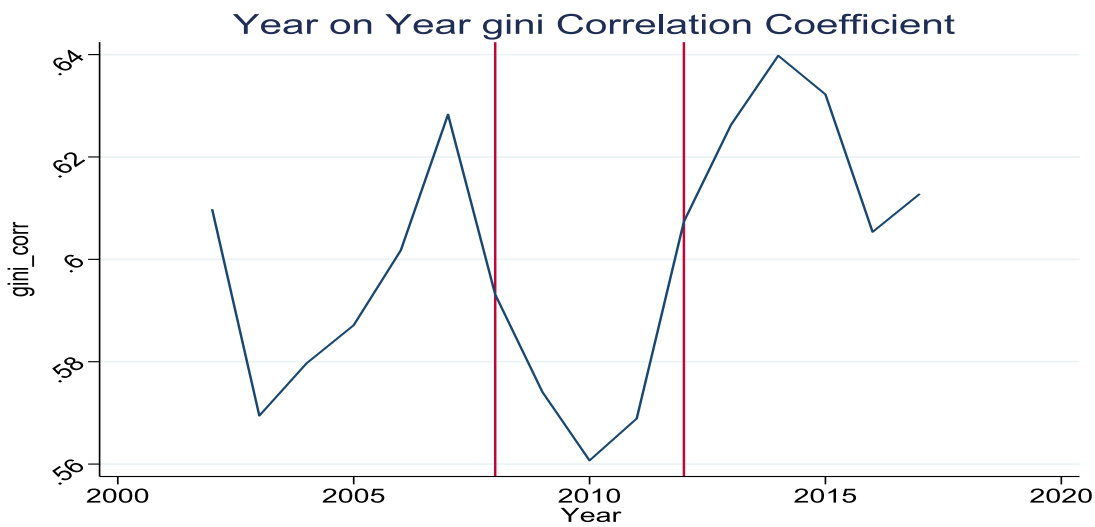

Figure 3. 16: Year on Year Correlation for the Gini Coefficient

Notes: The vertical lines delineate the period of the financial crisis.

Source: Author's calculations from the ONS ASHE dataset

Appendix Tables 3.A4, 3.A5 and 3.A6 show the high and low wage inequality areas relative to the national average. They rank the top 20 and lowest 20 wage inequality areas, based on the Gini, and the 90th-50th and the 50th-10th percentiles, over three years (2002, 2012, 2018). On average, there seems to be a degree of within-region wage inequality in both the northern and southern regions, across all three measures. Mostly, the wage dispersion is not affected by the financial crisis, with most areas with high wage dispersion prior to the financial crisis continuing to show high wage dispersion after the financial crisis. This suggests that local area specific characteristics may be driving these wage dispersions. In line with Lee *et al.* (2016), it can be noted that the cities with the lowest levels of overall wage inequality tend to be the former industrial cities in the Midlands and the north of England.

The bottom panel in Table 3.4 suggests that, in contrast to the correlation of the wage differential, the correlation in the measures of wage dispersion over the same periods is fairly weak. As already noted, between 2002 and 2018, overall wage inequality measured by the Gini coefficient, fell. Splitting this into the pre-crisis, crisis and post-crisis periods, it is observed that the weakest correlation between wage dispersion among the three sub-periods occurs in the post-crisis period. Overall, there is weak correlation of wage dispersion across TTWAs over time. This suggests that the degree of stability in the dispersion of earnings across the TTWAs differs from the regional wage differential case.

Figure 3.17 depicts the correlation in the deviations of the wage Gini. The period-on-period plots exhibit a very weak positive correlation across the periods. The Gini deviation correlation becomes even smaller during the post-crisis period.

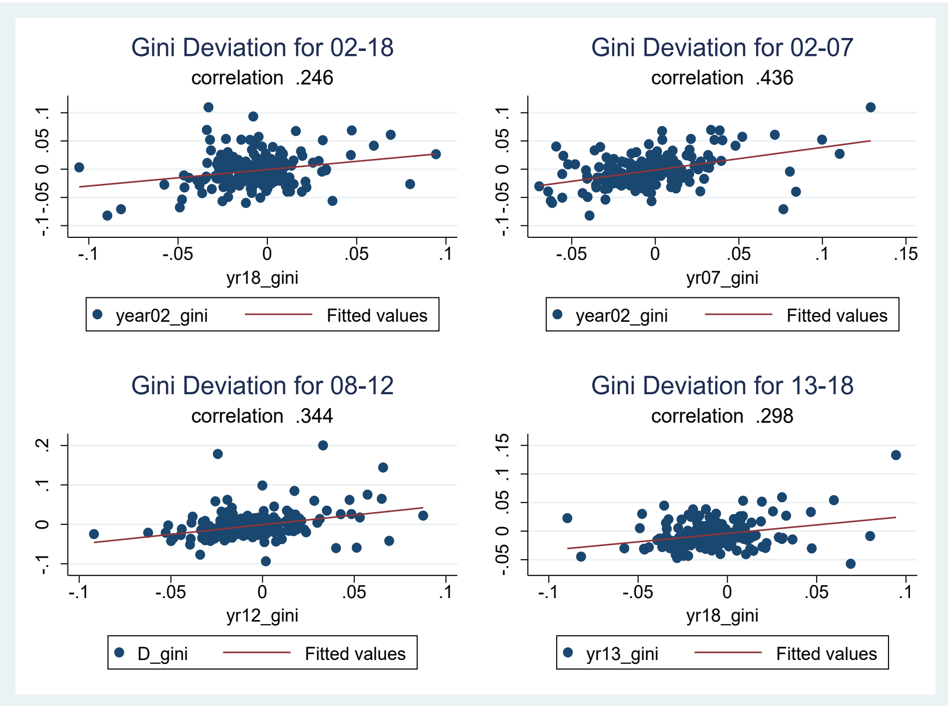

Figure 3. 17: Correlation of the Gini coefficient for Selected Periods

Source: Author’s calculations from the ONS ASHE dataset.

Similarly, the correlation in the deviations between the 90th-50th and the 50th-10th percentiles are very weak over time. Figures 3.18 and 3.19 indicate a very weak correlation across the deviations of both wage gaps over time. This provides further support for the weaker persistence in the rank order in the area wage inequality for the overall Gini and the wage gaps, relative to that for wage differentials.

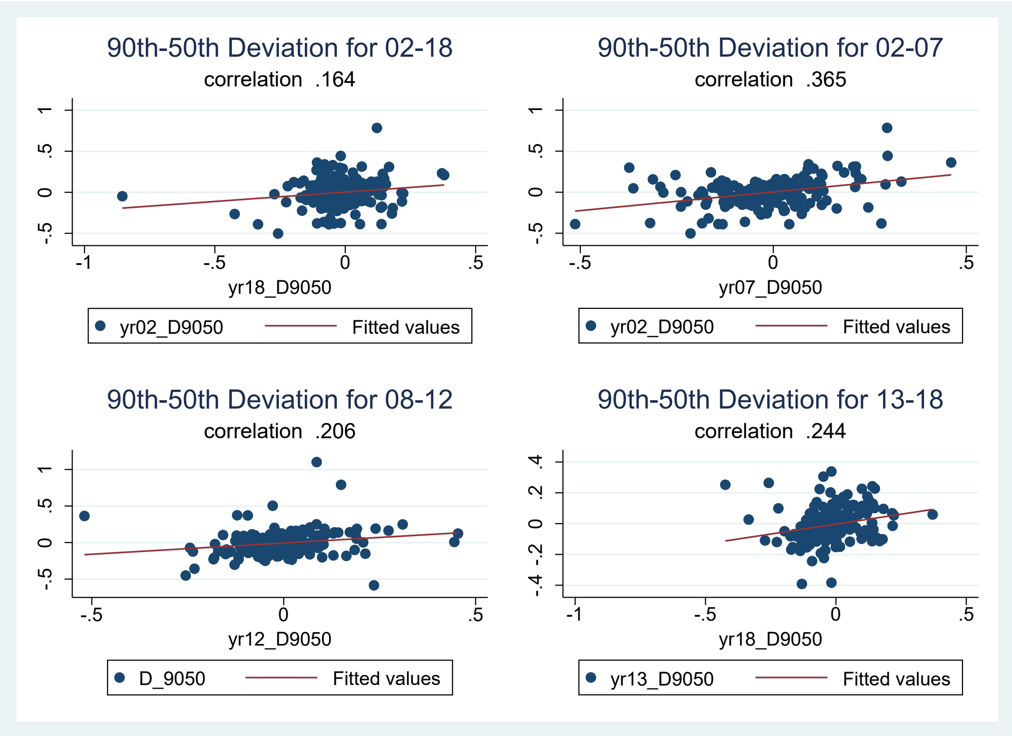

Figure 3. 18: Correlation for the 90th-50th Measure of Dispersion for Selected Periods

Source: Author's calculations from the ONS ASHE dataset.

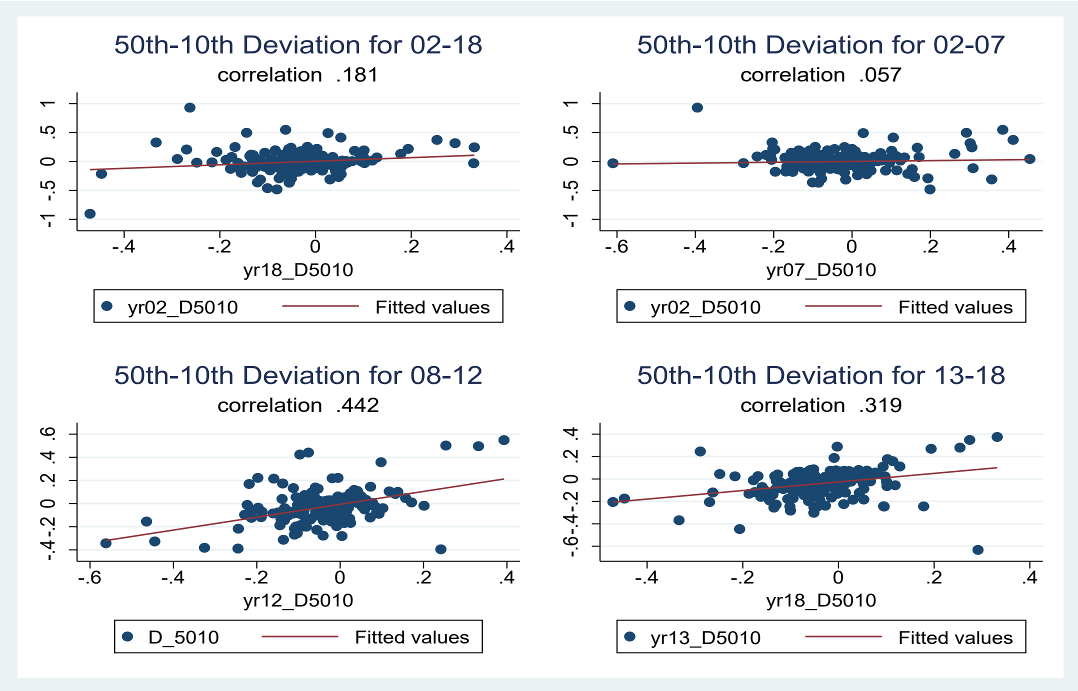

Figure 3. 19: Correlation for the 50th-10th Measure of Dispersion for Selected Periods

Source: Author's calculations from the ONS ASHE dataset.

3.8.3 TTWA Wage Differentials and Dispersion

Figure 3.20[52] is a period-on-period scatter plot of the wage differentials and the measures of wage dispersion. In both the pre-crisis and crisis periods, there seems to be a negative relationship between the wage differential and the wage dispersion, measured by the Gini coefficient. In the pre-crisis period, an increase in the wage differential is associated with falling wage dispersion. The TTWAs with high (low) wage differential relative to the national average are associated with a low (high) wage dispersion. However, in the post-crisis period, an increase (decrease) in the wage differential is associated with an increase (decrease) in the wage dispersion. This implies that areas that had a high (low) wage differential relative to the national average before the crisis, also experienced an increase (decrease) in the wage dispersion relative to the national average in the post-crisis period. There appears to have been a shift in the relationship between within-regional dispersion and differentials in the post-crisis period and an emergence of a co-existence of high wages and high inequality within local labour markets. However, the magnitude of the association between the inter-regional wage differential and the intra-regional dispersion remains relatively weak.

[52] The Spearman correlation coefficient is statistically significant for 2002 (prob=0.0114) and 2018 (prob=0.0008) and is statistically insignificant for 2007 (prob= 0.1803) and 2012 (prob=0.8653).

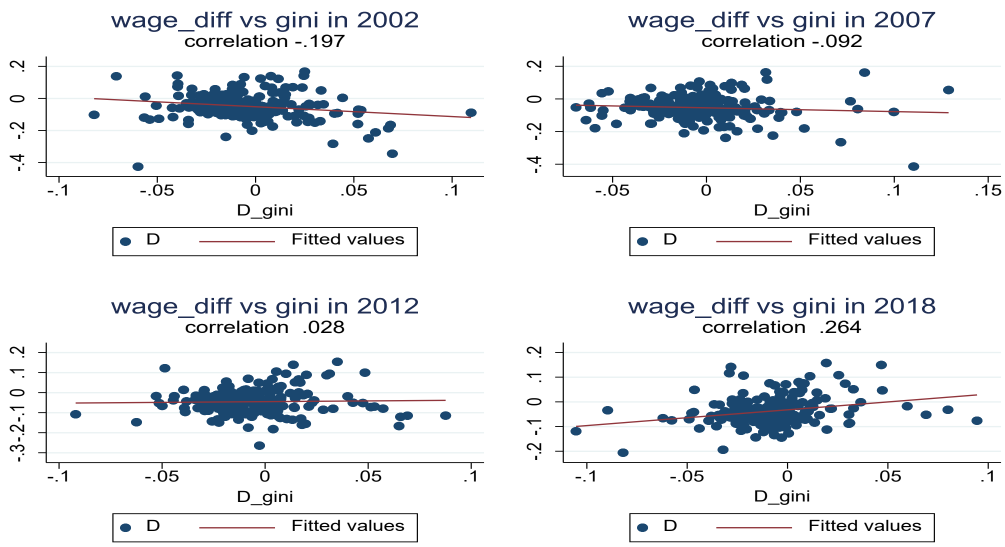

Figure 3. 20: Correlation Between Wage Differential and Wage Gini for Selected Years

Source: Author's calculations from the ONS ASHE dataset.

The correlation between the wage differential and the 90th-50th percentile gap shows a generally weak negative relationship in both the pre-crisis and post-crisis periods. Figure 3.21 depicts a flip in the recovery period, when the relationship became weakly positive. A wage premium or penalty in local labour market wage disparity relative to the national average is now associated with a falling gap between the 90th and 50th percentiles prior to the crisis, although the gap began to increase in the post-crisis period. This suggests that high wages come at the cost of high wage inequality at the top end of the distribution.

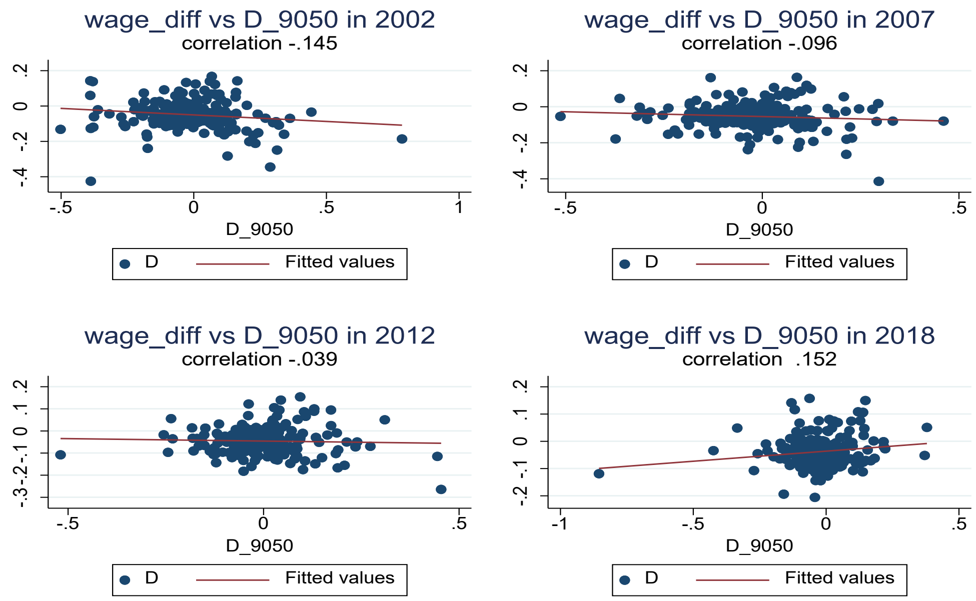

Figure 3. 21: Correlation Between Wage Differential and the 90th -50th for Selected Years

Source: Author's calculations from the ONS ASHE dataset.

In terms of the 50th-10th percentiles, Figure 3.22 shows a positive relationship between the 50th-10th percentile gap and the wage differential in the year before the financial crisis. The relationship became positive during the crisis and post-crisis periods. This implies that the increase in the wage differential relative to the national average within local labour markets is also associated with an increase in the wage inequality at the bottom end of the distribution, within local labour markets.

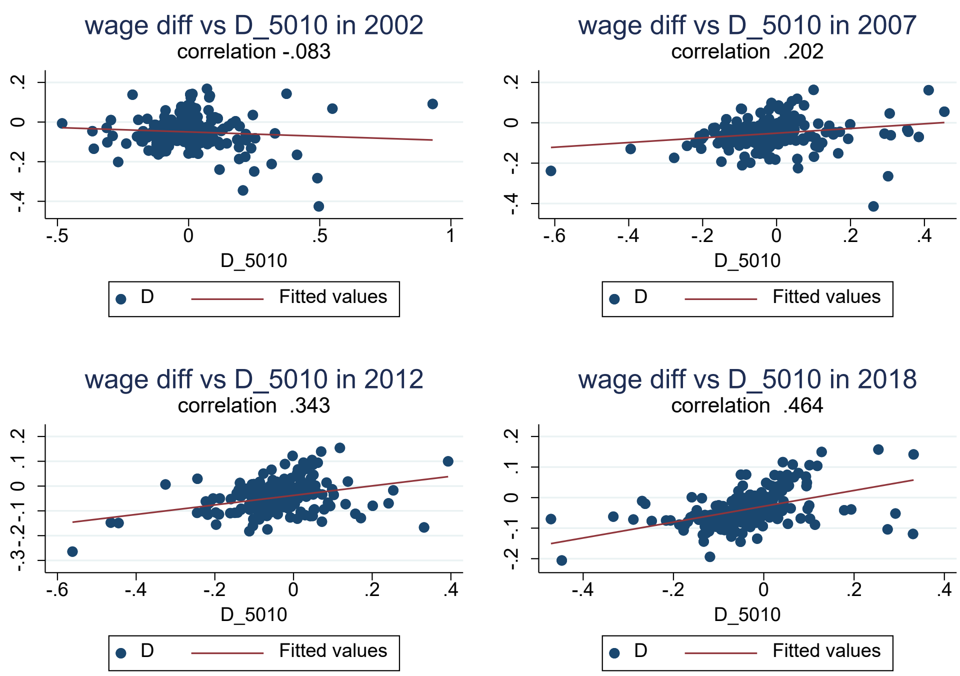

Figure 3. 22: Correlation Between Wage Differential and the 50th -10th for Selected Years

Source: Author's calculations from the ONS ASHE dataset.

In the pre-crisis period, the negative correlation between the Gini and the wage differential is driven mostly by the gap between the 90th and the 50th percentiles of the wage distribution. In the post-crisis period, a positive association between the Gini and the wage differential emerged - driven mostly by the narrowing gap between the 50th and the 10th percentiles of the wage distribution. This points to a shift within local labour markets. In the post-crisis period, an increase in wages relative to the national average was associated with an increase in within local market wage inequality, particularly at the top end of the wage distribution.

3.8.4 TTWA Regional Agglomeration Effects

Most empirical research that estimates agglomeration effects on the economy, estimates the effect of industrial or urban concentration on some measures of productivity. The general consensus is that agglomeration economies exist and that they induce higher productivity for firms and workers, but the estimates show differences in the magnitude of these effects (Graham and Gibbons, 2019). For the UK case, there is evidence suggesting that labour productivity varies across regions. Nguyen (2019) claims that most regions in the UK (72% of NUTS-3 regions) show output per hour worked below the national average, suggesting a strong regional dimension to the distribution of output in the UK. The chapter therefore investigates whether the factors that determine the spatial variation in productivity are also relevant in explaining the spatial variation in regional wages computed above. A second stage wage regression analysis is conducted to ascertain whether the wage differentials in these TTWAs change with respect to a set of attributes proxying for the presence of agglomeration economies. This is motivated by the notion of a strong relationship between productivity, inequality, economic growth and, ultimately, real wages (Hornbeck and Moretti, 2018).

This sub-section explores the degree to which spatial wage disparities are determined by agglomeration externalities. The aim is to establish whether firms in more agglomerated locations are more productive, and whether this translates to higher wage payments relative to the national average. In addition, this approach allows us to investigate explicitly the impact of the financial crisis on regional wage differentials and disparities. Also, of interest is whether the relationship between wages and agglomeration factors changed in the pre-financial crisis, the crisis and the post-crisis eras. This is investigated by regressing regional wage differentials on a set of variables proxying for agglomeration externalities, while controlling for time-varying area specific characteristics and other factors that influence wages. Agglomeration economies are usually categorized as urbanization economies or localization economies (Echeverri-Carroll and Ayala, 2011). The following regression model[53] is estimated using a panel of TTWAs over the period 2002-2018: [54]

$$D_{it}= \alpha_i +\beta_1 lnempdens_{it}+\beta_2 grad_{it}+\beta_3 hhi_{it}+\beta_4 hightech_{it}+\beta_5 gfc_{it}+ v_{it} \qquad \ldots\ldots\ldots. \qquad [3.12]$$

The variables are described in Table 3.5 below.

[53] The analysis employs a fixed effects estimator with TTWAs as the fixed effectsThe estimates for the *hhi*, the employment density are identified by variation in these measures within the TTWA over time.

[54] The dependent variable D_{it} is defined as in equation [3.2] and is estimated for the wage differential.

Table 3. 5: Variable Names and Description for the Agglomeration Analysis

Variable	Description
D	The wage differential of TTWA i at time t (calculated in equation [3.2])
lnempdens	The log of the numbers of employees in a TTWA divided by size of the TTWA measured in square kilometres.
grad	The total number of employees with at least a graduate qualification as a percentage of the total number of employees in a TTWA.
hhi	The sum of squares of TTWA employment shares for the two-digit industries and total employment in the local economy TTWA. The Hirschman Herfindahl Index (hhi) is used as a measure of industrial concentration of the TTWA. Values approaching zero indicate more highly diversified regional economies, while a value of one indicates complete specialization in a single sector.
high-tech	The proportion of high-tech industries in a given TTWA
gfc	A dummy taking the value of 1 if the year is 2008 to 2012, and 0 otherwise.

It is expected that the log of employment density will have a positive sign on the outcome variable. This is defined as the ratio of total employment in the local labour market to the total land area (in Kms) of the local labour market. It captures urbanization agglomeration externalities in a given TTWA. Combes *et al.* (2008) estimate that, in French employment areas, doubling the employment density raises wages by between 2% to 3%. The coefficient of the variable for percentage of graduates should have a positive sign and reflect the externality effects of higher levels of human capital in the labour market. Therefore, graduates have better job matches and earn higher wages (Moretti, 2004).

The estimated coefficient of the *hhi* (Herfindahl-Hirsch index) variable is expected to have a positive sign. The *hhi* is constructed across industry participation in employment in the local labour market in order to capture the presence of localization economies. In theory, industrial specialization is conducive to reduced production costs and increased innovation capacity, which enhances TFP and wages. Inclusion of the *hhi* is important and its estimated effects suggest that wages might be high because the local labour market is very specialized (Combes and Gobillon, 2015). This also applies to the potential effect of the proportion of workers employed in ‘high-tech’ industries. It is expected that the coefficient of the proportion of high-tech industries will have a positive sign because concentration of high-tech industries reflects increased demand for college-educated workers, which pushes up wages.

Finally, the signs of the coefficient of the financial crisis are agnostic. The financial crisis could be expected to have exerted a negative impact on relative regional wages although it is equally likely given the evidence documented earlier that the crisis exerts no independent effect on relative wages.

Table 3.6 presents summary statistics for the main explanatory variables for the overall sample used for the second-stage analysis to investigate agglomeration effects. An increase in the percentage of men with graduate qualifications across TTWAs over time is observed. On average, the value of the Herfindahl index fell over the years, suggesting more diversified TTWAs over time. There seems to be evidence of a very low presence of high technology industries across TTWAs over time.

Table 3. 6: Summary Statistics for the Agglomeration Regression Variables

Year	**2002-2007**		**2008-2012**		**2013-2018**		**2002-2018**	
Variable Name	**Mean**	**Std Dev.**	**Mean**	**Std Dev.**	**Mean**	**Std Dev.**	**Mean**	**Std Dev.**
D	-0.0518	0.0721	-0.0464	0.0630	-0.0417	0.0587	-0.0466	0.0651
grad	9.8196	5.3957	12.6427	6.7228	17.0232	7.5211	13.2057	7.2702
lnempdens	-2.1392	1.4979	-2.0117	1.5042	1.4853	1.4853	-2.0246	1.4978
hhi	0.0876	0.0691	0.0800	0.0547	0.0756	0.0506	0.0811	0.0591
high-tech	7.1205	6.7093	5.8402	5.9021	5.7004	5.7837	6.2405	6.1905
gfc	n/a	n/a	0.1979	0.3986	n/a	n/a	0.0581	0.2340
N	1,270		1,061		1,283		3,614	

Source: Author's calculations from the ONS ASHE dataset

Table 3.7 presents the results for the effect of agglomeration factors on spatial wage differentials. Economies of density are important for explaining differences in local wages. The log of employment density, *ceteris paribus,* has positive and statistically significant effect on regional wage disparity. In the literature this productivity advantage is associated with large cities or urbanization economies. This effect is invariant to controlling for the financial crisis. The industry concentration proxied by the *hhi* is found to increase spatial wage differentials. This means that working in an industry that is highly concentrated in a given TTWA, *ceteris paribus,* increases regional wage differentials. Areas with higher levels of industry concentration are correlated with high wages relative to the national average. They offer workers more labour market options, which, in turn, push up wages. This defines a localization economy.

Table 3. 7: Regional Wage Differentials and Agglomeration Effects

VARIABLES	(1)	(2)	(3)	(4)	(5)
	D	D	D	D	D
grad		0.0000	0.0000	0.0000	-0.0000
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
lnempdens	0.0073***	0.0072***	0.0085***	0.0084***	0.0082***
	(0.0027)	(0.0028)	(0.0026)	(0.0026)	(0.0026)
hhi			0.0905*	0.0906*	0.0902*
			(0.0490)	(0.0488)	(0.0487)
high-tech				-0.0002	-0.0002
				(0.0003)	(0.0003)
gfc					-0.0030
					(0.0032)
Observations	3,614	3,614	3,614	3,614	3,614
R-squared	0.6462	0.6480	0.6496	0.6497	0.6498
TTWAFE	Yes	Yes	Yes	Yes	Yes

Notes: The Robust standard errors reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: Author's calculations from the ONS ASHE dataset.

The regression output provides evidence that the financial crisis did not have a significant impact on wage differentials across the TTWAs. This confirms the notion that the persistence in wage differentials was not altered significantly by the crisis. The downward trend prior to the crisis continued into the crisis and post-crisis periods. Effectively the financial crisis did not exert any discernible effect on the structure of regional pay differentials.

To ascertain whether the effects of urbanization (employment density) or localization /specialization (*hhi*) economies prevail in local markets, the analysis compares the magnitude of the difference between the 95th and 5th percentiles of the two variables. It can be noted in Table 3.8 below that the log of employment density explains more of the spatial wage variation relative to the Herfindahl index.

Table 3. 8: Differences Between the 95 and the 5th Percentile for Agglomeration Effects

Variable	95^{th}-5^{th}	B_i*(95^{th}-5^{th} Percentile)	Percentage Difference
lnempdens	4.9403	0.0405	4%
hhi	0.1486	0.0134	1.3%

Source: Author's calculations from the ONS ASHE dataset.

The difference between the 95^{th} and the 5^{th} percentiles of the log of employment density multiply by its respective beta coefficient as given in Table 3.7 above (4.9403*0.0082) *100, yields 4%. This means that the wage difference between two locations – one in the 95^{th} and the other in the 5^{th} percentile of the log employment density distribution - is about 4%. Similarly, the *hhi* for the 95^{th} and 5^{th} percentiles is respectively 0.1875 and 0.0389. Multiplying the difference between these two percentiles and the coefficient of the *hhi* shows that 1.3% of the variation in wages between the two locations is explained by the *hhi*. This suggests that city size matters for the determination of wages. Effectively, wages are high in certain TTWAs merely because they are big and not necessarily because they are specialized. A strand of literature on labour economics (see Nygaard et al., (2021), Di Addario and Patacchini, (2008) Coombes et.al. (2008)) argues that this is due to the existence of congestion effects with increasing local labour market size. This suggests that wage differentials across TTWAs in Britain are compensative in nature. Employment density generates congestion costs (that could include housing costs, pollution and increased concentration of traffic, and social costs such as crimes). Higher wages (or non-wage benefits) compensate workers for living in congested regions.

3.8.5 Insights from the Analysis

The econometric analysis in this chapter is descriptive and does not provide causal insights. However, an emerging theme from this descriptive analysis is that the financial crisis had no discernible effect on regional wage disparities, wage dispersion or agglomeration effects.

However, it does highlight some important issues that suggest the need for more in-depth research on labour markets.

One of the features of the analysis in this chapter is highlighting the London TTWA and the dominance of the financial services sector in that local labour market. Although it has been shown that the London labour market followed national trends, it is a rather unique labour market. For instance, nominal wages in London were affected more adversely by the financial crisis than wages elsewhere. In London, however, wages rebounded fairly rapidly in the post-crisis period and remained as resilient to the shock as other local labour markets in Great Britain.

The main analysis provides strong evidence that regional wage disparities relative to the national average have been falling since the early 2000s, that is, well before the financial crisis. Specifically, the financial crisis appears to have provided neither impetus nor constraint to the process of regional wage narrowing in Great Britain. Although the current UK government states that it is committed to 'levelling-up', what this agenda implies, precisely, for the labour market, is unclear. It might be reasonably expected that one aspect of any 'levelling-up' would be a commitment to designing and implementing policies to narrow regional wage differentials. However, this chapter provides empirical evidence that this has already been happening across the regions of Britain and in the absence of any targeted regional labour market policies. However, the empirical evidence in this chapter suggests that there is strong persistence in rank ordering in these regional wage disparities. The TTWAs paying the highest wages pre-crisis have continued to do so in the post-crisis period, and *vice-versa*. This finding is robust to the impact of the financial crisis.

The empirical analysis sheds light on the fact that overall wage inequality has been falling in Great Britain. This appears to have occurred before the financial crisis and continued into the post-crisis period, although there is tentative evidence showing that it is increasing in more recent years. The evolution of wage inequality appears to be driven by increasing inequality at the top end of the distribution (90^{th}-50^{th}) and has contracted at the bottom end of the distribution. This suggests an impact of the minimum wage policy on wage dispersion, although this issue is not explicitly investigated here. What has remained hidden, however, is the evolution of inequality within local labour markets. This appears to be rising and to be more pronounced in the London labour market. The empirical analysis also provides evidence of a convergence over time in the degree of within wage inequality across regions. Therefore, even though male wage inequality appears to be falling *across* labour markets, there is evidence of rising wage inequalities *within* local labour markets. If levelling-up is to be a serious policy strategy aimed at regional labour markets, this finding underlines the need to ensure that this levelling-up is relevant both across and within labour markets.

The empirical analysis further provides evidence of a change in the relationship between wage disparities and wage dispersion at the TTWA-level over the last 20 years or so. In the pre-crisis period, the relationship was negative, but turned positive in the post-crisis period. In other words, in the pre-crisis period, TTWAs with high relative wages had lower than average wage inequality. This situation was reversed in the post-crisis period when TTWAs with high relative wages also registered high wage inequality relative to the average wage inequality. This implies that in the post-crisis period, areas that paid high wages relative to the national average, also had very high levels of wage inequality within their labour markets. Therefore, there seems to be an emergence of regional labour markets with increasing coexistence of very high and very low wage earners. This may reflect the emergence of a job polarization phenomenon within local labour markets. This is clearly an issue that requires further research.

The final part of the empirical analysis in this chapter links regional labour markets to some of the productivity themes researched in Chapter 2. In particular, this chapter provides evidence about the regional wages effects of agglomeration economies, proxied by employment density (urbanization) and the Herfindahl index (specialization or localization economies). However, employment density has a more pronounced effect on wage disparities relative to the Herfindahl index, and this reveals primarily that the reason why local labour markets pay high wages is their large size and not necessarily their higher degree of specialization. This can be likened to a congestion effect in the labour market compensating wage differentials literature, where workers are paid a premium for working and living in congested areas. The second-stage analysis again confirmed that the financial crisis did not exert an independent effect on regional wage differentials.

3.9 Summary and Conclusions

This chapter provided a descriptive analysis of local area wage disparities in Britain over a period that included the 2008 global financial crisis. The analysis focuses on male workers in Great Britain using the ONS ASHE dataset for the period 2002-2018. The analysis started by estimating a log wage regression model to partial out the effect of individual characteristics. The results of the analysis suggest that *ceteris paribus,* there are significant wage disparities across the 216 TTWAs analysed. The London labour market remains unique in comparison to most other TTWAs, although it generally follows the national trend. The TTWAs in Britain differ significantly in the variation across wage differentials and in terms of degrees of intra wage inequality. There seems to be strong persistence in the rank order of the regional wage structure despite the significant shock of the financial crisis. The TTWAs paying higher wages (relative to the national average) prior to the financial crisis continued to pay high wages in the post-crisis period.

The empirical evidence suggests that the financial crisis did not alter the regional wage structure as it seems to have neither slowed nor given it impetus and traction. The trend was contractionary or downward prior to the financial crisis and continued in these directions during and post the crisis. This has implications for policies aimed at narrowing spatial wage disparities. In some sense, this is consistent with the current government's levelling up agenda. However, if a large and sizeable shock to the British labour market, such as the 2008 financial crisis, failed to significantly modify the regional wage structure, robust policy shifts will be required if the levelling up agenda is to deliver in terms of narrowing regional wage disparities or altering existing trends in the British labour market.

The empirical evidence in this chapter suggests that the regional dispersion in male wages declined slightly over this period, but the rank ordering exhibits weaker persistence relative to the disparities. Although wage inequality has fallen across regions, a rise in intra-local labour market wage inequality is emerging. This indicates a convergence across labour markets in terms of wage inequality. The evidence seems to suggest that highly unequal local labour markets are converging in Britain. More importantly, in the post-crisis period, there is a positive correlation between high wage disparities and high inequality within local labour markets. What was seen prior to the financial crisis was that high wages were generally associated with low wage dispersion. Currently, the labour market is becoming one where those TTWAs with high wages are also experiencing high wage dispersion. Although high wages are observed, the associated high wage inequality may presage a greater but different type of regional inequality. This suggests the need for an effective levelling up agenda, not just across but also within regions, given the emergence of high wage inequality in the TTWAs that predominantly exhibit high regional wage disparities relative to the national average. Central to a levelling up agenda must be wage inequality across regions, although this should not come at the expense of ignoring what is happening within local labour markets. There are widening within labour market wage inequalities emerging that need to be the focus of any policy that aims at narrowing overall wage inequality.

The analysis has provided evidence that the high wage inequality in Britain is driven mostly by the gap between the 90th and the 50th percentiles, and that the gap between the 50th and the 10th percentiles has been driving the contraction of the Gini coefficient during the period under study. Although there is evidence of falling overall wage inequality in Great Britain over the period 2002 to 2018, there are some indications that this might be now reversing. The financial crisis quantitatively reinforced the downward trend in overall wage inequality, rather than reversing it. Piketty and Saez (2014) show that rising wage inequality is a key driver of rising income inequality. Effectively, high wages come at the price of greater inequality. High and low paying jobs complement each other, and labour markets are fast becoming areas where high and low wage earners are co-existing. Local costs of living are particularly likely to be problematic, and low waged workers are likely to face challenging housing and living costs, especially in TTWAs with more high wage earners. In this regard, policymakers need to consider the implications of rising wage inequality within regions.

In addition, this growth in wages at the top and bottom ends of the distribution relative to the median coincides with polarization in wages, with earnings in the middle of the wage distribution stagnating or falling and earnings at the top and the bottom ends of the distribution increasing. Therefore, the distribution of skills in a TTWA will be an important determinant of intra-regional wage inequality. It will also be imperative to monitor the impact of the COVID-19 crisis on spatial inequalities. Blundell *et al.*(2020) argue that remote working tends to be easiest for those on higher incomes for this reason the emergence of the COVID-19 pandemic and remote working might have exacerbated pre-existing inequalities within regions. It is likely that some of these changes will persist, leading to more workplace flexibility in the future. More people working from home may require support from low wage earners (cleaners, carers, etc.) to increase their leisure time; this could potentially increase wage disparities and engender wage polarization. The nature of local labour markets is changing. There is currently greater variation in jobs and wages than in the past.

The proposal of the devolution of powers from Whitehall to local leaders in the levelling up White Paper is a welcome development as this will ensure that local tailor-made solutions to address the inequalities within regions are likely to emerge. The proposal further underscores the need to fund local skills improvement plans and give local employer bodies and stakeholders a statutory role in planning skills training in their area, to better meet local labour market needs. The decentralization of training programmes to local authorities could be an effective way to address the issues giving rise to these within regional markets disparities. An important agenda for further research, however, would be to situate this analysis within the theme of job polarization.

The analysis in this chapter does not exploit any spatial econometrics to account for spatial autocorrelation and spatial heterogeneity. It could be argued that the introduction of spatial dependence might improve the quality of the statistical inferences (see LeSage and Pace, 2009), although given the sample sizes used in the current analysis, the value-added might be small. Also, despite its potential advantage, spatial econometric analysis is not well developed for the type of RIFs used in this analysis (McMillen, 2013). Nevertheless, this is a potential area for future research.

Finally, the results of the analysis in this chapter emphasize the importance of some agglomeration factors for determining spatial wage disparities. Urbanization economies (congestion effect) appear to explain more of the regional wage disparity between high and low wage earners within a local labour market than do localization economies. Effectively, TTWAs pay high wages because they are big and not necessarily because they are specialized.

3.10 Appendix

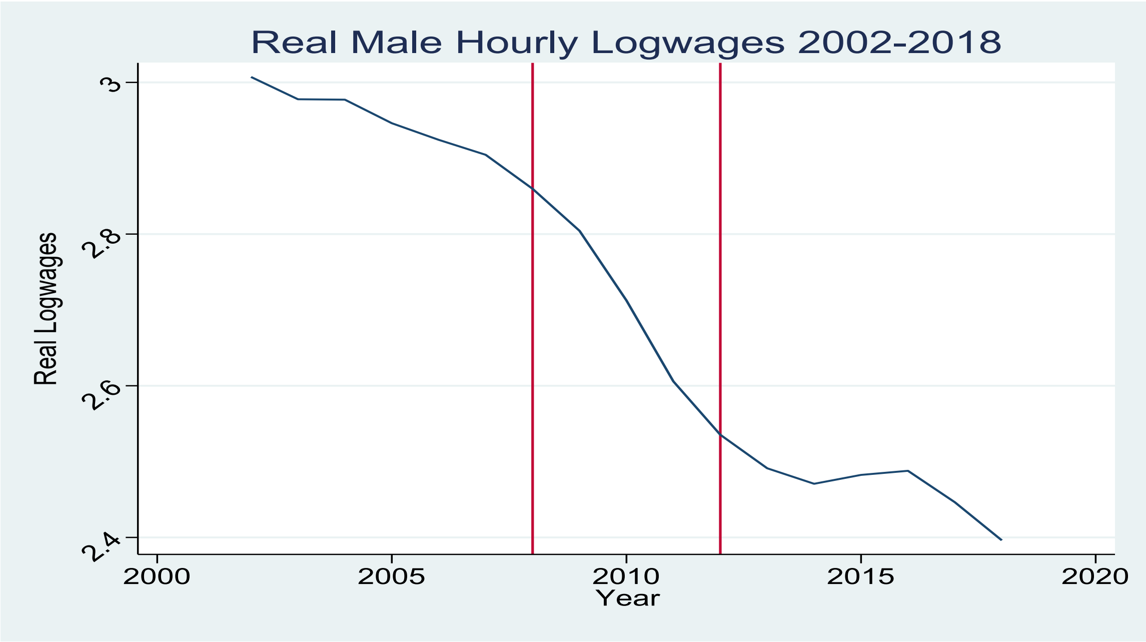

Figure 3A.1: Real Log Wages (2002-2018)

Notes: The vertical lines delineate the period of the financial crisis.

Source: Author's calculations from the ONS ASHE dataset.

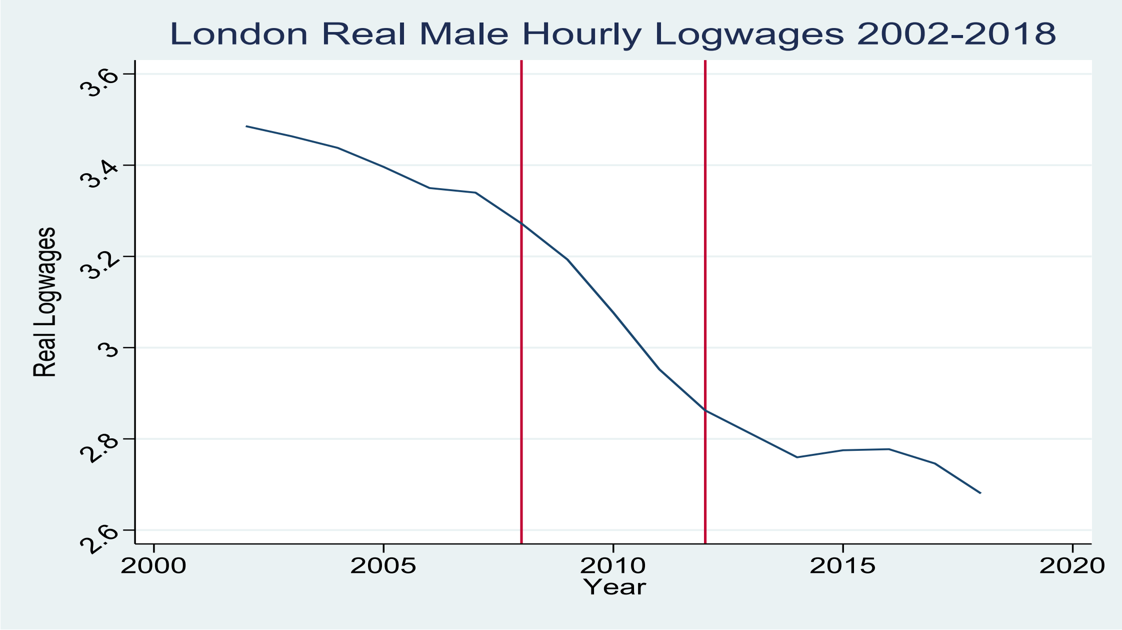

Figure 3A.2: Real London Log Wages (2002-2018)

Notes: The vertical lines delineate the period of the financial crisis.

Source: Author's calculations from the ONS ASHE dataset.

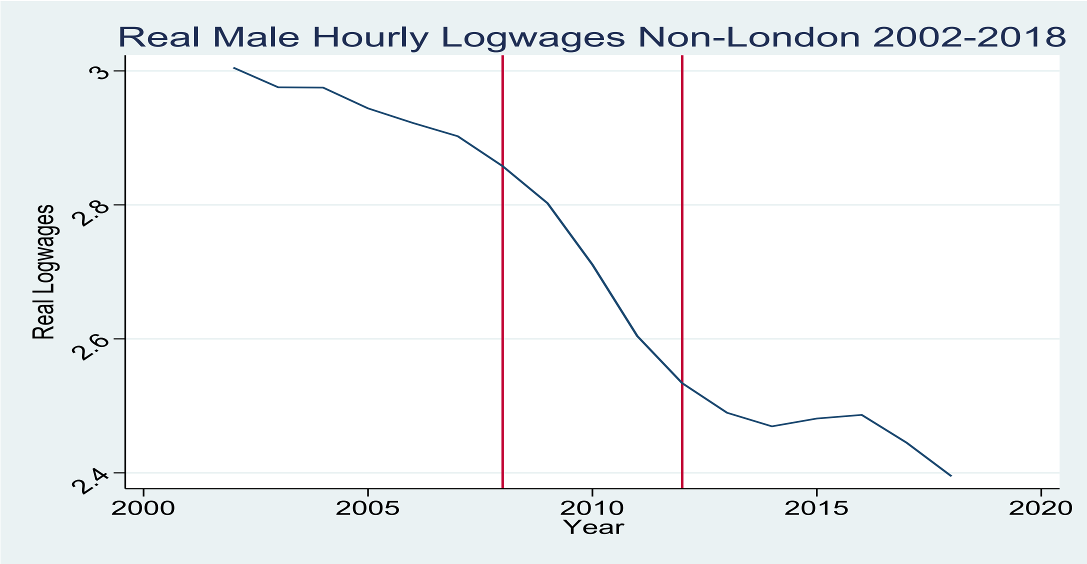

Figure 3A.3: Real Non-London Log Wages (2002-2018)

Notes: The vertical lines delineate the period of the financial crisis.

Source: Author's calculations from the ONS ASHE dataset.

Figure 3A.4: Relative Log Wage Inequality for London and Non-London TTWAs

Notes: The vertical lines delineate the period of the financial crisis.

Source: Author's calculations from the ONS ASHE dataset.

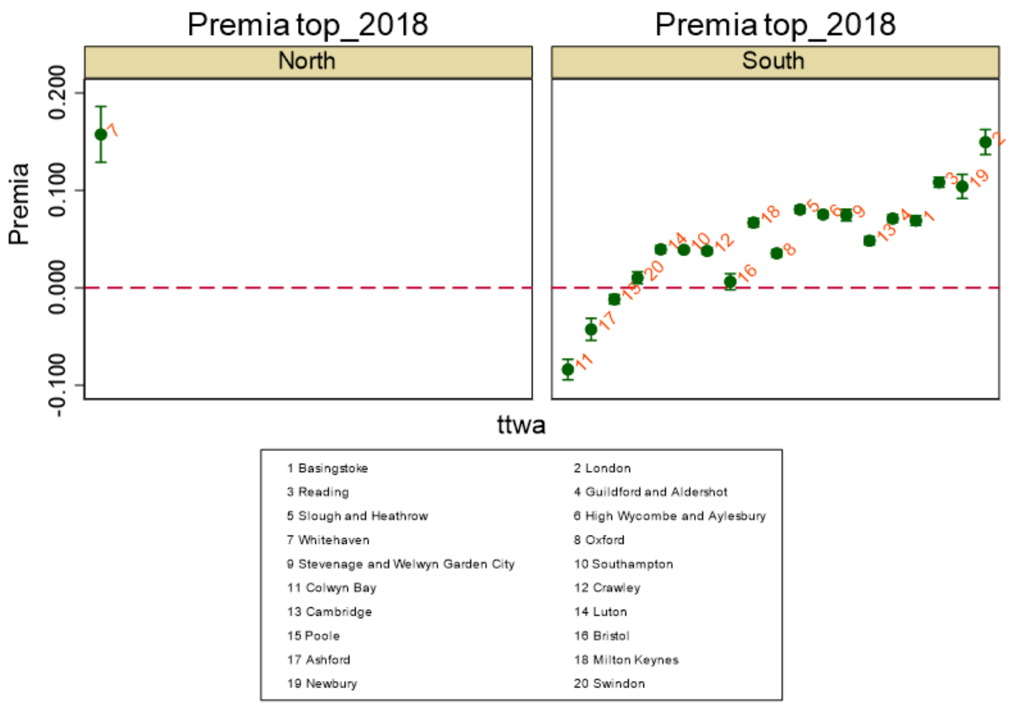

Figure 3A.5: Top 20 Mean Wage Area Differentials in 2018

Source: Author's calculations from the ONS ASHE dataset.

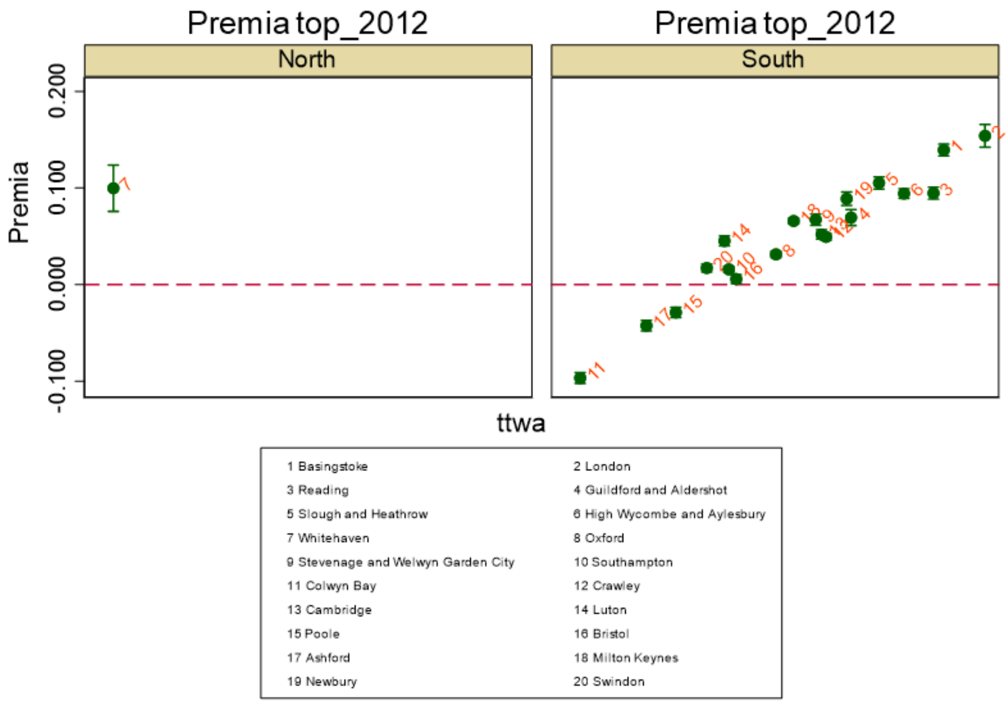

Figure 3A.6: Top 20 Mean Wage Area Differentials in 2012

Source: Author's calculations from the ONS ASHE dataset.

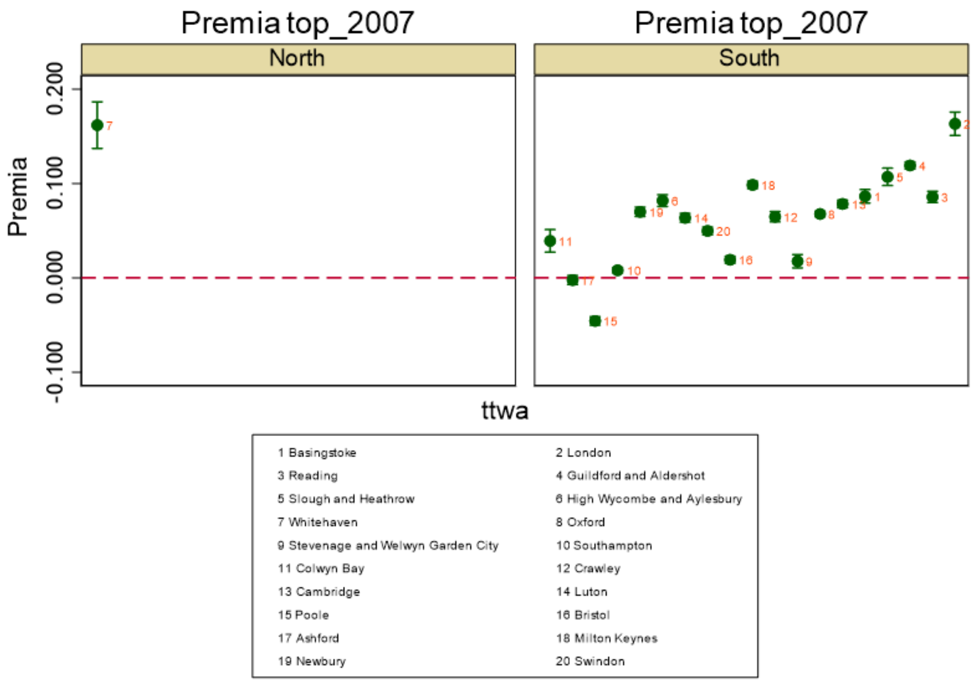

Figure 3A.7: Top 20 Mean Wage Area Differentials in 2007

Source: Author's calculations from the ONS ASHE dataset.

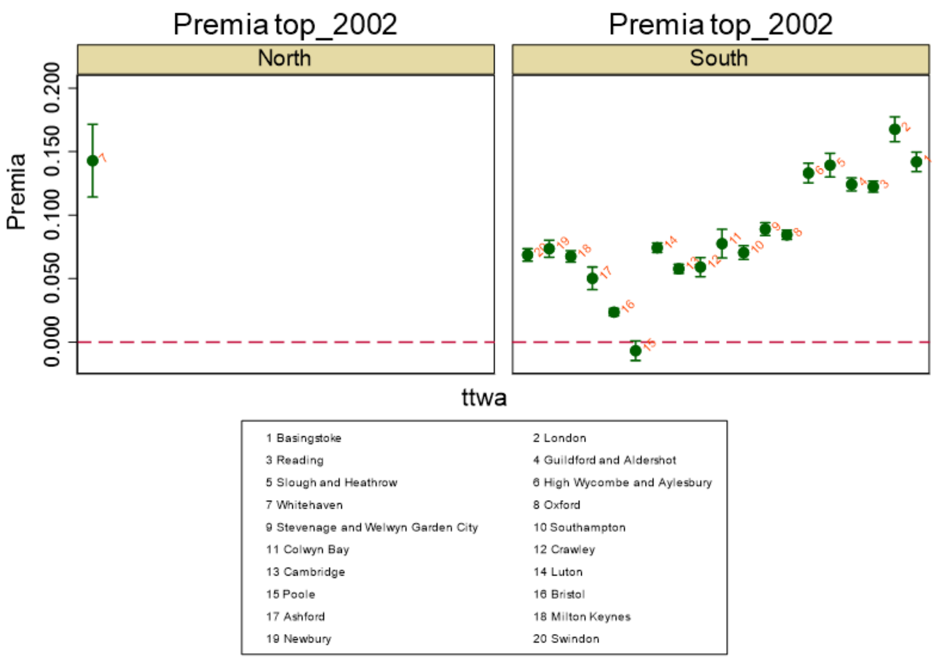

Figure 3A.8:Top 20 Mean Wage Area Differentials in 2002

Source: Author's calculations from the ONS ASHE dataset.

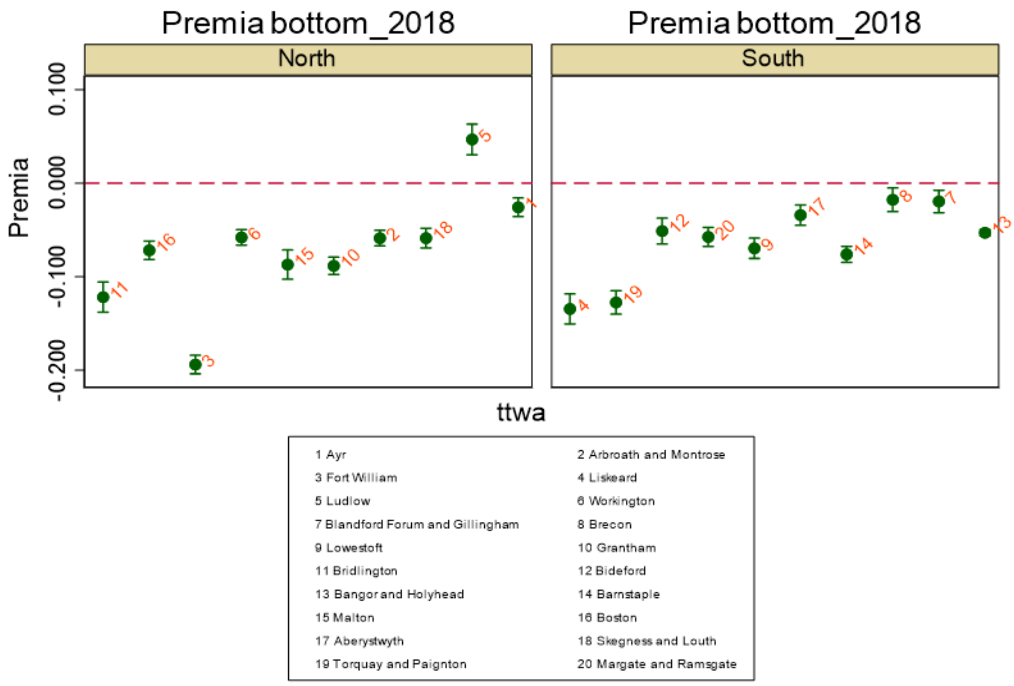

Figure 3A.9: Bottom 20 Mean Wage Area Differentials 2018

Source: Author's calculations from the ONS ASHE dataset.

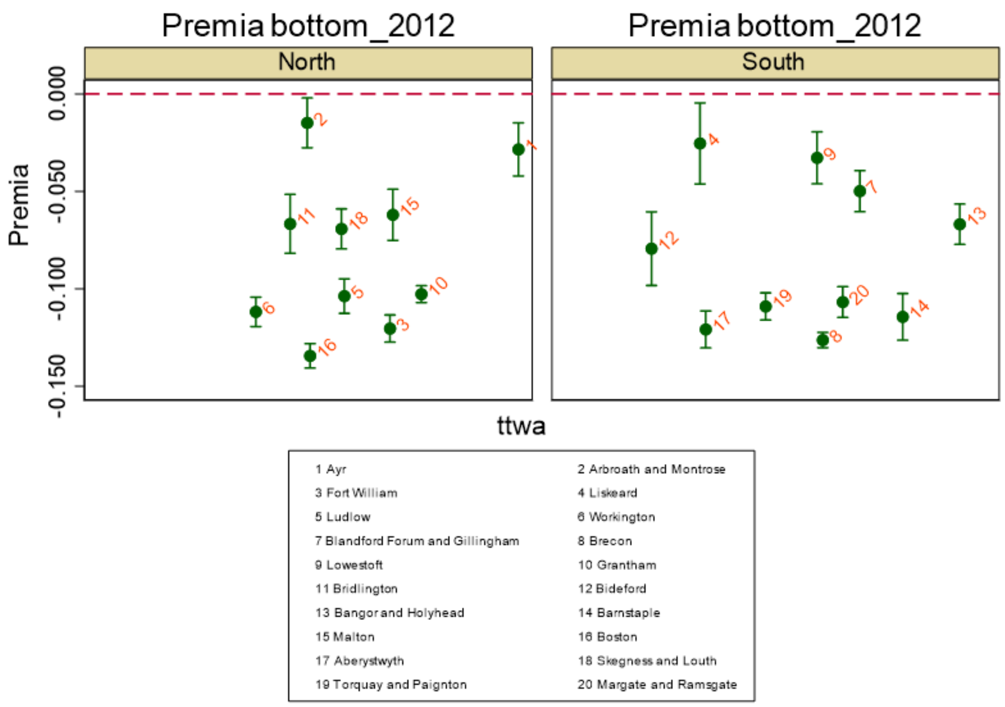

Figure 3A.10: Bottom 20 Mean Wage Area Differentials in 2012

Source: Author's calculations from the ONS ASHE dataset.

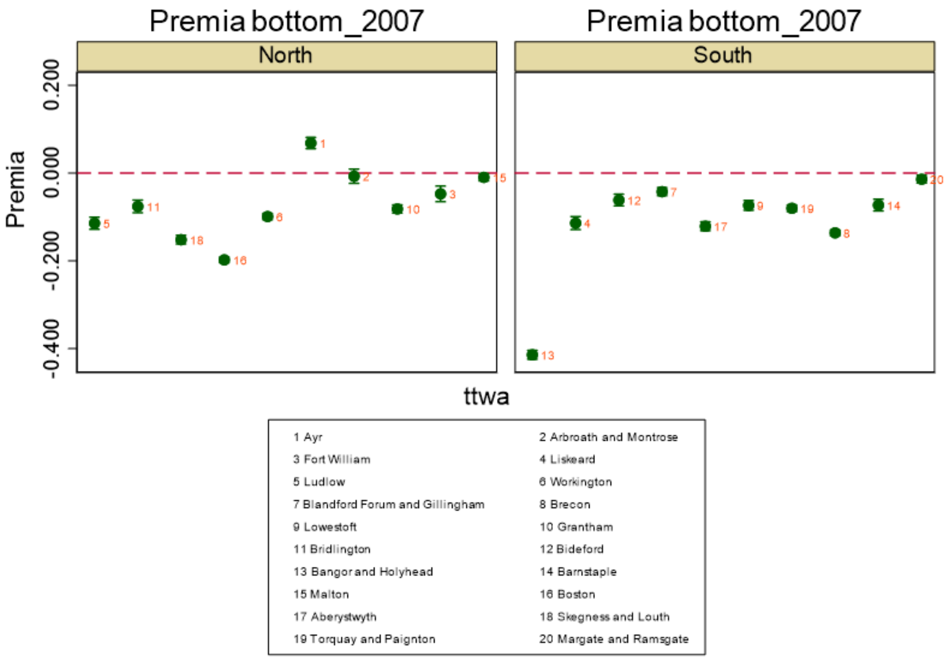

Figure 3A.11: Bottom 20 Mean Area Wage Differentials in 2007

Source: Author's calculations from the ONS ASHE dataset.

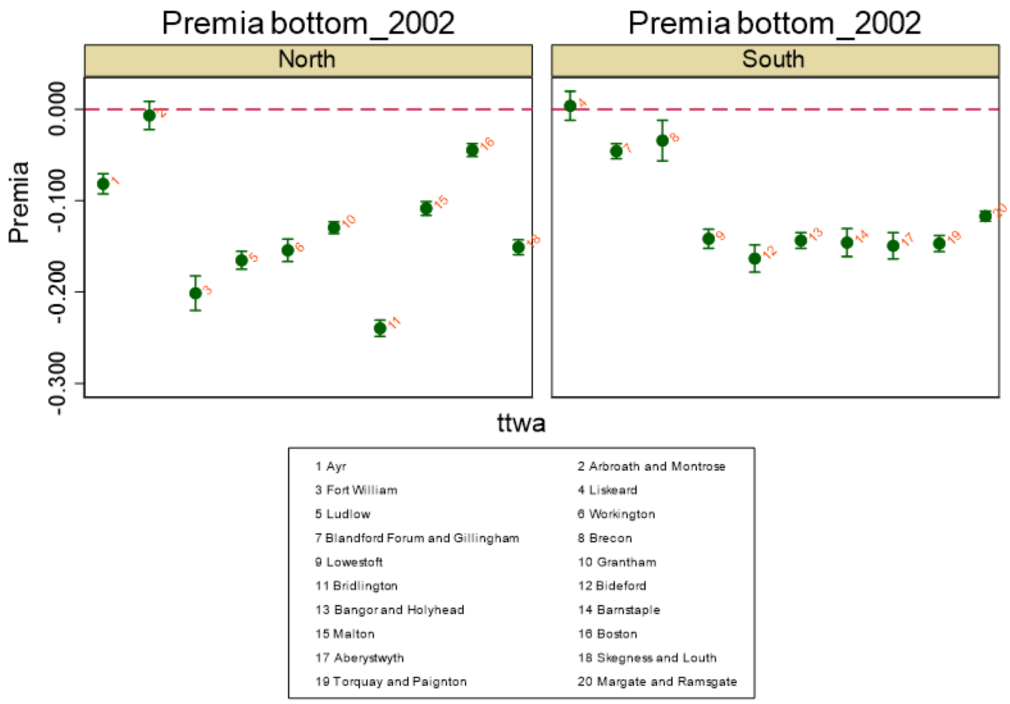

Figure 3A.12: Bottom 20 Mean Area Wage Differential in 2002

Source: Author's calculations from the ONS ASHE dataset.

Table 3A.1: UK Annual Inflation index

CPI INDEX 00: ALL ITEMS 2015=100	
Year	**CPI Index**
2002	0.745
2003	0.755
2004	0.765
2005	0.781
2006	0.799
2007	0.818
2008	0.847
2009	0.866
2010	0.894
2011	0.934
2012	0.961
2013	0.985
2014	1
2015	1
2016	1.007
2017	1.034
2018	1.059

Source: CPI INDEX 00: ALL ITEMS 2015=100 - Office for National Statistics (ons.gov.uk)

Table 3A.2: Cross Section Output for a Log Wages Regression for Selected Years

VARIABLES	(2002) lwageh	(2007) lwageh	(2018) lwageh
Age	0.0413***	0.0387***	0.0368***
	(0.0016)	(0.0015)	(0.0010)
age_sq	-0.0005***	-0.0004***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)
tenure1	0.0171***	0.0163***	0.0176***
	(0.0021)	(0.0022)	(0.0015)
tenure2	0.0076***	0.0102***	0.0026**
	(0.0012)	(0.0014)	(0.0010)
tenure3	0.0031***	0.0015***	0.0030***
	(0.0003)	(0.0004)	(0.0003)
Fulltime	0.0269	-0.0009	0.0049
	(0.0181)	(0.0096)	(0.0066)
Permanent	0.0541***	0.0649***	-0.0093
	(0.0140)	(0.0093)	(0.0168)
Public	-0.0045	0.0275***	0.0223**
	(0.0161)	(0.0088)	(0.0110)
size2	0.0916***	0.1225***	0.0968***
	(0.0129)	(0.0120)	(0.0127)
size3	0.1229***	0.1601***	0.1524***
	(0.0129)	(0.0108)	(0.0168)
size4	0.1703***	0.1784***	0.1788***
	(0.0106)	(0.0093)	(0.0131)
Observations	35,163	45,155	66,116
R-squared	0.9843	0.9850	0.9866
2Digit Industry dummies	Yes	Yes	Yes
2Digit Occupation dummies	Yes	Yes	Yes
Area FE	Yes	Yes	Yes

Notes: Variable Names as defined in Table 3.1

Source: Author’s calculations from ONS ASHE dataset.

Table 3A.3: High and low Wage Differential Areas (2002, 2007, 2018)

2002		2007		2018	
High	**Low**	**High**	**Low**	**High**	**Low**
London	Bude	London	**Brecon**	**Whitehaven**	Wadebridge
Whitehaven	Cromer*	**Whitehaven**	**Whitby**	London	**Pembroke***
Basingstoke	Penzance	Guildford*	**Boston**	Reading	**Liskeard**
Slough*	**Bridlington**	Slough*	Penzance	Newbury	Torquay*
High Wycombe*	**Whitby**	Milton Keynes	Wadebridge	Slough	**Bridlington**
Guildford*	Launceston	Basingstoke	**Colwyn Bay**	**Banbury**	Plymouth
Reading	**Ludlow**	Reading	**Pembroke***	High Wycombe*	**Bridgend**
Kingsbridge*	Bideford	High Wycombe*	**Hartlepool**	Stevenage*	Falmouth
Stevenage	Redruth*	Cambridge	**Skegness**	**Leamington Spa**	**Aberystwyth**
Oxford	**Workington**	Newbury	**Aberystwyth**	Guildford*	**Darlington**
Colwyn Bay	**Skegness***	Oxford	**Blackpool**	Basingstoke	**Cardigan**
Luton	**Aberystwyth**	Crawley	Bridport	Milton Keynes	**Scarborough**
Newbury	Torquay*	Luton	**Cardiff**	Cambridge	**Bradford**
Southampton	Barnstaple	Southend	Kingsbridge*	**Ludlow**	**Hereford**
Swindon	**Bangor***	Minehead	**Bangor***	Andover	**Blackpool**
Milton Keynes	Lowestoft	Swindon	Sidmouth	Luton	Folkstone*
Crawley	Falmouth	**Llanelli**	**Ludlow**	Southampton	Hastings
Cambridge	**Grantham**	Andover	Liskeard	Crawley	**Worksop***
Ashford	**Barnsley**	Chelmsford	**Durham**	**Hexham**	**Sunderland**
Huntingdon	St. Austell*	Street*	Falmouth	Cinderford*	**Grantham**

Notes: The Areas highlighted are in the northern part of Britain. The areas are listed in descending order from Highest paid and from lowest paid. Wage differential across the log wage distribution across the 216 TTWAs. Wages are primarily earnings per hour in nominal terms. Full names of the areas with an asterisk (*): Bangor and Holyhead, Cinderford and Ross-on-Wye, Cromer and Sheringham, Guildford and Aldershot, High Wycombe and Aylesbury, Kingsbridge and Dartmouth, Pembroke and Tenby, Redruth and Truro, Skegness and Louth, Slough and Heathrow, Stevenage and Welwyn Garden, St. Austell and Newquay, Street and Wells, Torquay and Paignton, Worksop and Retford.

Table 3A.4:High and Low Gini TTWAs (2002, 2007,2018)

2002		2007		2018	
High	**Low**	**High**	**Low**	**High**	**Low**
Minehead	Haverfordwest*	Minehead	Kingsbridge*	Barnstaple	Haverfordwest*
Ludlow	Bude	**Brecon**	Bude	Great Yarmouth	Bridport
Launceston	Andover	**Whitehaven**	Wadebridge	**Whitby**	**Darlington**
Whitby	**Corby**	Bideford	Andover	Newtown*	Llanelli
Penzance	Clacton	**Whitby**	**Corby**	**Ludlow**	Sidmouth
Scunthorpe	**Whitehaven**	Penzance	**Kettering**	London	**Corby**
Liskeard	Newbury	Newtown*	**Carlisle**	**Berwick**	**Carlisle**
Newtown*	Kingsbridge*	**Berwick**	Haverfordwest*	Bideford	Taunton
Wadebridge	Evesham	Chichester*	Ashford	**Leamington Spa**	Weston*
Cromer*	Brighton	**Ludlow**	Salisbury	Reading	Minehead
Worksop*	Redruth*	**Hexham**	Bury*	**Buxton**	Ashford
Ashford	Falmouth	Guildford*	Turnbridge	Street*	Brighton
Lowestoft	Canterbury	London	**Stafford**	**Whitehaven**	Chichester*
Derby	Cheltenham	**Barnsley**	**Darlington**	**Derby**	**Workington**
Skegness*	**Buxton**	Evesham	Cromer*	Launceston	Poole
Scarborough	**Grimsby**	Bangor*	Brighton	Southend	**Kettering***
Brecon	Wisbech	**Birkenhead**	Folkestone	**Hexham**	Bournemouth
St. Austell*	Sidmouth	**Scunthorpe**	Oxford	Bangor*	**Malton**
Barnstaple	Salisbury	**Worksop***	Aberystwyth	Kingsbridge*	**Grantham**
Bournemouth	Bridport	Barnstaple	Redruth*	**Barrow***	**Wakefield***

Notes: The Areas highlighted are in the northern part of Britain. The areas are listed in descending order from Highest paid and from lowest paid. Gini measures inequality across the log wage distribution across the 216 TTWAs. Wages are primarily earnings per hour in nominal terms. Full names of the areas with an asterisk (*): Bangor and Holyhead, Barrow-in-Furness, Bury St Edmunds, Chichester and Bognor Regis, Cromer and Sheringham, Guildford and Aldershot, Haverfordwest and Milford Haven, Kettering and Wellingborough, Kingsbridge and Dartmouth, Newtown Stewart, Redruth and Truro, Skegness and Louth, St. Austell and Newquay, Street and Wells, Worksop and Retford, Weston-Super-Mare

Table 3A.5: High and Low Wage Differentials 90th - 50th (2002, 2007 ,2018)

2002		2007		2018	
High	**Low**	**High**	**Low**	**High**	**Low**
Launceston	**Whitehaven**	Newton*	Bude	**Whitby**	Haverfordwest*
Brecon	Bude	**Brecon**	Wadebridge	Street*	**Darlington**
Malton	Andover	Launceston	Ashford	Kingsbridge*	**Corby**
Penzance	Haverfordwest*	**Grantham**	Kingsbridge*	Clacton	**Lancaster***
Minehead	Clacton	**Hexham**	Oswestry	Minehead	Sidmouth
Wadebridge	Cheltenham	Colwyn Bay	**Carlisle**	Great Yarmouth	Weston*
Birkenhead	**Hartlepool**	Falmouth	**Darlington**	London	**Buxton**
Skegness*	**Buxton**	Penzance	Eastbourne	**Ludlow**	**Northampton**
Blandford*	Colchester	**Whitby**	**Kettering***	Barnstaple	Swindon
Whitby	Bridport	Minehead	**Barrow***	Oswestry	Chichester*
Ludlow	Newbury	Blandford	Folkestone*	Newbury	**Carlisle**
Liskeard	**Hexham**	**Malton**	Andover	High Wycombe*	**Penrith**
Lowestoft	Redruth*	**Bridport**	**Skegness***	Bangor*	Oxford
Basingstoke	**Bridlington**	Liskeard	**Telford**	Launceston	**Birkenhead**
Bournemouth	Taunton	Dorchester*	Weston*	Reading	Llanelli
Scarborough	Brighton	**Ludlow**	**Penrith**	Isle of Wight	**Workington**
Colwyn Bay	Dorchester*	Milton Keynes	**Halifax**	Cardiff	Eastbourne
Ashford	Yeovil	Barnstaple	**Whitehaven**	Aberystwyth	Evesham
Falmouth	**York**	Guildford*	**Corby**	Newtown*	Milton Keynes
Kendal	**Barrow***	Margate*	Redruth*	Canterbury	**Bradford**

Notes: The Areas highlighted are in the northern part of Britain. The areas are listed in descending order from Highest paid and from lowest paid. $90^{th} – 50^{th}$ Percentile measures the gap between the top and the bottom end of the wage distribution. Wages are primarily earnings per hour in nominal terms. Full names of the areas with an asterisk (*): Bangor and Holyhead, Blandford Forum and Gillingham, Dorchester and Weymouth, Folkstone and Dover, Haverfordwest and Milford Haven, High Wycombe and Aylesbury, Kettering and Wellingborough, Kingsbridge and Dartmouth, Lancaster and Morecambe, Newtown Stewart, Redruth and Truro, Skegness and Louth, Street and Wells, Weston-Super-Mare

Table 3A.6: High and Low Wage Differentials 50th - 10th (2002, 2007 ,2018)

2002		2007		2018	
High	**Low**	**High**	**Low**	**High**	**Low**
Kingsbridge*	Blandford*	Minehead	Kingsbridge*	**Whitby**	Minehead
Bude	Falmouth	**Whitehaven**	Colwyn Bay	**Whitehaven**	Kingsbridge*
Cromer*	Haverfordwest	Haverfordwest*	Liskeard	Brecon	Oswestry
Ludlow	Street*	**Bideford**	**Kendal**	London	Bridport
Whitehaven	**Malton**	**Whitby**	**Burnley**	Newbury	**Grantham**
Whitby	**Wisbech**	Bude	**Grantham**	Colwyn Bay	Aberystwyth
Penzance	**Harrogate**	Brecon	Newtown*	**Hexham**	**Worksop***
Newtown*	**Corby**	Fort William	**Corby**	Basingstoke	Penzance
Launceston	Great Yarmouth	**Penrith**	**Northallerton**	**Hartlepool**	**Spalding**
Hartlepool	Thetford*	**Workington**	**Sunderland**	Slough*	Clacton
Chichester*	Evesham	Bangor*	**Buxton**	Milton Keynes	Wisbech
Bridport	Bangor*	**Bridlington**	**Harrogate**	Reading	Bude
Buxton	Gloucester	**Ludlow**	Margate	**Lancaster***	**Bridlington**
Blackburn	**Penrith**	**Hartlepool**	King's Lynn	Luton	Pembroke*
Brecon	Aberystwyth	London	**Launceston**	**Berwick**	**Harrogate**
Boston	Turnbridge*	**Spalding**	**Salisbury**	Cinderford*	Folkstone*
Bridlington	Clacton	Evesham	Isle of Wight	**Ludlow**	Sidmouth
Kendal	Hastings	**Hexham**	**Hereford**	Stevenage*	**Skipton**
Sidmouth	**Grimsby**	Basingstoke	Bridport	Northampton	Bridgend
Chester	Ipswich	**Blackburn**	**Banbury**	Bridgwater	Barnstaple

Notes: The Areas highlighted are in the northern part of Britain. The areas are listed in descending order from Highest paid and from lowest paid.50th – 10th Percentile measures the gap between the median and the bottom end of the wage distribution. Wages are primarily earnings per hour in nominal terms. Full names of the areas with an asterisk (*): Bangor and Holyhead, Cinderford and Ross-on-Wye, Chichester and Bognor Regis, Cromer and Sheringham, Folkstone and Dover, Haverfordwest and Milford Haven, Kingsbridge and Dartmouth, Lancaster and Morecambe, Newtown Stewart, Pembroke and Tenby, Slough and Heathrow, Stevenage and Welwyn Garden, Street and Wells, Thetford and Mildenhall, Turnbridge Wells, Worksop and Retford

Table 3A.7: Cell Sizes for each TTWA Across Selected Years

TTWA	TTWA Name	2002	2007	2012	2018
S22000060	Elgin	16	16	86	100
E30000051	Falmouth	17	40	59	54
S22000035	Orkney Islands	18	19	22	17
E30000177	Bridlington	19	15	28	32
E30000236	Ludlow	22	16	36	46
E30000039	Skipton	26	42	50	73
E30000192	Clacton	26	42	53	58
S22000061	Falkirk and Stirling	27	38	254	276
E30000172	Blandford Forum and Gillingham	27	43	48	67
E30000106	Penrith	28	34	47	58
E30000238	Malton	29	34	51	64
K01000014	Oswestry	30	33	49	43
E30000054	Grantham	32	46	55	57
E30000159	Andover	32	72	73	89
E30000274	Street and Wells	34	39	56	51
E30000290	Workington	34	55	66	78
E30000270	St Austell and Newquay	36	69	93	109
E30000185	Buxton	37	39	41	41
E30000194	Corby	37	61	87	104
E30000162	Barnstaple	38	63	88	87
E30000257	Redruth and Truro	39	86	107	148
E30000287	Wisbech	41	43	65	74
W22000016	Pembroke and Tenby	41	49	20	15
E30000205	Evesham	41	57	71	88
E30000279	Torquay and Paignton	41	71	103	102
E30000061	Hastings	43	70	98	106
E30000223	Kendal	44	55	77	108
E30000259	Scarborough	48	51	78	63
E30000210	Great Yarmouth	49	60	80	95
E30000124	Spalding	49	75	94	101
E30000191	Chichester and Bognor Regis	50	132	169	176
E30000264	Skegness and Louth	51	32	60	75
E30000241	Margate and Ramsgate	51	39	81	108
E30000246	Northallerton	52	75	88	94
K01000005	Cinderford and Ross-on-Wye	53	50	62	57

E30000160	Ashford	53	69	106	107
E30000215	Hartlepool	54	47	73	84
E30000174	Boston	55	49	69	89
E30000235	Lowestoft	55	67	88	100
E30000176	Bridgwater	57	60	90	107
E30000135	Thetford and Mildenhall	58	52	82	108
E30000285	Weston-super-Mare	59	78	90	118
W22000024	Cardiff	59	81	829	888
E30000076	Lancaster and Morecambe	59	101	134	129
E30000163	Barrow-in-Furness	62	66	113	77
E30000199	Darlington	64	103	106	116
E30000291	Worksop and Retford	65	72	127	141
E30000244	Newbury	65	81	146	174
E30000070	Isle of Wight	68	76	103	101
E30000262	Shrewsbury	68	103	133	160
E30000187	Canterbury	68	115	147	122
S22000070	Livingston	69	98	197	268
E30000184	Bury St Edmunds	70	109	150	166
E30000286	Whitehaven	72	56	84	100
E30000182	Burnley	72	93	135	217
E30000046	Dorchester and Weymouth	73	93	123	130
E30000161	Banbury	74	79	97	131
W22000021	Aberystwyth	74	95	51	63
E30000292	Worthing	75	123	147	157
S22000065	Glasgow	76	72	1420	1468
E30000214	Harrogate	76	101	149	172
E30000258	Salisbury	77	123	137	156
E30000277	Taunton	78	93	128	119
W22000028	Llanelli	80	85	103	128
E30000208	Folkestone and Dover	80	92	111	127
W22000022	Bangor and Holyhead	81	99	129	119
W22000003	Bridgend	84	101	140	149
E30000216	Hereford	86	101	134	138
E30000204	Eastbourne	88	101	140	167
S22000067	Hawick and Kelso	91	129	29	32
E30000173	Blyth and Ashington	92	85	132	136
E30000165	Bath	92	155	194	192

E30000193	Colchester	94	140	196	254
S22000081	Turriff and Banff	96	104	15	17
E30000271	Stafford	99	131	146	173
E30000183	Burton upon Trent	100	140	177	198
E30000225	King's Lynn	101	103	131	143
E30000168	Birkenhead	101	146	161	214
E30000190	Chesterfield	103	163	201	222
E30000260	Scunthorpe	106	136	165	162
E30000221	Huntingdon	111	142	153	188
E30000211	Grimsby	112	116	169	163
E30000171	Blackpool	113	132	195	231
E30000110	Poole	115	133	208	236
E30000189	Cheltenham	115	147	164	214
E30000004	Barnsley	121	156	185	271
E30000281	Tunbridge Wells	123	179	222	235
E30000224	Kettering and Wellingborough	124	145	213	280
E30000293	Yeovil	124	164	197	187
E30000179	Brighton	134	166	247	323
E30000280	Trowbridge	140	155	233	244
S22000059	Edinburgh	143	166	878	1015
E30000029	Halifax	144	124	187	211
E30000166	Bedford	147	173	214	248
E30000201	Doncaster	148	218	274	290
E30000240	Mansfield	148	230	308	334
E30000203	Durham and Bishop Auckland	152	199	211	263
S22000054	Dumbarton and Helensburgh	154	188	66	71
E30000278	Telford	161	179	238	267
E30000228	Leamington Spa	162	248	305	373
E30000164	Basingstoke	170	220	316	307
E30000209	Gloucester	171	204	295	346
E30000218	High Wycombe and Aylesbury	172	251	306	352
E30000253	Plymouth	179	255	335	358
E30000231	Lincoln	180	228	307	355
E30000219	Huddersfield	181	208	273	316
E30000175	Bournemouth	182	230	274	361
E30000197	Crewe	183	237	289	366
E30000247	Northampton	184	264	393	436

K01000013	Newport	193	224	315	317
E30000289	Worcester and Kidderminster	193	232	267	313
E30000188	Chelmsford	194	314	399	456
E30000243	Milton Keynes	207	258	383	537
E30000206	Exeter	207	352	466	505
S22000055	Dumfries	211	197	66	88
E30000170	Blackburn	217	216	284	375
E30000108	Peterborough	221	312	415	404
E30000272	Stevenage and Welwyn Garden City	223	328	393	448
W22000025	Cardigan	231	244	18	21
E30000222	Ipswich	241	358	390	396
E30000283	Wakefield and Castleford	246	257	351	389
E30000200	Derby	248	333	555	529
E30000268	Southend	249	309	385	405
E30000093	Middlesbrough and Stockton	250	335	395	428
S22000068	Inverness	251	313	134	158
E30000294	York	267	281	352	411
S22000039	Shetland Islands	267	334	24	35
E30000275	Sunderland	269	327	409	419
K01000011	Chester	270	272	343	434
E30000276	Swindon	274	311	373	401
E30000242	Medway	296	386	520	574
E30000255	Preston	298	390	492	518
E30000248	Norwich	301	375	458	498
E30000254	Portsmouth	304	384	475	530
E30000273	Stoke-on-Trent	320	337	493	525
E30000250	Oxford	321	404	575	657
E30000256	Reading	322	449	559	682
E30000237	Luton	336	505	667	729
E30000018	Bradford	341	349	431	457
E30000220	Hull	351	378	521	583
E30000212	Guildford and Aldershot	359	484	692	723
E30000202	Dudley	378	451	597	634
E30000288	Wolverhampton and Walsall	391	456	640	782
E30000196	Crawley	397	526	656	737
E30000195	Coventry	402	475	584	655

E30000267	Southampton	416	554	771	764
E30000186	Cambridge	458	585	738	824
E30000284	Warrington and Wigan	466	548	803	866
W22000011	Llandrindod Wells and Builth Wells	488	567	26	24
E30000249	Nottingham	512	622	733	795
E30000261	Sheffield	540	641	842	898
E30000233	Liverpool	547	650	874	1005
S22000057	Dunfermline and Kirkcaldy	583	721	221	265
E30000180	Bristol	610	833	1070	1127
E30000229	Leeds	620	745	932	1178
E30000230	Leicester	636	695	977	1015
E30000245	Newcastle	672	811	1050	1113
S22000063	Galashiels and Peebles	840	1007	52	51
E30000266	Slough and Heathrow	977	1363	1770	1548
E30000169	Birmingham	1060	1323	1658	1968
E30000239	Manchester	1587	2089	2537	2880
E30000234	London	4248	6197	8150	9343

Source: Author's Calculations from ONS ASHE dataset.

Chapter 4: The Evolution of the Male Public Sector Pay Gap in Great Britain between 2002 and 2019

4.1 Introduction

In Great Britain, public sector employment represents around a quarter of the total labour force. According to the Office for National Statistics (ONS),[55] an estimated 5.67 million people were employed in the public sector in March 2021. Employment in the public sector grew by 5.9% between 2002 and 2007. However, during the financial crisis between 2007 and 2012, public service employment fell by about 2.34%, and then decreased by a further 5.71% post-crisis during the period of fiscal austerity. The existing empirical literature suggests that, before the imposition of the public sector pay freeze in 2010, male and female public sector employees in the UK earned 4% more per hour than their private sector counterparts. Due to econometric issues raised by the labour participation of women in the labour market particularly in the early years of the data, the analysis in the current chapter is restricted to men only. It is worth noting that there is some heterogeneity in this differential with lower-skilled public sector workers earning a higher premium (See ONS,2017). The public sector pay premium is a well-established phenomenon in modern labour markets. The public sector earnings premium is the difference between average earnings of public sector and private sector employees after controlling for worker, job and firm characteristics.

Danzer and Dolton (2012) examined the public sector pay differential using a broader measure of remuneration that included pensions. This is beyond the scope of the current research given the absence of pension-related data. The more recent empirical evidence (See Cribb *et al.* (2019), Murphy *et al.*(2020), HM Treasury (2020)) reveals that the raw public wage premium fell throughout the financial crisis, potentially reflecting the effects of fiscal tightening. The UK was not the only economy that acted to restrain public sector pay in attempting fiscal consolidation. Many European countries imposed pay cuts (France, Greece – and particularly for high earners in Italy), others implemented pay freezes (Italy, UK) and some (Ireland, Portugal, Spain) used both mechanisms to reduce the size of the public sector in the aftermath of the financial crisis (Christofides and Michael, 2013; Michael and Christofides, 2020). The extent of empirical work on the average, *ceteris paribus,* public sector wage premium in the UK and its evolution throughout the financial crisis is illuminating. However, evidence related to the impact on

[55] See ONS (2021)

the public-sector wage premium of the austerity (wage freeze/wage cut) policies adopted in the wake of the financial crisis over time and across the unconditional pay distribution in the UK is more limited.

Previous research on the public sector wage gap in Great Britain has focused either on mean wage differentials or more rarely differentials in selected quantiles. The latter approach has exploited Conditional Quantile Regression (CQR) analysis using pooled data combined with an intercept shift to capture public sector employment (Disney and Gosling,1998; Blackaby *et al.,* 2018). The limitations inherent in the estimation of pooled models promoted the use of Oaxaca-Blinder (OB) decompositions (Oaxaca, 1973; Blinder, 1973; and see Bender, 2003; Bender and Elliott, 1999; Chatterji *et al.,* 2011), which exploit separate sector-specific wage equations. These studies provide a template for the present research.

The aim of Chapter 4 is to provide evidence on the evolution of the public-sector pay premium for men throughout the financial crisis and beyond with a particular emphasis on the impact of the wage policies adopted by the UK government over the period 2002 to 2019. The analysis exploits data from the Annual Survey of Hours and Earnings (ASHE) for full-time working men in Great Britain. The empirical methodology adopted is based on three estimation techniques: pooled regression, standard OB decompositions (as noted earlier), and a variant of the OB decomposition proposed by Firpo *et al.* (2011, 2018) that exploits a re-weighting procedure to address issues related to the difference in distributions of covariates across the two sectors. These three approaches enable decomposition of the pay gap at the mean and using a set of Unconditional Quantile Regressions (UQR) models, at selected quantiles. An advantage of the method based on the UQR is that it is not subject to the type of problems highlighted in some of the early literature that used the conditional quantile regression models for decomposition purposes (e.g., see Melly, 2005; Machado and Mata, 2005).

The estimation of public-private sector wage gaps at different points along the wage distribution using unconditional quantile regressions provides a richer picture of the role of the public sector wage-setting mechanism than a focus on the mean.

The results suggest that both the mean and median of the unadjusted public sector pay for full-time men are significantly higher than in the private sector. This finding is consistent with the empirical results reported for the UK (Disney and Gosling, 1998; Blackaby *et al*., 2018; Murphy *et al*., 2020). A simple comparison of raw public sector wages with those in the private sector, as typically reported in policy documents (e.g., see Ferguson and Devine, *House of Commons report*, 2021), can be misleading as it fails to capture productivity and other differences in workers across the two sectors. Empirical evidence shows that higher wages in public sector jobs can largely be explained by differentials in both the returns to characteristics and in the level of worker characteristics. When these differences are taken into account, the public sector wage premium either decreases or reflects a penalty relative to the private sector. The treatment component from the OB decomposition is the primary object of interest in the present empirical analysis.

This chapter provides evidence showing that the public sector pay premium across the log wage distribution appears to have changed little over time and was largely unaffected by both crisis and austerity. Public sector wages - at the bottom end of the distribution in particular - held up reasonably well in both the crisis and austerity periods. Therefore, despite the shock of the financial crisis and the subsequent introduction of fiscal consolidation measures, the wage position in the public sector relative to the private sector was ultimately unaffected over the longer term. The preferred empirical results for the austerity period, using a decomposition with a re-weighting procedure, tentatively suggests that public sector workers at the top end regained any losses initially incurred during the crisis.

The structure of the chapter is as follows. Section 4.2 presents the context for the analysis and Section 4.3 reviews the related empirical literature focused on the UK. Section 4.4 formulates the research questions, while Section 4.5 describes the data. Sections 4.6 and 4.7 discuss the empirical methodologies used for the analysis. Section 4.8 presents and discusses the results, and Section 4.9 concludes the chapter with some policy implications and suggestions for future research.

4.2 Context

It is informative for the current analysis to explain the historical evolution of the pay gap between the public and private sectors and the policies that impacted it. Specifically, the public sector wage determination policy in the UK during the recent past and discuss the economic conditions that led both Conservative and Labour-led governments to adopt public sector pay policies that affected the British labour market is explored. Since the 1970s, the UK government has undertaken significant fiscal consolidations with the aim of ensuring fiscal sustainability. The size of the public sector wage bill has been subjected to particular and intense scrutiny and several measures have been implemented over time to reduce this wage bill. For instance, the Thatcher administration, which came to power in 1979 and whose declared objective was to reduce government size, was determined to rein in public spending and set the economy on a new path led by private innovation and enterprise. In that same year, it established an ‘Efficiency Unit’ to investigate ways that government ministries could save money based on making major cuts to public expenditure. The Thatcher government was also highly critical of the civil service as a bureaucracy and was committed to implementing cuts to the numbers of civil servants. Over the period of this administration, public spending as a percentage of Gross Domestic Product (GDP) decreased by three percentage points from a high of 44% when the Thatcher government assumed power (Bolick, 1995).

The UK public sector is large in terms of both number of employees and its share of GDP. Wages constitute a substantial proportion of total current government spending, meaning that government policy decisions aimed at reducing the budget deficit will have implications for the wage bill. For instance, over the period of the current study, government spending on wages, as a percentage of total current government spending, fell from 28.5% in 2002-2003 to 25.2% in 2018-2019.[56] The public sector consists of central government and local authorities and during part of the Thatcher period also comprised the nationalized industries. Figure 4.1 plots the ratio of government spending to GDP. From 1979 to 2019, all governments attempted to keep public spending under relatively tight control. There is clear evidence of austerity during the Thatcher administration when public spending, as a percentage of GDP, fell from 41% in 1982 to about 35% in 1997. It fluctuated during the early 1990s, coinciding with the period when the UK withdrew from the European Exchange Rate Mechanism (ERM). Subsequently, the government exerted greater control and public sector spending as a proportion of GDP contracted. In contrast, the years of the next Conservative government led by John Major were relatively benign for public spending. This persisted at below 38% of GDP up to 1994 but then dropped. Despite the reductions in public spending implemented by both the Thatcher and Major administrations, the UK’s public sector remained a sizeable employer and a considerable force within the UK labour market, into the 21st century.

Tony Blair’s Labour government came to power in 1997 and public spending increased steadily as a percentage of GDP. This coincided with a period that witnessed reduced NHS waiting times, falling child poverty rates and increased education outcomes.[57] This was coupled with an increase in the size of the public sector. Public sector spending

---

[56] See ONS (2020a) and ONS (2020b)
[57] See Thorlby and Maybin (2010)

peaked in 2007 around the time of the start of the financial crisis. However, during the recovery period after the financial crisis (from 2013 to 2019), public sector spending as a percentage of GDP exhibited a downward trend, falling by almost 3 percentage points. This was largely as a result of the implementation of austerity measures.

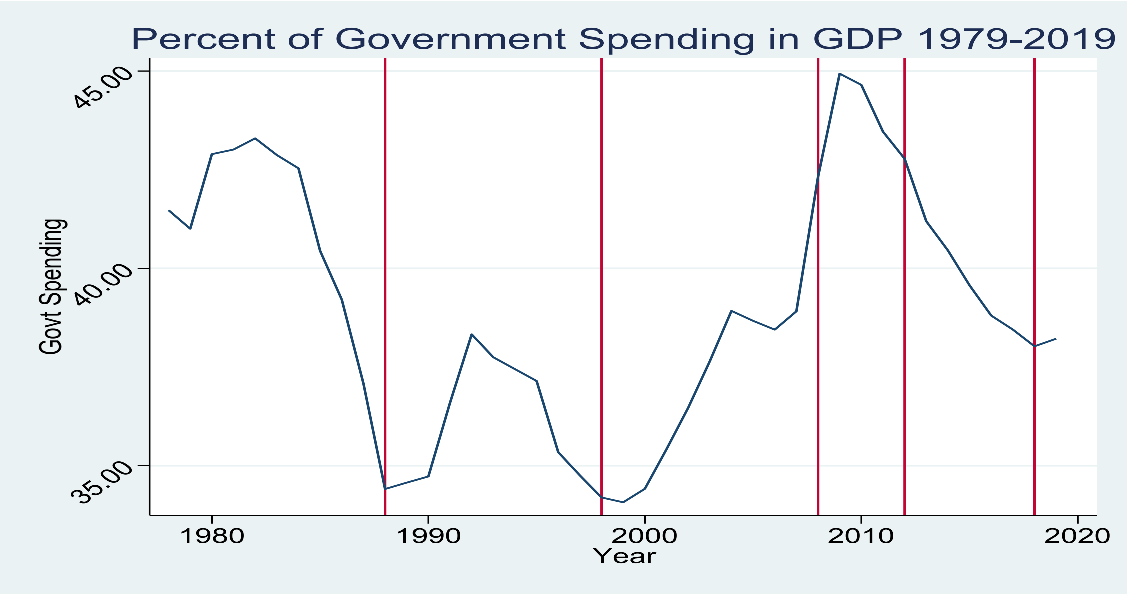

Figure 4. 1: Public Sector Spending to GDP Ratio (%)

Source: Office for Budget Responsibility (2020), UK[58]

Figure 4.2 shows the cyclically adjusted current budget deficit[59] as a percentage of GDP (see Appendix A Figure 4.A1, which depicts the aggregate cyclically adjusted current budget deficit in £ billion). During and after the financial crisis, the government's cyclically adjusted deficit declined, in part reflecting the effects of austerity. In the post-crisis period, government spending continued to fall and fell well below the level of government receipts in the most recent years.

[58] See Office for Budget Responsibility (2020)
[59] Cyclical adjustments are supposed to correct for the influence of the economic cycle on public finances and to capture a measure that better reflects the underlying or structural budgetary position. Estimating the cyclical component of the budget generally involves trying to measure: (i) where the economy stands in relation to its potential or trend level; and (ii) how different components of the budget normally respond to fluctuations in economic activity. Deficit measures are adjusted for the effect of the stage the economy is in the economic cycle. Therefore, it represents the 'structural' element of each aggregate or the value that would be seen if the output gap was actually at zero. Monthly Bulletin March 2012 (Europa.Eu).

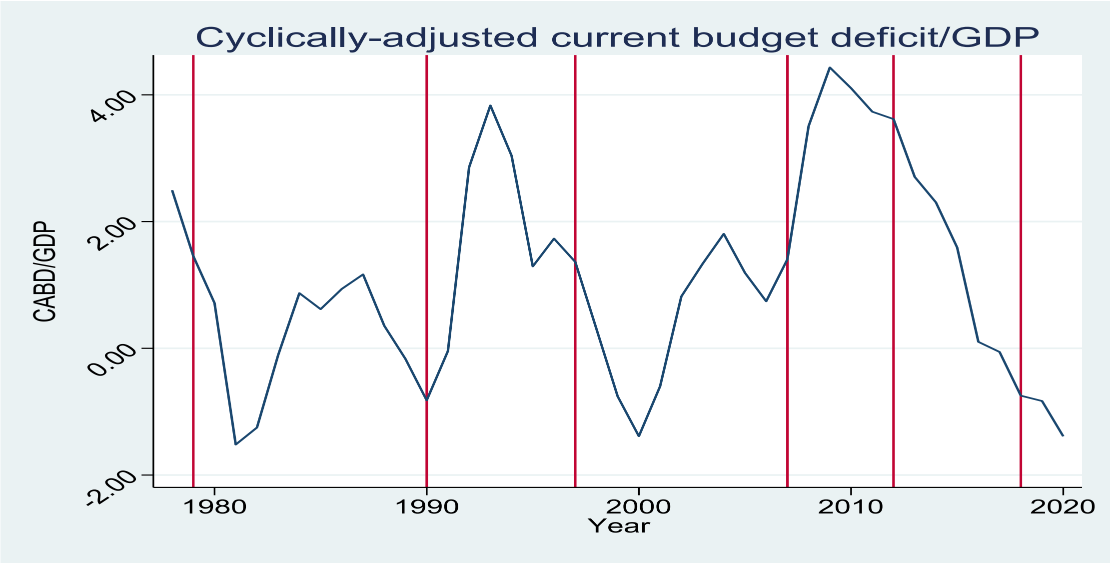

Figure 4. 2: Cyclically Adjusted Current Budget Deficit as a % of GDP (1979-2019)

Source: Office for Budget Responsibility (2020), UK

Historically, spending cuts have had implications for public sector employment and wages. Figure 4.3 shows that public sector employment, as a percentage of total employment, has been declining, particularly in the most recent years of the current chapter. At the onset of the financial crisis, total public sector male and female employment stood at 6 million, which accounted for 20.3% of total employment in the UK. This fell to 5.9 million at the end of the crisis period, representing almost 20% of total employment. The start of the austerity period (2013) saw a further fall of approximately 100,000; subsequently, employment in the public sector contracted steadily comprising a reduction of nearly 500,000 workers. The biggest cuts in public sector employment occurred during the austerity rather than the crisis period.

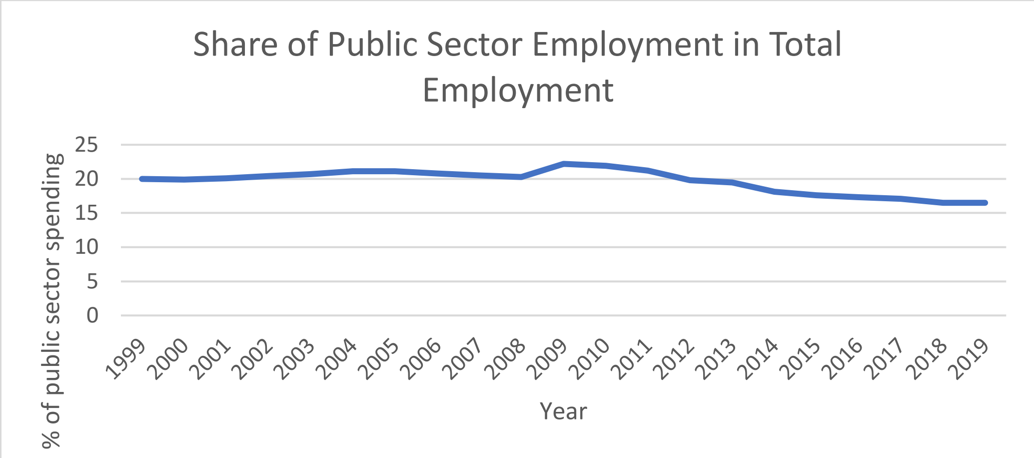

Figure 4. 3: Percentage of Public Employment in Total Employment

Source: ONS Public and Private Sector Employment, 2021[60]

The pressures associated with the government's fiscal position can be seen in the austerity measures adopted by the current government with respect to the reduction in the size of the public sector due to employee layoffs and in terms of pay freezes. Public sector employment fell by slightly over one million due to the fiscal consolidation measures implemented over the period 2010 to 2019. Nevertheless, public sector employment remains a large sector within the UK economy and was around 5 million in 2009 (see Figure 4.4).

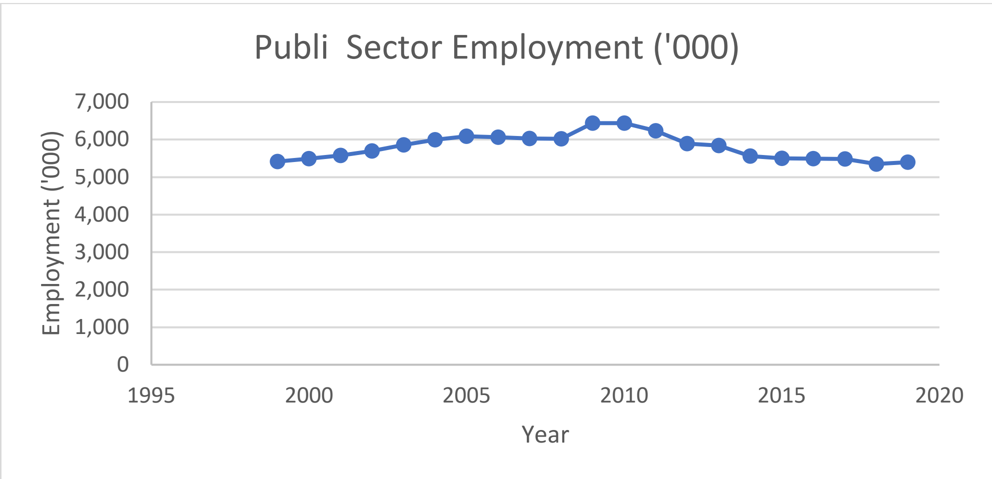

Figure 4. 4: Total Male and Female Public Sector Employment (1999-2019)

Source: ONS, Public Sector Employment[61]

---

[60] For a detailed monthly breakdown of the public and private sector employment see ONS(2022b).

[61] For quarterly estimates of UK and regional public sector employment, made up of central government (including Civil Service), local government and public corporations and a breakdown by industry, see ONS (2021).[61] For quarterly estimates of UK and regional public sector employment, made up of central government (including Civil Service), local government and public corporations and a breakdown by industry, see ONS (2021)

As already noted in the introduction to Chapter 4, pay levels are generally higher in the public sector compared to the private sector in the UK. However, after accounting for differences in education, age and workers' place of residence, the differences in pay levels for men contract. Since the onset of the financial crisis, the evolution of public and private sector pay trends has been different due to the austerity measures adopted by government.

In the pre-crisis period, the government did not have an explicit pay policy in place. From 2009, however, the Labour government imposed a pay settlement of up to 1% for public sector workers, excluding those staff on three-year pay agreements. Senior staff did not receive a pay rise, but no limits were imposed on personnel within the Armed Forces. The increased size of the government deficit following the 2007/08 financial crisis (and policies put in place to address it) led to an increased public focus on the size of the government sector workforce and the level of public sector pay.

In the immediate aftermath of the financial crisis, the coalition government announced a pay freeze for all pay scales, with the exception of an annual £250 pay increase over two years for public sector workers earning less than £21,000 per annum. For the years after the financial crisis (i.e., 2013-14 and 2014-15, 2015-16), the average increase was capped at 1% per year until 2019-2020. However, the pay cap was lifted in 2017 with pay awards above 1% for some public sector workers (primarily prison staff and police officers) announced in September 2017. This was followed by awards of 2% or higher that were announced in July 2018, July 2019 and finally July 2020. The raw data in Figure 4.5 reveal that between 2002 and 2019, the overall average nominal public sector wage rose by 18.9% compared to 17% in the private sector. The time period is split and observed that in the pre-crisis period (2002-2005), public sector wages grew by 7.02%, compared to 5.5% in the private sector and that during the crisis period (2006-2012), wages grew by over two percentage points more in the public relative to the private sector. However, in the post-crisis period, nominal wages grew by 6.28% in the private sector and by 5% in the public sector, reversing previous trends. Therefore, while a focus on the entire period is important, it potentially obscures the different patterns in pay awards evident within specific sub-periods.

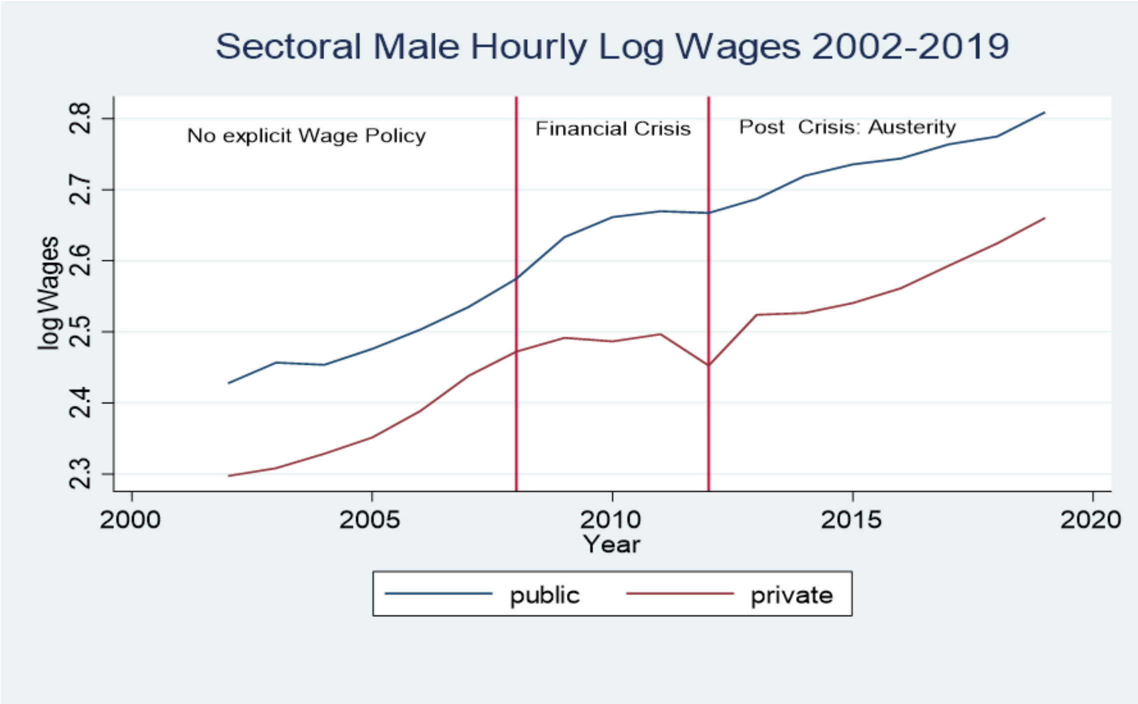

Figure 4. 5: Hourly Log Wages by Sector (2002 to 2019)

Source: Author’s calculations from the ASHE dataset.

Figure 4.5 shows that, on average, hourly pay rates were relatively higher in the public compared to the private sector. Before the financial crisis, the sectoral trends in pay were broadly similar. However, during the crisis and despite imposition of a public sector pay freeze, private sector pay exhibited a sharper downward adjustment than public sector pay. However, towards the end of the austerity period, pay grew more rapidly in the private relative to the public sector. Figure 4.5 reveals that before the financial crisis, the relativities were broadly comparable between sectors. During the financial crisis, they grew at a slower pace due to the pay freeze policy but fell more dramatically in the private sector. This widened the public sector wage gap. The relativities persisted over the crisis period but began to reduce during and towards the end of the austerity period. It is worth noting that the public sector wage gap widened during the crisis period, and this provides some tentative evidence of the countercyclical nature of the wage gap.

4.3 Literature Review

The public sector wage premium varies significantly across countries but also across the pay distribution within countries. There is a broad consensus in the literature that the wage premium is highest at the bottom end of the pay distribution and is either zero or negative at the top end (see Rees and Shah, 1995; Bargain and Melly, 2008; De Castro *et al.,* 2013; Depalo *et al.,* 2015). This pattern is generally explained by political and fiscal decisions that influence public sector pay-setting policy. Some have argued that a government is keen to be seen as a good employer, particularly by low-paid workers; this explains why low wage workers receive relatively higher wages than those paid in the private sector (Depalo *et al*., 2015). In addition, public sector employees often tend to be trades union members, giving them bargaining power relative to their private-sector counterparts. According to Giordano *et al.* (2011), a government sets the wages of the top-paid public sector workers at a lower level to avoid accusations of unwarranted or excess spending of government money on public sector employees. Along similar lines, Depalo *et al.* (2015) report that differences at the bottom end of the wage distribution can be attributed to the differences in the wage returns to characteristics, while wage differentials at the top end of the distribution are generally explained by differences in characteristics. Public sector employees (controlling for their characteristics) may be paid less than private-sector employees because of the political and fiscal decisions that influence public sector pay-setting policy, and not necessarily because the average quality of public sector workers is lower than that of comparable private-sector workers.

Centeno and Portugal (2001) use the 1995 wave of the European Community Household Panel (ECHP)[62] to compare wage differentials between the general government and private sectors in European Union (EU) member states. The wage structure for workers in the private sector of the economy is used as a benchmark. The study considered identical worker characteristics and found a wider wage gap in Portugal, Ireland, Luxembourg, Spain and Italy and a narrower gap in Austria, Belgium, Germany, and Denmark (where the differential is actually found to be negative).

Campos and Centeno (2012) also exploit ECHP data to analyse the evolution of public wages and the public-private wage gap in the period prior to adoption of the Euro by signatories to the Maastricht treaty. They used mean and quantile regressions and controlled for individual attributes in estimating the wage gaps. Their results suggest relative moderate growth of public sector wages in several European countries in the 1990s but imply an increase in the public-private wage differential over the same period for the majority of the countries in their sample. In particular, they found that public sector employees generally benefited more relative to private sector employees with the same observed (and unobservable) characteristics. The authors also report that even a significant economic policy such as the Euro becoming the common currency (which obliged European countries to undertake fiscal efforts to comply with the requirements

[62] The ECHP dataset is available from Eurostat. ECHP is a longitudinal survey of households and individuals covering 15 EU Member States. At the time of writing, eight waves of data were available, spanning 1994 to 2001.

for adoption of a single currency) does not appear to alter the public wage premia across Eurozone countries. However, their results should be treated with a degree of caution since their pooled regression framework implicitly assumes common returns to individual attributes and job characteristics across the public and private sectors. This assumption may not be appropriate in all circumstances.

Michael and Christofides (2020) examine the impact of public sector pay reforms on the public-private sector wage gap in 27 countries included in the European Union Survey of Income and Living Conditions (EU SILC). Reforms that were adopted in response to the financial crisis included austerity measures, ranging from pay freezes, pay cuts and other reforms related to the terms of employment. The crisis may also have induced voluntary adjustments to pay or to the terms of employment in the private sector, modifying the impact of austerity on the public-private sector wage gap. The authors used the standard Oaxaca and Ransom (1994)[63] methodology to conduct decomposition analysis at the mean. In addition, they also explored the differentials along selected quantiles of the wage distributions using the counterfactual decomposition proposed by Chernozhukov *et al.* (2013).

Michael and Christofides (2020) grouped the countries into three categories with respect to the total conditional public-private sector wage gap; low wage gap cases which includes all the Northern European countries (Denmark, Estonia, Finland, Iceland, Norway, and Sweden), more central European countries (Austria, Belgium, France, Germany, the Netherlands, and Switzerland), as well as the United Kingdom and Malta ; medium wage gap encompasses Bulgaria, the Czech Republic, Lithuania, Slovakia, Slovenia, Ireland and Italy while the and high wage gap countries are Cyprus, Portugal, Spain,Greece, Luxemburg, Hungary, Latvia, Romania, Poland and Croatia. Their results suggest that in the majority of the low gap countries, there are no particular changes along quantiles when comparing 2007 with 2013. With respect to the medium wage gap countries, fluctuations of the total gap tend to be due to changes in the unexplained portion. While most high gap countries at the median, have much larger gaps at the lower end of the wage distribution than at the top.

[63] This decomposition addresses the index number problem. It uses pooled parameter estimates to provide 'group-neutral' parameters to enable comparisons between groups and, subsequently, calculates the 'price' effect on the distance of the group-specific estimates from the pooled coefficients; in this case, this is effectively the counterfactual. The use of this type of approach has some limitations in the present case this is not an issue since the chapter is not interested in the issue of discrimination.

Overall, the results suggest that 14 countries had a very low pay gap in 2007 and nine of them did not adopt austerity (i.e., public sector freezes and/or pay cuts) measures during the following years; a public sector premium is not the norm. The top wage gap countries in 2007 subsequently had to apply for external financial assistance. Almost all countries display a negative quantile function slope: the lowest-paid public servants are better paid than similar colleagues in the private sector. The inter-quantile differences can be large even in countries with low pay gaps at the median. At the top end of the wage distribution, the gap can be negative. The panel static and dynamic estimates suggest that public sector wage freezes and cuts had negative, statistically significant, effects on the pay gap, particularly at the median and 90th quantiles. At the 10th quantile, positive but weaker effects can be discerned. Austerity measures shielded the lowest-paid public servants from their impact. The inter-quantile effects relating to the 90th minus the 10th quantile were found to be negative and reflect the attempts made by the policies introduces in several countries to protect the low-paid public sector workers.

Lausev (2014) provides a survey of the more recent studies in this area and compares their findings for the public/private pay differences in Eastern European transition economies with the findings for more developed market-based economies. Not surprisingly, the size of the public-sector pay premium is found to differ across countries, vary over time, and depends on both the specification of the earnings equation and the estimation method employed. Nonetheless, it provides some key stylized facts for the UK and some other market-based developed economies. For instance, the authors provide evidence that when quantiles are considered, the pay gap declines from the lower to the upper quantiles. This shows that the public sector pay is more compressed than private sector pay. The study also found that male public sector workers at the bottom end of the distribution fare better than their counterparts in the private sector.

Campos *et al.* (2017) investigate the effects of cross-country heterogeneity in public-private pay differentials for a set of OECD countries. The authors use the EU SILC data for the years 2003-2011 for selected countries in conjunction with macro-economic National Accounts data for 19 countries in the period 1970-2014. The study employs the difference in the Cyclically Adjusted Primary Balance (CAPB)[64] or the structural budget balance and reports significant cross-country correlations between the difference in the CAPB and the contraction in the public sector wage premium. The authors also report that the conditional public sector pay gap in Europe before the crisis (2004-2009) was

[64] This provides an estimate of the fiscal balance that would apply under current policies were output equal to potential. The cyclically adjusted budget balance (CAB) is the backbone of the EU framework of fiscal surveillance, both in its preventive and corrective arms. (See Mourre *et. al.*,2013)

about 9%. Over the period witnessing the implementation of austerity policies, the premium contracted to 4.8%. The authors note that the fall was larger for those countries with higher public sector wage premia prior to the crisis due to the greater fiscal stress they experienced during the crisis.

The general finding for Great Britain is that on average, similar to most European countries, civil servants earn more than comparable private sector workers (Rees and Shah, 1995; Disney and Gosling, 1998; Blackaby *et al.,* 1999; Elliott and Bender, 1997). In addition, most work investigating how the public-sector pay premium varies across the pay distribution finds that men in the public sector typically (Melly, 2005) benefit from a positive pay premium at the lower end of the distribution; a negative penalty is more common at the top end.

Rees and Shah (1995) exploit data from the 1983, 1985 and 1987 General Household Surveys (GHS) to estimate the public-sector pay premium. The authors use a decomposition method that allows the estimated coefficients of the explanatory variables to differ between the two sectors. This is obviously motivated by the OB decomposition technique but adjusts for employee sector selection. The authors demonstrate that while, for men, characteristic or endowment differences largely explain the public/private pay gap, in the case of women their characteristics tend to be rewarded more highly in the public compared to the private sector. This leads to a positive public-sector pay premium for women. Rees and Shah's study examines only mean differences; this might mask any variation that exists between the public and private sectors along different points of the earnings distribution. However, Bender (2003) obtained similar findings in a study of the differences in the distribution of public and private sector wages using SCELI[65] Survey data for 1986. Bender (2003) notes that differences in the wage structure and unobservable factors determining wages exert distinct effects at different points of the wage distribution.

Disney and Gosling (1998) estimated the public-sector wage premium, using CQR techniques and a simple intercept shift for employment in the public sector. The authors use data for the period 1979-1994 based on repeated cross-sections of the New Earnings Survey (NES), the British Household Panel Survey (BHPS), and the GHS. The study employs a panel data fixed effects approach and finds that, after taking account of worker occupations, the public-sector pay premium fell for both men and women over

[65] The Social Change and Economic Life Initiative (SCELI) Survey is based on a sample of six local labour markets (Aberdeen, Coventry, Kirkaldy, Northampton, Rochdale, Swindon), chosen to provide contrasting patterns of employment in Great Britain.

the period considered. In addition, the study finds that the average premium had all but disappeared for men by 1994. The empirical analysis reveals that the public sector pay gap varies along the distribution. It is found to be higher for the lowest deciles and decreases monotonically with movement up the wage distribution. Disney and Gosling (1998) found evidence that would seem to suggest that the public-private-sector pay gap in the UK exhibits counter-cyclical behaviour. It increased sharply in the two recession periods in the early and late 1980s, and then decreased as the economy moved towards a cyclical peak in the mid-1980s and the 1990s.

Lucifora and Meurs (2006) used micro-level data for Great Britain, France and Italy, to investigate public-private pay differentials. They employed CQR methods to model earnings and used the Oaxaca and Ransom (1994) method to decompose the public-private wage gap within and across countries and gender groups. Their results reveal that public sector wages for low-skilled workers are higher than those in the private sector for these three countries, with the reverse being the case for higher-skilled workers. The study confirmed that Great Britain appears to be characterized by the largest public-private differences in the returns to observed attributes. This suggests the existence of higher differences in pay discretion between sectors along the wage distribution. On the other hand, much of the difference in pay between sectors in France and Italy appears to be explained by differences in observed characteristics rather than in the returns to these characteristics. This supports the idea that in more regulated economic systems, general skills and work experience matter more for pay determination.

Heitmueller (2006) used the extended BHPS sample[66] for the year 2000 to assess the impact of devolution (i.e., establishment of the Scottish Parliament)[67] on the unconditional Scottish public sector earnings premium and asses how the findings differ compared to other UK studies. Heitmueller adopts the methodology outlined by Gang *et al.* (1999) to control for selection into public or private sector employment and to also control for selection linked to the labour market participation decision. Heitmueller employs the decomposition method proposed by Neuman and Oaxaca (1998) and finds that the gap in observable characteristics explains a large proportion of the smaller male earnings gap between sectors but leaves much of the gap in female earnings unaccounted for. The decomposition results for males are comparable to those obtained by Rees and Shah (1995) for Great Britain, but slightly higher than Bender's (2003)

---

[66] Since 1999, the samples for Scotland and Wales have been extended to increase the relatively small sample sizes available for these two nations.
[67] The Scottish Parliament has the largest set of devolved powers, including some authority on income tax and benefits.

findings for the whole of the UK. While earnings in the private sector can adjust to a tight labour market, the public sector often lacks regional flexibility. In this study, this is evidence of a male private sector wage premium due mainly to sector selection and emphasizing the need to control for selection bias. Despite the devolution of these powers in Scotland, wage setting in the public sector does not match the new institutional arrangements and has not changed significantly since 1999.

Chatterji and Mumford (2007) exploit pay data for Great Britain from the Workplace Employee Relations Survey (WERS)[68] for the year 2004 (WERS04) to analyse the magnitude of the public-private sector wage gaps for full-time working British men. This is undertaken across occupations and workplaces at both the mean and along the pay distribution. In addition to employing a workplace-specific fixed effects regression model, the authors use the decomposition method (without workplace fixed effects) proposed by Oaxaca and Ransom (1994). Their decomposition analysis reveals that, on average, full-time male public sector employees earn 12% more than their private-sector counterparts. This is because public sector employees' individual characteristics are associated with both higher pay and working in higher-paid occupations. Using a conditional quantile regression technique, the authors find little evidence of variation in the estimated rates of return to individual or job characteristics across the earnings distributions of either the public or private sector employees.

In a subsequent paper, Chatterji *et al.* (2011) used the same WERS04 pay data for Great Britain and estimated a separate semi-logarithmic earnings equation for each of the employee groups (i.e., public sector males and females, and private sector males and females). They find that, while individual, workplace and other observable attributes explain the gap in male earnings between the public and private sectors, almost four-fifths of the gap in female earnings remains unexplained.

Blackaby *et al.* (2018) estimated the magnitude of the public-sector pay premium for the UK pooling Labour Force Survey (LFS) data for two time periods (2009 Q2-2011 Q1 and 2011 Q2-2015 Q4). The authors estimated the size of the public wage differential by region, gender and firm size, and found that the pay premium is sensitive to the choice of variables used in the earnings equation and, in particular, to the inclusion of establishment size controls. Their findings suggest a distinct squeezing of the public sector differential as the economy recovered from the recession. The evidence for the two periods shows that, during the period from 2009 to 2015, male public sector

[68] WERS04 is a nationally representative survey of workplaces and their employees, where a workplace comprises the activities of a single employer located in a single premises.

employees did not earn more than private sector employees (controlling for a number of individual and workplace characteristics such as job tenure, plant size, occupation, and managerial position). The public sector pay premium fell from -3.9% to -4.8% for men, and from 5.6% to 2.4% for women between 2011 and 2015.

The analysis in this study confirms that after controlling for several regional characteristics, there are variations in the public sector pay differential across regions. For instance, there are substantial regional disparities in the wages offered to public sector workers, concentrated predominantly on London and the Southeast of England, where public sector workers are significantly disadvantaged relative to those in the private sector. However, similar to Disney and Gosling's (1998) study, they estimate a pooled regression model; it could be argued that this does not adequately capture differences in the wage-setting mechanisms between the two sectors. Also, Blackaby *et al.* (2018) focus only on mean effects and do not investigate variation in public sector effects across the earnings distribution.

Overall, the above review points to an historical average positive wage premium associated with public sector employment in the UK and provides evidence that its size is counter-cyclical in nature. However, a general finding is that after including a range of controls, the public sector pay gap declined over time and is either modest or zero for men. The review also provides evidence that the public sector premium is larger at the bottom end of the pay distribution than at the top. The research in this chapter extends this literature by investigating whether the financial crisis and the austerity measures introduced in the post-financial crisis era have affected the public sector wage premium. The average differential between the two sectors and the gap along the entire unconditional earnings distribution are investigated. In contrast to much of the empirical work to date, the analysis in this chapter exploits a number of different methodologies. These include the standard OB decomposition applied within a UQR framework and extended using the re-weighting procedure developed by Firpo *et al*. (2018).

4.4 Research Questions

The present study is similar to a recent study undertaken by Murphy *et al.* (2020) that also employed a variant of the OB decomposition based on Firpo *et al*.'s (2018) procedure. The authors investigate the magnitude of the public-sector wage differential in Great Britain during the period 1994-2017, using data for males and females based on the LFS datasets. They report their results for the 10th, 25th, 50th, 75th and 90th percentiles of the pay distribution. Their study suggests that apart from men in the lower part of the pay distribution, the public sector pay premium has declined for all public sector workers. This decline coincided with a decline in the overall pay gap that is associated with changes in both the composition of the public sector and private sector workforces.

This chapter uses a similar framework to that used Murphy *et al.* (2020). However, in this chapter every other percentile from the 5th along the wage distribution is restricted. The analysis is not restricted to just the 10th, 25th, 75th and 90th percentiles. Furthermore, Murphy *et al*. (2020) examine the differences in the outcomes between 1994 and 2017. This approach hides the effects of the austerity policies adopted in the pre-crisis and post-crisis periods and is why the present analysis splits the sample period into a set of pre-crisis (2002-2005), crisis (2006-2012) and post-crisis (2013-2019) periods. In addition, Murphy *et al.*(2020) employ the LFS while the present analysis exploits ASHE which is more robust to the LFS data.

Millard and Machin (2007) argue that the LFS public/private sector and industry classifications are based on survey respondents' views about their employer organizations, which suggests the potential for reporting errors. In this context, ASHE data are considered superior in terms of the pay measurement because they come from an employer-based survey. Employers provide detailed information on the earnings, hours and occupations of selected employees. Amadxarif *et al.* (2020) note that ASHE data are superior in terms of estimating the overall gaps. However, their use comes at a cost, since the LFS potentially includes a richer set of individual and job characteristics relevant to the type of analysis proposed here. Overall, the analysis undertaken here adds value to the work of Murphy *et al*. (2020) in terms of the data used as well as the timeframe analysed.

The present study applies a number of methods, including an austere pooled regression model approach, an extended Oaxaca-Blinder decomposition based on the use of Recentred Influence Function (RIF) methods, and a new methodological contribution of Firpo *et al*. (2011) and Firpo *et al*. (2018) that exploits re-weighting. The analysis uses annual data for the period 2002 to 2019 to provide an up-to-date picture of the evolution of the pay gap between public and private sector male employees over a period that witnessed one of the most significant global recessions since the 1980s.

The main research questions are:

(i) What is the magnitude of the average public sector pay gap for men in Britain over this period, and was it affected by the financial crisis?

(ii) What is the magnitude of the public sector pay gap for men in Britain over this period along the unconditional pay distribution, and did the financial crisis have a heterogeneous impact on the public sector pay gap along the pay distribution?
(iii) Did the austerity policies implemented in the aftermath of the financial crisis have a heterogeneous impact on the public sector pay gap along the pay distribution?

4.5 Data and Descriptive Statistics

The analysis draws on the ASHE data from HM Revenue and Customs Pay As You Earn (HMRC PAYE) records, collected and administered by the Office for National Statistics (ONS) and covering the years 2002 to 2019 (inclusive). Payroll questionnaires are sent to employers, who are legally required to complete them with reference to a period in April of the particular year. From a panel of employees without attrition, a randomly selected representative sample of 1% UK employees is drawn each year.

Only full-time working men aged between 16 and 65, with non-missing information for earnings and hours, are considered. Observations with missing records or with 1 or 100 or more basic paid weekly hours are dropped. Similarly, non-main jobs, such as trainee or apprentice level jobs, and those jobs incurring a loss of pay in the reference period for whatever reason, are also excluded. The key outcome variable is the hourly wage rate that excludes overtime and holiday pay. The hourly wage rate is defined as the ratio of employee gross weekly earnings to the corresponding basic weekly paid hours recorded (excluding overtime). An array of job characteristics is also included in the analysis. These include linear and quadratic variables in employee age, a set of job tenure splines[69], whether or not the job is permanent, the log of employment size that measures the firm's total workforce, the 2-digit industry of employment, the 2-digit occupation of the employee, and the region of employment. Since the ASHE dataset does not include an explicit education variable, the 2-digit occupation controls is used to proxy for the level of education (as done in Chapter 3). For the years 2002 to 2010, the occupations are classified using the 4-digit SOC2000 with the SOC2010 used for years 2011 to 2016. The SOC2000 is converted into SOC2010 using a table provided by the UK Data Service (UKDS) within the secure datalab. The ONS Standard Industrial Classification (SIC) 2003 is converted to 2007, using files made available by the UKDS.

[69] A 'spline' is a function constructed in a piecewise fashion from polynomial functions. The thresholds where the functions meet are known as knots and the set of piece-wise linear splines allow the estimated effect of the relevant variable on the outcome measure to differ.

In order to create a tenure variable, the individual's recorded employment start date is used. ASHE contains information on when an employee started working for an enterprise from 2002 onwards. A small number of unrealistic entry dates (start date in the future, for example) is dropped. The tenure variable is used to construct three separate linear splines capturing the length of current employment. The variable 'permanent' is a binary dummy that takes the value 1 if the employee is in a permanent job and 0 otherwise. The log of the variable 'Idbrnemp' (total firm employment) is used to capture the firm's employment size. Following Jewell *et al*. (2018) the analysis groups the industry sectors into four broad categories; this enables the construction of four industry 1-digit dummies.[70] Furthermore, 11 regional dummies at the NUTS1 regional level are included. The key public sector variable is defined using the employee's job status to determine whether it is in the private or public sector. Firms are assigned to the public or private sector using their status recorded in the ASHE variable 'idbrsta', which records the legal status of the enterprise according to the IDBR. For instance, the private sector is comprised of employees who work for private companies, sole ownerships, partnerships and non-profit institutions serving households. The public sector comprises central government, local authority and public corporation employees. The sample is restricted to non-agricultural employees and exclude employees with missing personal identifiers. All employees with missing employment start data are dropped, since this information is required to generate the job tenure variable. Employees in firms that are not amenable to classification as either being in the public or private sectors are excluded. Table 4.1 describes the variables used for the analysis.

[70] Industry sectors are aggregated as follows: 1. Manufacturing/Construction/Engineering sections C-F; = "Manufacturing," 2. Retail/Wholesale/Services sections G-H = "non-financial (sales) services", 3. Financial services sections J-K; 4. Public/other services = Other sections A-B, I and L-Q. T= "Other"

Table 4. 1: Variable Names and Description

Variable	Description
ln (W)	This is the dependent variable and is the log of basic nominal hourly wages.
age	This is the age of the individual at the time of the survey expressed in years
age_sq	This is the square of the age variable
ind	This variable provides the information for the one-digit standard industrial classification. One dummy is dropped and used as a reference category.
occ	This variable provides the information to construct 25 two-digit occupation categories. One category is dropped in the estimation as a reference category.
lsize	This is the logarithm of employment size for a firm where an individual works.
tenure_1	A piece-wise linear spline for less than 5 years working.
tenure_2	A piece-wise linear spline of between 5 and 10 years working
tenure_3	A piece-wise linear spline of more than 10 years working.
public	A dummy variable that takes the value of 1 if an individual is in a public sector job and 0 otherwise
permanent	A dummy variable that takes the value of 1 if an individual is in permanent employment and 0 otherwise
nuts3	Dummy variables for the 11 NUTS3 regions included in the analysis.

Table 4.2 presents selected descriptive statistics. The raw data show substantial differences between the public and private sectors.[71] On average, men employed in the public sector are paid more than their private sector counterparts. The descriptive statistics confirm that mean wages are higher in the public sector across all the years. For instance, in 2002 wages were 0.13 log points higher in the public sector. Using the standard deviation as a measure of dispersion, wages are more compressed in the public relative to the private sectors across all the years. In addition, the distribution of male log wages in the public sector confirms this compression compared to the private sector.

[71] Appendix Table 4.A7 gives the cell sizes for the two sectors.

This is further confirmed by a higher Gini coefficient for the private relative to the public sector. The descriptive statistics confirm that the differences are statistically significant

Table 4. 2: Summary Statistics for Selected Years

	Public										Private									
	2002		2006		2012		2013		2019		2002		2006		2012		2013		2019	
Variable	**Mean**	**sd**	**Mean**	**sd**	**Mean**	**sd**	**Mean**	**sd**	**Mean**	**sd**	**Mean**	**sd**	**Mean**	**sd**	**Mean**	**sd**	**Mean**	**sd**	**Mean**	**sd**
Log wageh	2.428	0.48	2.503	0.445	2.667	0.434	2.687	0.418	2.809	0.401	2.297	0.494	2.389	0.494	2.453	0.501	2.524	0.489	2.660	0.452
Age	42.21	9.95	42.32	10.72	42.96	11.01	42.80	10.67	42.71	11.27	40.92	10.96	40.45	11.67	40.083	12.395	40.774	11.860	40.846	12.170
Tenure	12.4	9.51	11.31	9.784	11.372	9.439	11.831	9.510	10.39	9.30	9.571	9.016	8.325	8.794	7.889	8.385	8.533	8.677	7.874	8.581
Permanent	0.98	0.15	0.959	0.198	0.939	0.239	0.944	0.230	0.932	0.25	0.982	0.134	0.971	0.168	0.944	0.229	0.960	0.197	0.962	0.192
Log employment	0.97	0.17	0.968	0.175	0.936	0.245	0.937	0.243	0.912	0.28	0.498	0.500	0.527	0.499	0.531	0.499	0.527	0.499	0.511	0.500
Gini	0.27	n/a	0.257	n/a	0.254	n/a	0.244	n/a	0.232	n/a	0.288	n/a	0.289	n/a	0.297	n/a	0.288	n/a	0.268	n/a
90-50	0.59	n/a	0.600	n/a	0.615	n/a	0.592	n/a	0.565	n/a	0.758	n/a	0.767	n/a	0.810	n/a	0.767	n/a	0.755	n/a
50-10	0.68	n/a	0.534	n/a	0.488	n/a	0.470	n/a	0.489	n/a	0.543	n/a	0.531	n/a	0.510	n/a	0.525	n/a	0.434	n/a
90-10	1.27	n/a	1.134	n/a	1.103	n/a	1.062	n/a	1.055	n/a	1.301	n/a	1.298	n/a	1.319	n/a	1.291	n/a	1.189	n/a
N	**8,615**		**12,738**				**12,048**		**8,848**		**33,647**		**51,341**		**56,801**		**51,567**		**51,005**	

Source: Author's Calculations from ASHE dataset.

In relation to employee characteristics, on average, public sector workers are older than private sector employees, public sector workers have considerably longer tenure periods and are more concentrated in larger establishments. Nearly all employees in both sectors were in permanent employment at the start of the period. However, the percentage of permanent employment in the public sector had fallen to 93% in 2019 from 98% in 2002. In contrast, private sector permanent employment fell by only 2 percentage points, from 98% to 96%, in 2019. There are also marked differences in economic activities across sectors. For example, public sector employment was dominated by public administration, education and health over the relevant time period, whereas in the private sector manufacturing was the dominant industry branch. The leading public sector occupations are community protective services, administration, and teaching and education, while in the private sector the leading occupations are corporate manager, director and skilled metal, electrical and electronics workers. There is an overlap in the distributions of the covariates (individual, industry and occupation characteristics); this ensures common[72] support, although demographics, skills and occupational profiles clearly differ between the public and private sectors.

In order to better describe the differences between the public and private sector wages over the entire period 2002 to 2020, non-parametric methods (kernel density estimator) are exploited to determine the density of hourly wages for both sectors (see Figure 4.6). The plots reveal differences in the wage distributions in the two sectors. In particular, the mass of the public sector distribution lies to the right of the private sector. In addition, the distribution in the public sector shows a peak and lower dispersion compared to the private sector. Based on this plot, it can be observed that mean wages are higher and show lower dispersion in the public compared to the private sector.

[72] There are jobs in all two-digit occupations and industries across both sectors. The proportions vary in magnitude. This is an issue that has more salience when three-digit or more occupational classifications are used.

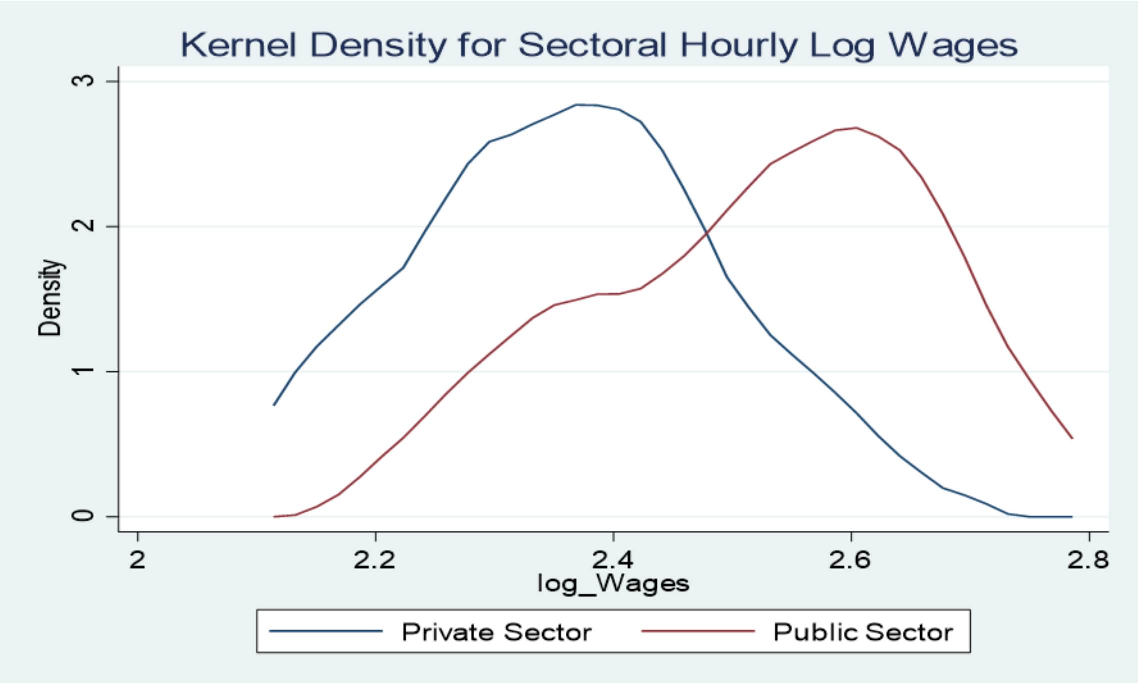

Figure 4. 6: Kernel Density of Log Hourly Wages by Employment Sector

Source: Author's calculations from ASHE dataset.

Figure 4.7 depicts the distribution of log wages between the two sectors for the 10th, 50th and 90th percentiles. The pay relativities for employees in the 10th percentile appear to have widened during the financial crisis but narrowed in the post-crisis period. The 50th percentile presents a different picture with wider relativities at the onset of the financial crisis. These relativities continued to widen in the austerity period up to 2019. On the other hand, the relativities plot for the 90th percentile reveals that immediately before the financial crisis, private sector wages were higher than public sector wages. However, this changed during the period of the financial crisis. The austerity period witnessed a contraction in these pay relativities at the 90th percentile, despite public sector workers' pay being higher than that received by their private sector counterparts over this period.

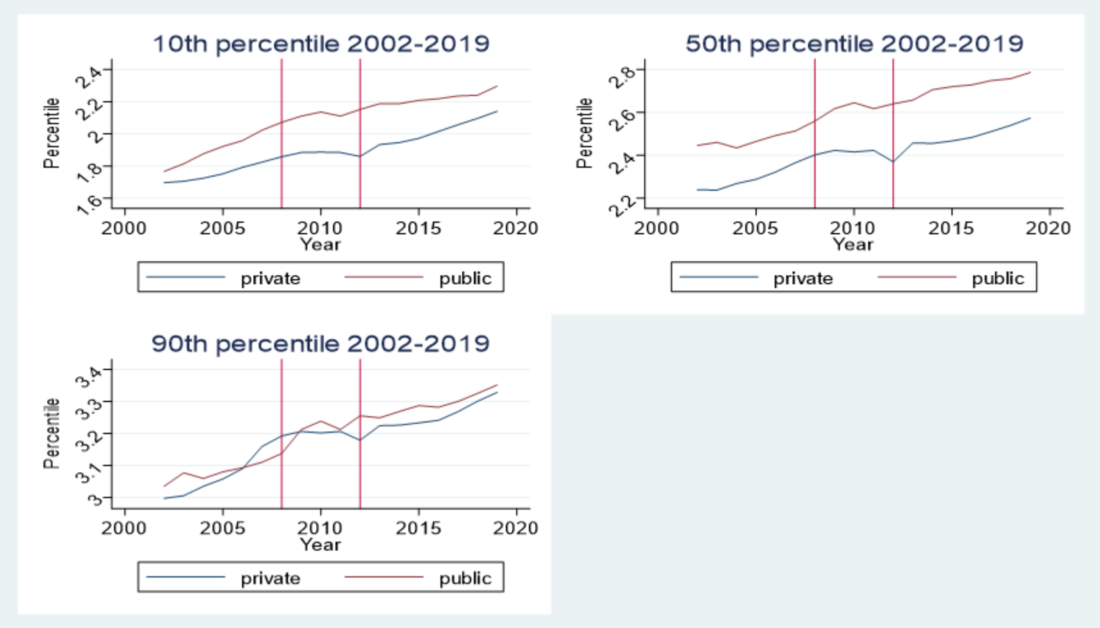

Figure 4. 7: Sectoral Log Hourly Wages for the 10th, 50th and 90th Percentile

Source: Author's calculations from ASHE dataset.

4.6 Econometric Methodology

As noted earlier, three different techniques are used to examine the evolution of the earnings gap between public and private sector male employees in Great Britain. The first technique is the pooled dummy variable regression approach discussed in Section 4.3 and used extensively in the past for this purpose (see Disney and Gosling, 1998; Blackaby *et al*., 2018). The second approach is the Oaxaca-Blinder (OB) decomposition methodology (Oaxaca, 1973 and Blinder, 1973); this allows for a detailed decomposition of the average wage differential among individuals between the two sectors. The third is a detailed decomposition method inspired by the OB methodology and developed by Firpo *et al.* (2018).

This last technique incorporates a re-weighting procedure, introduced originally by DiNardo *et al.* (1996). This approach allows OB-type decompositions for any distributional statistic with an Influence Function (IF). The re-weighting is based on parametrically estimated propensity scores (in this case, the probability of working in the public sector). The role of the re-weighting is to provide a more credible counterfactual than that used for the standard OB index number decomposition in terms of the distribution of covariates. The OB decomposition allows the average gap to be broken down into a component associated with worker characteristics (i.e., endowment differences) and a component related to structural differences in pay (differences in the coefficients, usually interpreted as a treatment effect). This can then be extended to selected quantiles when using the OLS estimated unconditional quantile regression models.

Firpo *et al.*'s (2009) original methodology requires an initial understanding that many common descriptive statistics can be expressed as statistical functionals. A statistical functional is any function of the outcome variable's distribution function (conventionally defined as F(·)) and can be expressed as T(F). Assuming the statistic is continuously differentiable, the first-order directional derivative is known as the Influence Function (IF). The IF provides a framework to assess the influence on a distributional statistic of interest of either adding or deleting an individual observation (or, more broadly, excluding data contamination issues), without the need to re-calculate the statistic.[73] Assume IF(y; v, F) is the influence function corresponding to an observed outcome variable y (e.g., the log wage in this case) and the distributional statistic is defined as $v(F_y)$. Assume the RIF corresponding to this case is defined as RIF (y; v) where:

$$RIF(y; v) = v(F_y) + IF(y; v, F) \quad [4.1]$$

The influence function (IF) of a quantile value q_τ for a random variable y is given by:

$$IF(y; q_\tau) = \frac{\tau - I(y \leq q_\tau)}{f_y(q_\tau)} \quad [4.2]$$

where:

τ = the quantile of interest (e.g., 10th percentile);

I(.) = an indicator that takes the value 1 if the expression in parentheses is satisfied and is 0 otherwise;

$f_y(q_\tau)$ = the density value corresponding to the quantile value q_τ

It is possible to move from the IF to the RIF by adding the quantile of interest (i.e., q_τ) to the IF, which yields:

$$RIF(y; q_\tau) = q_\tau + \frac{\tau - I(y \leq q_\tau)}{f_y(q_\tau)}$$

After some manipulation, this can be re-arranged as follows:

[73] The concept of IF has its origin in the field of applied robust statistics (e.g., Hampel *et al.*, 1986).

$$\mathrm{RIF}(y; q_\tau) = q_\tau + \frac{I(y > q_\tau)}{f_y(q_\tau)} - \frac{1 - \tau}{f_y(q_\tau)} \qquad [4.3]$$

In the case of quantiles, the RIF (like the IF in [4.2]), is a dichotomous variable that takes one of two values, either $q_\tau + \frac{\tau - 1}{f_y(q_\tau)}$ if the random variable is below (or equal to) the quantile value q_τ, or $q_\tau + \frac{\tau}{f_y(q_\tau)}$ if the random variable is above the quantile value q_τ. The RIF has several interesting properties, the most important for the current analysis is that the mean of the RIF corresponds to the quantile value of interest.

Following Firpo *et al.* (2009), the conditional expectation RIF regression can be expressed as follows:

$$E[\mathrm{RIF}(y; q_\tau) \mid \mathbf{X}] = \mathbf{X}'\boldsymbol{\beta} \qquad [4.4]$$

where the RIF is assumed to be a linear function of the covariates x contained in the data matrix defined here by **X** and, therefore, provides a linear approximation of a highly non-linear functional. This expression can be estimated using Ordinary Least Squares (OLS). Firpo *et al.* (2009) demonstrate that such an OLS regression provides estimates of **β** that represent the effect of the x covariates on the unconditional τ^{th} quantile of the outcome variable y.[74]

As a prelude to the estimation of equation [4.4] using OLS, the RIF expression [4.3] requires computation, given that expression [4.3] is unobserved in practice. Corresponding sample analogues that require that the sample quantile value $\hat{q}_\tau$ is computed from the data are used. The density value at this point is estimated using non-parametric kernel density methods (i.e., $f_y(\hat{q}_\tau)$). An estimate of the RIF for each observation is obtained by plugging the density estimates into expression [4.3]. The multiplication of the probability by the inverse of the density yields the quantile value in this case. Therefore, this procedure changes the outcome variable at each quantile in expression [4.3], such that the mean of the recentred influence function corresponds to the quantile of interest.

In summary, the RIF-OLS regression approach involves OLS estimation of a linear probability model for being above the quantile of interest (q_τ) in the first instance. This procedure yields estimated marginal effects (for the continuous variables) and impact effects (for the dummy variables), which are expressed in probability units. These

---

[74] If the RIF in [4.3] is re-cast in terms of the mean statistic, the application of OLS yields mean regression estimates identical to those obtained by OLS using the untransformed outcome variable y.

marginal/impact effects are then divided by the kernel (probability) density evaluated at the quantile of interest; this locally inverts the (unconditional) probability effects into their corresponding (unconditional) quantile effects.

The conditional RIF expectation can be modelled as a linear function of the predictor variables (i.e., E [RIF(y; q_τ | X) = Xβ_τ), where the regression coefficients represent the marginal effects of the variables on the quantiles of the wage distribution (Firpo *et al*., 2009). Since the true RIF is unobservable, its sample analogue is utilized in empirical studies (i.e., (y; $\hat{q}_\tau$)). As noted earlier, an important theoretical property of the RIF is that its mean at the τ^{th} quantile equals the unconditional quantile q_τ (Firpo *et al*., 2009).

In the current application, the RIF methodology is employed in three different ways. First, a pooled log wage equation is estimated. A set of individual characteristics, including age and its quadratic term, tenure splines, an indicator variable for permanent employment, 2-digit occupation dummies[75] and three 1-digit industry dummies are included. The variable 'Public' is the key variable of interest and, as already noted, is a binary variable that is equal to 1 if the individual is employed in the public sector and is 0 otherwise. The pooled equation is defined as:

$$E[RIF(y; q_\tau) \mid \mathbf{X}] = \mathbf{X}'\boldsymbol{\beta} + \gamma_\tau \mathbf{Public} \qquad [4.5]$$

where γ_τ represents the public sector quantile coefficient of interest.

As discussed above, a major shortcoming of the dummy variable approach in a pooled regression model is that the effect of the sector of employment is captured by a single coefficient. An alternative approach, which relaxes this constraint, is estimation of separate sector-specific wage equations in conjunction with the OB decomposition. This is the second empirical technique used. The RIF-based approach enables application of a standard OB decomposition across the quantiles of the public and private sector wage distributions (Firpo *et al*., 2011). The OLS procedure is then applied to expression [4.4] separately for the public and private sector groups. The unconditional quantile regressions for the public and private sector equations are expressed more compactly at the τ^{th} quantile by:

$$\mathrm{RIF}^{p}_{i,\tau} = \mathbf{X}^{\mathbf{p}\prime}\boldsymbol{\beta}^{p}_{\tau} + v^{p}_{i,\tau} \qquad [4.6]$$

---

[75] The ASHE dataset does not provide information on individual education levels so 2-digit occupation dummies are used as a proxy for level of education.

$$\mathrm{RIF}^{\mathrm{r}}_{\mathrm{i},\tau} = \mathbf{X}^{\mathbf{r}\prime}\boldsymbol{\beta}^{\mathrm{r}}_{\tau} + \mathrm{v}^{\mathrm{r}}_{\mathrm{i},\tau} \quad [4.7]$$

where the superscript p denotes the public sector, and the superscript r denotes the private sector. The terms $\mathrm{v}^{\mathrm{j}}_{\mathrm{i},\tau}$ where j=p,r are the error terms. It is acknowledged that the mean of the RIF at the τ^{th} quantile represents the value of this quantile. Therefore, these quantile values are expressed as a linear function of the covariates for each sector as:

$$\overline{\mathrm{RIF}}^{\mathrm{p}}_{\tau} = \overline{\mathbf{X}}^{\mathrm{p}\prime}\hat{\boldsymbol{\beta}}^{\mathrm{p}}_{\tau} \quad [4.8]$$

$$\overline{\mathrm{RIF}}^{\mathrm{r}}_{\tau} = \overline{\mathbf{X}}^{\mathrm{r}\prime}\hat{\boldsymbol{\beta}}^{\mathrm{r}}_{\tau} \quad [4.9]$$

where the circumflexes refer to the OLS estimates and the bars refer to the mean values. Assuming the private wage structure represents the pay rewards associated with a competitive labour market, the decomposition at the τ^{th} quantile is defined as:

$$\Delta_{\tau} = \overline{\mathrm{RIF}}^{\mathrm{p}}_{\tau} - \overline{\mathrm{RIF}}^{\mathrm{r}}_{\tau}$$

$$= (\overline{\mathbf{X}}^{\mathrm{p}} - \overline{\mathbf{X}}^{\mathrm{r}})'\,\hat{\boldsymbol{\beta}}^{\mathrm{r}}_{\tau} + \overline{\mathbf{X}}^{\mathrm{p}\prime}(\hat{\boldsymbol{\beta}}^{\mathrm{p}}_{\tau} - \hat{\boldsymbol{\beta}}^{\mathrm{r}}_{\tau}) \quad [4.10]$$

In other words, the decomposition is the same as in the mean regression OB case but uses the UQR (or RIF) estimates instead of the mean regression estimates. The first term on the right-hand side of [4.10] is the endowment (or 'composition') effect, and the second term is the treatment effect. In contrast to the CQR decompositions, the RIF approach exploits OLS for this type of decomposition analysis and the desirable linearity properties that the estimator possesses. Therefore, implementing the decompositions is straightforward. The sampling variances can be computed using the robust procedure.

In the third approach, the OB analysis is extended to estimate and decompose the overall mean and quantile hourly log wage gaps using the re-weighting procedure proposed by Firpo *et al.* (2011, 2018). The extension combines the RIF regression in Firpo *et al.* (2011) with the re-weighting procedure outlined in DiNardo *et al.* (1996). The role of the re-weighting is to provide a more accurate counterfactual given it simulates an appropriate distribution of the covariates based on the private sector for the public sector workers. The application of a re-weighting approach can also be particularly important in the context of RIF regressions since they may not be linear for distributional statistics other than the mean (Firpo *et al.*, 2011). An advantage of the re-weighting procedure applied here is its low dependence on functional form assumptions. The difference between the log quantiles for public (p) and private (r) sector employees can be expressed as:

$$\Delta_\tau = \overline{\mathbf{X}}^{\mathrm{p}\prime}(\hat{\gamma}_\tau^{\mathrm{p}} - \hat{\gamma}_\tau^{\mathrm{c}}) + [\,\overline{\mathbf{X}}^{\mathrm{p}} - \overline{\mathbf{X}}^{\mathrm{c}}]'\hat{\gamma}_\tau^{\mathrm{c}} + [\,\overline{\mathbf{X}}^{\mathrm{c}} - \overline{\mathbf{X}}^{\mathrm{r}}]'\hat{\gamma}_\tau^{\mathrm{r}} + \overline{\mathbf{X}}^{\mathrm{c}\prime}(\hat{\gamma}_\tau^{\mathrm{c}} - \hat{\gamma}_\tau^{\mathrm{r}}) \qquad [4.11]$$

where $\Delta_\tau = \overline{\mathrm{RIF}}_\tau^{\mathrm{p}} - \overline{\mathrm{RIF}}_\tau^{\mathrm{r}}$

The key estimate of interest is based on the first term in expression [4.11]. This resembles the treatment effect in the standard OB decomposition as outlined earlier. However, it differs in that the counterfactual estimate derived is based on use of public sector regression estimates in which the public sector sub-sample used for the estimation is re-weighted to have the same characteristics distribution as the private sector sub-sample. The motivation for using the differential $(\hat{\gamma}_\tau^{\mathrm{p}} - \hat{\gamma}_\tau^{\mathrm{c}})$ in this case is that it reflects only the differences in the price structures of the two sub-samples and is not influenced by differences in the distribution of the characteristics of the two sectors. In other words, this approach provides a counterfactual distribution that combines the characteristics of public sector workers with the private sector wage structure. It is especially salient if RIF regressions are used, since changes to the distribution of the covariates changes the RIF values, which has implications for the estimated coefficients. The use here of the counterfactual estimate $(\hat{\gamma}_\tau^{\mathrm{c}})$, rather than the group specific estimate $(\hat{\gamma}_\tau^{\mathrm{r}})$, overcomes this particular problem. The presence of a specification error $\overline{\mathbf{X}}^{\mathrm{c}\prime}(\hat{\gamma}_\tau^{\mathrm{c}} - \hat{\gamma}_\tau^{\mathrm{r}})$ in the composition term [4.11] above is linked to the fact that the RIF regression-based procedure provides only a first-order approximation of the composition effect. Therefore, an examination of the size of the specification error provides insights into the accuracy (or otherwise) of the approximation. Finally, the re-weighting error is defined as $[\,\overline{\mathbf{X}}^{\mathrm{p}} - \overline{\mathbf{X}}^{\mathrm{c}}]'\hat{\gamma}_\tau^{\mathrm{c}}$; this reflects the extent to which the re-weighting procedure has been effective. The size of these effects should also be vanishingly small. This is assessed in the empirical part in Section 4.7.

The decomposition approach entails two identifying assumptions: (i) people are selected into sectors based only on their observables; and (ii) distributions of the observables for the two sectors overlap. The first assumption ensures that neither effect is confounded by inter-sectoral differences in the conditional distribution of the unobservables. The second rules out any observable characteristic completely identifying an individual as belonging to one or other sector. The first assumption is potentially problematic since it is possible that some unobservables may be partly driving the individual sector choice. This potential issue is acknowledged, but econometric procedures for dealing with endogenous selection within a RIF are not well developed. Nevertheless, in undertaking the empirical analysis, a key exercise informing the conclusions relates to taking period differences. This provides an insight into the effects on the public sector wage gap over time, and efficaciously nets out any unobservable selection effects assuming these are constant over time. In the case of the second condition, there is adequate data overlap and common support across the majority of covariates to enable this analysis.

4.7 Empirical Results

In this section, the wage gaps are estimated in a number of different ways. First and foremost, evidence of the raw public sector wage gap across selected quantiles of the male log wages distribution is provided. The results of a pooled regression for the public sector dummy and compare these with the regression results based on the standard decomposition methodology popularized by Oaxaca (1973) and Blinder (1973) is then discussed. The analysis using the recently introduced re-weighted RIF decomposition attributable to Firpo *et al.* (2011, 2018) is provided. These results are presented to see how the estimates from conventional procedures change when more sophisticated procedures are used. A discussion of the evolution of the unexplained (treatment effect) wage gaps across quantiles across both the crisis period (2006-2012) and the austerity period (2013-2019 is provided. The empirical results are reported graphically[76] in this section. Appendix A to this chapter reports the main point estimates and the corresponding standard errors. The key results include the employment size variable. These represent our preferred estimates as this is now the conventional approach adopted in the literature. The results in Appendix B that exclude the employment size variable are used to show how sensitive the estimation is to exclusion of employment size controls given there may be an issue with common support in this application.

4.7.1 The Public Sector Raw Wage Gap

Figure 4.8 contains the difference between the raw nominal public and private sector wages, at the mean and at selected points in the log wage distribution (viz., 10th, 25th, 50th, 75th and 90th percentile) for each year between 2002 and 2019. Overall, the raw difference between public and private sector wages is statistically significant and positive. In particular, it can be noted at the onset of the financial crisis, public sector workers at the top end of the wage distribution incurred a sizeable penalty.

[76] Given the volume of estimates, an appendix containing the underlying RIF estimates are available from the author on request.

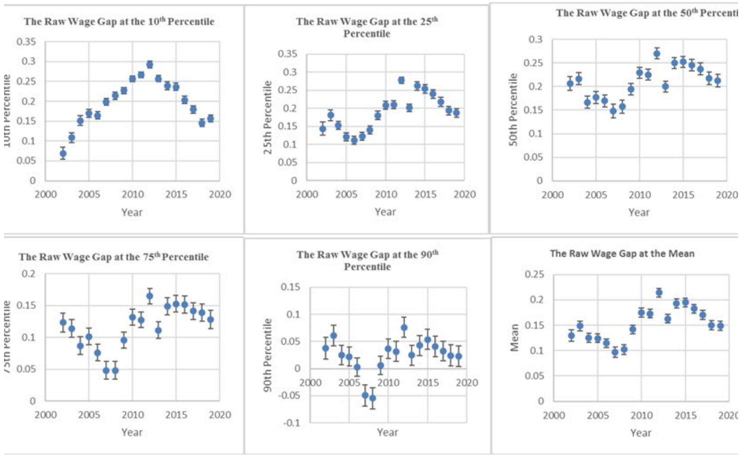

Figure 4. 8: Unadjusted Wage Gaps Across the Distribution (2002 to 2019)

Source: Author's calculations from the ASHE dataset.

This chapter examines the two-period difference splitting the sample size into the year immediately before the onset of the crisis (2006) and the year signalling the end of the crisis period (2012) is examined; The analysis considers 2006-2012 as the financial crisis period while the post-crisis or austerity period is 2013-2019. The analysis considers the difference for every 2nd percentile in the raw gaps from the 5th to the 95th percentiles: see Figure 4.9 and Figure 4.10. There seems to be a clear positive unadjusted public sector wage premium across the entire distribution during the crisis period. This implies that the financial crisis did not affect the raw public sector wage premium. However, over the austerity period (2013-2019), public sector employees at the bottom end of the distribution suffered a raw wage penalty. In summary, the raw pay of public sector workers relative to their private sector counterparts exhibits sizeable advantages enjoyed over the period of the financial crisis. However, during the austerity programme, the adjustments to public sector raw pay impacted the bottom end of the distribution in particular. Therefore, the less well-paid public-sector workers suffered a raw wage cut during the course of the austerity period. In order to address this, the policy adopted during this period was a pay freeze for all pay scales, with the exception of an annual £250 pay increase over two years for public sector workers earning less than £21,000 per annum (see Ferguson and Francis-Devine, 2021).

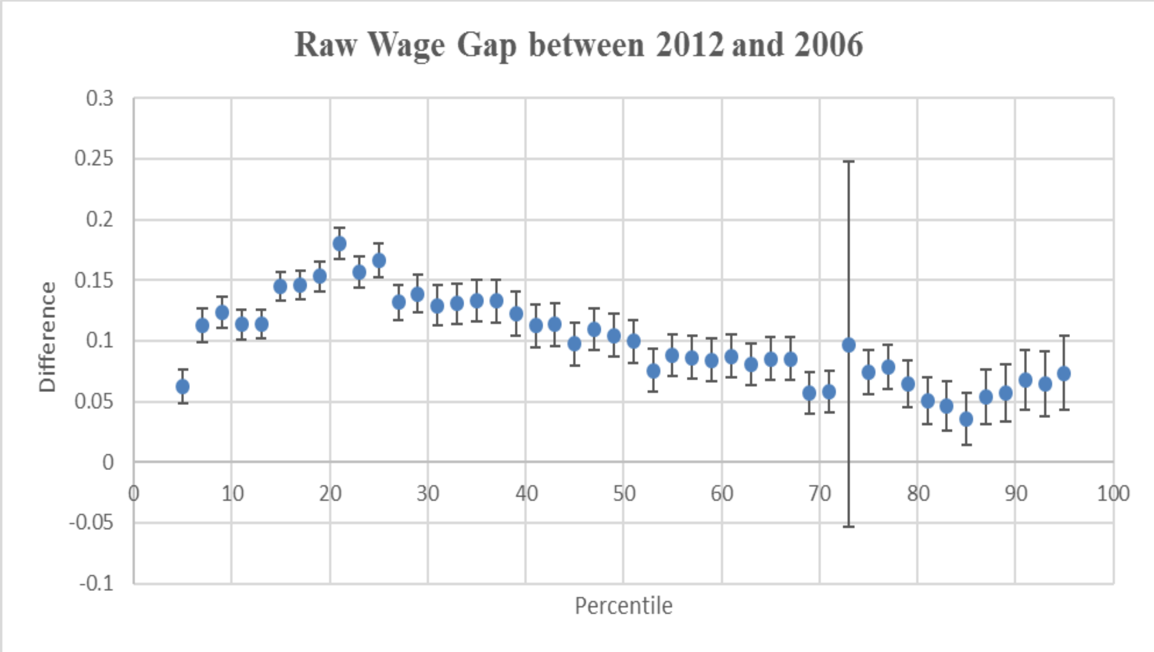

Figure 4. 9: The Unadjusted Wage Gap (Crisis Period)

Source: Author's calculations from the ASHE dataset.

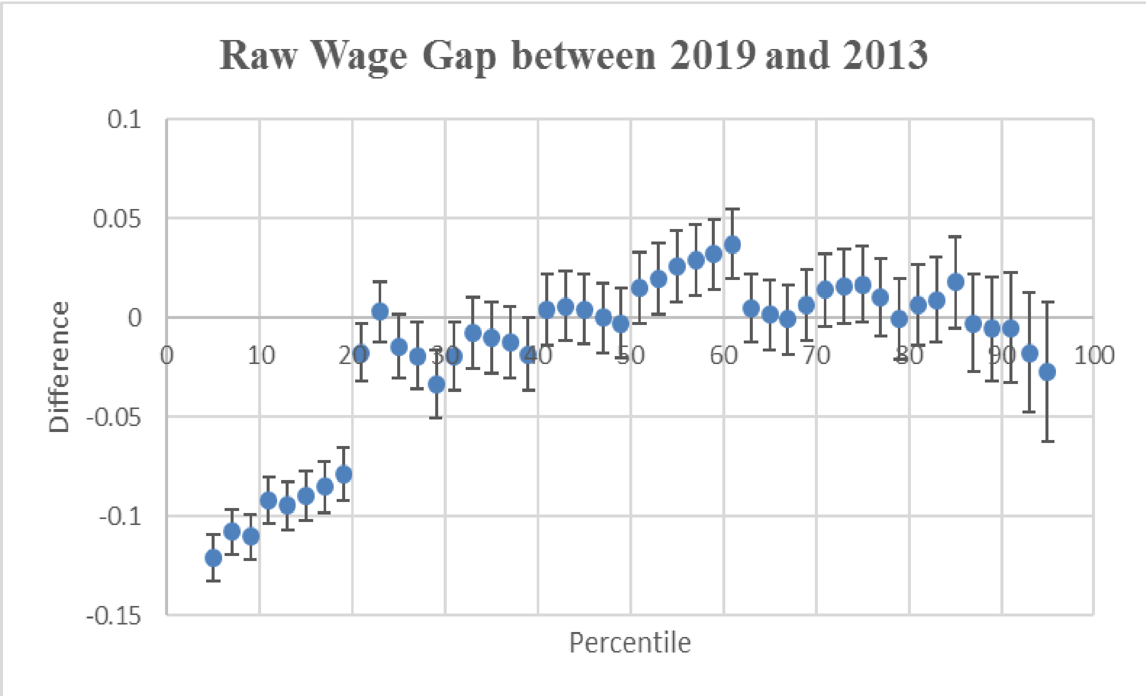

Figure 4. 10: The Unadjusted Wage Gap (Austerity Period)

Source: Author's calculations from the ASHE dataset

4.7.2 The Pooled Regression Models

Having examined the raw data in the previous section, the analysis controls for characteristics within a pooled regression framework. This allows us to adjust the public sector pay gap for productivity and other characteristics. The results based on the pooled sample provide some initial insights into how, *ceteris paribus,* the public sector wage gap changed along the log wage distribution. Figure 4.11 depicts the pooled regression model estimates for the public sector dummy variable and their corresponding confidence intervals. Appendix A Tables 4.A1, 4.A2 and 4.A3 present the OLS regression estimates for the pooled regression, and the separate OLS regression estimates for the public and private sectors, across selected years respectively. Table 4. A4 also reports the coefficient and standard errors for these plots in Figure 4.11.

The results generally suggest the absence of a public sector wage premium at the bottom end of the wage distribution. However, the 25th percentile reveals the existence of a public sector premium that seems to increase over the time of the financial crisis. In the austerity period, the wage gap narrows and disappears in the most recent years. However, in the period analysed, public sector employees, from the mean and median up to the 90th percentile, appeared to have suffered a wage penalty.

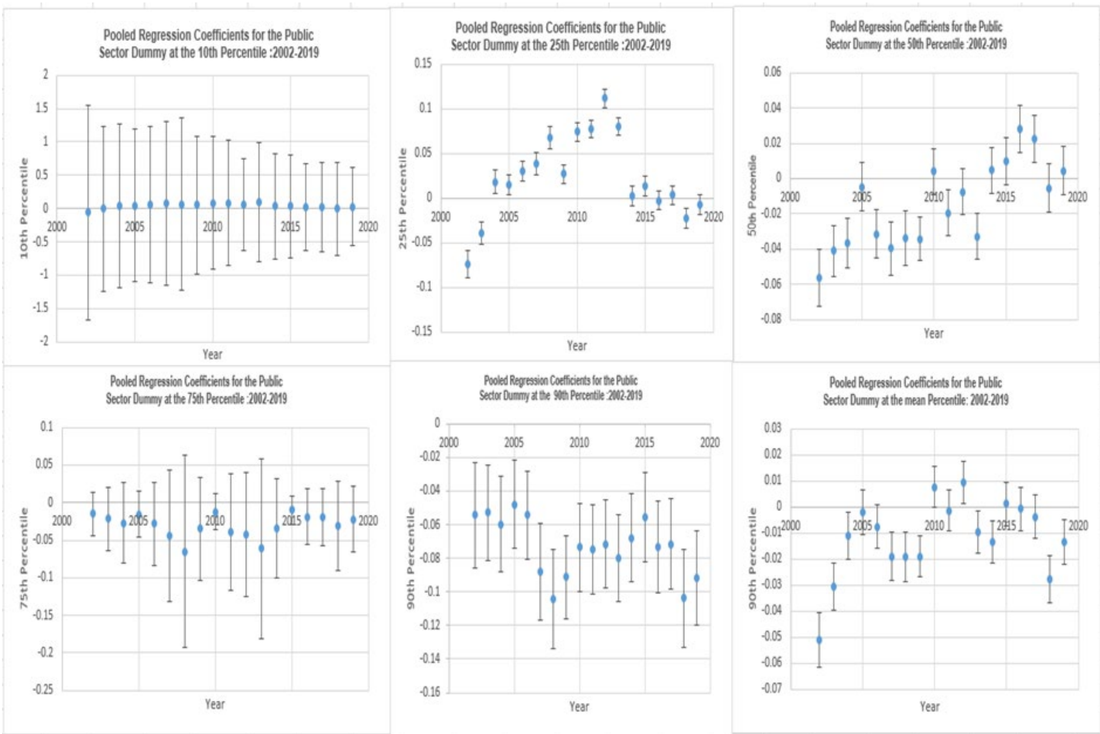

Figure 4. 11: Pooled Regression Coefficients by Selected Quantiles (2002 to 2019)

Notes: *Ceteris paribus* public sector estimates based on estimation of regression model [4.5] across selected percentiles

Overall, the evidence derived from estimating the pooled regression model [4.5] is fairly consistent with the findings in the literature related to the public sector pay gap in Great Britain (Disney and Gosling, 1998; Blackaby *et al.*, 2018). Next a more granular examination, focusing on period-on-period differences for every second percentile, from the 5th to the 95th percentile of the log wage distribution is conducted. Figure 4.12 plots the differences among these percentiles in the coefficients of the public sector dummy over the period 2006 to 2012. It suggests that during the period of the financial crisis, the public sector pay gap at the bottom end of the distribution increased relative to the private sector, but that from about the 50th percentile onwards little else changed. This in turn suggests that public sector workers at the bottom end of the distribution experienced an increase in their wage premium during the period of the financial crisis, while high wage-earning workers were largely unaffected.

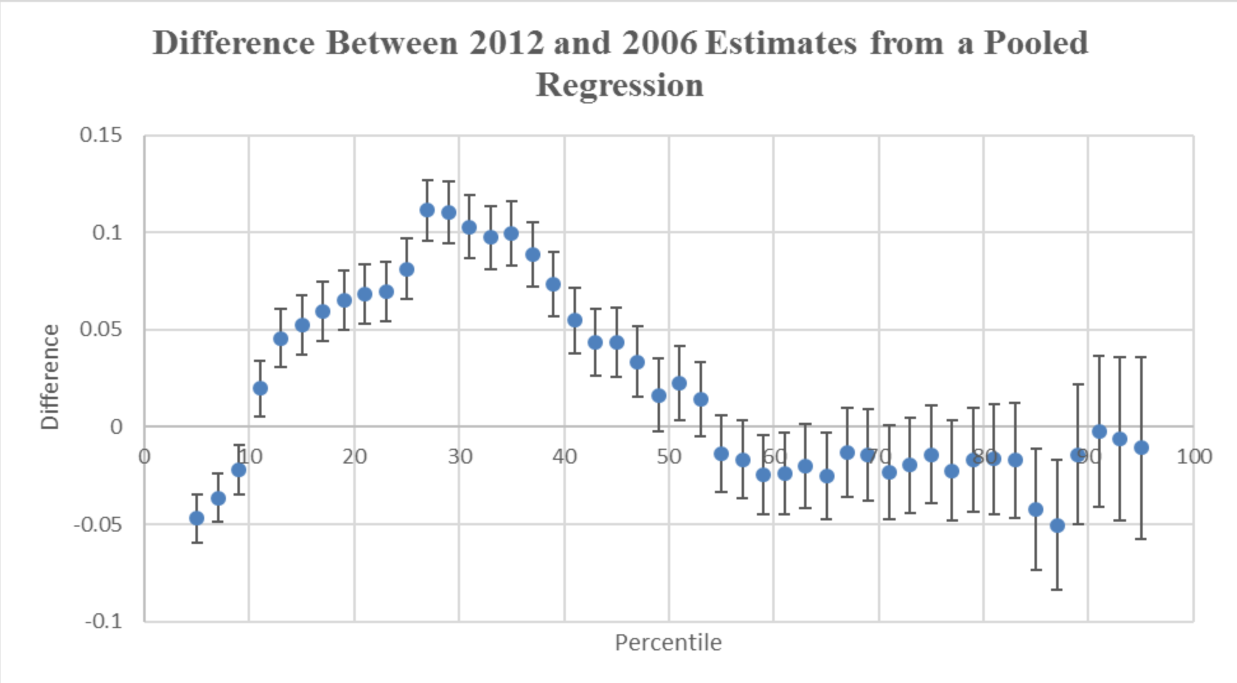

Figure 4. 12: Pooled Regression Coefficients Differential (Crisis Period)

Notes: *Ceteris paribus* public sector estimates differences based on estimation of regression model [4.5] across selected percentiles

The result in Figure 4.13 suggests that conditions flipped during the austerity period, and the workers that suffered the biggest hit were at the bottom end of the public sector log wage distribution. However, significant wage premium effects for those around the 50th percentile and above are observed. Appendix B Figures 4.B1 and 4.B2 provide evidence that these results are invariant to the exclusion of the employment size variable, but that the standard errors are larger. However, they do reveal a broadly consistent picture.

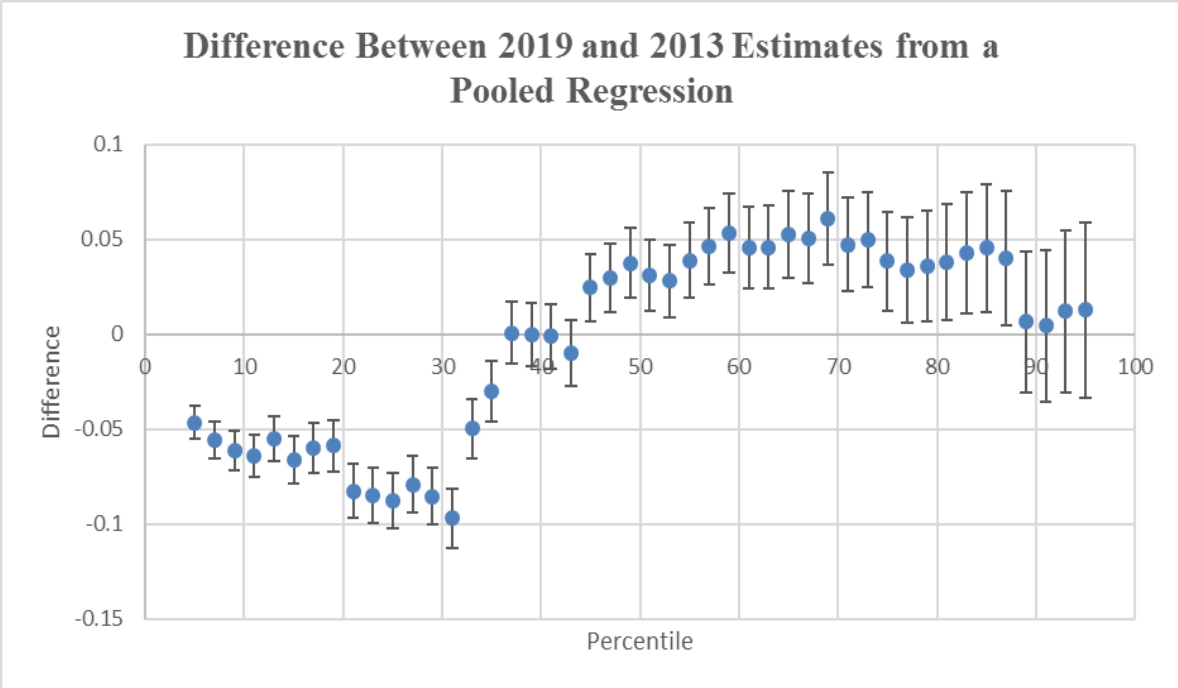

Figure 4. 13: Pooled Regression Coefficients Differential (Austerity Period)

Notes: *Ceteris paribus* public sector estimates differences based on estimation of regression model [4.5] across selected percentiles

Overall, the empirical evidence derived from the pooled regression models suggest that the austerity policy measures appear to have had an adverse effect on public sector employees at the bottom end of the distribution. On the other hand, both the financial crisis and the austerity shocks appear to have had significant positive effects on the wage setting mechanism from about the median to the top end of the wage distribution. Workers from the 50^{th} percentile and above, who were penalized during the financial crisis, appear to have enjoyed a premium during the austerity period.

4.7.3 The Oaxaca-Blinder Decomposition

As already noted, the coefficients in the pooled regression models suffer from the major drawback that individual characteristics are likely to be priced differently between the two sectors. In order to address this limitation, the standard OB approach within the quantile regression framework (see expression [4.10]) is used. This decomposition allows us to determine the unexplained (treatment) and explained (endowment) components of the total wage differential. In this case, the interest is primarily in the unexplained component, given that it provides a treatment estimate and is interpreted as a wage premium (penalty) for the public sector if positive (negative).

Figure 4.14 reports that the treatment effect of the public sector wage gap fluctuated during the period of the financial crisis but remained slightly positive and stable across the selected percentiles of the wage distribution. This significant treatment effect is more pronounced at the mean and the median. The public sector wage premium persisted during the financial crisis across the 10th, 25th, 50th, 75th, 90th percentiles and the mean, and was unaltered in the post-crisis period. Overall, there is a relatively stable public sector premium across the selected percentiles of the wage distribution that do not appear to have been affected by either the financial crisis or the austerity measures adopted in the aftermath of the crisis. Appendix A Table 4.A5 provides the point estimates and standard errors for the plots in Figure 4.14, confirming that the treatment effects are significant across the selected years and percentiles of the wage distribution.

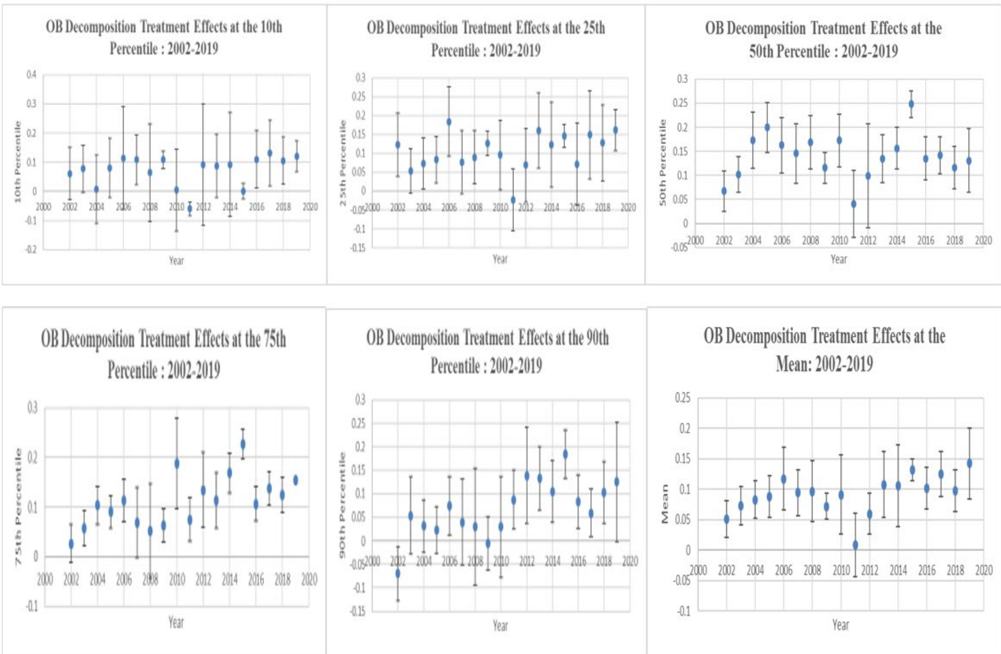

Figure 4. 14: OB Public Sector Treatment Effects by Selected Quantiles (2002 to 2019)

Notes: Public sector difference in treatment effects estimates based on regression model [4.10] using the ASHE dataset

Figure 4.15 reports the differences in the treatment effect over the period of the crisis. The results seem to suggest that, during the period of the financial crisis, the public sector premium was relatively stable across the entire log wage distribution, with the exception of workers in the 13th to the 21st percentiles. Overall, this decomposition method reveals that the public sector premium was again unaltered during the crisis period.

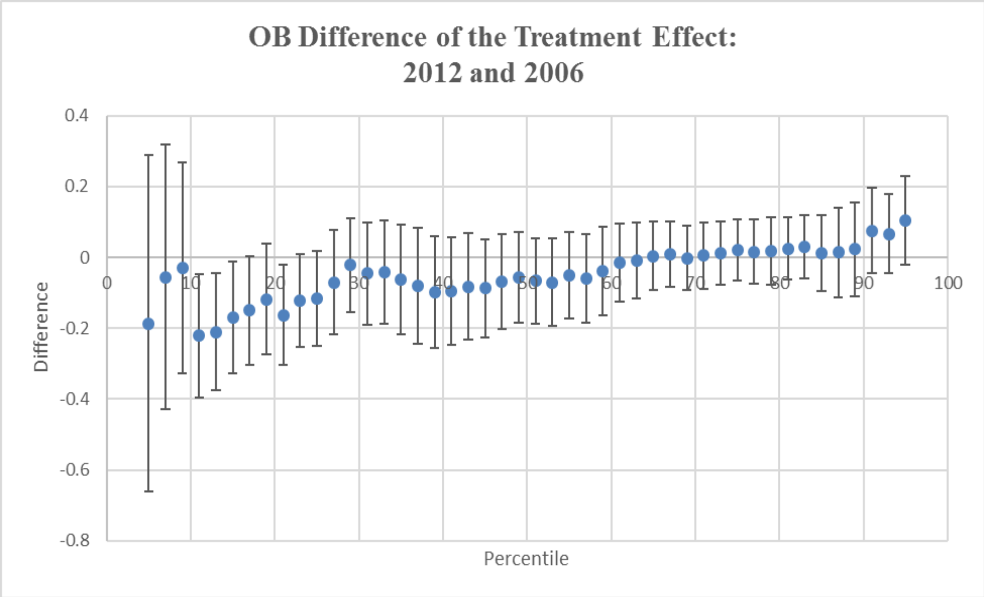

Figure 4. 15: OB Public Sector Differential Treatment Effects (Crisis Period)

Notes: Public sector difference in treatment effects estimates based on regression model [4.10] using the ASHE dataset

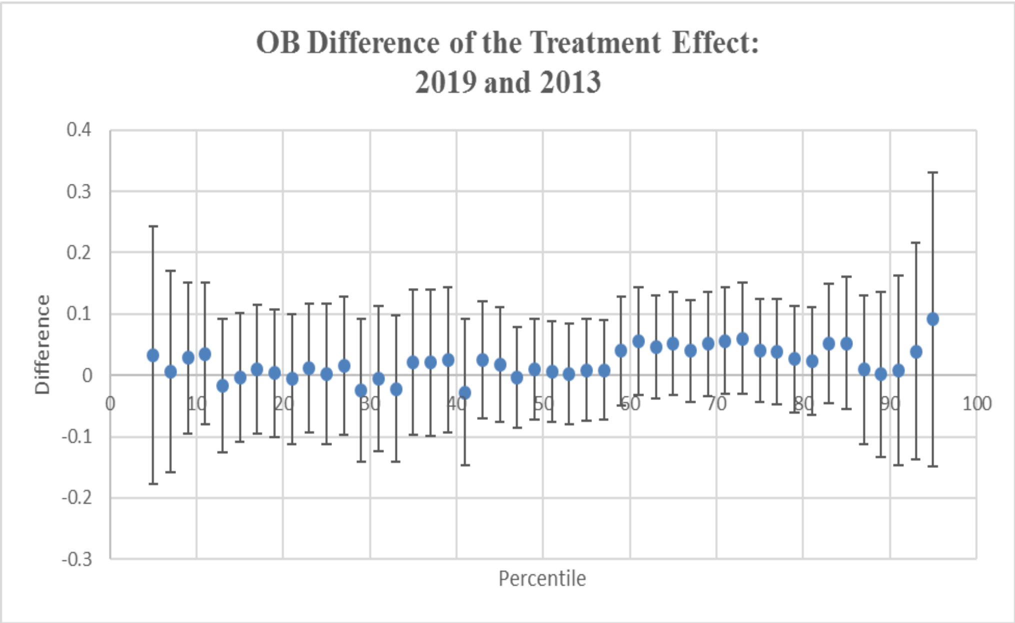

Figure 4. 16: OB Public Sector Differential Treatment Effects (Austerity Period)

Notes: Public sector difference in treatment effects estimates based on regression model [4.10] using the ASHE dataset

Figure 4.16 records that the public sector wage premium changed little during the austerity period. In general, the OB decomposition reveals that there was no statistically significant change in the unexplained part of the pay gap during either the crisis or the austerity periods. None of the estimates are statistically different from zero. In addition, during the period of public sector wage freezes and cuts, there were no statistically significant changes to the wage premium across the entire unconditional distribution. The fiscal consolidation measures adopted during this period appear not to have had an adverse impact on the public sector wage premium across the entire log wage distribution; this result is invariant to the inclusion or exclusion of an employment size variable, as shown in Appendix B Figures 4.B4 and 4.B5.

4.7.4 The Re-weighted Oaxaca-Blinder Decomposition

Building on the contribution of Firpo *et al*. (2011, 2018), the re-weighted regression approach to further analyse the public sector pay gap across the unconditional basic[77] pay distribution is used. As noted above, the focus is on the first term on the right-hand side of expression [4.11].

The specification and reweighting errors are two components that can be used to assess the overall goodness of fit of the decomposition technique. The reweighting error evaluates the quality of the reweighting strategy and is expected to be close to 0 in large samples. A large significant reweighting error implies that the counterfactual is not well identified and that the specification of the probit or logit models used for the estimation of reweighting factors may need to be modified. The specification error is used to assess the quality of the model specification and the RIF approximation. A large and significant specification error may be an indication that the RIF regression is mis-specified or that the RIF is providing a poor approximation for the distributional statistic. In the current application both errors were found to be vanishingly small and statistically insignificant.

Figure 4.17 confirms that at the 10th and 25th percentiles, public sector workers were no better off than private sector workers during most of the pre-crisis and crisis periods. However, during the austerity period, the public sector wage premium held up well at the bottom end of the log wage distribution. In contrast, highly paid public sector workers were not impacted by either the financial crisis or the austerity measures adopted post-crisis. This confirms that neither the financial crisis nor the austerity periods substantially altered the public sector wage premium along the entire log wage distribution. The point estimates for some key selected years are provided in Appendix A Table 4.A6.

[77] The analysis only focuses on basic pay; however, it is acknowledged that performance related pay is likely to be more of an issue as we move up the pay distribution and it is likely to be more of a feature in the private sector than the public. Furthermore, total remuneration may reveal different patterns to salary.

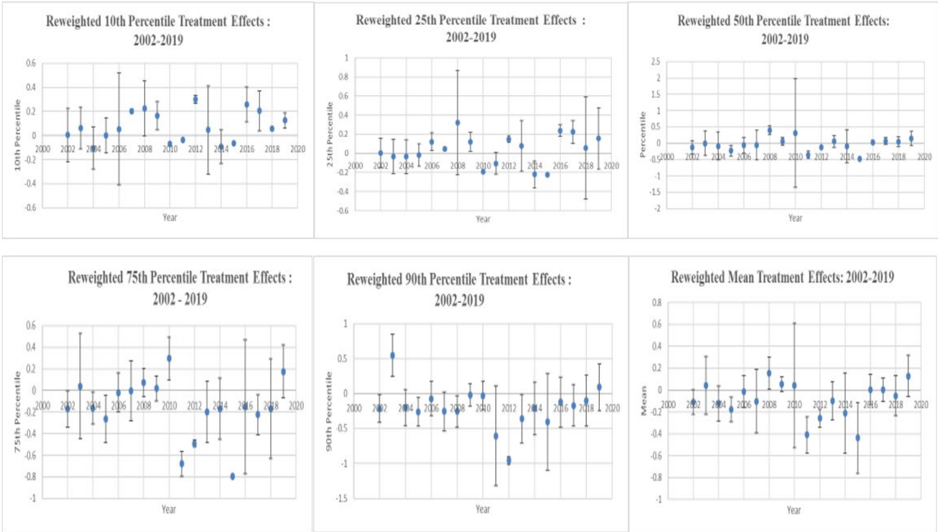

Figure 4. 17: Re-weighted Public Sector Treatment Effects by Selected Quantiles

Notes: Public sector difference in treatment effects estimates based on regression model [4.11] using the ASHE dataset for selected quantiles

The differentials in the treatment gaps are depicted in Figure 4.18 and suggest that from the 5th to the 95th percentiles, the financial crisis had heterogeneous effects on the log wage distribution, with public sector workers between the 65th and 89th percentiles experiencing a wage penalty. There is no discernible impact on the other percentiles. However, note that the re-weighting approach yields a slightly different picture and reveals that during the crisis, there was a significant decline in the public sector wage premium at the top end of the distribution. The financial crisis seems to have had a heterogeneous effect on the public sector wage setting mechanism, with a wage penalty at the top end of the distribution but no effect on the wage premium at the bottom end. This wage penalty may reflect the wage freeze policy related to highly paid public sector workers that was adopted during this period.

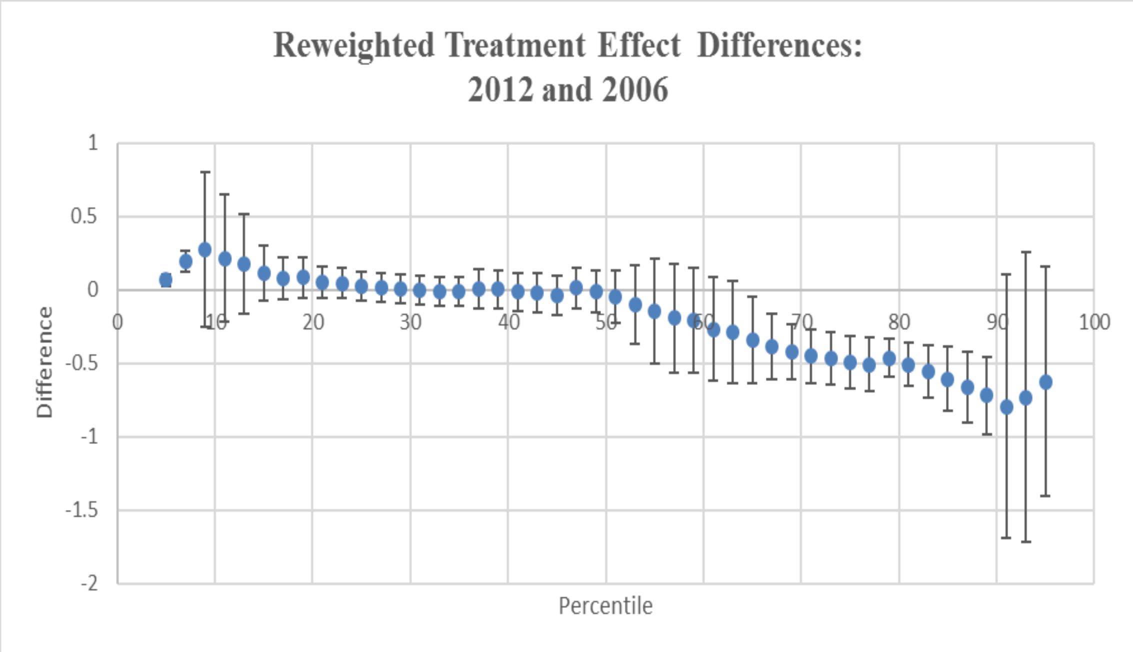

Figure 4. 18: Re-weighted Public Sector Differential Treatment Effects (Crisis Period)

Notes: Public sector difference in treatment effects estimates based on regression model [4.11] using the ASHE dataset.

Focusing on the austerity period, Figure 4.19 provides evidence that the public sector workers at the top end of the distribution began to experience improvements in their position, but there is an indication that the fiscal consolidation measures adopted during this period exerted no significant effect on the treatment effect at the bottom end of the wage distribution. [78]Most public sector workers received pay awards above 2% from 2018; this might have led to a bounce back of the pay premium for workers at the top end of the distribution. These results are sensitive to controlling for employment in the regression. Appendix B Figures 4.B5 and 4.B6 show that the effects of the wage structure policies adopted during these periods disappear if employment size is not controlled for in both periods. Blackaby *et al.* (2018) reported the sensitivity of their results to the introduction of establishment size controls, and this finding confirms that this is indeed a potential issue here.

---

[78] In contrast to Murphy *et al. (*2020) the result from this chapter shows the absence of a public sector premium post-2012 at the lower part of the distribution. This might be due to the fact that Murphy *et al*. (2020) analyses a different period (1994 and 2017) and use a different dataset (the LFS) while this Chapters uses the ASHE dataset.

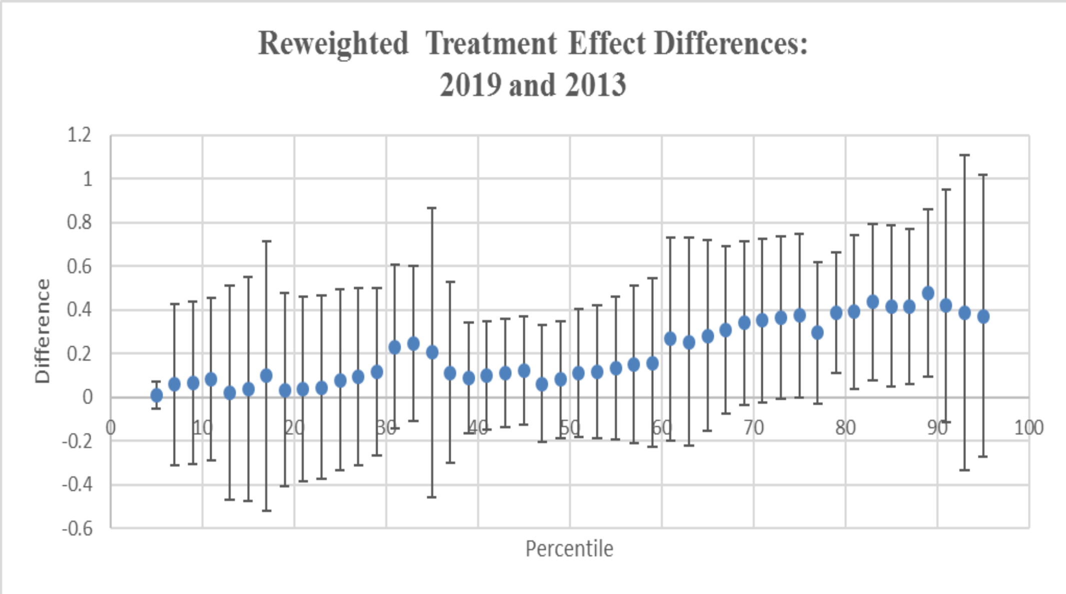

Figure 4. 19: Re-weighted Public Sector Differential Treatment Effects (Austerity Period)

Notes: Public sector difference in treatment effects estimates based on regression model [4.11] using the ASHE dataset.

In summary, allowing for differential effects between the two sectors, little change across the two periods (crisis and austerity) is detected. However, applying the more sophisticated re-weighting technique, reveals that over the period of the financial crisis that public sector workers at the top end of the distribution experience a reduction in their pay but their wage premium then increased over the austerity period. This would seem to provide evidence suggesting that the public sector wage policy adopted during this period to favour low-skilled over more highly skilled workers (see Ferguson and Francis-Devine, 2021) did have an effect. This was particularly so for those in the top end of the distribution.

4.8 Conclusions and Policy Implications

It is a stylized fact that unadjusted hourly pay levels in the UK are higher in the public compared to the private sector. This is reconfirmed by the empirical analysis in this chapter that examined the period from 2002 to 2019 in detail. However, the empirical evidence suggests that a large part of this difference reflects differences in worker endowments and difference in the returns to these endowments between the two sectors. The difference in the returns to worker endowments is described in the literature as the treatment effect. This chapter estimated the public sector wage treatment effect using a variety of related methods including a pooled regression model, the standard OB decomposition technique, and the re-weighting procedure within the OB framework, which was originally proposed by Firpo *et al*. (2011, 2018). Furthermore, the difference between the treatment effects for the two main periods that suffered an economic shock, to obtain the impact of the financial crisis (2006-2012) and the period of austerity (2013-2019) on the public sector pay gap is investigated.

Overall, the pooled regression model estimates and the OB decompositions provide evidence that the public sector wage premium was counter-cyclical in nature. During the financial crisis, public sector wages held up reasonably well across the entire distribution, such that the gap was not adversely affected. In addition, although austerity policies were introduced and implemented, the wage positions of public sector workers remained largely unaffected. This suggests that wages did not adjust in the public sector; this might suggest that neither the financial crisis nor the austerity policy had implications for the public sector wage setting mechanism. However, this finding does not preclude a possible effect of the financial shock and the austerity programme on the size of public sector employment. In other words, the key adjustment to the financial crisis and the austerity programme might be along the dimension of employment size rather than worker wages.

The adjustment to the wage bill might also have been achieved by an increase in the number of hours worked by public sector employees; this would have reduced the number of workers required to provide a given quality of service. There was a decline in employment size during both periods and this might suggest that the public sector might have adjusted to the financial crisis and austerity by reducing employment and not necessarily wages. The public sector workforce shrank, with some lower paid jobs shifting to the private sector. In addition, public sector wages for full-time working men might have held up well relative to those received by men working in the private sector. However, the analysis in this chapter does not identify the impact on part-time workers where the effects may potentially be starker. This is an agenda for future research. Additionally, women make up a sizable proportion of total employment in the public sector, but the analysis undertaken in this chapter only examined the pay structure for men. Repeating this analysis focusing only on women would seem a fruitful direction to undertake as part of an agenda for future research.

The earlier discussions above regarding the public sector wage gap are based on a public sector dummy in a pooled regression framework. This would seem to be an insufficient strategy, since it constrains the returns to the covariates to be uniform between the two sectors. This questions the conclusion about the strength of the public sector wage gap over the two periods. There is some evidence that taking into consideration the re-weighting the distribution of public covariates to align it with those of the private sector suggests that during the financial crisis, workers at the at the top end of the distribution (or the higher paid workers) experienced a narrowing of their wage gap with the private sector. However, during the austerity period, there is some evidence that this did not occur. In some sense, this is consistent with the policies adopted during the two periods. It is true that a policy of implementing public pay cuts or freezes would be made easier if the highest-paid were seen to be bearing their share of the pain. This has an implication for policy in that a wage policy that seeks to support low wage earners while penalizing high wage earners in the public sector might have an implication in attracting and retaining of high skilled and talented workers. This could compromise the quality of the delivery of public services.

Appendix A: Figures and Tables for Primary Estimation

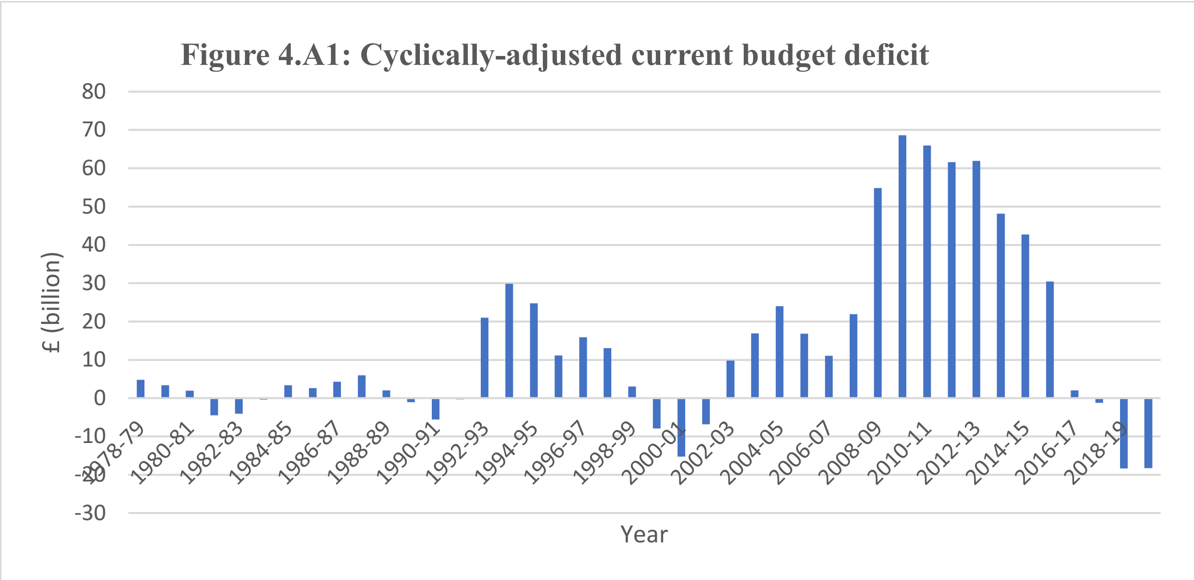

Figure 4A.1: Cyclically Adjusted Current Budget Deficit in Billion (£): (1978-2020)

Source: Office for Budget Responsibility, UK

Table 4A.1: Pooled Regression Estimates for Selected Years

VARIABLES	(2002) lwage	(2006) lwage	(2012) lwage	(2019) lwage
age	0.0468***	0.0422***	0.0377***	0.0417***
	(0.0011)	(0.0008)	(0.0007)	(0.0008)
age squared	-0.0005***	-0.0005***	-0.0004***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log employment	0.0177***	0.0126***	0.0161***	0.0167***
	(0.0007)	(0.0005)	(0.0005)	(0.0005)
tenure1	0.0166***	0.0204***	0.0184***	0.0145***
	(0.0015)	(0.0011)	(0.0010)	(0.0049)
tenure2	0.0055***	0.0081***	0.0085***	0.0035
	(0.0011)	(0.0009)	(0.0009)	(0.0027)
tenure3	0.0032***	0.0026***	0.0033***	0.0025***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
permanent	0.0810***	0.0945***	0.0788***	0.0986***
	(0.0115)	(0.0076)	(0.0057)	(0.0084)
public	-0.0511***	-0.0076*	0.0094**	-0.0135***
	(0.0053)	(0.0043)	(0.0041)	(0.0044)
Observations	42,262	64,079	70,578	59,853
R-squared	0.5935	0.5967	0.5926	0.5388
1Digit Industry dummies	Yes	Yes	Yes	Yes
2Digit Occupation dummies	Yes	Yes	Yes	Yes
Nuts1 dummies	Yes	Yes	Yes	Yes

Notes: Robust Standard Error in Parentheses *** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations from the ASHE dataset.

Table 4A.2: OLS Regression Estimates for Selected Years (Public Sector)

	(2002)	(2006)	(2012)	(2019)
VARIABLES	**lwage**	**lwage**	**lwage**	**lwage**
age	0.0397***	0.0332***	0.0361***	0.0413***
	(0.0023)	(0.0017)	(0.0018)	(0.0020)
age squared	-0.0004***	-0.0004***	-0.0004***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log employment	-0.0043**	-0.0133***	-0.0054***	-0.0092***
	(0.0022)	(0.0016)	(0.0016)	(0.0022)
tenure1	0.0230***	0.0276***	0.0185***	0.0213***
	(0.0032)	(0.0023)	(0.0027)	(0.0027)
tenure2	0.0085***	0.0081***	0.0121***	0.0078***
	(0.0022)	(0.0017)	(0.0017)	(0.0021)
tenure3	0.0052***	0.0040***	0.0018***	0.0024***
	(0.0006)	(0.0004)	(0.0004)	(0.0006)
permanent	0.0476**	0.0636***	0.0772***	0.1335***
	(0.0218)	(0.0141)	(0.0139)	(0.0156)
Observations	**8,615**	**12,738**	**13,777**	**8,848**
R-squared	0.6948	0.6807	0.5980	0.5556
1Digit Industry dummies	Yes	Yes	Yes	Yes
2Digit Occupation dummies	Yes	Yes	Yes	Yes
Nuts1 dummies	Yes	Yes	Yes	Yes

Notes: Robust Standard Error in Parentheses *** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations from the ASHE dataset.

Table 4A.3: OLS Regression Estimates for Selected Years (Private Sector)

VARIABLES	(2002) lwage	(2006) lwage	(2012) lwage	(2019) lwage
age	0.0478***	0.0438***	0.0378***	0.0416***
	(0.0012)	(0.0009)	(0.0008)	(0.0009)
age squared	-0.0005***	-0.0005***	-0.0004***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log employment	0.0196***	0.0147***	0.0178***	0.0182***
	(0.0007)	(0.0006)	(0.0005)	(0.0006)
tenure1	0.0163***	0.0192***	0.0178***	0.0139***
	(0.0017)	(0.0012)	(0.0011)	(0.0052)
tenure2	0.0050***	0.0085***	0.0076***	0.0025
	(0.0013)	(0.0011)	(0.0010)	(0.0029)
tenure3	0.0025***	0.0021***	0.0040***	0.0024***
	(0.0004)	(0.0003)	(0.0003)	(0.0003)
permanent	0.0803***	0.0987***	0.0771***	0.0902***
	(0.0134)	(0.0090)	(0.0062)	(0.0093)
Observations	33,647	51,341	56,801	51,005
R-squared	0.5709	0.5811	0.5827	0.5337
1Digit Industry dummies	Yes	Yes	Yes	Yes
2Digit Occupation dummies	Yes	Yes	Yes	Yes
Nuts1 dummies	Yes	Yes	Yes	Yes

Notes: Robust Standard Error in Parentheses *** p<0.01, ** p<0.05, * p<0.1

Source: Author calculations from the ASHE dataset.

Table 4A.4: Pooled Regression Dummy Estimates for Selected Years

Percentile	2002	2006	2012	2019
	Public sector Coefficient	**Public sector Coefficient**	**Public sector Coefficient**	**Public sector Coefficient**
10	-0.0600 (0.0082)	0.0583*** (0.0060)	0.0586*** (0.0035)	0.0260*** (0.0030)
25	-0.0739*** (0.0080)	0.0304*** (0.0059)	0.1118*** (0.0053)	-0.0072 (0.0054)
50	-0.0565*** (0.0083)	-0.0314*** (0.0069)	-0.0076 (0.0066)	0.0044 (0.0069)
75	-0.0150 (0.0107)	-0.0282*** (0.0090)	-0.0423*** (0.0091)	-0.0224** (0.0099)
90	-0.0544**** (0.0161)	-0.0543*** (0.0134)	-0.0716*** (0.0135)	-0.0917*** (0.0145)
mean	-0.0511*** (0.0053)	-0.0076* (0.0043)	0.0094*** (0.0041)	-0.0135*** (0.0044)

Notes: Robust Standard Error in Parentheses *** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations from the ASHE dataset.

Table 4A.5: Oaxaca Quantile Treatment Effects Estimates for Selected Years

Percentile	2002	2006	2012	2019
	Treatment	Treatment	Treatment	Treatment
10	0.0616 (0.0427)	0.1148 (0.0894)	0.0916 (0.1060)	0.1210*** (0.0268)
25	0.1232 (0.0785)	0.1840*** (0.0469)	0.0688 (0.0494)	0.1621*** (0.0277)
50	0.0673*** (0.0214)	0.1625*** (0.0292)	0.0992* (0.0551)	0.1310*** (0.0336)
75	0.0267 (0.0197)	0.1138*** (0.0217)	0.1341*** (0.0383)	0.1540*** (0.0319)
90	-0.0700*** (0.0298)	0.0737*** (0.0316)	0.1391*** (0.052)	0.1252* (0.0646)
mean	0.0507*** (0.0153)	0.0117 (0 .0263)	0.0597*** (0.0169)	0.1426*** (0.0297)

Notes: Robust Standard Error in Parentheses *** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations from the ASHE dataset.

Table 4A.6: Re-weighted Quantile Treatment Effects Estimates for Selected Years

Percentile	2002		2006		2007		2012		2019	
	Total	**Treatment**	**Total**	**Treatment**	**Total**	**Treatment**	**Total**	**Treatment**	**Total**	**Treatment**
10	0.0692***	0.0037	0.1643***	0.0546	0.1987***	0.2021***	0.2921***	0.3001***	0.1570***	0.1268***
	(0.0076)	(0.1124)	(0.0049)	(0.2377)	(0.0047)	(0.0104)	(0.0043)	(0.0171)	(0.0044)	(0.0322)
25	0.1442***	0.004	0.1115***	0.1215***	0.1229***	0.0469***	0.2776***	0.1480***	0.1871***	0.1548
	(0.0094)	(0.0785)	(0.0054)	(0.0477)	(0.0058)	(0.0105)	(0.0045)	(0.0171)	(0.0062)	(0.1628)
50	0.2065***	-0.1237	0.1696***	-0.0657	0.1485***	-0.0580	0.2703***	-0.1275***	0.2126***	0.1492
	(0.0077)	(0.0997)	(0.0064)	(0.1252)	(0.0074)	(0.2307)	(0.006)	(0.0172)	(0.0068)	(0.1117)
75	0.1232***	-0.1706**	0.0763***	-0.0188	0.0484***	-0.0036	0.1647***	-0.4915***	0.1282***	0.1763
	(0.0077)	(0.0862)	(0.0067)	(0.0913)	(0.0072)	(0.1428)	(0.0063)	(0.0172)	(0.0073)	(0.1244)
90	0.0377***	-0.2137***	0.0024***	-0.0716	- 0.0494***	-0.2531*	0.0762***	-0.956***	0.0227***	0.0897
	(0.0101)	(0.1027)	(0.0087)	(0.1234)	(0.0099)	(0.1428)	(0.0092)	(0.0278)	(0.0099)	(0.1709)
mean	0.1302***	-0.108*	0.01145***	-0.0133	0.0968***	-0.1032	0.2143***	-0.2581***	0.1488***	0.1286
	(0.0058)	(0.0571)	(0.0045)	(0.0740)	(0.005)	(0.1474)	(0.0043)	(0.0408)	(0.0047)	(0.0958)

Notes: Robust Standard Error in Parentheses *** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations from the ASHE dataset.

Table 4A.7: Cell Sizes for The Analysis of the Public Sector Male Wage Gap

Year	Total Sample Size	Public	Private
2002	42,280	8,615	33,647
2003	59,577	11,008	48,569
2004	60,648	12,185	48,463
2005	63,570	12,964	50,606
2006	64,099	12,738	51,341
2007	52,922	9,976	42,946
2008	52,240	9,927	42,313
2009	62,105	13,260	48,845
2010	61,894	13,458	48,436
2011	64,893	13,623	51,270
2012	70,637	13,777	56,801
2013	63,615	12,048	51,567
2014	64,551	10,543	54,008
2015	63,426	10,357	53,069
2016	61,871	10,087	51,784
2017	62,124	9,873	52,251
2018	61,859	9,297	52,562
2019	59,853	8,848	51,005

Source: Author’s calculations from using the ASHE dataset.

Appendix B: Estimation Results Without the Employment Size Variable

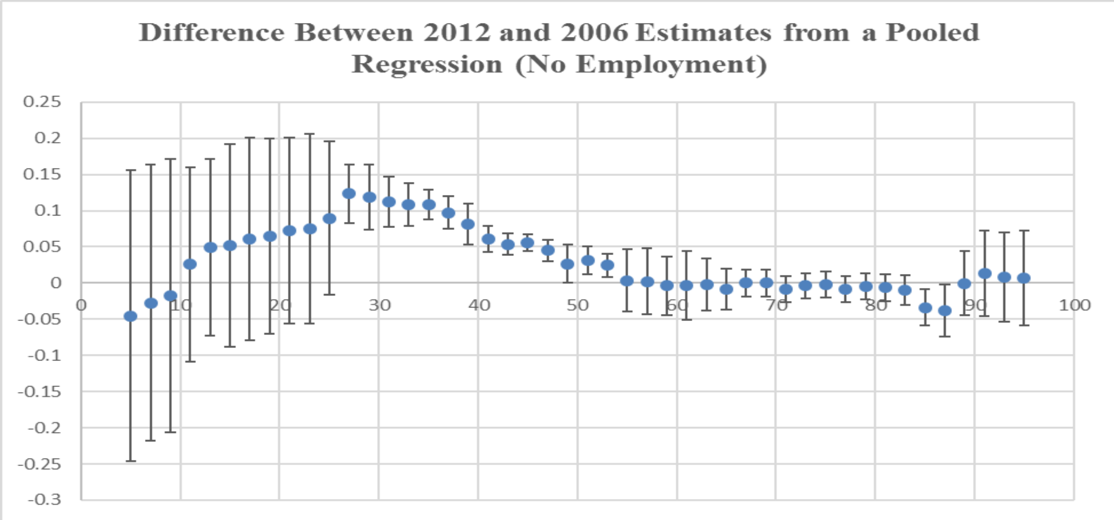

Figure 4B.1: Pooled Regression Differential for the Crisis Period

Source: Author's calculations from the ASHE dataset.

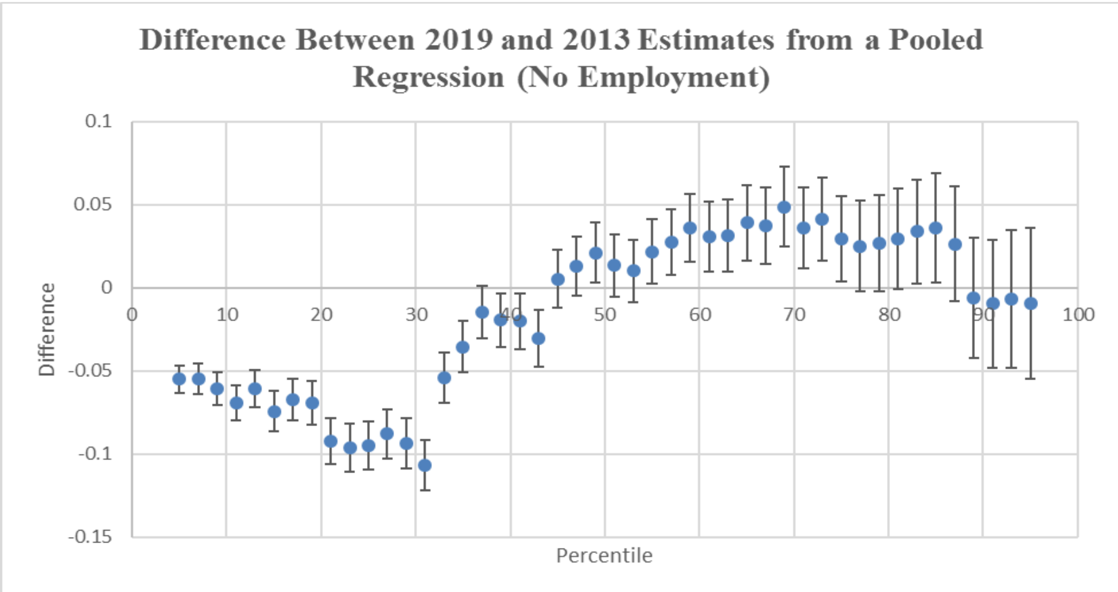

Figure 4B.2: Pooled Regression Differential for the Austerity Period

Source: Author's calculations from the ASHE dataset.

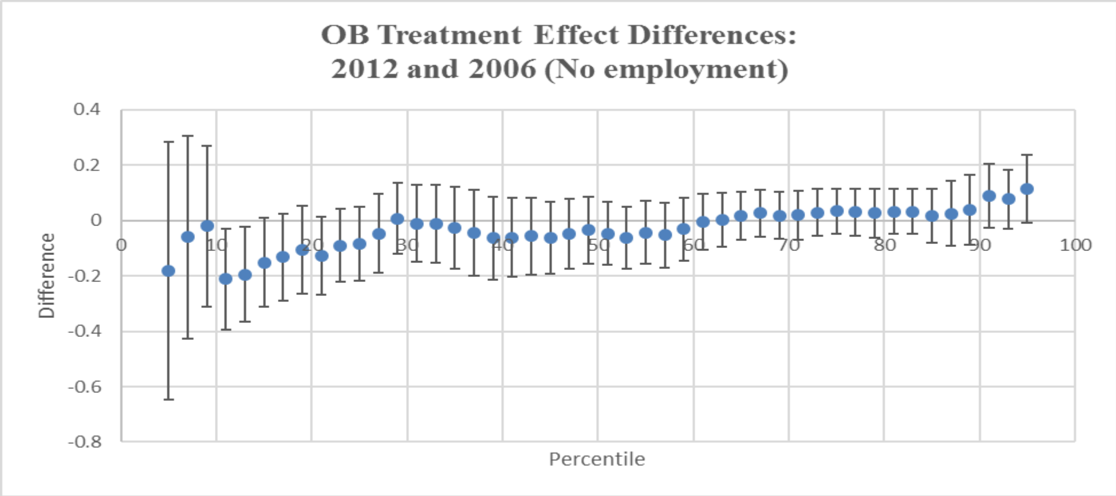

Figure 4B.3: OB Public Sector Differential Treatment Effects for the Crisis Period

Source: Author's calculations from the ASHE dataset.

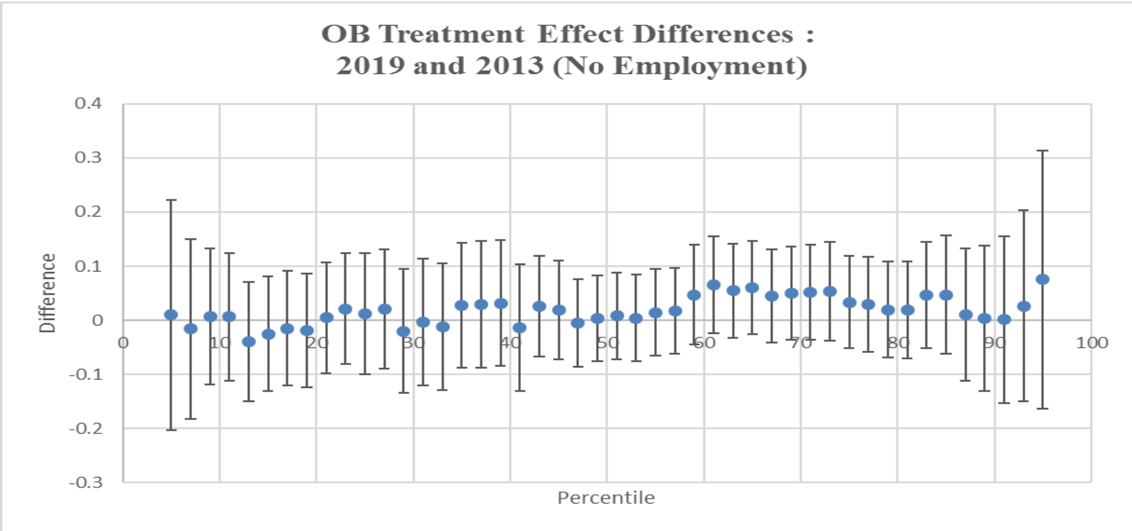

Figure 4B.4: OB Public Sector Differential Treatment Effects (Austerity Period)

Source: Author's calculations from the ASHE dataset.

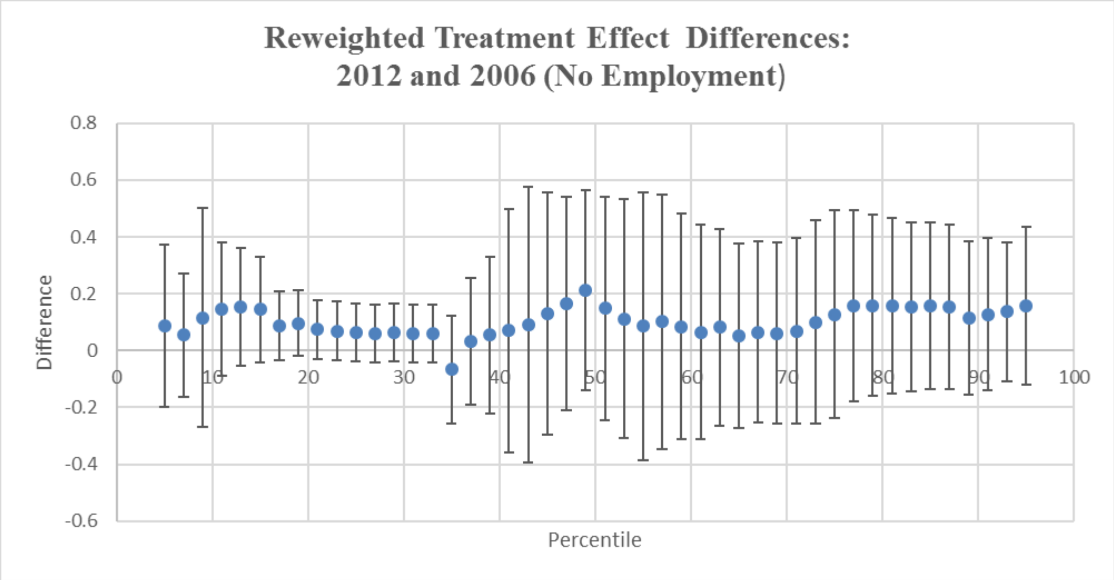

Figure 4B.5: Re-weighted Public Sector Differential Treatment Effects. (Crisis Period)

Source: Author's calculations from the ASHE dataset.

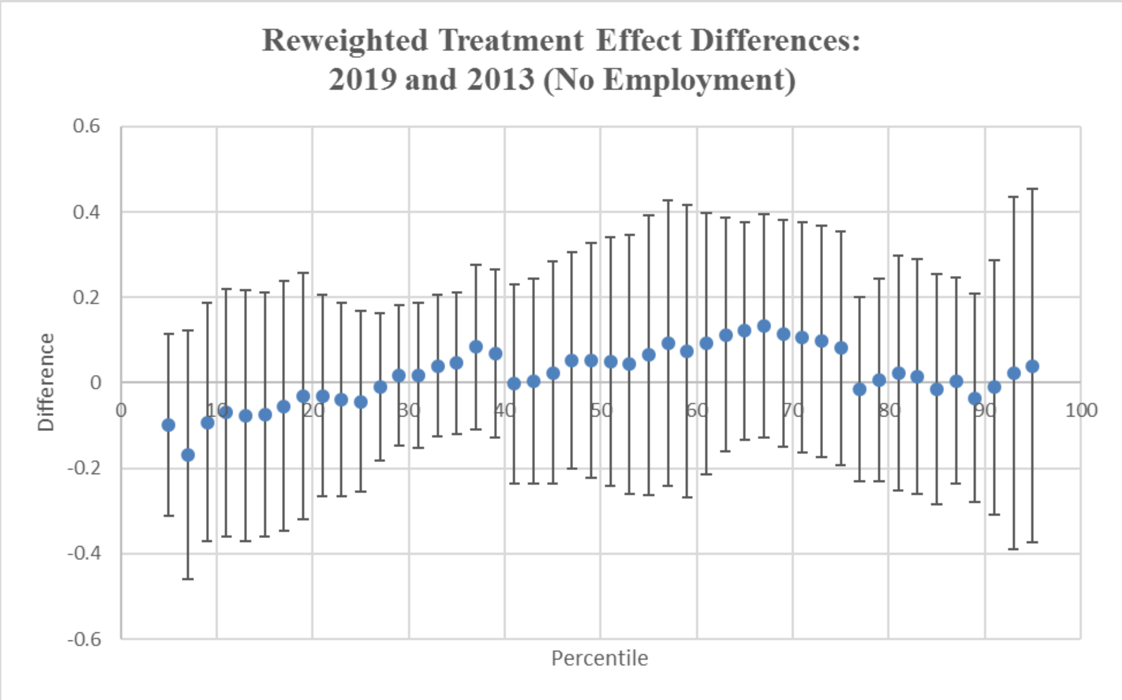

Figure 4B.6: Re-weighted Public Sector Differential Treatment Effects (Austerity Period)

Source: Author's calculations from the ASHE dataset.

Chapter 5: Conclusions and Future Research Suggestions

The research undertaken for this thesis focused on output and labour market themes, which was implicitly linked to the impact of the financial crisis. Specifically, it explored the impact of the recent financial crisis on aggregate productivity (or output) growth, using both TFP and LP measures. It also investigated the input market and the effect of the crisis on regional wage disparities, and then examined the impact of both the financial crisis and the government's austerity programme on the public sector pay gap for men. It should be noted that this research does not claim to causally identify the effect of the financial crisis on either productivity growth or wage disparities. Rather it investigates, econometrically and descriptively, the evolution of these selected outcomes over a period of huge volatility in the UK/British economy.

In Chapter 2 the empirical results show that the financial crisis disproportionately affected productivity growth, measured using either a simple LP measure or a TFP measure. A key empirical finding is that *within*-firm restructuring has been pro-cyclical and was implicated as a key factor in determining overall changes in both TFP and LP growth during and after the financial crisis. The results of the research for this thesis also suggest the existence of an inherent weakness in the allocation of resources across firms in the UK economy, a weakness that has not declined over time. This misallocation of resources has been a trend since the pre-crisis period. Therefore, one priority for policymakers should be a focus on interventions that provide support and encouragement to firms, such as targeted tax breaks and firm-specific training to improve resource allocation within and across firms. This could help to enhance future aggregate productivity growth and underlines the importance of establishing a framework for the proper functioning of market-driven intra-firm and inter-firm resource reallocations. It should be the approach adopted rather than pursuing traditional industrial policies aimed at supporting only the better performing firms and sectors.

Chapter 2 provides evidence that productivity growth in non-financial services firms relative to manufacturing sector firms was initially hit harder at the start of the crisis. However, in the post-crisis period, the non-financial services sector rebounded to eventually surpass pre-crisis growth rates. In contrast, manufacturing productivity growth has remained rather subdued since the end of the crisis. This might be due to the failure to account for confounding variables in the analysis, such as intangible capital, which has become increasingly more important in the services sector. There are indications that the UK economy has experienced a structural transition to a knowledge-based economy, where intangibles are significant drivers of firm-level productivity. Future research should exploit emerging data on intangible capital, available from the FAME dataset, to explore the explicit role of intangible capital in explaining aggregate productivity growth, perhaps at a more granular level than undertaken here.

Chapter 3 provided persuasive descriptive empirical evidence that the financial crisis had either vanishingly small or no obvious effects on regional wage differentials for men in Great Britain. The labour market trend in wage disparities appears to be narrowing steadily, relative to the national average, and the evolution of this trend appeared immune to the financial crisis. Nevertheless, there remains very strong persistence in the wage-level rank ordering of TTWAs. In addition, the evidence is suggestive of the emergence of increasing wage inequality *within* local labour markets coincidental with an overall contraction in wage inequality nationally. The evidence is suggestive of the co-existence of high wages and high inequality within local labour markets.

The current government states that its aim is to achieve a ‘levelling-up’ across labour markets. However, the empirical analysis in Chapter 3 provides evidence that a process of levelling up between regions in terms of wages has been in train for some time. It suggests that a more appropriate and urgent policy response would involve a focus on what is happening within regional labour markets. In particular, the emerging polarization of wages within local labour markets is an issue that would benefit from further research investigation.

Chapter 4 analysed the public sector wage structure and investigated whether it has been affected by either the financial crisis or the austerity measures adopted by the UK government in the post-crisis period. The results obtained from the decomposition analysis suggest that the wages of workers at the top end of the distribution were disproportionately affected during the financial crisis but that, in the post-crisis period, these workers appear to have regained their relative pay position with respect to the private sector. Overall, the results in Chapter 4 would suggest that, across most parts of the pay distribution, the public sector wage structure has not been impacted permanently, either by the financial crisis or the fiscal consolidation measures imposed in the post-crisis period.

It is acknowledged that the public sector employs more women than men and that future research should focus more explicitly on women in relation to the public sector pay gap. This is complicated econometrically by selection issues related to participation in the labour market, the choice of labour market sector, and type of employment contract (i.e., part-time versus full-time). However, an understanding of the determinants of the female public sector wage gap by type of employment contract, and its impact across the pay distribution over time, would be informative for policy and clearly merits further research.

The thesis has provided a descriptive analysis linking the financial crisis to productivity growth, and male wages at the regional level and within the public sector. Further work needs to be done to causally identify the relationships of key interest here to complement the findings in this thesis. In more specific terms, for the first chapter a revenue measure of TFP, as with most papers cited in the literature review section is used. However, it is widely acknowledged that when productivity is measured using the available total revenues, a number of measurement errors are invariably incurred. One of the most prominent issues is the extent to which the ‘quality’ of the output sold is reflected in its price. When this is not the case, the recorded (revenue) productivity not only reflects production efficiency but also a complex object involving a number of other factors, including (i) tastes on the demand side and (ii) of product market conditions – most notably a degree of prevailing market competition – on the supply side. The more recent framework developed by Forlani *et al.* (2016) and the increasing availability of firm-level datasets such as PRODCOM (a production database with a finer degree of product-level disaggregation containing information on both physical quantities and sales) provides a remedy to this, and a probable agenda for future research.

The analysis in Chapter 3 does not exploit any spatial econometrics to account for spatial autocorrelation and spatial heterogeneity. It could be argued that the introduction of spatial dependence might improve the quality of the statistical inferences, although, given the sample sizes used in the analysis, the value-added might be small. However, this could be explored given the increasing availability of level microdata.

A common theme running through the analyses in this thesis is the impact of an economic shock (in this chapter, the 2008 financial crisis) on a range of outcomes. An obvious extension to this research in the current context would be an exploration of the effect of the COVID-19 pandemic on firm-level productivity and the regional wage structure. It conjectures that, in the context of the latter labour market, its effects are likely to be more engendered and persistent and lead to more permanent changes than the financial crisis. This represents an interesting and topical research issue to investigate.

Bibliography

Agrawal, S. and Phillips, D., 2020. *Catching up or falling behind? Geographical inequalities in the UK and how they have changed in recent years,* s.l.: The Institute for Fiscal Studies.

Amadxarif, Z., Angeli, M., Haldane, A.G. and Zemaityte, G., 2020. *Understanding pay gaps,* Bank of England Working Paper No. 877. Available at SSRN: https://ssrn.com/abstract=3647190 or http://dx.doi.org/10.2139/ssrn.3647190.

Armstrong, A., Davis, E.P., Liadze, I. and Rienzo, C., 2013. *Evaluating changes in bank lending to UK SMEs over 2001-12- ongoing tight credit?* NIESR Discussion Paper No. 408, National Institute of Economic and Social Research, UK.

Autor, D.H., Dorn, D. and Hanson, G.H., 2013. The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, *103*(6), pp.2121-68.Autor, D.H., Katz, L.F. and Kearney, M.S., 2008. Trends in U.S. Wage Inequality: Revising the Revisionists. *The Review of Economics and Statistics, 90*(2), pp.300-323.

Baily, M.N., Hulten, C., Campbell, D., Bresnahan, T. and Caves, R.E., 1992. Productivity Dynamics in Manufacturing Plants. *Brookings Papers on Economic Activity*, *23*, pp.187-267.

Baily, M.N., Bartelsman, E.J. and Haltiwanger, J., 2001. Labor Productivity : Structural Change and Cyclical Dynamics. *Review of Economics and Statistics, 83*(3), pp.420-433.

Bargain, O. and Melly, B., 2008. Public Sector Pay Gap in France: New Evidence Using Panel Data. IZA Working Paper No. 3427. Available at SSRN: https://ssrn.com/abstract=1136232 or http://dx.doi.org/10.2139/ssrn.1136232.

Barnett, A., Batten, S., Chiu, A., Franklin, J. and Sebastiá-Barriel, M., 2014a. The UK productivity puzzle. *Bank of England Quarterly Bulletin, 54*(2), pp.114-128.

Barnett, A., Chiu, A., Jeremy, F. and Sebastiá-Barriel, M., 2014b. The Productivity Puzzle: A Firm-Level Investigation into Employment Behaviour and Resource Allocation Over the Crisis. Bank of England Working Paper No. 495. Available at SSRN: https://ssrn.com/abstract=2428177 or http://dx.doi.org/10.2139/ssrn.2428177.

Bartelsman, E., Haltiwanger, J. and Scarpetta, S., 2013. Cross-Country Differences in Productivity: The Role of Allocation and Selection. *American Economic Review, 103*(1), pp.305-334.

Bartelsman, E.J. and Doms, M., 2000. Understanding Productivity: Lessons from Longitudinal Microdata. *Journal of Economic Literature, 38*(3), pp.569-594.

Baum, C.F., Schaffer, M.E. and Stillman, S., 2003. Instrumental Variables and GMM: Estimation and Testing, The Stata Journal, 3(1), pp.1–31.

Bell, B. and Van Reenen, J., 2010. Bankers' pay and extreme wage inequality in the UK. *Centre for Economic Performance special papers (CEPSP21),* London School of Economics and Political Science, Volume CEPSP21.

Bell, D., Elliott, R.F., Ma, A., Scott, A. and Roberts, E., 2007. The Pattern and Evolution of Geographical Wage Differentials in the Public and Private Sectors in Great Britain. *The Manchester School, 75*(4), pp.386-421.

Bender, K.A., 2003. Examining Equality between Public- and Private-Sector Wage Distributions. *Economic Inquiry, 40*(1), pp.62-79.

Bender, K.A. and Elliott, R., 1999. Relative Earnings in the UK Public sector: The Impact of Pay Reform on Pay Structure. In: Elliott, R., Lucifora, C., Meurs, D. (Eds): *Public Sector Pay Determination in the European Union* (pp.285-339). Palgrave Macmillan, London.

Bernard, A.B. and Jensen, B.J., 2000. *Understanding Increasing and Decreasing Wage Inequality.* s.l.:University of Chicago Press.

Bernard, A.B., Redding, S.J. and Schott, P.K., 2006. *Multi-Product Firms and Product Switching*. CEPR Discussion Paper No. 5708. Available at SSRN: https://ssrn.com/abstract=923453

Bernanke, B.S., and Parkinson, M.L.,1990. *Procyclical Labour Productivity and Competing Theories of the Business Cycle: Some Evidence from Interwar U.S. Manufacturing Industries*, National Bureau of Economic Research, Working Paper Number 3503.

Blackaby, D., Murphy, P., O'Leary, N. and Staneva, A., 2018. Regional pay? The public/private sector pay differential. *Regional Studies, 52*(4), pp.477-489.

Blackaby, D.C., Murphy, P.D. and O'Leary, N.C., 1999. The payment of public sector workers in the UK: Reconciliation with North American findings. *Economics letters, 65*(2), pp.239-243.

Blackaby, D.H. and Manning, D.N., 1990. The North-South Divide: Questions of Existence and Stability. *The Economic Journal, 100*(401), pp.510-527.

Blinder, A.S., 1973. "Wage Discrimination: Reduced Form and Structural Estimates. *The Journal of Human Resources,* 8(4), pp. 436-55.

Blundell, R., Robert, J., Dias, M., and Xu, X., 2020. Covid-19: The impacts of the pandemic on inequality*, Institute for Fiscal Studies*. DOI10.1920/BN.IFS.2020.BN0291

Bolick, C., 1995. Thatcher's Revolution: Deregulation and Political Transformation. *Yale Journal on Regulation, 12*, p.527.

Brewer, M., Muriel, A. and Wren-Lewis, L., 2009. *Accounting for changes in inequality since 1968: decomposition analyses for Great Britain,* s.l.: Government Equalities Office.

Broadbent, B., 2012. *Productivity and the allocation of resources*. Speech given at Durham Business School..

Campos, M.M. and Centeno, M., 2012. *Public-private wage gaps in the period prior to the adoption of the euro: an application based on longitudinal data,* Lisbon: Banco de Portugal.

Campos, M.M., Depalo, D., Papapetrou, E., Pérez, J.J. and Ramos, R., 2017. Understanding the public sector pay gap. *IZA Journal of Labor Policy, 6*(1), pp.1-29.

Centeno, M. and Portugal, P., 2001. Wages of Civil Servants. *Economic Bulletin and Financial Stability Report Articles and Banco de Portugal Economic Studies.*

Chatterji, M. and Mumford, K.A., 2007. *The Public-Private Sector Wage Differential for Full-Time Male Employees in Britain: A Preliminary Analysis*. IZA Discussion Paper No. 2781, Available at SSRN: https://ssrn.com/abstract=987025 or http://dx.doi.org/10.2139/ssrn.987025.

Chatterji, M., Mumford, K. and Smith, P.N., 2011. The public-private sector gender wage differential in Britain: evidence from matched employee-workplace data. *Applied Economics, 43*(26), pp.3819-3833.

Chernozhukov, V., Fernandez-Val, I. and Melly, B., 2013. Inference on Counterfactual Distributions. *Econometrica, 81*(6), pp.2205-2268.

Christofides, L.N. and Michael, M., 2013. Exploring the public-private sector wage gap in European countries.. *IZA Journal of European Labor Studies, 2*(1), pp.1-53.

Combes, P.-P. and Gobillon, L., 2015. The Empirics of Agglomeration Economies. In: Duranton, G., Henderson, V.J. and Strange, W.C. (Eds): *Handbook of Regional and Urban Economics.*North Holland:Elsevier, pp.247-348.

Combes, P.P., Duranton, G., Gobillon, L., Puga, D. and Roux, S., 2012. The Productivity Advantages of Large Cities: Distinguishing Agglomeration From Firm Selection. *Econometrica, 80*(6), pp.2543-2594.

Combes, P.P., Duranton, G. and Gobillon, L., 2008. Spatial wage disparities: Sorting matters!. *Journal of Urban Economics, 63*(2), pp.723-742.

Costa, R. and Machin, S., 2017. *Real Wages and Living Standards in the UK*. *CEP Election Analysis*, *36*, LSE, UK. 11pp.

Crawford, R. and Johnson,P., 2015. *The UK coalition government's record, and challenges for the future*. *Institute for Fiscal Studies*.

Cribb,J., Emmerson,C. and Sibieta, L., 2019. Public sector pay in the UK,IFS Report R97, London, UK.

Danzer, A. M., & Dolton, P. J., 2012. Total Reward and pensions in the UK in the public and private sectors. Labour Economics, 19(4), 584–594. https://doi.org/10.1016/J.LABECO.2012.05.010.

D'Costa, S. and Overman, H.G., 2014. The urban wage growth premium: Sorting or learning? *Regional Science and Urban Economics, 48*, pp.168-179.

De Castro, F., Salto, M. and Steiner, H., 2013. *The gap between public and private wages: new evidence for the EU.*European Economy – Economic Papers 2008-2015, directorate General Economic and Financial Affairs (DG ECFIN), European Commission.

Depalo, D., Giordano, R. and Papapetrou, E., 2015. Public–private wage differentials in euro-area countries: evidence from quantile decomposition analysis. *Empirical Economics, 49*(3), pp.985-1015.

Department for Levelling Up, Housing and Communities, 2022. *Levelling Up the United Kingdom*. Department for Levelling Up, Housing and Communities, HM Government, London. Available at: https://www.gov.uk/government/publications/levelling-up-the-united-kingdom

Deutsche Bank Research. 2010. Housing Markets in OECD Countries, Current Issues—International Topics, 3 March, London: Deutsche Bank.

Di Addario, S., Patacchini, E., 2008. Wages and the City. Evidence from Italy, Labour Economics, Vol.15, Issue 5, pp. 1040-1060,

https://doi.org/10.1016/j.labeco.2007.09.003.

Dias, D., Richmond, C. and Marques, C., 2016. *A Tale of Two Sectors: Why is Misallocation Higher in Services than in Manufacturing?* IMF Working Papers, Volume 16.

Dickey, H., 2007. Regional Earnings Inequality in Great Britain: Evidence From Quantile Regressions. *Journal of Regional Science, 47*(4), pp.775-806.

Diewert, E. W. and Fox, K.J., 2017. Decomposing productivity indexes into explanatory factors. *European Journal of Operational Research*, *256*(1), pp.275-291.

DiNardo, J., Fortin, N. and Lemieux, T., 1996. Labor Market Institutions and The Distribution of Wages,1973-1993: A Semi-Parametric Approach. *Econometrica, 64*(5), pp.1001-1044.

Disney, R.F. and Gosling, A., 1998. Does It Pay to Work in the Public Sector. *Fiscal Studies, 19*(4), pp.347-374.

Disney, R., Haskel, J. and Heden, Y., 2003. Restructuring and Productivity Growth in UK Manufacturing. *The Economic Journal, 113*(489), pp.666-694.

Dorling, D., 2010. Persitent North-South divides. In: N. M. Coe & A. Jones, eds. *The Economic Geography of the UK.* London: Sage, pp. 12-18.

Du, J. and Bonner, K., 2016. *Decomposing UK aggregate labour productivity and growth: 1998-2013 using the ONS Business Structure Database data (No. 48 edn).* Enterprise Research Centre. Available at: https://www.enterpriseresearch.ac.uk/wp-content/uploads/2016/07/ERC-ResPap48-DuBonner-final.pdf.

Duranton, G. and Monastiriotis, V., 2002. Mind the Gaps: The Evolution of Regional Earnings Inequalities in the U.K., 1982–1997. *Journal of Regional Science, 42*(2), pp.219-256.

Echeverri-Carroll, E.L. and Ayala, S. G., 2011. Urban Wages: Does City Size Matter?. *Urban Studies, 48*(2), pp.253-271.

Elliott, R.F. and Bender, K., 1997. Decentralization and Pay Reform in Central Government: a Study of Three Countries. *British Journal of Industrial Relations, 35*(3), pp.447-475.

Elming, W., Emmerson, C., Johnson, P., and Phillips, D., 2015. *New analysis of the potential compensation provided by the new 'National Living Wage' for changes to the tax and benefit system*, Press release.

Emmerson, C., Johnson, P. and Miller, H. (Eds), 2013. *IFS Green Budget: February 2013*, IFS Report, No. R74, ISBN 978-1-909463-02-8, Institute for Fiscal Studies (IFS), London. Available at: http://dx.doi.org/10.1920/re.ifs.2013.0074

Essama-Nssah, B. and Lambert, P.J., 2011. *Influence functions for distributional statistics,* s.l.: ECINEQ, Society for the Study of Economic Inequality.

Ferguson, D. and Francis-Devine, B., 2021. *Public Sector Pay,* London: s.n.

Fernandez-Macias, E., Vacas-Soriano, C. and European Foundation for the Improvement of Living, 2015. *Recent developments in the distribution of wages in Europe.* 1st ed. Luxembourg: Eurofound, Publications Office of the European Union, ISBN: 978-92-897-1377-1.

Field, S. and Franklin, M., 2013. *Micro-data Perspectives on the UK Productivity Conundrum - An Update,* s.l.: Office for National Statistics.

Firpo, S.P., Nicole, F.M. and Lemieux, T., 2018. Decomposing Wage Distributions Using Recentered Influence Function Regressions. *Econometrics, 6*(2), p.28.

Firpo, S., Fortin, N. and Lemieux, T., 2011. Decomposition Methods in Economics. In: Ashenfelter, O. and Card, D. (Eds): *Handbook of Labor Economics.* s.l.:Elsevier, pp.1-102.

Firpo, S., Fortin, N.M. and Lemieux, T., 2009. Unconditional Quantile Regressions. *Econometrica, 77*(3), pp.953-973.

Forlani, E., Ralf, M., Mion, G. and Muûls, M., 2016. *Unraveling Firms: Demand, Productivity and Markups Heterogeneity,* s.l.: CEPR Discussion Paper 11058.

Fosberg, R. H. 2012. Capital structure and financial crisis. Journal of Finance and Accountancy 11:46–52.

Foster, L., Haltiwanger, J.C. and Krizan, C.J., 2001. Aggregate Productivity Growth. Lessons from Microeconomic Evidence. In: Hulten, C.R., Dean, E.R. and Harper, M. (eds), *New Developments in Productivity Analysis.* University of Chicago Press, USA, pp.303-372.

Galego, A. and Pereira, J., 2014. Decomposition of Regional Wage Differences Along the Wage Distribution in Portugal: The Importance of Covariates. *Environment and Planning A*, *46*(10), pp.2514-2532.

Gang, I.N., Yun, M.-S. and Co, C.Y., 1999. *Switching models with self- selection: Self-employment in Hungary*. Working Paper No. 1999-12, Rutgers University, Department of Economics, New Brunswick, NJ.

Gibbons, S., Overman, H.G. and Pelkonen, P., 2010. *Wage Disparities in Britain: People or Place?* SERC Discussion Papers (SERCDP0060), Spatial Economics Research Centre (SERC), London School of Economics and Political Science, London, UK.

Giordano, R., Depalo, D., Pereira, M.C., Eugene, B., Papapetrou, E., Perez, J.J., Reiss, L. and Roter, M., 2011. *The Public Sector Pay Gap in a Selection of Euro Area Countries*. ECB Working Paper No. 1406. Available at SSRN: https://ssrn.com/abstract=1965450 or http://dx.doi.org/10.2139/ssrn.1965450.

Goodridge, P., Haskel, J. and Wallis, G., 2013. Can Intangible Investment Explain the UK Productivity Puzzle? *National Institute Economic Review*, *224*, pp.R48-R58.

Goodridge, P., Haskel, J. and Wallis, G., 2016. UK Intangible Investment and Growth: New measures of UK investment in knowledge assets and intellectual property rights, The Intellectual Property Office, Newport.vailable at UK Intangible Investment and Growth: New Measures of UK investment in knowledge assets and intellectual property rights (publishing.service.gov.uk).

Goodridge, P., Haskel, J. and Wallis, G., 2018. Accounting for the UK Productivity Puzzle: A Decomposition and Predictions. *Economica*, *85*(339), pp.581-605.

Graham, D.J. and Gibbons, S., 2019. Quantifying Wider Economic Impacts of agglomeration for transport appraisal: Existing evidence and future directions. *Economics of Transportation, 19*, p.100121.

Haisken-DeNew, J.P. and Schmidt, C., 1997. Interindustry and Interregion Differentials: Mechanics and Interpretation. *The Review of Economics and Statistics, 79*(3), pp.516-521.

Haldane, A.G., 2014. *Twin Peaks*. Speech given at Kenilworth Chamber of Trade Business Breakfast, Bank of England. Available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.670.5988&rep=rep1&type=pdf.

Haltiwanger, J., 1997. Measuring and analyzing aggregate fluctuations: the importance of building from microeconomic evidence. *Review,* pp.55-78.

Hampel, F. R., Ronchetti, E. M., Rousseeuw, P. J. and Stahel, W. A., 1986. Robust Statistics. The Approach Based on Influence Functions. New York: John Wiley and Sons.

Harris, R. and Moffat, J., 2011. *R&D, innovation and exporting*. SERC Discussion Papers (SERCDP0073), Spatial Economics Research Centre (SERC), London School of Ecocnomics and Political Sciences, London, UK.

Harris, R. and Moffat, J., 2017. The UK productivity puzzle, 2008-2012 : evidence using plant-level estimates of total factor productivity. *Oxford Economic Papers*, *69*(3), pp.529-549.

Harris, R. and Moffat, J., 2019. The Decline of British Manufacturing, 1973–2012: The Role of Total Factor Productivity. *National Institute Economic Review*, *247*, pp.R19-R31.

Heitmueller, A., 2006. Public-private Sector Pay Differentials in a Devolved Scotland. *Journal of Applied Economics, 9*(2), pp.295-323.

Herz, B. and van Rens, T., 2020. *The labor market in the UK,2000–2019*. IZA World of Labor 2020: 422. Available at https://doi: 10.15185/izawol.422.v2.

HM Treasury, 2021. Economic Evidence to the Pay Review Bodies.

Hornbeck, R. and Moretti, E., 2018. *Who Benefits From Productivity Growth? Direct and Indirect Effects of Local TFP Growth on Wages, Rents, and Inequality,* s.l.: National Bureau of Economic Research.

Hsieh, C.T. and Klenow, P.J., 2007. *Misallocation and Manufacturing TFP in China and India,* s.l.: National Bureau of Economic Research.

Jewell, S., Razzu, G. and Singleton, C., 2018. *Who works for whom and the UK gender pay gap?,* s.l.: s.n.

Kaplanis, I., 2010. *Wage effects from changes in local human capital in Britain*. SERC Discussion Papers (SERCDP0039). Spatial Economics Research Centre (SERC), London School of Economics and Political Sciences, London, UK.

Kierzenkowski, R., Machlica, G. and Fulop, G., 2018. The UK productivity puzzle through the magnifying glass: A sectoral Perspective. OECD Economic Department Working Papers, No. 1496, OECD Publishing, Paris. Available at: https://doi.org/10.1787/e704ee28-en.

Kline, P. and Moretti, E., 2014. People, Places, and Public Policy: Some Simple Welfare Economics of Local Economic Development Programs. *Annual Review of Economics, 6*(1), pp.629-662.

Krueger, A.B. and Summers, L.H., 1988. Efficiency Wages and the Inter-Industry Wage Structure. *Econometrica, 56*(2), pp.259-293.

Krugman, P., 1994. *The age of diminished expectations: U.S. Economic Policy in the 1990s.* 3rd ed. MIT Press, Cambridge, MA, USA.

Lausev, J., 2014. What has twenty years of public-private pay gap literature told us?. *Journal of Economic Surveys, 28*(3), pp.516-550.

Lee, N., Sissons, P. and Jones, K., 2013. *Wage inequality and employment polarisation in British cities*. London, Work Foundation.

Lee, N., Sissons, P. and Jones, K., 2016. The Geography of Wage Inequality in British Cities. *Journal of Regional Studies, 50*(10), pp.1714-1727.

LeSage, J. and Pace, R.P., 2009. *Introduction to Spatial Econometrics.* 1st ed. New York:Chapman and Hall/CRC.

Levinsohn, J. and Petrin, A., 2000. Estimating Production Functions Using Inputs to Control for Unobservables. NBER Working Paper No. 7819. National Bureau of Economic Research. Available at: https://ssrn.com/abstract=238143.

Lindley, J. and Machin, S.J., 2014. Spatial Changes in Labour Market Inequality. *Journal of Urban Economics*, *79*, pp.121-138.

Lucifora, C. and Meurs, D., 2006. The Public Sector Gap in France, Great Britain and Italy. *Review of Income and Wealth, 52*(1), pp.43-59.

Machado, J.A.F. and Mata, J., 2005. Counterfactual decomposition of changes in wage distributions using quantile regression. *Journal of Applied Econometrics, 20*(4), pp.445-465.

Machin, S., 1996. Wage inequality in the UK. *Oxford Review of Economic Policy, 12*(1), pp.47-64.

Machin, S., 2011. Changes in UK Wage Inequality Over the Last Forty Years. In: Gregg, P. and Wadsworth, J. (Eds): *The Labour Market in Winter: The State of Working Britain.* Oxford: Oxford University Press, pp.156-169.

Machin, S. and Van Reenen, J., 2008. Changes in wage inequality. In: Durlauf, S.N. (Ed.): *The New Palgrave Dictionary of Economics.* Basingstoke: Palgrave Macmillan, pp.658-666.

Manning, A., 2011. Minimum Wages and Wage Inequality. In: Marsden, D. (Ed.): *Employment in the Lean Years: Policy and Prospects for the Next Decade.* Oxford: Oxford University Press.

Martin, B. and Rowthorn, R.E., 2012. *Is the British economy supply constrained II? A renewed critique of productivity pessimism*. UK Innovation Research Centre, University of Cambridge, UK.

Mayer, T., Melitz, M.J. and Ottaviano, G.I.P., 2014. Market Size, Competition, and the Product Mix of Exporters. *American Economic Review*, *104*(2), pp.495-536.

McMillen, D. P., 2013. *Quantile Regression for Spatial Data.* Berlin: Springer, Berlin, Heidelberg.

Melitz, M.J. and Polanec, S., 2015. Dynamic Olley-Pakes productivity decomposition with entry and exit. *The RAND Journal of Economics*, *46*(2), pp.362-375.

Melly, B., 2005. Decomposition of differences in distribution using quantile regression. *Labour Economics*, *12*(4), pp.577-590.

Michael, M. and Christofides, L.N., 2020. The impact of austerity measures on the public - private sector wage gap in Europe. *Labour Economics*, *63*, p.101796.

Millard, B. and Machin, A., 2007. Characteristics of public sector workers. *Economic and Labour Market Review, 1*(5), pp.46-55.

Mincer, J., 1974. Introduction to "*Schooling, Experience, and Earnings*". In: Mincer, J. (Ed.): *Schooling, Experience, and Earnings*. Cambridge, MA:National Bureau of Economic Research, Inc, pp.1-4.

Moretti, E., 2004. Human Capital Externalities in Cities. In: Henderson, V.J. and Thisse, J. (eds): *Handbook of Regional and Urban Economics: Cities and Geography.* Elsevier, The Netherlands, pp.2243-2291.

Moretti, E., 2010. Local Labor Markets. In: Ashenfelter, O. and Card, D. (Eds): *Handbook of Labor Economics*. North Holland:Elsevier, pp.1237-1313.

Mourre,G., Isbasoiu, G., Paternoster , D. and Salto, M. 2013, The cyclically adjusted budget balance used in the EU fiscal framework: an update, European Economy. Economic Papers 478, Brussels.

Murphy, P., Blackaby, D., O'Leary, N. and Staneva, A., 2020. Understanding What Has Been Happening to the Public-Sector Pay Premium in Great Britain: A Distributional Approach Based on the Labour Force Survey. *British Journal of Industrial Relations, 58*(2), pp.273-300.

Nygaard, C., Parkinson, S. and Reynolds, M., 2021. Agglomeration effects and housing market dynamics, AHURI Final Report No. 366, Australian Housing and Urban Research Institute Limited, Melbourne, Available at: https://www.ahuri.edu.au/research/final-reports/366, doi: 10.18408/ahuri5122401

Neuman, S. and Oaxaca, R., 1998. *Estimating labor market discrimination with selectivity-corrected wage equations: Methodological considerations and an illustration from Israel*. Centre for Economic Policy Research, London, UK.

Nguyen, D., 2019. *Regional Economic Disparities and Development in the UK*. London: National Institute of Economic and Social Research.

Oaxaca, R., 1973. Male-Female Wage Differentials in Urban Lbour Markets. *International Economic Review,* 14(3), pp. 693-709.

Oaxaca, R.L. and Ransom, M.R., 1994. On discrimination and the decomposition of wage differentials. *Journal of Econometrics, 61*(1), pp.5-21.

O'Brien, R., 2018. Experimental estimates of investment in intangible assets in the UK: 2015. *UK Office for National Statistics*.

Olley, S.G. and Pakes, A., 1996. The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica*, *64*(6), pp.1263-1297.

OBS, 2020. Public finances databank 2019-20. [Online] Available at: Data - Office for Budget Responsibility (obr.uk)

ONS, 2006. *Business Structure Database User Guide.* New Port: Office for National Statistics.

ONS, 2012. *Annual Survey of Hours and Earnings: 2011 (based on SOC 2010).* [Online] Available at: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/bulletins/annualsurveyofhoursandearnings/2012-03-21 [Accessed 22 May 2019].

ONS,2015. What is the productivity Puzzle?. [Online] Available at: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/labourproductivity/articles/whatistheproductivitypuzzle/2015-07-07 [Accessed 28 May 2019].

ONS, 2016. *Analysis of factors affecting earnings using Annual Survey of Hours and Earnings (ASHE): linear regression datataset.* [Online] Available at: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/datasets/analysisoffactorsaffectingearningsusingtheannualsurveyofhoursandearningsashelinearregressiondataset/current [Accessed 12 June 2020].

ONS, 2016. International Comparisons of Productivity Summary; An international comparison of productivity across the G7 nations, in terms of the level of and growth in GDP per hour and GDP per worker.

ONS, 2017. UK Public and private sector earnings in the UK: The results of statistical models that explore the relationship between mean hourly earnings and a range of independent variables, based on Annual Survey of Hours and Earnings (ASHE) 2017 provisional results data. Accessed on 10 June 2021 https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/articles/analysisoffactorsaffectingearningsusingannualsurveyofhoursandearnings/2017

ONS, 2018. The 2008 recession 10 years on: A decade after the beginning of the recession, how has the UK economy recovered?

ONS, 2019. *Producer price inflation (MM22 dataset),* accessed 8 March 2019, https://www.ons.gov.uk/economy/inflationandpriceindices/datasets/mm22producerpriceindices

ONS, 2019b. Experimental industry deflators, UK, non-seasonally adjusted*,* accessed 12 May 2019, https://www.ons.gov.uk/economy/inflationandpriceindices/datasets/experimentalindustrydeflatorsuknonseasonallyadjusted

ONS, 2019c. Capital stocks and fixed capital consumption*,* accessed 25 May 2019, https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/datasets/capitalstocksconsumptionoffixedcapital

ONS, 2020a. GG: Total Compensation of employees, Paid(D1) Source dataset: Maastricht supplementary tables (EDP1) time series dataset (EDP1), accessed 5 June 2020, https://www.ons.gov.uk/economy/governmentpublicsectorandtaxes/publicspending/timeseries/nmxs/edp1?referrer=search&searchTerm=nmxs

ONS, 2020b. GG: Total current expenditure: £m CPNSA Source dataset: Public sector finances time series (PUSF), accessed 7 June 2020, https://www.ons.gov.uk/economy/governmentpublicsectorandtaxes/publicsectorfinance/timeseries/anlr/pusf/previous

ONS,2021. Public Sector Employment: Estimates of People employed in the Public and Private Sectors in the UK, accessed 10 January 2022, https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/publicsectorpersonnel/bulletins/publicsectoremployment/september2021

ONS,2022 Labour market statistics time series: Large dataset which contains labour market statistics data time series, accessed 15 January, 2022, https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/datasets/labourmarketstatistics/current

ONS,2022b. EMP02: Public and private sector employment.

Oulton, N., 2016. Prospects for UK growth in the aftermath of the financial crisis. In: Chadha, J.S., Crystal, A., Pearlman, J., Smith, P. and Wright, S. (Eds): *The UK Economy in the Long Expansion and its Aftermath.* Cambridge: Cambridge University Press, pp.17-80.

Oulton, N. and Sebastiá-Barriel, M., 2013. *Long and Short-Term Effects of the Financial Crisis on Labour Productivity, Capital and Output*. Bank of England Working Paper 470, Available at SSRN: https://ssrn.com/abstract=2206347 or http://dx.doi.org/10.2139/ssrn.2206347.

Oulton, N. and Wallis, G., 2015. *Integrated Estimates of Capital Stocks and Services for the United Kingdom: 1950-2013.*CEP Discussion Papers (CEPDP 1342). Centre for Economic Performance, London School of Economics and Political Science, London, UK.

Overman, H.G. and Gibbons, S., 2011. Unequal Britain: how real are regional disparities? *CentrePiece*, *17*(1), pp.23-25.

Overman, H. G., 2022. *Levelling-Up':The Government's Plans Aren't Enough To Promote Economic Growth And Tackle Inequality*, LSE Politics and Policy, 2 February 2022. Available at: 'Levelling up': the government's plans aren't enough to promote economic growth and tackle inequality | British Politics and Policy at LSE.

Pessoa, J.P. and Van Reenen, J., 2013. *Wage growth and productivity growth: the myth and reality of 'decoupling'. CentrePiece – the Magazaine for Economic Performance*, *401*, Centre for Economic Performance.

Pessoa, J.P. and Van Reenen, J., 2014. The UK Productivity and Jobs Puzzle: Does the Answer Lie in Wage Flexibility? *The Economic Journal*, *124*(576), pp.433-452.

Piketty, T. and Saez, E., 2014. Inequality in the long run. *Science, 344*(6186), pp.838-843.

Pryce, V., 2015. Why should we Care about Productivity? *National Institute Economic Review, 231*(1), pp.R30-R35.

Redding, S. and Venables, A.J., 2004. Economic geography and international inequality. *Journal of International Economics, 62*(1), pp.53-82.

Rees, H.J. and Shah, A.R., 1995. Public/private sector wage differential in the UK. *The Manchester School of Economic & Social Studies*, *63*(1), pp.52-68.

Rice, P.G. and Venables, A.J., 2021. The Persistent Consequences of Adverse Shocks: How the 1970s Shaped UK Regional Inequality. *Oxford Review of Economic Policy, 37*(1), p.132–151.

Rice, P., Venables, A.J. and Patac, E., 2006. Spatial determinants of productivity: Analysis for the regions of Great Britain. *Regional Science and Urban Economics, 36*(6), pp.727-752.

Riley, R., Rincon-Aznar, A. and Samek, L., 2018. *Below the Aggregate: A Sectoral Account of the UK Productivity Puzzle*. ESCoE Discussion Paper 2018-06, London: Economic Statistics Centre of Excellence (ESCoE). 72pp.

Riley, R., Rosazza-Bondibene, C. and Young, G., 2015. *The UK productivity puzzle 2008-13: evidence from British businesses*. Bank of England Working Paper No. 531. Available at: SSRN: https://ssrn.com/abstract=2623635 or http://dx.doi.org/10.2139/ssrn.2623635.

Riley, R., Rosazza-Bondibene, C. and Young, G., 2014. The Financial Crisis, Bank Lending and UK Productivity: Sectoral and Firm-Level Evidence. *National Institute Economic Review*, *228*(1), pp.R17-R34.

Ritchie, F., Whittard, D. and Dawson, C., 2014. *Understanding official data sources: Final report for the low pay commission.*, London: low pay commission.

Schran, F., 2019. *Locational Choice and Spatial Wage Inequality,* Bonn: Institute of Labor Economics (IZA).

Senftleben-König, C. and Wielandt, H., 2014. *Spatial Wage Inequality and Technological Change*. SFB 649 Discussion Paper No. 2014-038, Humboldt University of Berlin, Collaborative Research Center 649 - Economic Risk, Berlin

Solow, R.M., 1957. Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics*, *39*(3), pp.312-320.

Stewart, M.B., 2011. The Changing Picture of Earnings Inequality in Britain and the Role of Regional and Sectoral Differences. *National Institute Economic Review, 218*(1), pp.R20-R32.

Taylor, K., 2006. UK Wage Inequality: An Industry and Regional Perspective. *JO, 20*(1), pp.91-124.

Teichgräber, A. and Van Reenen, J., 2021. *Have productivity and pay decoupled in the UK?* Centre for Economic Performance Discussion Paper 1812, London School of Economics and Political Science, London, UK.

The World Bank, 2016. Doing Business 2016, Measuring Regulatory Quality and Efficiency, 13th edition, Washington DC.

Thorby, R. and Maybin, J., 2010. A high-performing NHS? A review of progress 1997–

2010, The King’s Fund.

UKCES, 2014. The Labour Market Story: The UK Following Recession, Briefing Paper. Available at: The_Labour_Market_Story-_The_UK_Following_Recession.pdf (publishing.service.gov.uk).

UK Parliament, 1999. Sharing The Nation's Prosperity. Westminster Hall, House of Commons.

Walsh, D. and Whyte, B., 2018. *Even money? Trends in earnings and income inequalities in Scotland and the UK, 1997-2016,* Glasgow: Glasgow Centre for Population Health.

Wooldridge, J.M., 2009. On estimating firm-level production functions using proxy variables to control for unobservables. *Economics Letters*, *104*(3), pp.112-114.

Zanchi, L., 1998. Interindustry wage differentials in dummy variable models. *Economics Letters, 60*(3), pp.297-301.

Zymek, R. and Jones, B., 2020. *UK Regional Productivity Differences: An Evidence Review*. A report for the Industrial Strategy Council, London, UK.