Wage Inequality in the United Kingdom: A Microeconometric Analysis

by

Damon James Morris

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Abstract

This thesis is an econometric investigation of wage inequality in the UK. It consists of three pieces of empirical work using large UK micro-datasets. The datasets used include the individual level New Earnings Survey (NES), Annual Survey of Hours and Earnings (ASHE), and the Labour Force Survey (LFS). Use is also made of firm level data from the Annual Respondents Database (ARD). The first piece of empirical work aims to identify trends in the UK wage distribution over time at the aggregate level and at the level of population sub-groups. This analysis is performed by fitting parametric distributions to annual cross sections of data using maximum likelihood estimation. The second piece of analysis is an investigation into the driving factors behind the change in the distribution of wages over this period using the LFS. This is analysed using a human capital framework and a decomposition analysis, dividing changes in wage inequality into price, quantity, and residual effects. The final empirical investigation contributes to the literature investigating the relationship between wage inequality and firm performance. Using matched employer/employee data, a Cobb-Douglas production function with a wage inequality term is used to estimate the relationship between the performance of enterprises and wage inequality. Overall, the findings in this thesis show that the finance sector stands out sharply in the UK as a high inequality industry both in levels and in growth. Despite a slow-down compared to the 1980s, wage inequality has continued to grow. Human capital effects have played a role in the changes in wage inequality but a more sophisticated model is needed to more fully explain these changes at the within-group level. There is only weak evidence of a link between inequality and corporate performance overall. Results for manufacturing are, however, consistent with earlier work by Beaumont and Harris (2003).

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Notes and Disclaimers

This work was based on data from the *Annual Survey of Hours and Earnings (1997-2012)*, the *Annual Respondents Database (1973-2008)*, the *Capital Stock Dataset (1979-2005)* and the *New Earnings Survey Panel Dataset (1975-2012)*, produced by the Office for National Statistics (ONS) and supplied by the Secure Data Service at the UK Data Archive. The data are Crown Copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the data in this work does not imply the endorsement of ONS or the Secure Data Service at the UK Data Archive in relation to the interpretation or analysis of the data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

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Chapter 1 Introduction

1.1 Aims and Motivation

The issue of inequalities has long been of interest to economists, with a large literature studying its patterns, causes, and consequences. Inequality remains a significant issue today, of interest not just to economic researchers but also to governments and international organisations such as the International Monetary Fund (IMF) and the Organisation for Economic Co-operation and Development (OECD).

Economic growth can be impacted on by inequality by making investment in education difficult for the poor. At the same time, some inequality is necessary to provide incentives. Berg and Ostry (2000) find longer spells of economic growth to be associated with more equality in the income distribution, accounting for other macroeconomic determinants of growth.

Perotti (1994) and Alesina and Perotti (1996) examine the relationship between the distribution of income and investment. In these papers support is found for a mechanism by which higher inequality increases political instability which in turn reduces investment. As investment is the driver of long-run growth, this inverse relationship between investment and income inequality therefore implies an indirect channel through which income inequality can reduce growth.

Social cohesion and mobility are also affected by income inequality, with links being drawn between income inequality and inter-generational mobility (Corak (2013)) and the incidence of violent crime (Fajnzylber et al. (2002)).

The distribution of pay has recently become a central issue in the UK with the pay of executives in the public sector coming under scrutiny by the government. A review of fair pay in the public sector, Hutton (2011), recommended (amongst other things) the reporting of ratios of top to median pay in public sector organisations, making these available to the public, and a fair pay code to integrate principles of fairness into executive pay. Importantly, this report also suggested that the reporting of pay ratios should become common practice across the whole economy.

The public sector is not the only part of the economy where the pay of those at the top has gained increasing interest. The issue of banker's pay has become a high profile issue in the UK due to the necessity of bail-outs during the financial crisis leading to majority government (and therefore tax payer) shareholding in some banks, particularly notable examples of which are Northern Rock and the Royal Bank of Scotland (RBS). Hutton (2011) also indicates that the growth rate of the earnings of those at the top of the distribution is driven by the private sector, with median pay for FTSE 100 CEO's rising from 47 times UK median earnings in 2000 to 88 times by 2009.

The growth in earnings at the top end of the distribution is not necessarily an issue by itself, however the key concern is that the observed growth in the pay of the top earners (in particular, executives) has not been matched by a corresponding increase in productivity. This suggests that the top earners are extracting rents from firms rather than pay increases being linked to marginal productivity and this makes earnings inequality an issue on fairness grounds. This decoupling of earnings growth from productivity growth is suggested by Hutton (2011) Chart 1C which shows that the earnings of the top 1% grew by approximately 55% between 2000 and 2009 while GDP per worker only grew by approximately 35%.

The Hutton Review also illustrates the fact that earnings inequality is something which is misunderstood by the general public. Despite the fact that of the top 1% of earnings only 1% is earned by public sector employees, 25% of individuals surveyed believed public sector executives earn more than private sector executives. The growth in the pay of executives of both sectors has been faster than that of the median worker. In 2008 the median worker earned approximately 10% more than in 2000 compared to 30% for Local Authority chief executives, 50% for FTSE 250 chief executives and almost 80% for FTSE 100 chief executives (Chart 1D).

There has also been greater scrutiny in the media of the remuneration of top executives in the banking sector, with large bonuses being perceived as unfair against the backdrop of failures in the banking sector and the rising unemployment/falling real wages due to the recession. As recently as January 2012, the £963,000 bonus of RBS CEO Stephen Hester and £1.4 million bonus of Chairman Philip Hampton were still controversial issues receiving media attention BBC (2012).

Inequality therefore remains a relevant and interesting area for research. This thesis focuses on inequality in wages as opposed to income. Labour market earnings represent the dominant component of income for the majority of individuals and so inequality in wages is a significant area of interest for empirical research.

The aim of this thesis is to highlight recent trends in UK wage inequality and set this in the context of the longer term shifts in wage inequality. This analysis is conducted at the level of population sub-groups in addition to considering the economy as a whole. It then addresses what has caused the recent changes in wages inequality, and finally considers the potential economic impact of wage inequality by analysing its relationship with firm performance. The thesis makes use of high quality individual and firm level micro-data recently made available to researchers via the Secure Data Service in order to address these research questions.

1.2 Thesis Structure

The following three chapters each consist of a micro-econometric investigation related to the theme of wage inequality.

Chapter 2 examines the change in wage inequality in the UK over the last four decades with a particular focus on more recent developments using maximum likelihood estimation of parametric distribution models. As well as examining the changes in wage inequality at the aggregate level, industry and occupation sub-groups are separately analysed and particular attention is given to the top end of the wage distribution.

The underlying drivers of these recent changes in UK wage inequality are analysed in Chapter 3 using a decomposition analysis and a human capital framework. The particular decomposition technique which is used enables any distributional statistic to be decomposed into price, quantity, and unobservables effects and is therefore suitable for decomposing changes in wage inequality. This chapter makes use of the Labour Force Survey.

Chapter 4 adds to the literature studying the relationship between wage inequality and firm performance. In order to do this both the New Earnings Survey and the Annual Respondents Database are utilised and matched at an industry level. A variety of regression methods including OLS, fixed effects, and system GMM are then used to estimate a parameter measuring the sensitivity of firm performance to wage inequality.

Chapter 5 summarises the conclusions obtained from the preceding chapters and discusses areas for further research.

Chapter 2 Changes in the Wage Distribution 1975-2011

2.1 Introduction

This chapter highlights the recent experience of the UK in terms of changes in wage inequality. This is motivated by the current interest in issues of inequality discussed in the introduction to the thesis.

Given the level of interest of pay in the public sector (which can be seen in the commissioning of the Hutton (2011) Review of Fair Pay) and in banking, it is of interest to see to what extent the wage distribution in the UK has changed recently and to examine all sectors of the economy to isolate those sectors which are the main drivers of wage inequality. This chapter examines the distribution of wages and wage inequality over the period 1975 to 2011 at the aggregate level and also for several population sub-groups; private and public sectors, industries, and occupations.

The chapter also uses regression analysis to assess how inequality differs between sectors once other factors are controlled for, as composition effects may be causing differing levels of wage inequality between sectors. For example, inequality is higher amongst more highly educated individuals, therefore if wage inequality is higher in the finance sector than the rest of the economy this may reflect a higher proportion of highly educated individuals in that sector.

In order to address these issues this chapter makes use of a parametric distribution modelling approach. This technique is a relatively popular approach in the income distribution literature but applications to wages are much less common. This approach has the advantage of providing a unified framework from which a variety of inequality measures can be calculated as functions of the distribution parameters, also allowing for statistical inference to be made on the inequality measure estimates.

This technique is particularly useful for the analysis of inequality amongst the highest earners where observations are relatively sparse and calculations are more sensitive to extreme values. Fitting a distribution to the upper tail of the overall wage distribution makes use of all of the observations and, as will be shown later in the chapter, unbiased and normally distributed estimates of the Pareto distribution parameter which is used to model high earnings can be achieved for reasonable sample sizes.

The remainder of this chapter is structured as follows; section 2.2 gives some background to inequality measurement and reviews the literature on the estimation of parametric distribution models, 2.5 presents results of a simulation study into the properties of the Pareto distribution, section 2.3 describes the main datasets used in the analysis, section 2.4 outlines the methodological approach, section 2.6 presents the results and section 2.7 concludes.

2.2 Background and Literature Review

This section gives a brief overview of the trends in wage inequality in the UK over the last approximately 50 years. It also gives some background to the concept of inequality and how it can be measured. It then presents a review of the literature which makes use of parametric techniques to estimate empirical distributions. This draws mostly from the income distribution literature, where these methods have been most commonly applied.

2.2.1 Wage Inequality in the UK

Gosling et al. (1994) show that male wage inequality remained relatively stable until the early 1980s using Family Expenditure Survey (FES) data. Real hourly wages grew at approximately the same rate at the 90th, 50th, and 10th percentiles between 1966 and 1978. From 1978 to 1992 there was a divergence in real wage growth rates across the distribution. The growth in the 10th percentile levelled off and remained at approximately the same level whereas median wages continued to grow (by 27% between 1978 and

1992) and wages at the 90th percentile grew even faster at a rate of 44% over the same period.

Estimates of the 90th/50th and 50th/10th percentile differentials for full time male manual workers as far back as 1886 show that by the 1990s inequality in wages was both at its highest level and that the changes since the 1970s was larger than anything that can be observed previously. The trend in the 90/10 differential of hourly wages between 1966 and 1992 is also comparable to the trend in the 90/10 differential of household income. Gosling et al. (2000) show the same trends in inequality, using the same FES data extended to 1995. Both Gosling et al. (1994) and Gosling et al. (2000) highlight the importance of the role of growing inequality within education sub-groups as well as the growing returns to observable skill in this period.

More recently, Machin and Van Reenen (2010) and Van Reenen (2011) have shown that wage inequality continued to increase into the 21st century, at a slower rate than previously observed in the 1980's and 1990's.

2.2.2 Inequality Measurement

Inequality in wages occurs because some individuals earn higher wages than others, and therefore possess a proportionately larger share of the total wage bill in the economy. Analysis of inequality is based on an underlying social welfare function, which is decreasing in the level of inequality. With perfect wage equality every individual earns the same wage and $x\%$ of the population earns x% of total wages. If there is wage inequality, then the bottom $x\%$ of the wage distribution earns less than $x\%$ of the total wage bill and the top $(1-x)\%$ earns greater than $(1-x)\%$ of total wages. Inequality can be shown graphically by the Lorenz curve, as depicted in Figure 2.1 for the UK in 2011.

The perfect equality line is a 45 degree line representing the Lorenz curve if all individuals earned the same wage. The Lorenz curve shows the level of inequality; at each point on the Lorenz curve the given proportion of the population earns less than that proportion of wages. A summary measure of inequality which can be obtained from the Lorenz curve is the Gini coefficient. The Gini coefficient is calculated as the area between the Lorenz curve and the 45 degree line divided by the total area under the 45 degree line. This produces a coefficient value between 0 and 1, with 0 representing no inequality and 1 representing complete inequality.

The advantage of having a single coefficient to describe the level of inequality in a distribution is that it allows distributions to be ranked in order of inequality. In the context of social welfare there are a number of properties which it is desirable for a measure of inequality to possess[1]:

- *Symmetry*; Inequality does not depend on the characteristics of individuals; if two individuals were to swap incomes, inequality would be unchanged.
- *Transfer Principle*; A transfer from a richer individual to a poor individual reduces inequality
- *Scale invariance/ Mean Independence*; An equally proportionate increase or decrease to all wages should leave overall inequality unchanged.
- *Decomposability*; Overall inequality can be expressed as a weighted sum of inequality values as calculated for a given number of population subgroups

The only class of inequality measures which fulfil the property of additive decomposability is the generalised entropy class of inequality measures (denoted $I(\gamma)$). Additive decomposability means that overall inequality can be expressed as the sum of a within-group and between-group term, where the within-group term is a weighted sum of the sub-group levels of inequality (Shorrocks (1980)). The parameter γ in the generalised entropy family represents the sensitivity of the measure to changes at the top of the distribution. A higher value of γ indicates that the measure gives relatively more weight to inequality at the top of the wage distribution.

The generalised entropy class of measures is connected to the Atkinson class of inequality measures developed by Atkinson (1970) (denoted A_ε) but the latter is not additively decomposable. Similar to the generalised entropy measures, the parameter ε in the Atkinson

[1] Lambert (2001) describes each of these in detail

family of inequality measures represents the degree of inequality aversion with sensitivity to transfers at the bottom of the distribution increasing with ε.

2.2.3 Models of Income/Earnings Distribution

A variety of distributions have been considered appropriate for the modelling of income, earnings, and wages. Most of these distributions are related to each other, with the more complex distributions nesting the simpler ones. Figure 2.2 summarises the relationships between each of the distributions discussed in this section[2].

A two parameter distribution which has been proposed for the modelling of income distributions is the log-logistic, which is considered by Fisk (1961). An advantage of using this distribution is ease of estimation and interpretation of a limited number of parameters. Using UK and US earnings data, the distribution is considered to be more useful when modelling homogeneous income distributions such as at a single occupational level.

The log-normal distribution is fitted to UK New Earnings Survey data for the year 1972 by Harrison (1981). A two parameter[3] Pareto distribution is also used in order to model the upper tail of the distribution. The log-normal distribution is found to fit the earnings distribution poorly, particularly to the tails of the distribution but also for the bulk of the data. When extreme values are removed the log-normal distribution is found to perform better. It is therefore concluded that the inability of the log-normal distribution to cope with the extreme upper tail of the earnings distribution is the cause of its poor fit overall.

Log-normal distributions are also estimated for disaggregated occupational groups and at this level the fit of the distribution is found to improve. This corresponds to the Fisk (1961) finding for the log-logistic distribution that a simple two parameter distribution is more appropriate for more homogeneous groups of incomes. The Pareto distribution is found to fit the upper tail better than the log-normal, although it is concluded that

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[2] This is taken from Bandourian et al. (2002) Figure 1

[3] Only one of which is estimated, the second parameter is the mode of the distribution and is chosen by the researcher.

the previously held convention that the top 20% of the distribution can be adequately modelled this way does not hold. Once the data are disaggregated it is found that Pareto distribution estimates are unstable.

The Pareto distribution is also considered by Cowell et al. (1998) to model the tail of the household income distribution in Brazil between 1981 and 1990. Brazil is characterised by a highly skewed distribution and so the bulk of the distribution is modelled non-parametrically and a Pareto distribution is fitted to the upper tail of the distribution. Incomes over \$1,000 and incomes over \$5,000 are modelled in this way. A Pareto's α (the estimated parameter of the Pareto distribution) for the former group of 2.925 and for the latter of 3.684 in 1981 suggested inequality within the very rich was lower than amongst the rich as a whole. This is because Pareto's α is inversely related to the level of inequality in the distribution. Throughout the 1980's Pareto's α fell indicating rising inequality.

Thurow (1970) estimates a two parameter beta distribution to US Bureau of Census household income data between 1949 and 1966. A limitation of the beta distribution for estimating income distributions is that it is bounded between 0 and 1. Income therefore needs to be converted to a 0-1 scale, which implies a maximum income value (this is chosen to be \$15,000 at 1959 prices which affects less than 5% of the sample). These beta distributions are estimated separately for white and black households and Gini coefficient estimates are calculated from the parameters. The parameters are also modelled as functions of macroeconomic indicators such as the employment rate and government expenditure. R^2 values greater than 0.9 suggest this distribution fit the US income data well.

Salem and Mount (1974) highlight the ease of interpretation of the parameters of distributions such as these and estimate log-normal and gamma densities for the distribution of household income in the US using the Current Population Survey in 1960 and 1969. Their results show that both distributions exaggerate the skew of the income distributions but that the gamma distribution outperforms the log-normal. Additionally they model the inequality parameter of the gamma distribution as a function of macroeconomic variables, as in Thurow (1970), and find reducing unemployment and inflation to be associated with a more equal income distribution.

The log-normal and gamma distributions are also compared by Prieto-Alaiz and Victoria-Feser (1996) who estimate the income distribution for Spain. Three income measures are used - total household income, equivalised household income, and per capita household income. For the first of these measures the gamma distribution is found to out-perform the log-normal distribution but the reverse is true for the latter two measures.

Given the drawback that two parameter distributions are potentially too inflexible, Singh and Maddala (1976) propose a three parameter distribution, referred to thereafter in the literature as the Singh-Maddala distribution. This is a generalisation of the Weibull and log-logistic distributions. The Singh-Maddala distribution was found to provide a significantly better fit than both the log-normal and gamma distributions using the same 1960's US data as the Salem and Mount (1974) study. Another three parameter distribution which is also a generalisation of the log-logistic distribution was developed by Dagum (1977).

Kloek and van Dijk (1978) estimate the distribution of Dutch earnings in 1973. Their paper initially estimates log-normal and gamma distributions but conclude them to be overly simplistic and therefore inappropriate. The three parameter generalisation of the gamma distribution is found to provide a much better fit to the data but this is subject to the trade-off between goodness of fit and parameter interpretation. The generalised gamma distribution parameters do not have a direct economic interpretation, and it is reported that there are substantial estimation problems for this distribution.

McDonald and Ransom (1979) provide a comparison of the Singh-Maddala, gamma, beta, and log-normal distributions. The same 1960-1969 US family income data as used by Salem and Mount (1974) and Singh and Maddala (1976) is utilised to compare the performance of these distributions by a number of estimation techniques. Regardless of the estimation technique used, the log-normal distribution is found to be inferior to the gamma distribution and likewise the three parameter beta and Singh-Maddala distributions are superior to the gamma.

The Singh-Maddala, generalised gamma and beta distributions are generalised to the four parameter generalised beta of the first (GB1) and second kind (GB2) distributions by McDonald (1984). The GB2 is found to significantly outperform all models, followed by the Singh-Maddala, in an application to US data 1970-1980. Amongst the two parameter distributions the Weibull is found to perform best. McDonald and Mantrala (1995) perform similar comparisons, additionally including the Dagum distribution. Their findings are consistent with McDonald (1984) with the additional finding that the Dagum distribution is the best performing three parameter distribution - rather than the Singh-Maddala.

Kleiber (1996) compares the Dagum and Singh-Maddala distributions theoretically. The Dagum distribution is closely related to the Singh-Maddala as both are nested special cases of the GB2 distribution and are generalisations of the log-logistic distribution. Referring to the McDonald and Mantrala (1995) results, this paper indicates that the Dagum distribution provides a better fit to income distributions than the Singh-Maddala distribution and performs almost as well as the GB2.

The ability to fit distributions almost as well as the GB2 while maintaining the relative simplicity of a three parameter model makes the Dagum distribution an ideal one to fit income distributions. In terms of wages, the superiority of the GB2 is further supported by Parker (1999) who shows that under neo-classical assumptions the theoretical wage distribution will correspond to the GB2.

McDonald and Xu (1995) develop the five parameter generalised beta (GB) model which nests the GB1 and GB2. Using US family income data, the GB model performs better than the GB1 and GB2 but not significantly better than GB2. Their findings regarding the fit of other distributions are consistent with other work; the GB2 and Dagum distributions are the best fitting four and three parameter models respectively.

The five parameter GB and its nested models are estimated for 23 different countries over time by Bandourian et al. (2002) using household income data from the Luxembourg Income Study. In the case of the US in 1997, the Weibull and Dagum distributions are found to fit best of the two and three parameter models respectively. The improvement of the GB over the GB2 and the GB2 over the Dagum were both found to be insignificant using the likelihood ratio test. Overall, the Dagum distribution was found to be the best fitting three parameter model in all time periods considered for 15 of the 23 countries and the best model in at least 50% of time periods considered for all but 3 of the countries. The GB2 is the best four parameter model but is only significantly better than the respective best three parameter model in 44% of cases.

In summary, the GB distribution is the most flexible at five parameters but has not been found to significantly outperform the nested four parameter GB2 distribution. The GB2 distribution in turn nests the Dagum, Singh-Maddala, generalised gamma, and beta 2 distributions, with the Dagum typically being the best performing of these three parameter models and in many cases performing just as well as the GB2. This suggests that a three or four parameter distribution is an appropriate choice for modelling incomes/earnings.

2.2.4 Estimation Techniques for Parametric Distribution Models

A number of methods of estimating the parameters of parametric distribution models have been used. Common estimators are the minimum χ^2 - Harrison (1981), Kloek and van Dijk (1978)), McDonald and Ransom (1979), and Majumder and Chakravarty (1990) - and maximum likelihood approaches - McDonald (1984), McDonald and Mantrala (1995), McDonald and Xu (1995), Prieto-Alaiz and Victoria-Feser (1996), Bandourian et al. (2002) and Jenkins (2009).

Other less frequently used estimation techniques include non-linear least squares (NLS) - used by Singh and Maddala (1976), and McDonald and Ransom (1979) - a modified method of moments estimator used by Parker (1997), and the optimal B-robust estimator (OBRE) used by Prieto-Alaiz and Victoria-Feser (1996).

Some studies use more than one estimation technique, allowing for comparisons. McDonald and Ransom (1979) compare three estimators in fitting Singh-Maddala and other models; minimum χ^2, NLS and an MLE based technique method of scoring. The results showed that the method of scoring and minimum χ^2 methods provide better estimates (and more comparable to each other) than NLS based on sum of squared errors and χ^2 value criterion. This is due to the asymptotic efficiency of MLE and the asymptotic equivalence of the minimum χ^2 and method of scoring estimators.

McDonald (1984) argues that MLE is the most efficient estimator when using grouped data, and maximum likelihood estimation on individual data is more efficient than that. MLE and minimum χ^2 are both used by McDonald and Mantrala (1995). Maximum likelihood produces sum of squared errors and sum of absolute levels either equal to or slightly less than those obtained by minimum chi squared when fitting lognormal, gamma, generalised gamma, Dagum, Singh-Maddala, and GB2 distributions.

Prieto-Alaiz and Victoria-Feser (1996) compare the OBRE and MLE. The OBRE is an estimator based on robust statistics and accounts for the possibility of errors in the data or extreme observations which may prevent the data from exactly following the parametric model. In the OBRE framework the data is assumed to be generated by a distribution which approximates a parametric model but accounts for a small probability that the data comes from a "contamination" distribution. The data are therefore modelled as a mixture distribution of the contamination distribution and the parametric distribution, weighted by the probabilities that an observation comes from either distribution.

The OBRE technique is found to be more robust than maximum likelihood estimation, and is found to give better gamma and lognormal distribution fits to Spanish income data. In using the OBRE there is, however, a trade-off between robustness and efficiency whereas MLE is the most efficient estimator. MLE is therefore more efficient but under the potentially strong assumption that the parametric functional form is correctly specified.

2.3 Data

This section describes the two datasets used in the analysis in this chapter. These are the New Earnings Survey (NES) and the Annual Survey of Hours and Earnings (ASHE).

2.3.1 The New Earnings Survey

The New Earnings Survey[4] is a 1% random sample of all employees in the UK registered to pay income tax through PAYE (Pay As You Earn). The sample is obtained by examining individuals whose National Insurance numbers end with a specific two digits. The

[4] Office for National Statistics, New Earnings Survey, 1975-2011: Secure Data Service Access [computer file]. Colchester, Essex: UK Data Archive [distributor], May 2012. SN: 6706.

survey is completed by employers for their employees using company payroll records, as a result of which the data relating to earnings collected from this survey can be considered more reliable than those from self-completed questionnaires such as those used by the Labour Force Survey. The NES data covers the period 1975-2011 and is used to estimate the aggregate level wage distributions as a complement to the ASHE data which is used to model the wage distribution in more recent years.

2.3.2 The Annual Survey of Hours and Earnings

The ASHE[5] was introduced in 2004 in order to address the shortcomings of the NES. The design of the NES can lead to biased estimation of earnings statistics etc for four main reasons; coverage of employees is incomplete, responses are un-weighted, differential non-response, and also it misses employees who change jobs between the sample selection and survey dates.

The first issue - incomplete coverage - is specifically related to the under-representation of low earners i.e. people who earn below the PAYE threshold. Employees in businesses not included on the Inter-Departmental Business Register (IDBR) cannot be identified and therefore cannot be included in the survey. These types of workers would tend to earn below the PAYE threshold but this bias is not thought to be large based on the number and size of businesses not in the IDBR.

Within the IDBR there are other sources of potential bias; VAT only businesses - where employees are paid less than the PAYE threshold. Selected businesses in this category are asked if they have employees outside the PAYE scheme and if so are sent an ASHE questionnaire for each of these employees. The other source of bias is employees paid outside of PAYE, however it is thought to be too difficult to obtain data for this group and they are therefore excluded from the survey (but are accounted for in the weights). Unit non-response - in particularly that which occurs when individuals change jobs between the survey date and the sample being identified - is also dealt with using a supplementary

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[5] Office for National Statistics, Annual Survey of Hours and Earnings, 1997-2011: Secure Data Service Access [computer file]. Colchester, Essex: UK Data Archive [distributor], May 2012. SN: 6689.

survey.

The issue of weighting (required due to the sample no longer being a 1% purely random sample) is dealt with by creating a calibration weight; responses are divided into calibration groups (108 in total) based on occupation, sex, age, and workplace region. The total number of employee first and second jobs in the Labour Force Survey (spring quarter) is used to create calibration totals for the 108 groups.

Item non-response can cause problems when results are weighted and so missing values for certain ASHE variables are imputed using a stochastic imputation method - the missing variable is estimated from the responses of individuals with similar characteristics to the employee with the missing value. Similarity of two employees is determined by occupation, region, sex, age, and whether or not they are paid the full adult rate. The ASHE therefore represents a better coverage of employees than the NES, particularly at the bottom end of the distribution. A more detailed description of the ASHE methodology and its improvement over the NES is given in Bird (2004). The ASHE methodology has been retrospectively applied to the NES, providing ASHE data for the period 1997-2003. ASHE data used in this study covers the period 1997-2011.

2.3.3 Variables

The variable which is modelled is the individual's average hourly wage, as opposed to earnings or total income. Total income is not modelled as this thesis focuses on labour market income. An individual's earnings are their total payments from their employment over a given period of time, whereas the wage is labour market earnings per hour; the price per unit of labour. Earnings are driven by an individual's labour supply decision and firms' labour demand decisions (on hours) as well as wages and DiNardo et al. (1996) argue that it is better to model wages than earnings as the wage is more directly linked to models of wage determination and can therefore be related to economic theory.

The hourly wage variable used here consists of all aspects of the employees pay; their basic pay, incentive pay, overtime pay, and other pay which consists of, for example, additional payments for working at "unsociable" hours. This total earnings figure is averaged across the employee's total working hours - basic hours plus overtime hours. The distribution models are estimated based on the hourly wage earned from the individual's main job (if the individual has more than one job). The wage variable is adjusted for inflation using the Retail Prices Index (RPI) at 2011 prices.

The histogram in Figure 2.3 illustrates a typical wage distribution (truncated to £50 or less per hour), in this case from the ASHE data for 1997. The skew of the distribution is positive, indicating the bulk of the data is located in the bottom of the distribution with outliers in the right hand tail, as would be expected from a wage distribution.

The standard industrial and occupational classification codes are used to create population sub-groups for which the distributions are also estimated. Five industrial groups are used: primary industries (which consists of agriculture, fishing, mining, construction, energy, and water supply); manufacturing; finance; distribution (consisting of wholesale, retail, motor vehicles, and hotels and catering); and all other services.

Two occupational groups are created termed ”high skilled” and ”low skilled”. These groups are composed of, respectively, SOC major groups 1-3 (managers and senior officials, professional, and associate professional/technical occupations) and the remaining groups 4-9 (administrative, skilled trades, personal services, sales, plant and machine operatives, and elementary occupations). A dummy variable is also used to split the sample into public and private sector employees.

2.4 Methodology

The methodology of this chapter is to use parametric distribution modelling techniques to model the distribution of UK wages using the NES and ASHE data. An advantage of using non-parametric techniques such as the kernel density approach of Cowell et al. (1998) is that the distribution can be modelled without making any assumptions about the appropriate functional form of the distribution. The drawback to this approach is that the lack of parametrisation of the model means quantitative results cannot be obtained for analysis. A parametric approach is therefore the preferred option for this chapter in order to estimate measures of wage inequality.

Parametric modelling of the wage distribution involves choosing and imposing a specific functional form on the data, and estimating the parameters of the chosen functional form by an appropriate estimation technique. Appropriate distributions for modelling wage data are those which are supported for all strictly positive values of the wage and are positively skewed to allow for outliers in the upper tail of the distribution, and the distributions considered are those identified in the literature review.

Three parameter models of distributions represent a compromise between two parameter models (which are simpler to estimate and interpret, but relatively inflexible and provide poorer fits) and four/five parameter models (which provide better fits to data but are more difficult to estimate and interpret). A common finding in the literature is that the Dagum (1977) distribution is the best fitting three parameter size distribution to income/wage data and often performs just as well as the four parameter Generalised Beta 2 distribution. Figure 2.3 compares the log-normal, Dagum, and GB2 distributions estimated for 1997 using the ASHE data.

As Figure 2.3 shows, the log-normal distribution provides a relatively poor fit to the distribution of wages, whereas the Dagum and GB2 distributions both fit well and cannot easily be distinguished from each other visually. The null hypothesis that $q = 1$ for the GB2 distribution is, however, rejected at the standard significance levels, therefore significantly distinguishing it from a Dagum distribution. The Dagum distribution is still preferred, however, as the maximum likelihood estimator of the GB2 distribution suffers from convergence problems for a number of the annual cross-sections.

2.4.1 Dagum Distribution

The probability and cumulative distribution functions for the Dagum distribution are given by:

$$f(x;a,b,p) = \frac{apx^{ap-1}}{b^{ap}[1+(\frac{x}{b})^{a}]^{p+1}}; (a,b,p>0), x \in (0,\infty) \tag{2.1}$$

$$F(x;a,b,p) = [1+(\frac{x}{b})^{-a}]^{-p}; (a,b,p>0), x \in (0,\infty) \tag{2.2}$$

The estimated parameters of the distributions can be used to calculate estimates of different features of interest of the distribution such as the moments or the quantiles as functions of those parameters. Measures of inequality can also be calculated for the empirical distributions. The measures which are calculated are the Gini coefficient, the 90/10, 50/10, and 90/50 percentile ratios, and three indices from the generalised entropy (GE) family of inequality measures. Estimates of Pareto's α are also obtained to analyse wage inequality at the top of the distribution at the aggregate level and sectoral level. Further disaggregation results in an insufficient sample size with which to estimate Pareto models, Pareto's α estimates are consequently not estimated for the industry and occupation level models.

The GE measures - denoted I(γ) - are calculated for γ = 0, 1, and 2. The γ term is a parameter indicating the sensitivity of the GE measure to inequality at the top of the distribution, with the sensitivity increasing with the value of γ. The formulae for obtaining the GE measures from the Dagum distribution are adapted from those presented by Jenkins (2009) for the GB2 distribution. The Gini coefficient for this distribution was derived by Dagum (1977).

The formulae for calculating these measures of inequality from the Dagum distribution parameters are[6]:

$$Gini = \frac{\Gamma(p)\Gamma(2p+\frac{1}{a})}{\Gamma(2p)\Gamma(p+\frac{1}{a})} - 1 \tag{2.3}$$

$$I(0) = \gamma(p+\frac{1}{a}) + \gamma(1-\frac{1}{a}) - \gamma(p) - \frac{\psi(p)}{a} - \frac{\psi(1)}{a} \tag{2.4}$$

[6] In these formulae Γ denotes the gamma function, ψ denotes the digamma function (first derivative of the gamma function), and γ denotes the log-gamma function.

$$I(1) = \frac{\psi(p+\frac{1}{a})}{a} - \frac{\psi(1-\frac{1}{a})}{a} - \gamma(p+\frac{1}{a}) - \gamma(1-\frac{1}{a}) + \gamma(p) \tag{2.5}$$

$$I(2) = -\frac{1}{2} + \frac{\Gamma(p)\Gamma(p+\frac{2}{a})\Gamma(1-\frac{2}{a})}{2\Gamma^2(p+\frac{1}{a})\Gamma^2(1-\frac{2}{a})} \tag{2.6}$$

and the quantile function used to calculate the percentile ratios is given by:

$$F^{-1}(u) = b[u^{-\frac{1}{p}} - 1]^{-\frac{1}{a}}, for 0 < u < 1 \tag{2.7}$$

2.4.2 Pareto Distribution

While the Dagum distribution is useful for modelling the entire distribution, the top of the distribution can be independently modelled using a Pareto distribution. The Pareto distribution is given by the probability and cumulative density functions:

$$f(x;\alpha,x_0) = \frac{\alpha_0^{\alpha}}{x^{\alpha+1}}, (\alpha, x_0 > 0), x \in (x_0, \infty) \tag{2.8}$$

$$F(x;\alpha,x_0) = 1 - (\frac{x_0}{x})^{\alpha}, (\alpha, x_0 > 0), x \in (x_0, \infty) \tag{2.9}$$

Kleiber and Kotz (2003) show that all measures of inequality are inversely proportional to the α parameter - also known as ”Pareto’s α”. The parameter itself can therefore be interpreted as a measure of inequality. In addition to the Dagum distribution estimates and the inequality measures derived from their parameters, the analysis also includes estimates of the Pareto distribution where the x_0 parameter (representing the minimum point of the support of the Pareto distribution) is chosen *a priori* so as to model the upper 10%, 5%, and 1% of the wage distribution.

2.4.3 Estimation

The empirical wage distributions are estimated by maximum likelihood (ML) estimation - this is due to the asymptotic properties of ML which can be exploited due to the large sample sizes of the datasets. It has also been commonly used in the literature for fitting parametric distribution models to income and wage data. The distributions are estimated in repeated cross sections for each year of the available data in order to show how the distributions and various inequality measures have changed over time.

This approach is applied at the aggregate level, the sectoral (public/private) level, the industry level, and the occupational level. Maximum likelihood estimation of the distribution parameters involves maximising the following log-likelihood functions for the Dagum, and Pareto distributions[7] respectively:

$$\begin{aligned}\ell(\theta|x_i) &= log(a) + log(p) + (ap-1)log(x_i) \\ &\quad -(ap)log(b) - (p+1)log[1+(\frac{x_i}{b})^a]\end{aligned} \tag{2.10}$$

$$\ell(\theta|x_i) = log(\alpha) + (\alpha)log(x_0) - (\alpha+1)log(x_i) \tag{2.11}$$

2.4.4 Regression Models

The analysis also consists of regression models, showing the impact of various characteristics on wage inequality once other factors are accounted for. Inter-quantile regression models are estimated in a similar approach to Stewart (2011) which models wage inequality as measured by the log of the percentile ratios as a function of the included variables. Variables included are occupation, industry, sector, regional dummies, and gender.

The inter-quantile regression is an extension of standard quantile regressions in which the

[7] These are expressed as the likelihoods for a single observation, which are aggregated over all observations.

conditional quantile of the dependent variable y (as opposed to the mean) is modelled for some given quantile q as a linear function of independent variables x. The inter-quantile regression technique models the difference between two quantiles in the distribution of y

$$y_{i,q} = x_i' \beta_q + \varepsilon_{i,q} \tag{2.12}$$

The inter-quantile regression approach estimates an equation which is the difference between two equations of the form in equation 2.12 which are distinguished by two different values of q. If, for example, the two values of q chosen are 90 and 10 (the 90th and 10th percentiles), the inter-quantile regression model is the difference between two quantile regressions, one for the 90th percentile and one for the 10th:

$$y_{i,90} - y_{i,10} = x_i'(\beta_{90} - \beta_{10}) + \varepsilon_{i,90} - \varepsilon_{i,10} \tag{2.13}$$

$$y_{i,90} - y_{i,10} = x_i' \beta^* + \varepsilon_i^* \tag{2.14}$$

The estimated coefficient in the inter-quantile regression model for a given independent variable is therefore the difference between the coefficients from two separate quantile regressions. In using this approach to model wage inequality the difference in wage inequality between population sub-groups can be analysed while controlling for compositional factors. For example, a significant positive coefficient on a dummy variable for being male would indicate greater wage inequality amongst males than females having accounted for the fact that males may be disproportionately represented in higher inequality sectors such as finance.

A regression approach is also taken to analyse wage inequality at the top of the distribution. As in Thurow (1970) and Salem and Mount (1974), the parameters of the maximum likelihood estimated distributions can be modelled conditional on a set of explanatory variables. This is performed for the Pareto distribution in this case to model the inequality at the top of the distribution as a function of the same variables used in the inter-quantile regressions.

As the estimated parameter of the Pareto distribution can itself be considered a measure of inequality it is straightforward to extend the estimates of this parameter to the case where the parameter is conditioned on explanatory variables. As in the inter-quantile regressions, this will show the differences in inequality between groups having controlled for composition effects.

2.5 Simulation

This section presents the results of a simulation study of the maximum likelihood estimator of Pareto's α. A similar study of the properties of the maximum likelihood estimator of the Dagum distribution parameters is provided by Domanski and Jedrzejczak (1998). It finds that estimates of the scale parameter, b, of the Dagum distribution are biased for sample sizes less than 4,000 and are not normally distributed for any of the sample sizes they consider (up to 10,000). The scale parameter does not, however, affect the inequality of the distribution. The parameters which do influence the level of inequality are unbiased when estimated by maximum likelihood for samples of 2,000 - 3,000 and are also normally distributed and efficient. Given the large sample sizes available in the ASHE (even when disaggregating the analysis) the results of their simulation study suggest that the MLE of the Dagum distribution in this chapter will produce reliable estimates of the parameters and inequality measures and also valid statistical inference.

The simulation of the Pareto distribution is based on the same procedure as the Domanski and Jedrzejczak (1998) paper. The finite sample properties of the MLE of the Pareto distribution are examined by selecting a range of sample sizes and for each sample size examining the performance of the estimator for a range of values of the α parameter. The parameter values should be chosen so as to cover plausible situations in the real data. The lower bound parameter of the distribution x_0 is fixed at 25.76 for all simulations as this is the 90th percentile of the pooled 1997-2011 real wage data in the Labour Force Survey. The values of Pareto's α used are 2, 3, 4, and 5 and the sample sizes selected are 1,000, 2,000, 3,000, 40,00, 5,000, 6,000, 7,000, 8,000, 9,000, and 10,000.

For each simulation random samples of size $n = 1,000, 2,000, ..., 10,000$ are drawn from a Pareto distribution with parameter values of $x_0 = 25.76$ and $\alpha = 2,3,4,5$ in turn. The maximum likelihood estimator is then used to fit an empirical Pareto distribution to the random samples. The simulation is performed with 5,000 replications for each combination of sample size and parameter value and the empirical bias and variance calculated. The Shapiro-Francia test for normality is also performed. Under the null hypothesis for this test, the parameter estimate is normally distributed.

Table 2.1: Empirical Bias of the Pareto Distribution MLE

	α=2		α=3		α=4		α=5	
Sample Size	Bias	t statistic	Bias	t statistic	Bias	t statistic	Bias	t statistic
1,000	0.002	2.106	0.003	2.364	0.001	-0.291	0.006	2.772
2,000	0.000	0.285	0.003	2.735	0.000	0.235	0.002	1.482
3,000	0.000	-0.687	0.001	0.876	0.000	-0.168	0.001	-0.528
4,000	0.000	0.496	0.000	0.269	0.000	-0.208	0.002	1.652
5,000	0.000	1.106	0.001	1.377	0.001	1.508	0.002	1.733
6,000	0.000	0.652	0.000	-0.214	0.001	-0.905	0.002	1.835
7,000	0.000	0.538	0.000	-0.547	0.000	-0.279	0.001	1.023
8,000	0.000	0.596	0.001	1.296	0.001	1.298	0.000	0.529
9,000	0.001	2.628	0.001	-1.866	0.000	-0.798	0.001	-0.852
10,000	0.001	2.493	0.000	-0.513	0.001	1.614	0.001	0.924

Table 2.1 reports the first of the simulation results. For each of the four parameter values and each sample size considered the absolute value of the empirical bias and a t statistic for the null hypothesis that the expected value of the estimates of α is equal to the value for the underlying data generating process (i.e. that the bias is equal to zero). With the exception of when α is equal to two the estimator is unbiased for relatively small sample sizes (3,000 and higher). Where the bias is significantly different from zero it is still small in magnitude. The consequences of any bias in the estimator therefore do not appear to have any economic significance.

Table 2.2 reports the results of the simulation for the variance and normality of the parameter estimates. The p values for the Shapiro-Francia test show that the null hypothesis cannot be rejected at the 5% level for samples larger than 7,000. For feasible sample sizes it is therefore valid to perform statistical inference on the MLE of the Pareto distribution. The variance in the estimator is also declining asymptotically for each value of α.

Table 2.2: Empirical Variance and Normality of the Pareto Distribution MLE

	α=2		α=3		α=4		α=5	
Sample Size	σ^2	SF Test	σ^2	SF Test	σ^2	SF Test	σ^2	SF Test
1,000	0.004	0.001	0.009	0.000	0.016	0.004	0.026	0.018
2,000	0.002	0.145	0.005	0.003	0.008	0.189	0.013	0.387
3,000	0.001	0.001	0.003	0.034	0.005	0.002	0.008	0.009
4,000	0.001	0.374	0.002	0.324	0.004	0.034	0.006	0.178
5,000	0.001	0.102	0.002	0.097	0.003	0.187	0.005	0.465
6,000	0.001	0.272	0.002	0.016	0.003	0.915	0.004	0.033
7,000	0.001	0.616	0.001	0.959	0.002	0.643	0.003	0.091
8,000	0.000	0.625	0.001	0.286	0.002	0.308	0.003	0.676
9,000	0.000	0.152	0.001	0.069	0.002	0.240	0.003	0.373
10,000	0.000	0.058	0.001	0.610	0.002	0.912	0.003	0.143

Note: SF Test columns report p values for the Shapiro-Francia test

2.6 Analysis

This section presents the results of the analysis previously outlined. Table 2.3 summarises the results of the aggregate and sub-group analyses, showing percentage changes in each level of wage inequality between 1997 and 2011 calculated from the Dagum distribution estimates using the ASHE data. Figures which show the year-on-year changes in inequality can be found in Appendix 2A to this chapter and further quantitative results showing the estimated levels of inequality in select years can be found in Appendix 2B.

Table 2.3: Percentage Changes in Inequality (ASHE)

	Aggregate	Private	Public	High Skilled	Low Skilled	Primary	Manufacturing	Distribution	Finance	Services
Gini	2.76	-0.5	0.01	8.11	-11.9	-1.57	6.43	-17.31	21.04	1.47
90/50	3.70	1.15	1.56	7.48	-3.13	0.17	5.84	-9.72	17.48	3.22
50/10	-6.95	-7.99	-5.75	-3.49	-11.40	-4.95	-3.25	-11.12	5.19	-9.07
90/10	-3.52	-6.93	-4.28	3.74	-14.17	-4.78	2.39	-19.76	23.57	-6.15
I(0)	4.73	-1.71	-0.94	14.13	-23.84	-4.20	12.67	-31.81	48.01	1.41
I(1)	13.69	5.10	4.46	24.20	-19.47	-0.77	21.00	-32.42	68.63	11.22
I(2)	59.91	34.35	17.54	50.04	-16.39	4.70	50.58	-42.22	141.89	49.85

2.6.1 Aggregate Level Wage Inequality

The aggregate levels of wage inequality are estimated using both the NES and ASHE data. Table 2.5 gives the estimates of the inequality measures for selected years from the ASHE data for selected years between 1997 and 2011. Gini coefficient estimates shown in Figure 2.4 indicate increasing inequality over time until the late 1990's, at which point the increases slow down substantially. Both datasets show comparable trends in inequality with the exception of a peak in the NES data around the year 2000.

The ASHE data yields significantly higher estimates of wage inequality than NES, as would be expected due to the sampling of both datasets in which ASHE gives better coverage of the bottom of the wage distribution. The increase in the Gini coefficient is 2.76% points. As can be seen in Figure 2.4 the rate of the increase in inequality between 1997 and 2011 has declined in comparison to the 1980's/early 1990's. This Figure is similar to Van Reenen (2011) Figure 2 which also showed the rapid increase in wage inequality - measured by the 90/10 ratio - until the late 1990's, followed by a slowdown but continued increase.

Figures 2.5 and 2.6 show the change over time in the three generalised entropy measures of wage inequality, respectively using the NES and the ASHE. In both cases inequality can be seen to have increased over the 1975-2011 period as well as from 1997-2011 by each of the measures. The increase in inequality is the most dramatic by the I(2) level of inequality - 60% between 1997 and 2011 compared to 14% by I(1) and 5% by I(0).

The 90/50 ratio has significantly increased since 1975, meanwhile the 50/10 ratio increased up to around 1995 in the models estimated from the NES data, the ASHE results suggesting a peak at 1998. After 1998 both the NES and ASHE results show a significant and sharp decline in the 50/10 ratio. This decline coincides with the introduction of the National Minimum Wage (NMW) in 1999 and persists until 2011. Between 1997 and 2011 the decline in the 50/10 ratio was 6.95% compared to a 3.70% increase in the 90/50 ratio.

Figures 2.7 to 2.9 show the change in Pareto's α - the estimated parameter of the Pareto distribution which is inversely related to the level of inequality. For the top 10% and 5%

of the distribution, inequality has significantly increased from 1975 to 2011 and for the top 1% has increased until approximately 1995 and remained relatively constant since. These increases in the top 5% and 10% mainly occurred during the 1980's and 1990's, in common with the changes in inequality in the wage distribution as a whole.

Unlike the estimates of wage inequality for the entire distribution, there is no significant difference between the estimated level or patterns over time of Pareto's α between the ASHE and the NES data. This is likely due to the fact that the methodological differences between ASHE and NES were to better account for the bottom end of the distribution, it should therefore be expected that there would be no significant impact on estimates based on the top 10% of the wage distribution between the two datasets.

The aggregate level results therefore give a picture of increasing wage inequality, and that this is being driven by the top of the wage distribution. The exception to this is the 90/10 differential which declined despite an increase in the (more comprehensive) Gini coefficient. This indicates that the increases in wage inequality picked up by the other measures are driven at least in part by the extremes (the top and bottom deciles) of the distribution and most likely the top 10%. The 90/50 and 50/10 differentials indicate the increase in wage inequality is a high-earners phenomenon.

The introduction of the minimum wage in 1999 also makes it unlikely that inequality increased in the very bottom tail of the distribution. The Pareto distribution estimates provide evidence that there has been an increase in inequality within the top 10% of the aggregate wage distribution. The generalised entropy measures also indicate the importance of inequality amongst the highest earners, with the estimated increase in wage inequality increasing as more weight is attached to the top of the distribution.

These range of inequality measures calculated here give some indication of why inequality growth has slowed down. The figures indicate that the top of the wage distribution has played a role, with the change in inequality within the top 10%, 5%, and 1% levelling off in the last few years of the sample. The decline in inequality within the bottom of the distribution also clearly has some role in slowing down overall inequality growth.

2.6.2 Sectoral Level Wage Inequality

Private and public sector level estimates are presented in Tables 2.6 and 2.7. The Gini coefficient did not change substantially for either sector, with a 0.5% decline for the private sector and a 0.01% increase for the public sector. These changes can be seen to be insignificant in Figure 2.10. The Figure shows that private sector wage inequality has remained consistently greater than public sector wage inequality.

Both private and public sector saw a slight increase in the 90/50 ratio (1.15% and 1.56% respectively) over time but much more apparent significant declines in the 50/10 ratio (7.99% and 5.75% respectively). This results in an overall decline in the 90/10 ratios for both sectors. As with the Gini coefficient these results suggest that the gap between public and private sector wage inequality has declined.

Whether inequality increased or decreased depends on the sensitivity placed on the top end of the distribution, as shown by the GE estimates. Interpreting the I(0) measure, both sectors saw a decline in wage inequality. The I(1) and I(2) measures both saw an increase between 1997 and 2011, however, with particularly large increases by the I(2) measure of 34% in the private sector and 18% in the public sector. This relatively large change in I(2) compared to the other GE measures is apparent in Figures 2.11 and 2.12.

In contrast to the percentile ratios and the $I(0)$ measure, the $I(1)$ and $I(2)$ inequality measures indicate rising wage inequality in both sectors and also suggest the gap between the two is rising rather than falling, so the comparison of these two sectors is sensitive to the inequality measure interpreted.

Compared to the other levels of analysis the change in inequality is particularly sensitive to the measure chosen, both in terms of comparing the change in inequality within the sector and when comparing the two together. There are some indications that the gap between the two has narrowed with only the measures most sensitive to the top of the distribution suggesting the the gap has continued to widen.

Higher inequality in the private sector than the public sector has an intuitive explanation. As public sector workers are paid for by taxation there is greater scrutiny of public sector pay than that of employees in private firms. This is especially the case at the top of the distribution, particularly as it is harder to justify high pay on the grounds of performance. Performance in a public sector firm is more difficult to measure compared to a private firm where performance can be judged as profits or shareholder return. There are therefore tighter "outrage" constraints on top pay in the public sector which restricts growth in wage inequality compared to in the private sector.

2.6.3 Occupational Level Wage Inequality

The two different levels of occupation - high and low skilled - exhibit different trends in inequality over time. As can be seen in Table 2.3, wage inequality unambiguously declined amongst low skilled occupations, and, with the exception of the 50/10 ratio, increased by every inequality measure in high skilled occupations.

Figures 2.13 to 2.15 show the changes in each of the inequality measures for the high skilled and low skilled occupational subgroups. In each figure it is clear that the change in the inequality measures over time are all significant.

The Gini coefficient increased by approximately 8% for high skilled occupations and declined by 12% for low skilled occupations. The change in the 90/10 ratio is driven primarily by the bottom of the distribution for low skilled occupations, with an 11% decline in the 50/10 ratio contributing to an overall decline in the 90/10 ratio of 14% which is suggestive of the NMW affecting the bottom end of the wage distribution after 1999 for the low skilled occupations.

The 50/10 ratio declined by a smaller magnitude of 3.5% points in high skilled occupations and partially offset an increase in the 90/50 ratio of 7.5% points, leading to an overall increase in the 90/10 ratio.

As in the aggregate and sectoral cases, the GE measures change by a monotonically increasing amount moving from the $I(0)$ measure to $I(2)$. In the case of low skilled occupations this means the magnitude of the decline in wage inequality decreases, from 24% points by the $I(0)$ measure to 16% points by the $I(2)$ measure. For high skilled occupations $I(0)$ increased by 14%, $I(1)$ by 24%, and $I(2)$ by 50%.

The occupational level results could be indicative of an effect of changes in the skill distribution on wage inequality. All measures of inequality for the low skilled decline and all of them (except the 50/10 differential) increase for the high skilled.

The explanation for these results could be greater educational attainment. The widening of participation in higher education in the UK would be expected to have introduced a larger variety of abilities into the high-skilled occupations which require a university degree by inducing those with less ability to acquire higher education. Consequently (assuming individuals are paid according to their marginal product of labour) the distribution of wages within the higher skilled occupations will have widened. Assuming those individuals would have been at the top of the distribution of wages in the lower skilled occupations, the distribution of wages for those occupations will have narrowed.

These results link back to the aggregate level analysis, where falling inequality was found at the bottom of the distribution and rising inequality at the top. These occupational level results provide an indication for why this has been observed, as the low skilled occupations will be found primarily within the bottom of the aggregate wage distribution and the high skilled occupations at the top. This educational attainment explanation for the different trends in wage inequality within the occupational level distributions can therefore potentially explain the observed trends in the aggregate distribution.

2.6.4 Industry Level Wage Inequality

The results for the industry level analysis are presented in Tables 2.10 to 2.14 and Figure 2.16.

The Gini coefficient results in Figure 2.16 show two industries in which wage inequality has declined (primary and distribution). The decline of 1.57% in primary industries is not significant but the 17.31% decline in the wholesale/retail distribution and catering industries is. In the other industries the Gini coefficient has increased, particularly in finance where the increase was 21.04%. The Gini coefficient for the remaining industries

- manufacturing and other services - increased significantly. Although relatively small in magnitude, the increase in the Gini coefficient for other services of 1.47% is significant.

The finance industry is the only one for which inequality increased according to each of the estimated measures. It is also the only population sub-group for which the estimated 50/10 ratio increased over the 1997-2011 period. Table 2.3 shows that the magnitudes of these changes also substantially exceed the changes seen in other industries, or at the occupational/sectoral/aggregate level. This can particularly be seen for the $I(2)$ measure, for example, which increased by 142% in finance - 91% points more than the increase for manufacturing, which exhibited the next largest increase in the $I(2)$ measure.

$I(0)$ and $I(1)$ decreased for primary industries but $I(2)$ increased (although not significantly). Wholesale/retail distribution and catering is the only industry in which inequality unambiguously declined by all inequality measures with a significant fall in $I(2)$ of 42%. It is notable that the wholesale/retail and catering industries are the only case of the change in the GE measures monotonically decreasing rather than increasing as more weight is given to observations at the top of the distribution. The decline in the $I(0)$ measure is 32% compared to a 42% decline in $I(2)$. In all other industries and occupational/sectoral/aggregate level analysis, giving more weight to the top of the distribution increases the observed change in wage inequality - either increasing the growth in inequality or reducing the decline.

In the services sector, the decline in the 50/10 ratio offset the increase in the 90/50 ratio which results in an overall decline in the 90/10 ratio of 6.15% despite the other measures of inequality exhibiting significant increases in wage inequality. The increases in the $I(0)$ and $I(1)$ measures are smaller than those of manufacturing and finance but the increase in the $I(2)$ measure of 50% is comparable to the increase for manufacturing.

The industry level results add to the conclusion that the top of the distribution is an important factor in the recent trends in wage inequality. In each case, regardless of whether inequality increased or decreased, the largest magnitudes are found for $I(2)$ than $I(1)$ and in turn $I(0)$.

Changes in, and levels of, inequality may differ across industries because of compositional factors. For example, the distribution sector consists of retail and catering which are both relatively low-waged industries. This greater proportion of low-wage jobs compared to other industries make it more susceptible to the introduction of the minimum wage which could partially account for the decline in wage inequality which is observed. The minimum wage can only at best be a partial explanation for declining wage inequality in this sector, as amongst the generalised entropy measures the decline in wage inequality is greater when the most weight is put on the top of the distribution. Also, the 90/50 differential indicates that inequality within the top of the distribution declined and this would not be affected by the minimum wage.

As wage inequality within low skilled occupations declined while increasing within high skilled occupations, the relative proportions of these types of occupation in each industry will impact on the change in inequality within each industry as these proportions are likely to differ across industries. Wage inequality falling in distribution but increasing in financial services could in part be a reflection of the fact that finance is likely to have a greater proportion of high skilled occupations and therefore the impact of growing wage inequality within those occupations will have a stronger impact on finance than distribution. This is another composition effect which will account for differences in wage inequality growth across industries.

If the factors which affect the relative demand for skilled labour have differential impacts across industries this would explain the differences in wage inequality found in this analysis. There are likely to be differences in the adoption of production processes which require skilled labour across industries, for example, the increasing adoption of computer technology. Industries which make heavier use of computer technology will increase their relative demand for skilled labour by more than industries which do not and this could be part of the difference between the catering, retail, and wholesale sectors and finance.

2.6.5 Regression Results

This section extends the analysis of the previous sections by considering differences in inequality by population sub-group once other factors are controlled for. For example, greater wage inequality in finance compared to manufacturing may be due to a greater proportion of high skilled labour. A regression approach allows for an interpretation of the difference in inequality between those two industries when controlling for other compositional factors.

Interquantile Regressions

Following the approach of Stewart (2011), who performed a similar analysis for earnings inequality between 1997 and 2002, Table 2.15 presents the results of inter-quantile regressions for the 90/10, 90/50, and 50/10 percentile ratios. For this analysis the wage variable is transformed into logs as the difference in two log percentiles of the distribution is equivalent in interpretation to the log of the ratio of the two percentiles. Coefficients are therefore interpretable as the impact of the independent variable on the log percentile ratio.

The regressions include four industry dummies with primary industries as the base category, a private sector dummy, high skilled occupations dummy (indicating an individual in the SOC major groups 1 to 3), a gender dummy equal to one if the individual is male, and regional dummies (only the coefficient for London is reported for these). Results are reported for each of the three percentile ratios from separate cross-sectional regressions for 1997 and 2011. Standard errors are estimated by bootstrapping with 400 replications.

The results show that in 1997 wage inequality was not significantly different in the finance sector than the base category for all three percentile ratios, despite the unconditional inequality estimates reporting a 90/10 ratio of 3.53 in primary industries (Table 2.10) and 4.38 in finance (Table 2.13). In 1997, therefore, the difference between inequality in finance and primary industries can be explained by accounting for occupational, sectoral, gender, and regional composition.

Overall wage inequality in wholesale/retail and catering was also insignificantly different from primary industries in 1997, however inequality in the top of the distribution - the 90/50 ratio - was significantly higher but significantly lower in the bottom of the distribution - the 50/10 ratio. Controlling for other factors still leaves some inter-industry wage inequality differences, with a significantly higher 90/10 ratio in the other service industries and significantly lower in manufacturing.

The picture changes by 2011. In 2011 the 90/10 ratio for manufacturing and services is insignificantly different from primary industries. The 90/10 ratio for finance is approximately 10% points larger than primary industries despite the 50/10 ratio in 2011 being significantly lower by 3% points. Controlling for other factors, the increase in wage inequality in finance relative to other industries is still apparent and driven by the top end of the wage distribution. Similarly, the wholesale/retail distribution and catering 90/10 ratio moved to being significantly less than primary industries by 16% points.

In both 1997 and 2011 high skilled occupations are more unequal than low skilled occupations once the other factors are controlled for. All six coefficients for the high skilled dummy are highly significant. This difference is large in magnitude with a 26% points larger 90/10 ratio for high skilled occupations in 1997 which increased to 40% points by 2011. This pattern is reflected in the coefficients for both the 90/50 and 50/10 ratios which increased from 0.133 to 0.181 and from 0.126 to 0.220 respectively.

For both the male and London dummy variables the coefficients can be interpreted similarly but with much smaller magnitudes. Wage inequality amongst males is significantly larger than females and by each of the three inequality measures this wage inequality has increased between 1997 and 2011, with a 3% point increase in the additional wage inequality amongst males over females from 10% to 13%. The 90/10 ratio in London compared to the base region (Scotland and Wales) increasing from 9% points to 21% points.

All six coefficients are also highly significant for the private sector. In this case, the level of wage inequality in the private sector relative to the public sector has fallen between 1997 and 2011, with the 90/10 ratio falling from 20% points larger than that of the public sector to 12%, driven mainly by a relative fall in the 50/10 ratio coefficient of 0.076 points to 0.012 point. The gap between public and private sector wage inequality has therefore fallen but wage inequality remains significantly higher in the private sector. This narrowing of the private/public sector difference in wage inequality contrasts with the faster growth of private sector wage inequality during the 1980's and 1990's found by Disney and Gosling (1998).

Pareto Regressions

As well as overall wage inequality, inequality at the top of the distribution is similarly analysed by modelling the Pareto distribution as a function of the same independent variables used in the interquantile regression analysis. Table 2.16 presents the results of this analysis. The models are estimated for the top 10% and 5% of the wage distribution in 1997 and 2011. As the value of α is inversely proportional to the level of wage inequality a negative coefficient indicates a greater level of wage inequality.

For each of the four industries, inequality amongst the top 10% and top 5% has declined relative to the base industry. In the case of manufacturing the value of Pareto's α is not significantly different from the base industry. In both time periods for both the top 10% and 5% of the wage distribution finance is the most unequal industry, followed by wholesale/retail/catering and services. In 2011, for the top 5%, the only significant industry coefficient is that for finance, for the remaining three industries inequality is not significantly different from that of primary industries.

Unlike for the wage distribution as a whole, the coefficients for the male and London dummy variables have declined in magnitude for both the top 10% and 5%. This is also the case for the private sector. This means that in each case the difference in wage inequality between the variables and their base categories has declined. Inequality amongst the highest earners is therefore significantly higher in London, for males, and in the private sector but the gap has shrunk. The difference in inequality between high and low skilled occupations remained approximately the same between 1997 and 2011 for the top 10% but in the top 5% the coefficient is negative and significant for 1997 but insignificant in 2011.

In the top 10%, the most important factor determining the level of wage inequality is whether or not the individual is high skilled or low skilled in 2011. This differs from the case in 1997 where the coefficients for finance, gender, and working in the private sector are all larger in magnitude than being high skilled.

Amongst the top 5% the factor which exerts the largest impact on the level of wage inequality is whether or not the individual is in the finance industry in 2011. In 1997 the impact of working in the finance industry is still one of the most important determinants of the level of inequality, smaller in magnitude only than the effect of working in the private sector.

2.6.6 Comparison of Measures of Pay

Results are likely to be sensitive to the decision to model hourly wages rather than earnings. The impact of this on the results of the analysis is examined by comparing the previously estimated distributions with equivalent distributions modelled for weekly earnings - the same variable used in the construction of the gross hourly wage variable but not divided by hours.

The results may also be affected by using gross weekly earnings and total hours in the construction of the hourly wage variable, therefore a comparison is also made with a wage measure calculated from basic weekly earnings and basic hours. Basic weekly earnings omits any earnings accrued which is not basic pay, including overtime pay, shift/premium pay for working "unsociable" hours, and incentive pay. This wage measure therefore also omits overtime hours from the construction of the wage variable.

The results of these comparisons are presented in Figure 2.17. Tables 2.17 and 2.18 present aggregate level results equivalent to Table 2.5 for basic pay and weekly earnings respectively. As seen in Figure 2.17 the Gini coefficient for weekly earnings follows a similar pattern as that for hourly wages but produces a significantly larger estimated Gini coefficient, indicating that some inequality in earnings is due to differences in labour supply across the earnings distribution. The qualitative conclusion of a gradual significant increase in inequality since 1997 holds for earnings as well as wages.

Comparing basic pay to total pay also reveals some differences in the results of the analysis. Until 2004 the level of wage inequality estimated using basic pay/hours does not differ significantly from the estimates using total pay/hours. After 2004 however the two series' diverge and inequality calculated from basic pay/hours can be seen to be significantly lower. It appears therefore that after 2004 differences in incentive and overtime pay per hour across the wage distribution forms a significant component of the patterns in wage inequality.

Table 2.17 shows that the Gini coefficient declined slightly, with a much more substantial and significant decline in the 90/10 ratio also observed. The $I(0)$ generalised entropy measure of inequality also declined but $I(1)$ and $I(2)$ both increased significantly. This runs contrary to the less ambiguous results obtained for total pay, for which $I(0)$ and the Gini coefficient also increased.

2.6.7 Comparison to the Labour Force Survey

This section presents the results of the aggregate level analysis when using data from the Labour Force Survey (LFS). The sample is restricted in the same way as the NES and ASHE data (i.e. uses only hours and earnings from the individual's main job) and the wage variable constructed in the same way as the main wage measure used so far in the analysis - gross weekly earnings divided by actual hours.

Figure 2.18 presents results equivalent to those of Figure 2.4. Overall, the Gini coefficient increases in the LFS data results as in the NES/ASHE. There are, however, some differences. The LFS results show the Gini coefficient declining significantly until 2005 before beginning to increase again. The increase in the Gini coefficient in the ASHE data is more continuous over the 1997-2011 period. The estimated Gini coefficients in the LFS are also smaller than those from ASHE. The values from the LFS range between 0.305 and 0.315 The ASHE estimates of the Gini coefficient range from 0.341 and 0.351, and the difference is clearly significant.

Similar conclusions can be drawn from the comparison of generalised entropy estimates between the LFS data, (presented in Figure 2.19) which is the equivalent of the ASHE results in 2.6. The trends in the LFS and ASHE generalised entropy measures look similar, including the relative ranking of the measures in terms of the higher the sensitivity to the top of the distribution, the higher the estimated inequality. As with the Gini coefficient, however, the LFS understates the level of wage inequality compared to the ASHE. This can be most clearly seen with the I(2) measure which is consistently larger than 0.4 in the ASHE data but remains between 0.25 and 0.30 in the LFS.

Unlike the Gini coefficient, the generalised entropy estimates from the LFS data do not show a distinct decline in wage inequality between 1997 and 2005 followed by a subsequent increase.

Table 2.4 shows the percentage change in each inequality measure for the same sectors, occupational groups, and industries as the analysis using the ASHE data. It is comparable to Table 2.3. The column for the aggregate level results shows that the magnitude of all changes in wage inequality are smaller when using the LFS data. The sign of each change is the same for both datasets with the exception of I(0) which increased by 4.73% in the ASHE estimates but declined by 0.15% in the LFS estimates.

Table 2.4: Percentage Change in Inequality 1997-2011 (LFS)

	Aggregate	Private	Public	High Skilled	Low Skilled	Primary	Manufacturing	Distribution	Finance	Services
Gini	0.92	1.00	-1.57	1.87	-13.43	0.23	3.17	-11.63	12.17	-0.65
90/50	2.08	2.14	-0.21	1.75	-6.47	1.89	3.95	-6.71	9.94	1.18
50/10	-5.06	-5.38	-3.1	-0.82	-9.74	-5.52	-4.55	-6.37	1.38	-6.38
90/10	-3.09	-3.35	-3.3	0.92	-15.58	-3.73	-0.78	-12.65	11.45	-5.28
I(0)	-0.15	0.21	-4.29	2.75	-26.46	-2.36	3.92	-22.3	25.07	-3.84
I(1)	5.14	5.86	-2.49	4.76	-25.5	2.82	10.7	-23.39	34.98	1.33
I(2)	16.21	19.69	-0.86	8.26	-28.08	10.35	24.03	-29.46	93.72	9.39

The occupational level results are similar in the LFS and ASHE estimates. Each of the magnitudes for the high skilled occupations are larger in the ASHE results than the LFS. The same is true of the magnitudes of the decreases in wage inequality in the low skilled occupations (which decreased by 11.4% in the ASHE estimates but only 9.74% in the LFS). Each change in inequality is the same sign for both sets of results.

All changes in wage inequality are negative for the wholesale/retail distribution industry and positive for the finance industry, as in the ASHE results. The finding that the increases in wage inequality were much larger in the finance industry than any other is again observed in the LFS estimates. Again, the changes in wage inequality are smaller in magnitude for both of these industries in the LFS compared to the ASHE results.

In manufacturing the 90/10 ratio declined by 0.78% in the LFS estimates as opposed to the increase of 2.39%. Otherwise the manufacturing sector exhibits the second largest increases in wage inequality after finance as was found in the ASHE results. The direction of change for the Gini coefficient and $I(1)$ changes from negative in the ASHE results to positive in the LFS, however in both cases the magnitudes of the changes in each measure of wage inequality are relatively small.

2.7 Conclusions

The results presented here give some indication of what has happened to wage inequality on the whole in Great Britain, along with underlying differences between public and private sectors, industries, and occupations in the period 1997-2011. It also sets this in the context of the sharp increases in UK wage inequality throughout the 1980's and early 1990's. While this chapter primarily aimed to give a descriptive account of the changes in wage inequality some attempt has been made to speculate on the potential causes of these changes, using comparisons of different inequality measures and differential changes across industries and occupations. The causes of change in inequality is the focus of the next chapter where some of these speculative ideas will be revisited.

At the aggregate level, both the ASHE and NES based estimates show increasing wage inequality from 1975 until the mid-late 1990's. From this point onwards, the interpretation of what has happened to wage inequality is more sensitive to the choice of inequality measure. The NES and ASHE results give similar estimates of wage inequality but those from ASHE are consistently significantly larger. However, both estimates result in the same time trend due to ASHE being an extension of NES aimed at better accounting for the lower end of the distribution. Estimates of the Pareto distribution indicate that inequality amongst the top earners in the distribution also increased significantly from 1975 until the late 1990's, and continued to increase but at a slower rate after this. For these estimates the disparity between the NES and ASHE results disappears as the main differences between the two relate to the bottom end of the earnings distribution.

The private sector has consistently remained a higher inequality sector than the public sector, however the results differ on whether or not the gap is shrinking or widening -

the results which put greater emphasis on the top of the wage distribution give stronger evidence that growth in wage inequality has been faster in the private sector. Regression results indicate that public sector inequality has been catching up to that of the private sector. Certain sections of the economy have experienced a reduction in wage inequality - low skilled occupations have seen a reduction in wage inequality while inequality amongst high skilled occupations have grown. The wholesale/retail distribution and catering industries have also experienced unambiguous declines in wage inequality. The finance sector stands out as the greatest source of increasing wage inequality during this period with the most conservative estimate being a 21% increase in inequality but with estimates reaching as high as 142%.

Conditional models of wage inequality show that being in a high skilled occupation and being in the private sector are amongst the most important determinants of higher wage inequality both overall and within the top 10% of the wage distribution. Inter-quantile regressions show that, even controlling for compositional factors, within-group inequality is still significantly higher for the high skilled than the low skilled, in the private sector than the public sector, and for males than females.

The results of this chapter also offer some insight into the differences between the considered measures of inequality and when one might be preferred over another. In general, the Gini coefficient may be considered the preferred measure as it is a single coefficient which is representative of the entire distribution while remaining neutral about the relative importance that may be attached to high or low earners. It can therefore be used to describe inequality in the whole distribution without making normative judgements about the relative importance of certain observations over others.

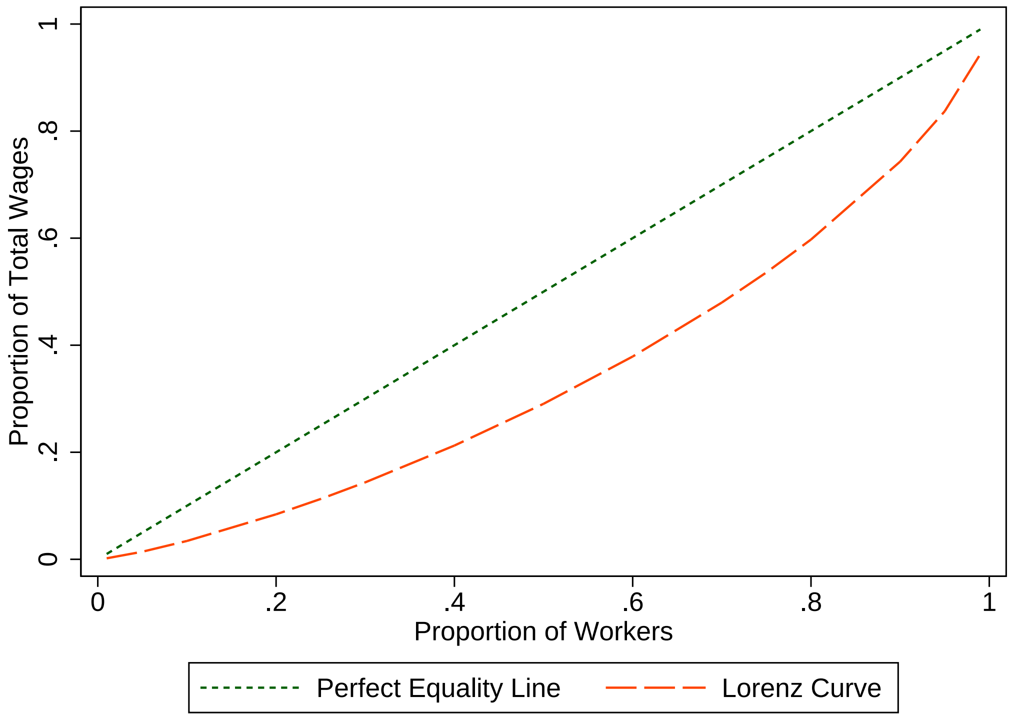
Unlike the Gini coefficient, the generalised entropy family of inequality measures implies a judgement on the relative importance of high earners. In an empirical application, the choice of a particular inequality measure from this family implies a value judgement on the part of the researcher regarding the weight which should be attached to inequality at the top of the distribution. As is the case in this chapter when using a generalised entropy measure of inequality a selection of these measures should be calculated in order to show how sensitive the preferred measure is to changes in the weight placed on high earners. As has been demonstrated in this chapter the magnitude in the change in inequality can vary substantially. If the aim of calculating the level of inequality involves examining the importance of those higher earners then these are appropriate measures to use.

The use of percentile differentials, in focussing on the difference between two specific data points, is problematic in that they ignore the rest of the distribution. The 90/10 differential says nothing about inequality amongst the very lowest and very highest earners. The advantage of this measure is however in the ease with which a particular section of the distribution can be analysed independently from the rest, as was the case in this application in order to separately examine inequality above and below the median. This is an important feature when the two regions of the wage distribution appear to behave differently, as they do here. This type of measure also has the advantage of being an intuitive and reliable way of describing inequality within the bulk of the distribution. As with the Gini coefficient, these measures do not attach any weight to any observations over the others.

Chapter Appendices

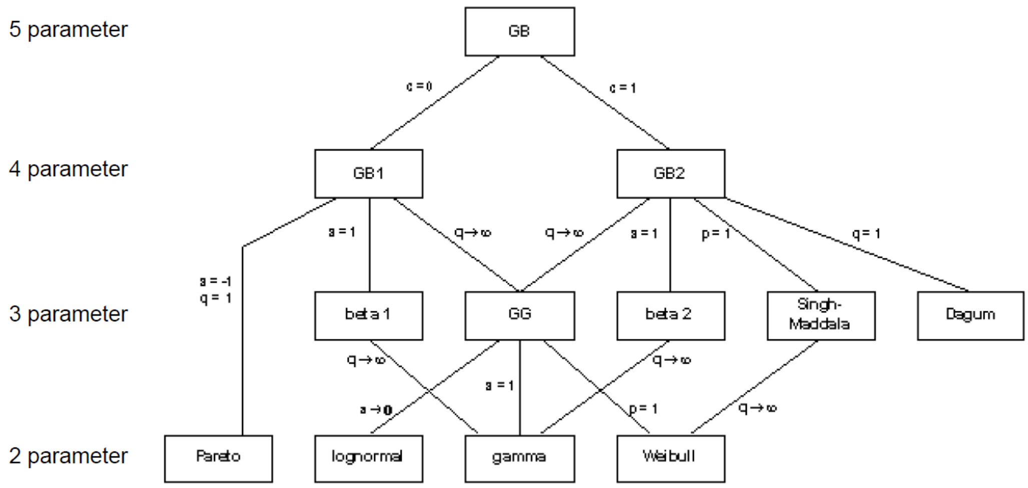
2.A Chapter 2 Figures

Figure 2.1: **Lorenz Curve: UK Wages 2011**



Source: Labour Force Survey

Figure 2.2: Models of Income and Earnings Distribution



Source: Bandourian et al. (2002)

Figure 2.3: Comparison of Distributions

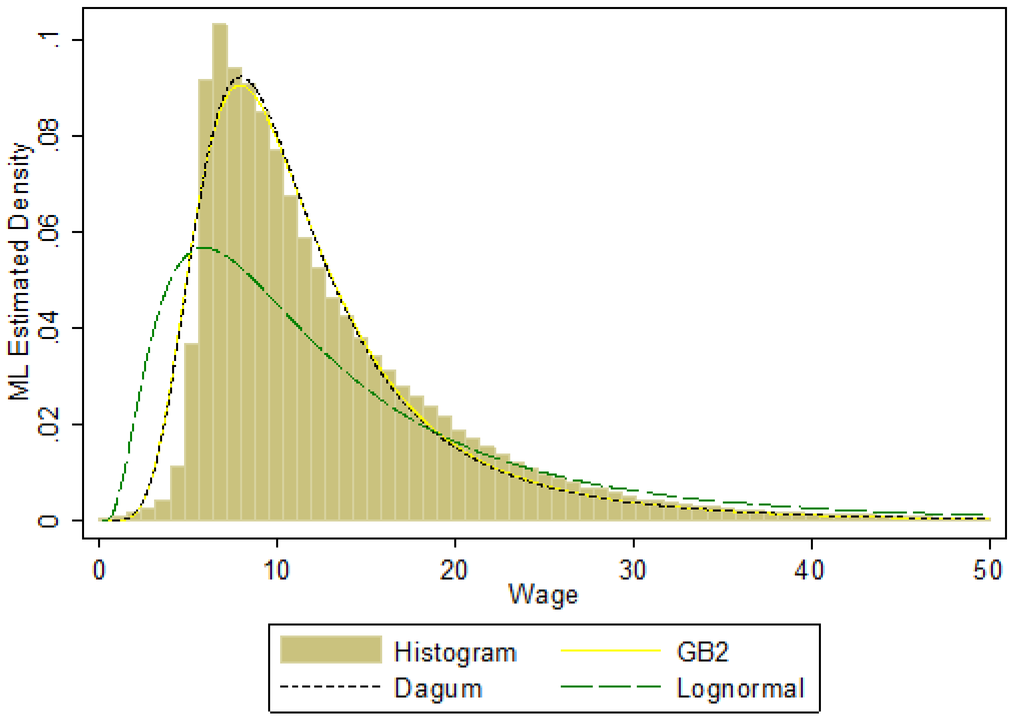


Figure 2.4: **Aggregate Gini Coefficient Estimates**

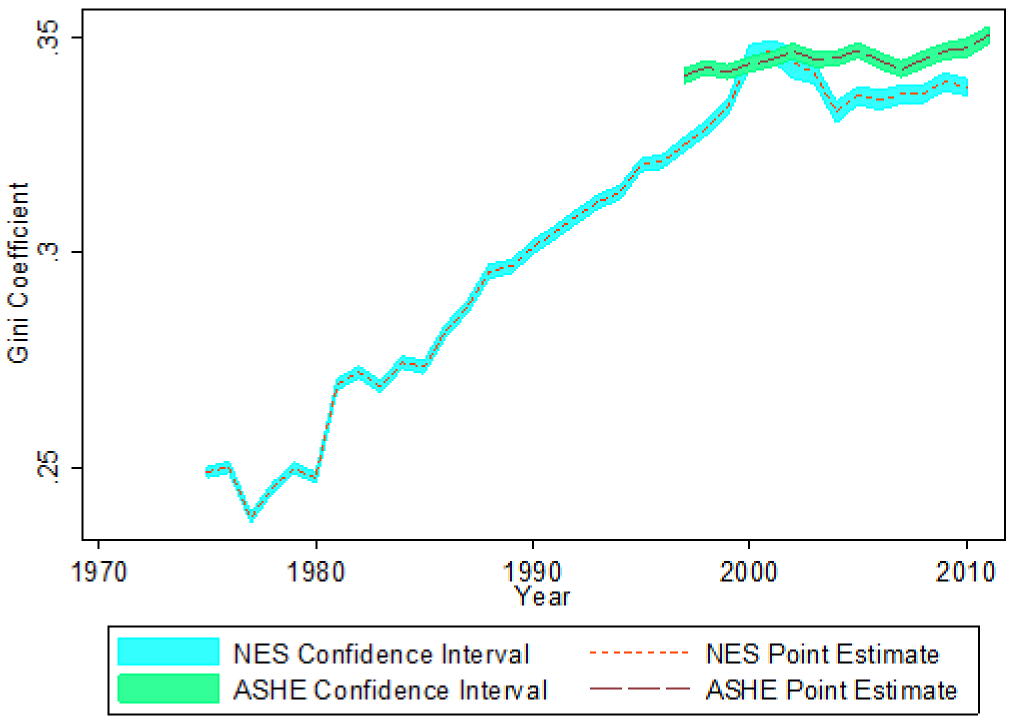


Figure 2.5: **Aggregate Generalised Entropy Estimates - NES**

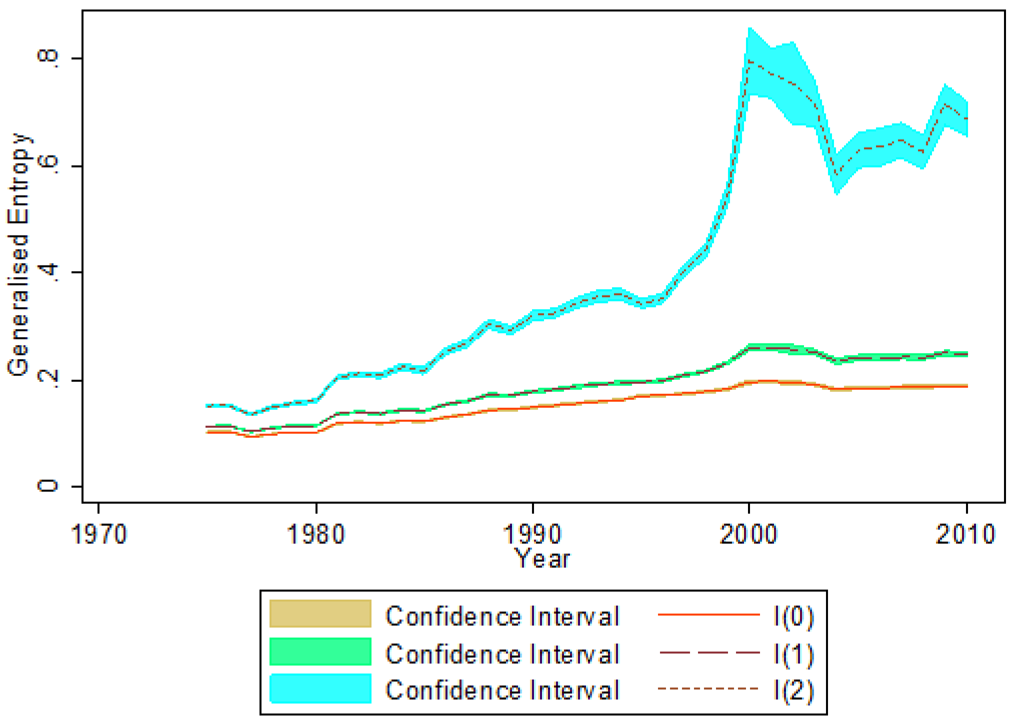


Figure 2.6: Aggregate Generalised Entropy Estimates - ASHE

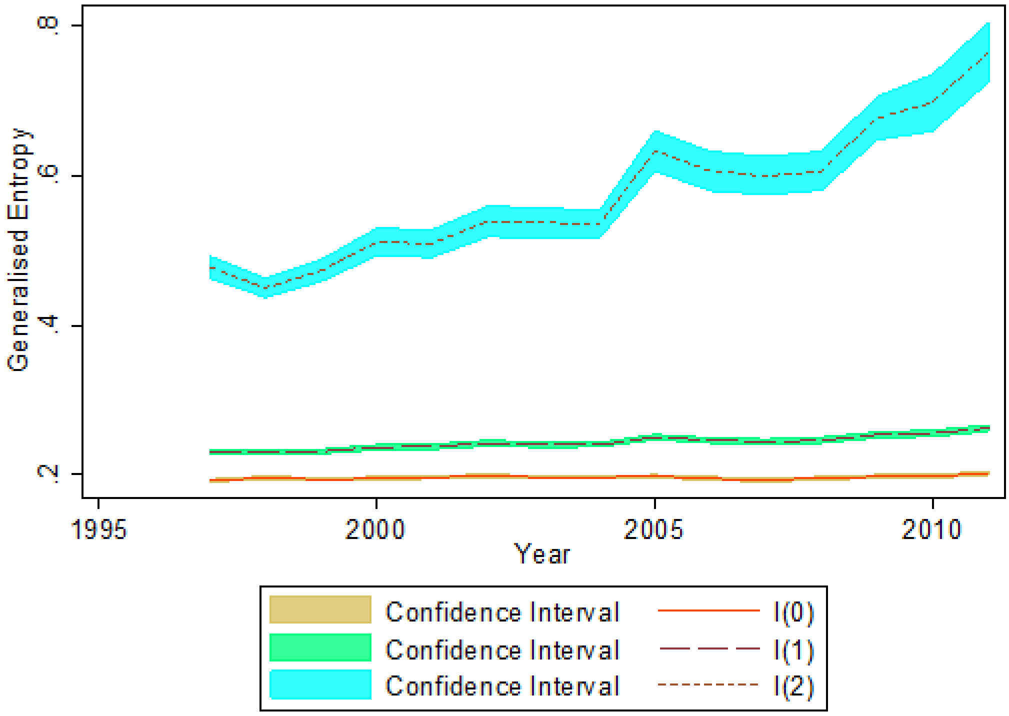


Figure 2.7: Aggregate Pareto's α - Top 10%

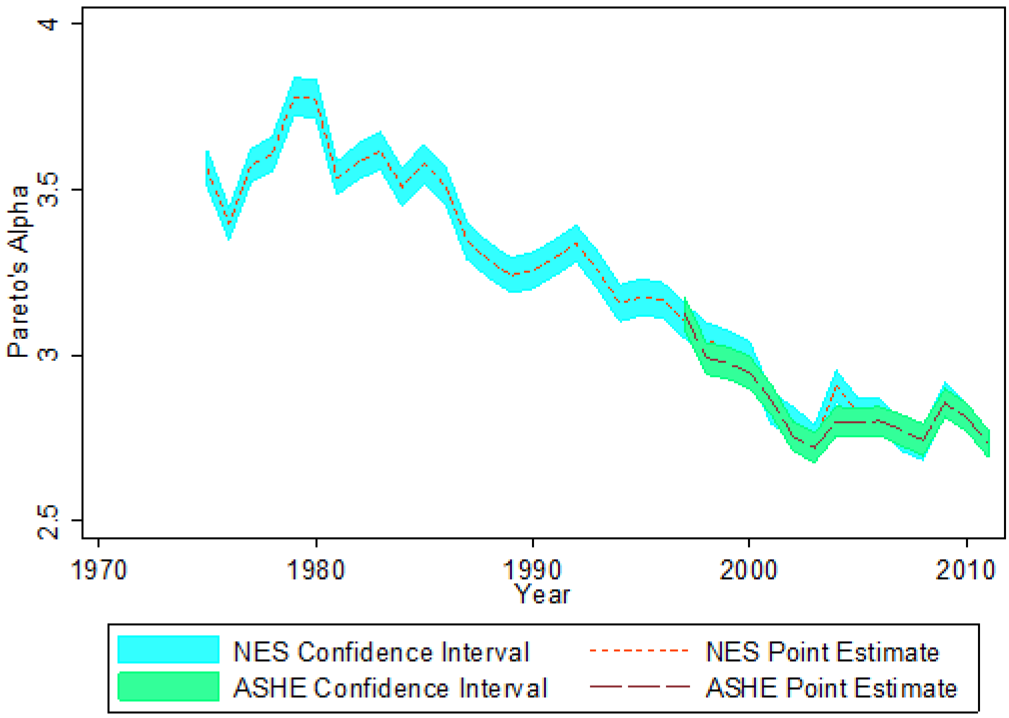


Figure 2.8: **Aggregate Pareto's α - Top 5%**

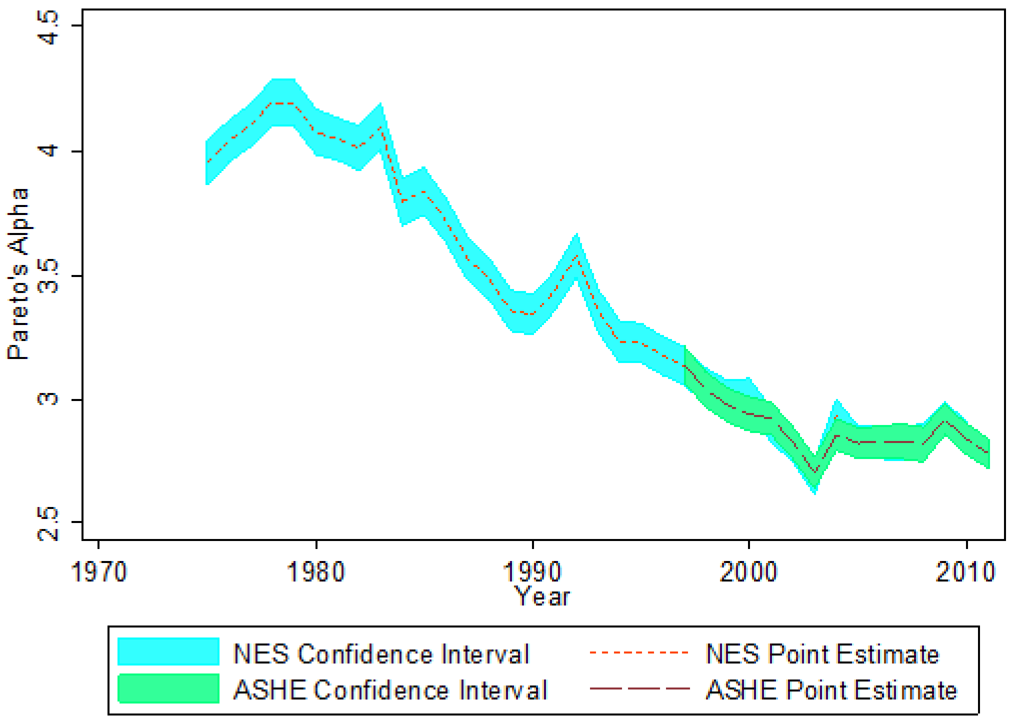


Figure 2.9: **Aggregate Pareto's α - Top 1%**

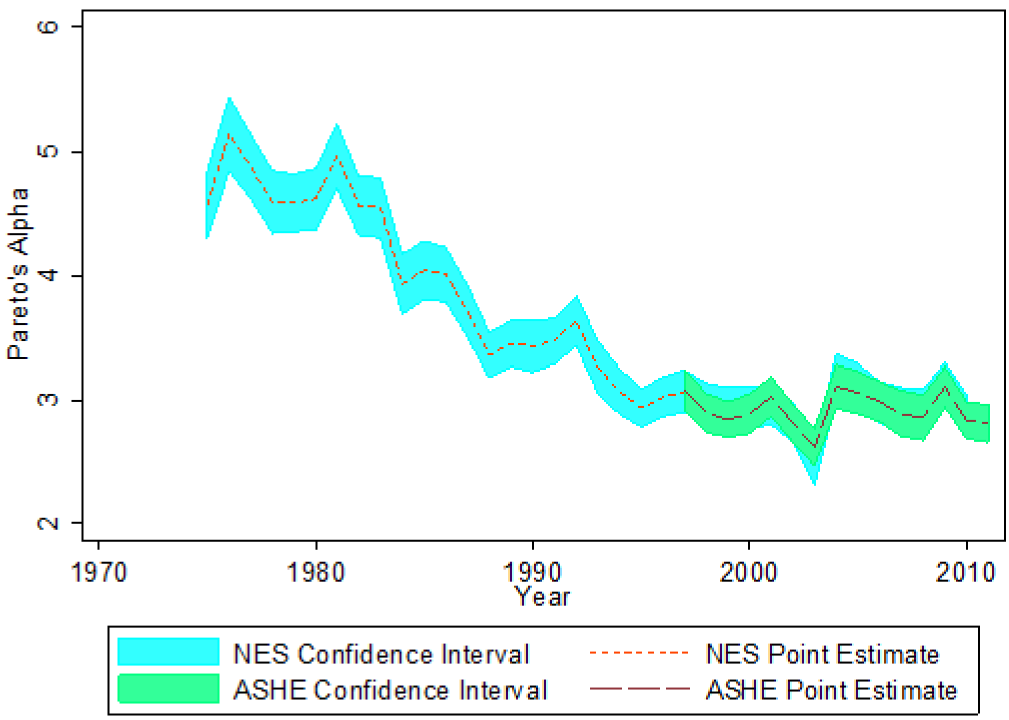


Figure 2.10: **Sectoral Level Gini Coefficients**

Figure 2.11: **Private Sector Generalised Entropy**

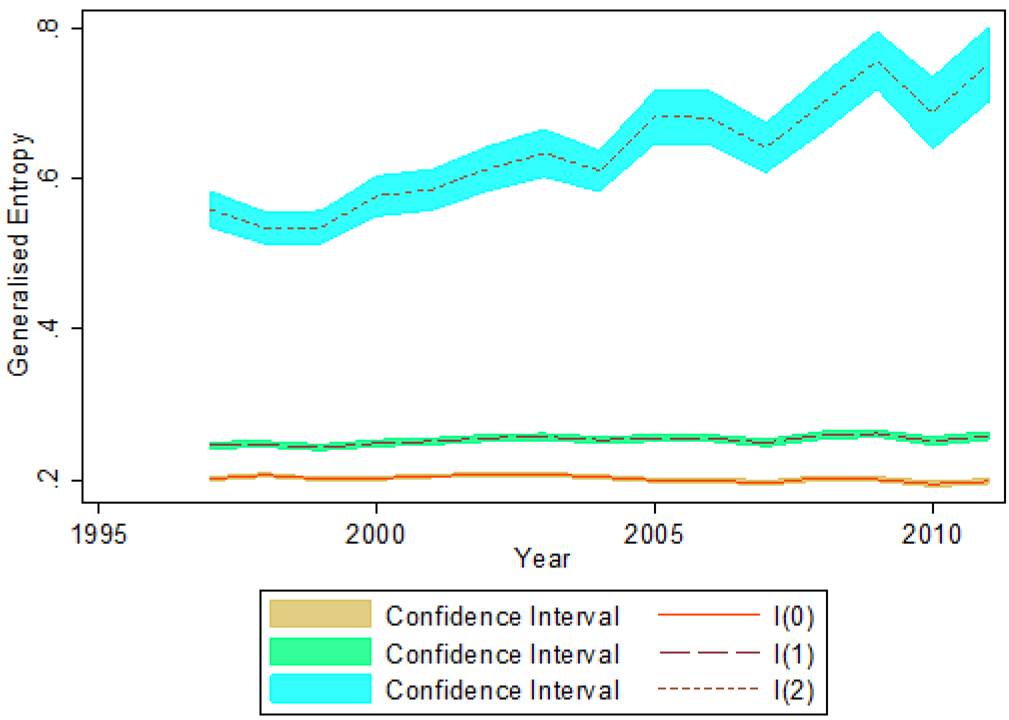


Figure 2.12: **Public Sector Generalised Entropy**

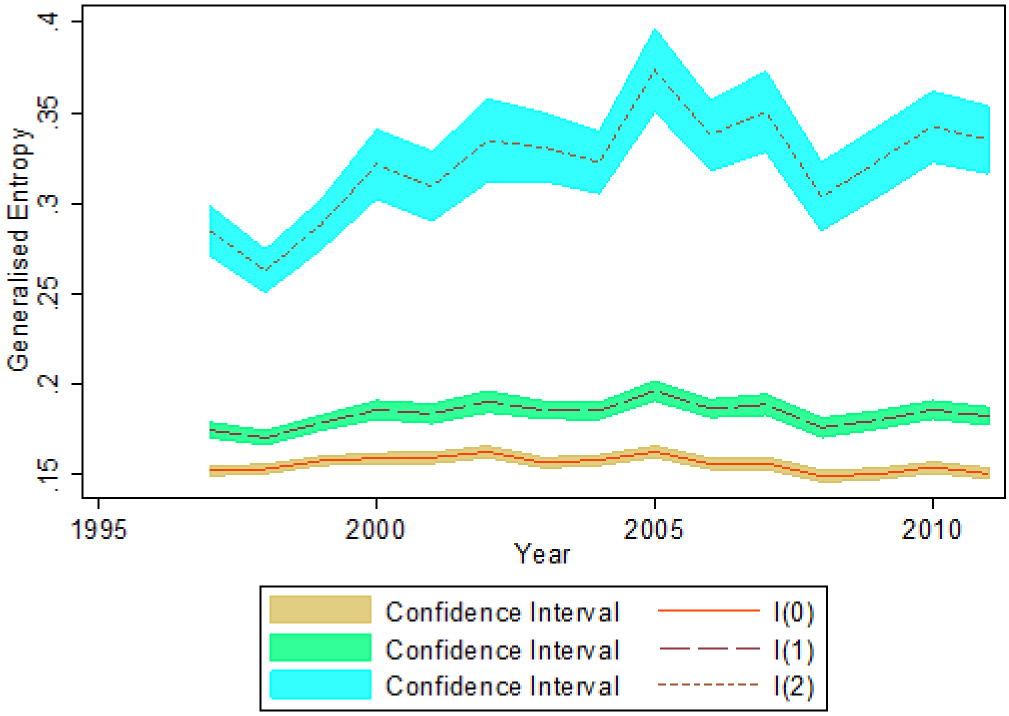


Figure 2.13: **Occupational Level Gini Coefficients**

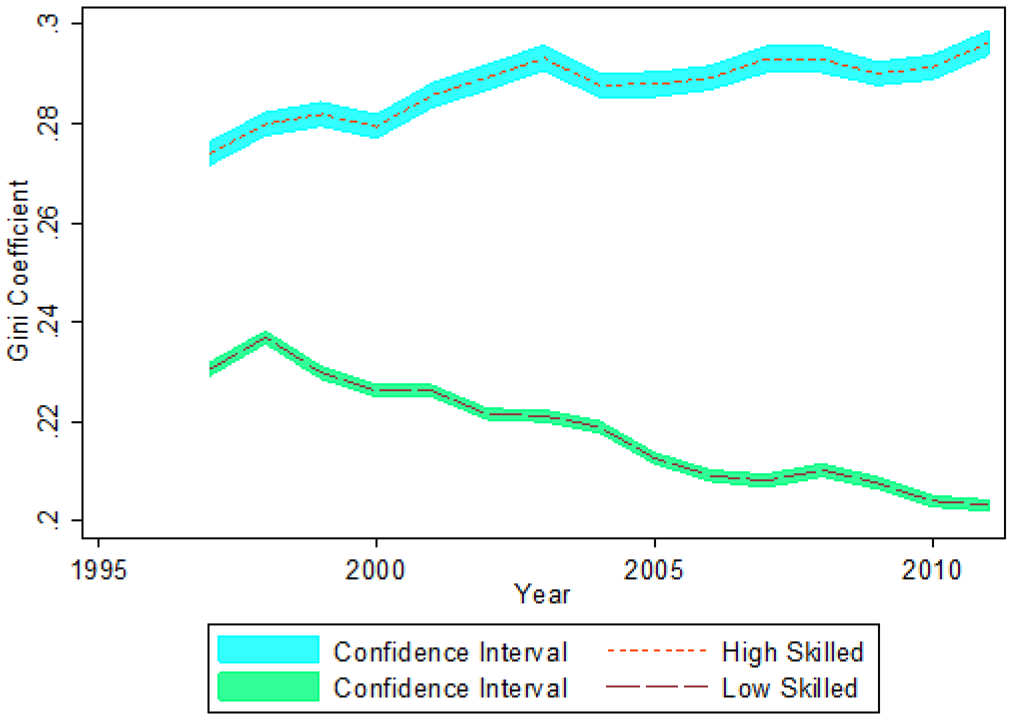


Figure 2.14: **High Skilled Generalised Entropy**

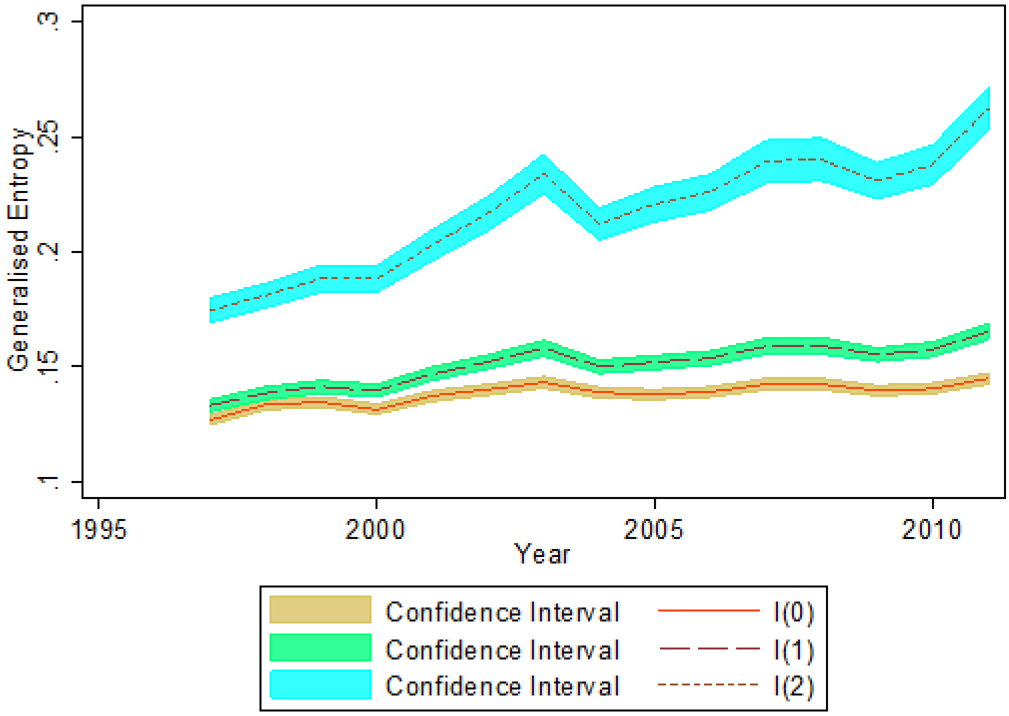


Figure 2.15: **Low Skilled Generalised Entropy**

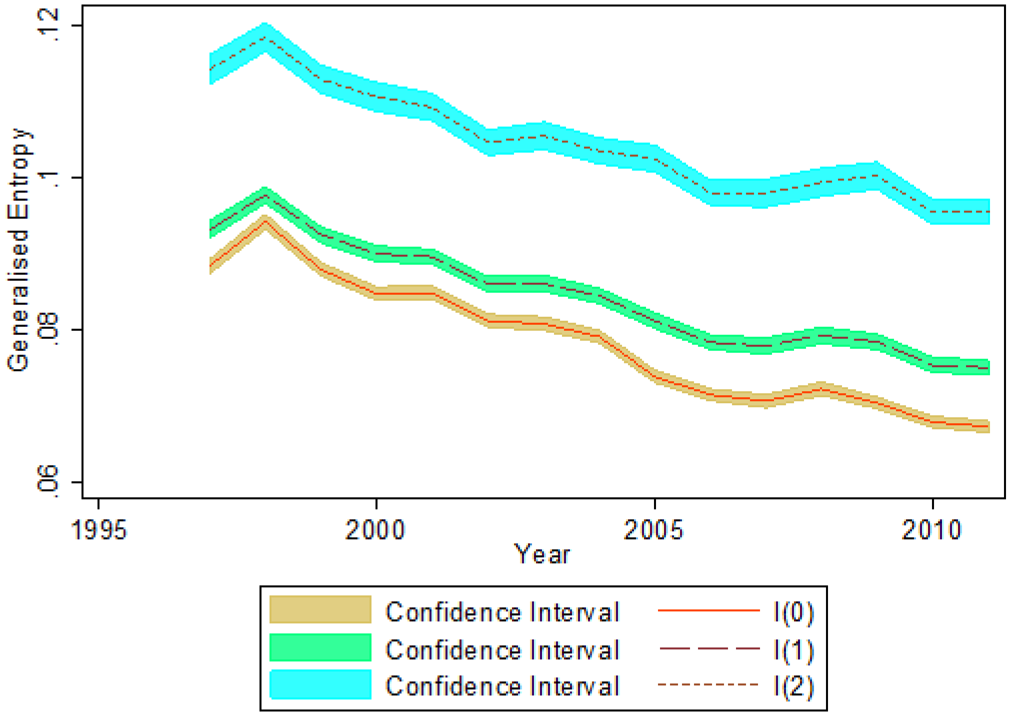


Figure 2.16: Industry Level Gini Coefficients

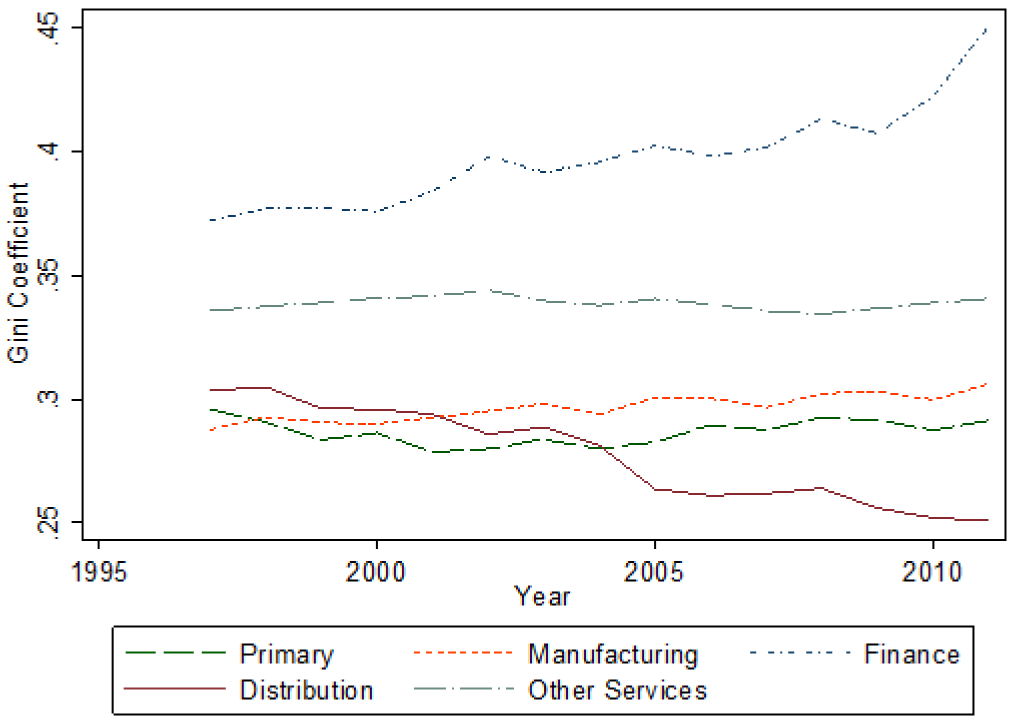


Figure 2.17: Comparison of Pay Measures

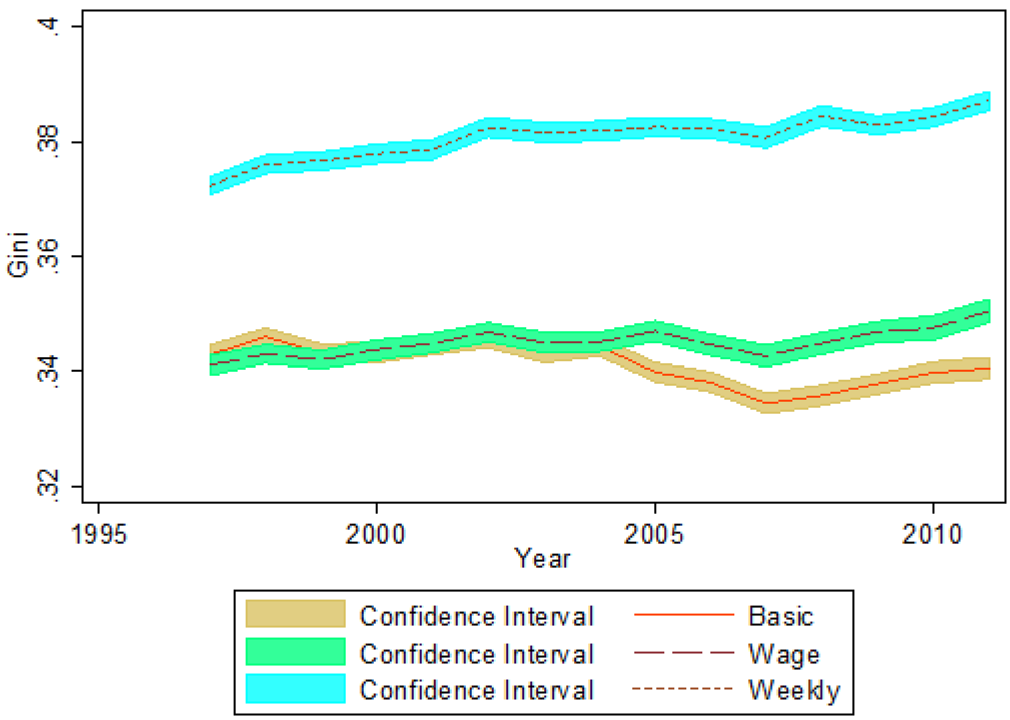
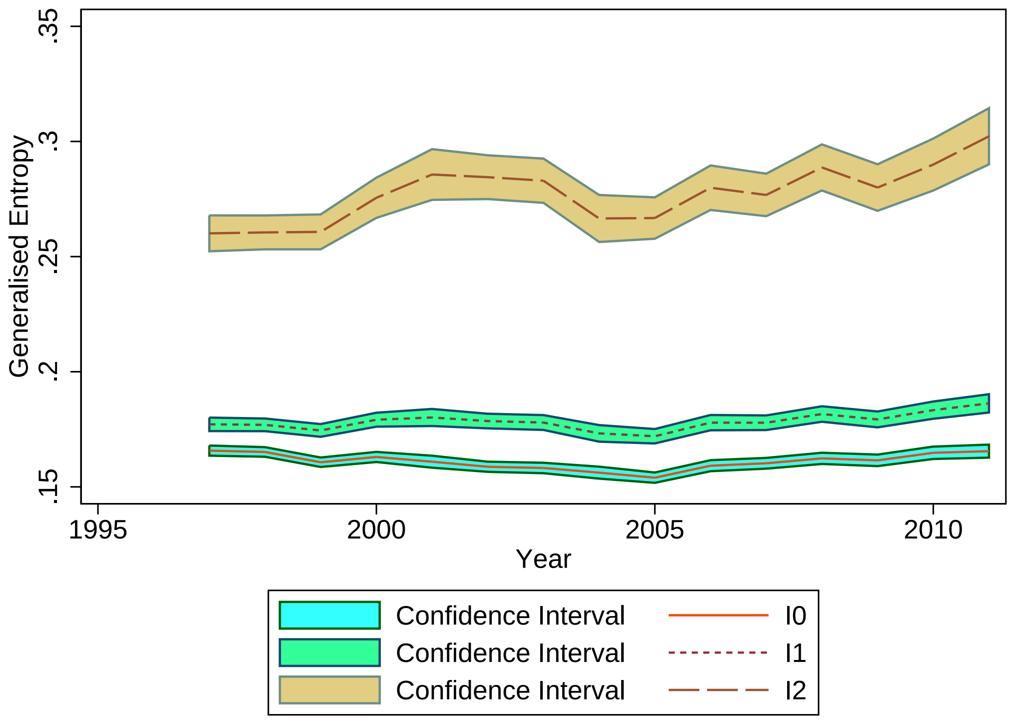


Figure 2.18: **Aggregate Gini Coefficient - LFS**

Figure 2.19: **Aggregate Generalised Entropy Estimates - LFS**



2.B Chapter 2 Tables

Table 2.5: Aggregate Wage Inequality

	1997	2000	2003	2005	2008	2011
Gini	0.341	0.344	0.345	0.347	0.345	0.351
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
90/50	2.169	2.185	2.195	2.22	2.209	2.249
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
50/10	1.878	1.868	1.853	1.792	1.791	1.747
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
90/10	4.073	4.081	4.068	3.979	3.957	3.929
	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)	(0.011)
I(0)	0.193	0.195	0.196	0.198	0.195	0.202
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
I(1)	0.231	0.237	0.24	0.25	0.246	0.263
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
I(2)	0.478	0.511	0.537	0.633	0.606	0.764
	(0.008)	(0.009)	(0.010)	(0.013)	(0.013)	(0.020)
N	139,904	148,379	151,344	158,607	133,846	171,689

Standard errors in parentheses

Table 2.6: Wage Inequality in the Private Sector

	1997	2000	2003	2005	2008	2011
Gini	0.349	0.35	0.354	0.349	0.351	0.347
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
90/50	2.212	2.219	2.242	2.234	2.243	2.237
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
50/10	1.875	1.869	1.865	1.778	1.789	1.725
	(0.005)	(0.005)	(0.006)	(0.004)	(0.005)	(0.004)
90/10	4.147	4.146	4.182	3.97	4.012	3.859
	(0.016)	(0.015)	(0.016)	(0.014)	(0.016)	(0.014)
I(0)	0.201	0.202	0.207	0.2	0.203	0.198
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
I(1)	0.246	0.249	0.258	0.256	0.259	0.259
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
I(2)	0.56	0.577	0.634	0.682	0.699	0.752
	(0.012)	(0.014)	(0.016)	(0.018)	(0.019)	(0.025)
N	96,220	103,127	102,766	106,122	92,055	113,397

Standard errors in parentheses

Table 2.7: Wage Inequality in the Public Sector

	1997	2000	2003	2005	2008	2011
Gini	0.304	0.311	0.309	0.315	0.302	0.304
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
90/50	1.992	2.03	2.032	2.066	2.001	2.023
	(0.008)	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)
50/10	1.794	1.791	1.751	1.742	1.729	1.69
	(0.007)	(0.008)	(0.007)	(0.006)	(0.007)	(0.005)
90/10	3.572	3.635	3.557	3.598	3.46	3.419
	(0.017)	(0.016)	(0.016)	(0.016)	(0.017)	(0.015)
I(0)	0.152	0.159	0.157	0.163	0.149	0.151
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
I(1)	0.175	0.186	0.186	0.197	0.176	0.183
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
I(2)	0.285	0.322	0.331	0.374	0.304	0.335
	(0.007)	(0.010)	(0.010)	(0.012)	(0.010)	(0.009)
N	35,242	37,393	38,965	41,709	33,063	46,876

Standard errors in parentheses

Table 2.8: Wage Inequality in High Skilled Occupations

	1997	2000	2003	2005	2008	2011
Gini	0.274	0.279	0.293	0.288	0.293	0.296
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
90/50	1.824	1.852	1.929	1.907	1.935	1.961
	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)
50/10	1.833	1.835	1.822	1.802	1.797	1.77
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)
90/10	3.344	3.399	3.514	3.436	3.478	3.469
	(0.016)	(0.017)	(0.017)	(0.016)	(0.017)	(0.015)
I(0)	0.127	0.132	0.143	0.138	0.143	0.145
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
I(1)	0.133	0.14	0.158	0.152	0.159	0.166
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
I(2)	0.175	0.188	0.234	0.221	0.24	0.262
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
N	48,944	52,463	55,987	58,345	52,051	67,426

Standard errors in parentheses

Table 2.9: **Wage Inequality in Low Skilled Occupations**

	1997	2000	2003	2005	2008	2011
Gini	0.231	0.226	0.221	0.213	0.21	0.203
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
90/50	1.671	1.661	1.646	1.639	1.63	1.619
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
50/10	1.632	1.603	1.578	1.5	1.495	1.446
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)
90/10	2.727	2.662	2.598	2.458	2.436	2.34
	(0.008)	(0.007)	(0.007)	(0.006)	(0.007)	(0.005)
I(0)	0.0884	0.0847	0.0808	0.0739	0.0723	0.0673
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
I(1)	0.0932	0.09	0.0861	0.0812	0.0792	0.0751
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
I(2)	0.114	0.111	0.106	0.103	0.0994	0.0956
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	90,960	95,916	95,357	100,262	81,795	104,263

Standard errors in parentheses

Table 2.10: Wage Inequality in Primary Industries

	1997	2000	2003	2005	2008	2011
Gini	0.296	0.286	0.284	0.283	0.293	0.291
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
90/50	1.944	1.898	1.887	1.888	1.941	1.948
	(0.016)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)
50/10	1.816	1.802	1.797	1.777	1.77	1.726
	(0.015)	(0.016)	(0.017)	(0.014)	(0.014)	(0.012)
90/10	3.531	3.421	3.392	3.354	3.437	3.362
	(0.045)	(0.043)	(0.045)	(0.042)	(0.043)	(0.040)
I(0)	0.146	0.137	0.134	0.133	0.142	0.139
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
I(1)	0.162	0.15	0.147	0.147	0.16	0.161
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
I(2)	0.246	0.216	0.209	0.211	0.247	0.257
	(0.011)	(0.009)	(0.009)	(0.009)	(0.012)	(0.013)
N	7,113	7,985	7,906	7,795	7,869	8,440

Standard errors in parentheses

Table 2.11: **Wage Inequality in Manufacturing**

	1997	2000	2003	2005	2008	2011
Gini	0.288	0.29	0.298	0.301	0.302	0.306
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
90/50	1.932	1.929	1.981	2.001	2.003	2.044
	(0.009)	(0.009)	(0.011)	(0.011)	(0.013)	(0.012)
50/10	1.72	1.766	1.736	1.713	1.732	1.664
	(0.006)	(0.008)	(0.009)	(0.007)	(0.009)	(0.006)
90/10	3.322	3.407	3.439	3.428	3.47	3.401
	(0.020)	(0.022)	(0.023)	(0.024)	(0.030)	(0.025)
I(0)	0.136	0.139	0.146	0.148	0.15	0.153
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
I(1)	0.156	0.157	0.171	0.176	0.177	0.189
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
I(2)	0.245	0.239	0.284	0.307	0.305	0.369
	(0.007)	(0.006)	(0.010)	(0.011)	(0.013)	(0.016)
N	29,112	26,981	23,405	22,006	14,459	17,807

Standard errors in parentheses

Table 2.12: Wage Inequality in Wholesale/Retail and Catering

	1997	2000	2003	2005	2008	2011
Gini	0.303	0.296	0.289	0.264	0.264	0.251
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
90/50	2.018	1.986	1.954	1.869	1.87	1.822
	(0.009)	(0.009)	(0.008)	(0.007)	(0.009)	(0.008)
50/10	1.701	1.683	1.667	1.556	1.555	1.512
	(0.008)	(0.009)	(0.009)	(0.005)	(0.007)	(0.005)
90/10	3.433	3.341	3.257	2.907	2.908	2.754
	(0.025)	(0.026)	(0.025)	(0.019)	(0.022)	(0.017)
I(0)	0.151	0.143	0.136	0.114	0.114	0.103
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
I(1)	0.181	0.171	0.162	0.136	0.136	0.123
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
I(2)	0.328	0.297	0.271	0.217	0.217	0.189
	(0.009)	(0.008)	(0.007)	(0.005)	(0.006)	(0.005)
N	25,867	27,404	28,770	33,575	27,834	38,259

Standard errors in parentheses

Table 2.13: **Wage Inequality in Finance**

	1997	2000	2003	2005	2008	2011
Gini	0.372	0.376	0.392	0.403	0.413	0.451
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.006)
90/50	2.336	2.342	2.428	2.483	2.533	2.745
	(0.023)	(0.022)	(0.022)	(0.025)	(0.024)	(0.031)
50/10	1.875	1.954	1.956	1.976	2.044	1.972
	(0.014)	(0.019)	(0.019)	(0.022)	(0.021)	(0.016)
90/10	4.38	4.576	4.749	4.907	5.178	5.413
	(0.060)	(0.067)	(0.068)	(0.071)	(0.076)	(0.077)
I(0)	0.229	0.235	0.255	0.269	0.285	0.339
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.009)
I(1)	0.295	0.295	0.331	0.355	0.375	0.497
	(0.010)	(0.009)	(0.010)	(0.012)	(0.011)	(0.019)
I(2)	0.947	0.865	1.336	1.816	2.214	2.29
	(0.107)	(0.082)	(0.176)	(0.347)	(0.437)	(0.892)
N	7,780	7,954	8,407	8,111	7,975	8,124

Standard errors in parentheses

Table 2.14: **Wage Inequality in Other Services**

	1997	2000	2003	2005	2008	2011
Gini	0.336	0.341	0.34	0.341	0.335	0.341
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
90/50	2.13	2.169	2.168	2.187	2.157	2.198
	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)
50/10	1.922	1.871	1.854	1.791	1.784	1.748
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.003)
90/10	4.094	4.058	4.02	3.918	3.848	3.842
	(0.016)	(0.015)	(0.015)	(0.014)	(0.014)	(0.012)
I(0)	0.188	0.192	0.191	0.191	0.184	0.191
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
I(1)	0.218	0.231	0.231	0.238	0.227	0.243
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
I(2)	0.408	0.481	0.487	0.554	0.497	0.611
	(0.008)	(0.012)	(0.012)	(0.016)	(0.013)	(0.015)
N	70,507	78,450	83,169	87,363	76,031	99,340

Standard errors in parentheses

Table 2.15: Conditional Inequality Models: Interquantile Regressions

	90/10 1997	90/10 2011	90/50 1997	90/50 2011	50/10 1997	50/10 2011
Finance	0.0113	0.0984***	-0.000356	0.132***	0.0116	-0.0333***
	(0.467)	(0.000)	(0.976)	(0.000)	(0.292)	(0.000)
Manufacturing	-0.0283*	0.00574	-0.0220**	0.0530***	-0.00632	-0.0472***
	(0.012)	(0.592)	(0.010)	0.000	(0.449)	(0.000)
Distribution	0.00827	-0.156***	0.0309***	0.0209**	-0.0227*	-0.177***
	(0.469)	(0.000)	(0.001)	(0.005)	(0.014)	(0.000)
Services	0.0931***	-0.00509	0.0366***	0.0747***	0.0565***	-0.0798***
	(0.000)	(0.624)	(0.000)	(0.000)	(0.000)	(0.000)
High Skilled	0.259***	0.401***	0.133***	0.181***	0.126***	0.220***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Private Sector	0.202***	0.124***	0.126***	0.112***	0.0757***	0.0115***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.0964***	0.133***	0.0480***	0.0739***	0.0484***	0.0586***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
London	0.0895***	0.213***	0.0621***	0.113***	0.0274***	0.0991***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	139,904	171,689	139,904	171,689	139,904	171,689

P values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.16: Conditional Inequality Models: Pareto Regressions

	1997 Top 10%	2011 Top 10%	1997 Top 5%	2011 Top 5%
Finance	-1.126***	-0.901***	-0.994***	-0.884***
	(0.000)	(0.000)	(0.000)	(0.000)
Manufacturing	-0.480**	0.000938	-0.347	-0.0297
	(0.005)	(0.995)	(0.179)	(0.904)
Distribution	-0.735***	-0.380**	-0.692**	-0.427
	(0.000)	(0.006)	(0.007)	(0.069)
Services	-0.658***	-0.276*	-0.489*	-0.325
	(0.000)	(0.032)	(0.048)	(0.143)
High Skilled	-1.021***	-1.069***	-0.468**	0.200
	(0.000)	(0.000)	(0.008)	(0.525)
Private Sector	-1.054***	-0.552***	-1.164***	-0.300***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	-1.117***	-0.659***	-0.842***	-0.629***
	(0.000)	(0.000)	(0.000)	(0.000)
London	-0.954***	-0.632***	-0.957***	-0.513***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	6.911***	5.253***	6.338***	3.942***
	(0.000)	(0.000)	(0.000)	(0.000)
N	13,991	17,169	6,994	8,584

P values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.17: Aggregate Wage Inequality - Basic Pay

	1997	2000	2003	2005	2008	2011
Gini	0.343	0.343	0.343	0.34	0.336	0.341
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
90/50	2.182	2.19	2.192	2.19	2.171	2.204
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
50/10	1.862	1.837	1.828	1.764	1.756	1.718
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
90/10	4.063	4.024	4.008	3.863	3.812	3.788
	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.010)
I(0)	0.194	0.194	0.194	0.19	0.185	0.19
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
I(1)	0.236	0.239	0.24	0.239	0.233	0.246
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
I(2)	0.507	0.534	0.544	0.577	0.541	0.653
	(0.008)	(0.010)	(0.010)	(0.011)	(0.010)	(0.015)
N	139,902	148,237	151,179	158,465	133,805	171,659

Standard errors in parentheses

Table 2.18: Aggregate Wage Inequality - Weekly Earnings

	1997	2000	2003	2005	2008	2011
Gini	0.372	0.378	0.382	0.383	0.385	0.387
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
90/50	2.135	2.176	2.215	2.22	2.234	2.248
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
50/10	3.342	3.276	3.12	3.133	3.12	3.143
	(0.014)	(0.013)	(0.012)	(0.012)	(0.012)	(0.011)
90/10	7.134	7.13	6.911	6.955	6.97	7.066
	(0.036)	(0.036)	(0.033)	(0.032)	(0.035)	(0.031)
I(0)	0.284	0.287	0.285	0.287	0.289	0.293
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
I(1)	0.239	0.248	0.256	0.258	0.261	0.265
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
I(2)	0.292	0.317	0.35	0.352	0.363	0.372
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
N	147,948	149,262	152,098	159,015	134,342	172,926

Standard errors in parentheses

Chapter 3 Decomposition Analysis of Changes in the UK Wage Distribution

3.1 Introduction

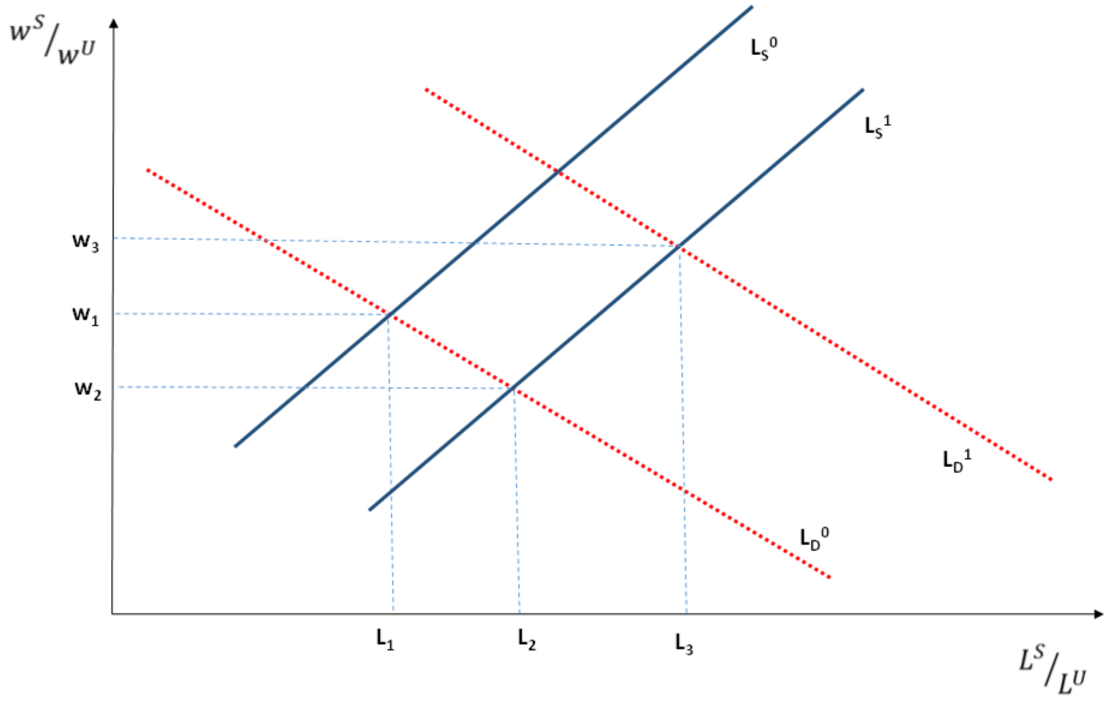
This chapter builds on the work of the previous chapter which examined the patterns in wage inequality in the UK over the 1975-2011 period. In this chapter the focus is on the causes of change. A large literature has grown on this subject with a lot of attention being given to factors on the demand side of the labour market. A main feature of this literature has been the debate between technological change and international trade as the dominant cause of increasing shifts in the relative demand for labour. This chapter investigates the effects of supply-side changes in the UK labour market in recent years.

Figure 3.1 outlines the basic model of wage inequality based on relative supply and demand for skilled labour presented by Katz and Murphy (1992). The y axis shows the relative wage (the ratio of skilled wages to unskilled wages) and the x axis shows relative employment (the ratio of skilled employment to unskilled employment). This model was put forward by Katz and Murphy (1992) who found that the relative wage of more skilled workers in the USA had increased, despite an increase in the labour market share of skilled labour.

Referring to Figure 3.1 the effect of relative labour supply shifting from L_S^0 to L_S^1, increasing relative employment from L_1 to L_2 should decrease the relative wage of skilled workers - from w_1 to w_2. As the relative wage of skilled workers had also increased, the only explanation for this is that there was also a shift in the relative labour demand curve favouring skilled workers from L_D^0 to L_D^1, of a magnitude which would result in an overall increase in the relative skilled wage to w_3.

Figure 3.2 illustrates how the relative supply/demand of skilled labour has changed in the

Figure 3.1: Relative Supply and Demand for Skills and Wage Inequality



UK between 1997 and 2012 using data from the Labour Force Survey. The premium is defined as the difference in mean log wages between those with some university level education and those without university level education[1]. It shows that since the late 1990s the skill premium in the UK has been declining as the skilled have substantially increased their share of employment (approximately by 15% points from 25% to 40%). This is a reversal of the findings of Machin (1996) that throughout the 1980's there was increasing relative employment and wages of skilled workers relative to unskilled, with similar processes at work for non-manual relative to manual workers, and older workers relative to younger. In terms of Figure 1 this would suggest that the growth in the relative supply of skilled labour started to outpace the growth in relative demand from the late 1990s.

This does not mean that the effect of increasing educational attainment amongst the population on wage inequality is as straightforward as a decline through the narrowed skill premium. The skill premium represents between-group wage inequality - the difference in

[1] The observed patterns in the skilled wage premium and employment shares hold for other definitions of "skilled", ranging from a postgraduate degree to anyone with any post-compulsory education i.e. more educated than GCSE level or equivalent.

Figure 3.2: **Change in Skilled Wage Premium and Employment Share**

Source: Labour Force Survey

average wages of the skilled and unskilled. Within-group wage inequality should also be considered. This is wage inequality within the population of skilled workers and within the population of unskilled workers and increasing the relative supply of skilled labour is likely to have an impact on this. Considering individuals with university education as skilled and those without university education as unskilled, as higher education participation rates increase the marginal individual who participates will be lower in the population distribution of ability which would ultimately widen the distribution of wages for skilled workers at the lower end. Machin (1996) also finds that there is growing within-group (i.e. within education/experience groups) inequality as well as between-group (across education/experience groups) inequality.

There is also a composition effect to consider. Even if changes in the relative supply of skilled workers had no effect on the between-group and within-group levels of wage inequality, wage inequality overall would still change because of the changing structure of the workforce. Unless wage inequality was equivalent for both the skilled and the unskilled, increasing the proportion of skilled workers will change wage inequality by increasing the proportion of workers in a higher-inequality skill group even if that level of inequality itself is held constant.

The effect of increases in the relative supply of skilled labour on wage inequality are, therefore, not straightforward to identify. The aim of this chapter is to identify these effects of the changes in the supply side of the labour market on UK wage inequality. Use is made of a decomposition technique which is able to separate out the effects discussed above so that the contribution of each to the overall change in wage inequality can be identified. The decomposition can be applied to any distributional statistic and can therefore be used for this analysis. It is hypothesised that the between group effect on wage inequality is negative, but the within-group and composition effects have had a positive effect on wage inequality.

The remainder of this chapter is structured as follows; section 3.2 gives an overview of the literature covering, in particular, UK and US wage inequality; the framework within which the change in the wage distribution is analysed. Methods which can be used to decompose changes in wage distributions over time based on the paper by Juhn et al. (1993) followed by the specific methodological approach taken in this study are explained in section 3.3. A description of the main dataset used in the analysis and some descriptive results are presented in section 3.4. Section 3.5 presents the results of the analysis and section 3.6 concludes.

3.2 Background and Literature Review

This section examines the development of the empirical literature which seeks to explain changes in wage inequality. This is a large literature which began with relatively simple demand and supply models which have over time become more refined. A summary of much of this literature with respect to UK wage inequality is given by Machin (2008). This section is divided into sections to cover the demand-side, supply-side, and labour market institutions explanations respectively.

3.2.1 Demand-Side Effects on Wage Inequality

Skills-Biased Technological Change

A common explanation for rising wage inequality in the US and UK is skills-biased technological change (SBTC). SBTC means that new technology is complementary to skilled labour and/or a substitute for unskilled labour. This means that the demand for skilled labour relative to unskilled labour will increase, increasing the skilled wage premium and the share of skilled workers in total employment[2]. This results in a higher relative expected wage for the high skilled and hence greater wage inequality.

The SBTC explanation can be formally modelled using a constant elasticity of substitution (CES) production function with skilled and unskilled labour as inputs:

$$Y = [(A_u L_u)^{\rho} + (A_s L_s)^{\rho}]^{\frac{1}{\rho}} \tag{3.1}$$

Equation 3.1 is an aggregate production function for the economy at a given time period (time subscripts are omitted to simplify notation). Subscripts u and s denote unskilled and skilled labour respectively and A and L respectively represent the labour augmenting technology terms for each type of labour and the quantity of each type of labour respectively. The elasticity of substitution between these types of labour is given by $\sigma = 1/(1-\rho)$.

Obtaining the marginal products of each type of labour and equating the ratio of the skilled and unskilled wage to the ratio of the skilled and unskilled marginal products gives the relative labour demand function:

$$(\frac{w_s}{w_u}) = (\frac{A_s}{A_u})^{\frac{\sigma-1}{\sigma}}(\frac{L_s}{L_u})^{-\frac{1}{\sigma}} \tag{3.2}$$

[2] Depending on the nature of the technological progress, this SBTC can occur at the aggregate level or be industry specific.

In this model SBTC is represented by an increase in the ratio $\frac{A_s}{A_u}$. Equation 3.2 shows that when $\sigma > 1$ - as is typically found in the literature e.g. the Katz and Murphy (1992) estimate of 1.4 - increasing relative supply of skilled labour will reduce the skill premium and SBTC will increase it. This model can be empirically estimated by simple linear regression techniques, taking a logarithmic transformation of equation 3.2.

Autor et al. (1998) examine the role of technological change in affecting the US labour market by measuring SBTC as the adoption of computers. Their results indicate stronger shifts in the relative demand for skilled labour in the computer intensive industries, and that growth in the relative demand for skilled labour has been a consistent phenomenon throughout the whole 1940-1996 period which they analyse, with the most rapid increases occurring in the 1980's. They do acknowledge however that their results leave room for other forces to have affected the skill premium in the US such as international trade and changing labour market institutions.

Machin and Van Reenen (1998) investigate the SBTC explanation of changes in wage inequality by creating industry level data from the USA, UK, Denmark, France, Germany, Sweden, and Japan. This is done by estimating a regression model of the non production share of the wage bill as a function of capital, value added, the stock of technology (measured as both R&D expenditure and computer usage as a robustness check) and the relative wages of non production workers. This model is estimated in first differences in order to eliminate the industry fixed effects. A significant positive effect of technological progress is found on the skilled labour share of the wage bill supporting the SBTC argument. They conclude however that factors other than technology are likely to account for the changing structure of the labour market but favour the role of labour market institutions rather than a direct effect of trade.

Haskel (1999) also supports the SBTC argument, investigating the growth in wage inequality in the UK in the 1980's. His paper concludes that around 50% of the increase in the skill premium during the 1980's can be explained by the introduction of computers. This paper is limited to UK manufacturing firms.

Similarly, computer usage is found to explain around 60% of the increase in relative demand for skilled labour (defined as college graduates) over the 1970-1998 period in the

US by Autor et al. (2003). The paper finds a significant positive association between changes in technology and changes in the skill structure and technology accounts for a larger fraction of the change in the skill shares in those countries where changes were smaller. Results are also robust to the potential endogeneity of R&D i.e. a higher proportion of skilled workers might induce extra R&D as it is more profitable to do so when there is a larger skilled workforce capable of applying/using the new technology[3]. Another result of the paper was that controlling for spillover effects (change in R&D in other countries) did not have a significant impact on the UK/USA but made own R&D insignificant for the other countries.

Berman and Machin (2000) extend this type of analysis to look for the existence of SBTC in the manufacturing industries of developing countries. They find evidence that SBTC has occured in middle income countries as well as OECD economies, although there is no evidence of it in low income countries. Gregory et al. (2001) conclude that technological change is the main cause of shifts in relative demand to favour skilled workers, and that the effect of international trade is relatively minor.

The results of the analysis by Acemoglu (2003) are supportive of the SBTC argument as it helps to explain international differences in changes in wage inequality, in particular the experiences of the UK and US compared to continental Europe. In his analysis, the relative supply and demand for labour framework provides a good explanation of these differences when the shifts in relative labour demand are allowed to vary between countries. The argument of the paper is that wage compression in Europe, due to relatively strong trade unions and high levels of unemployment benefit, provides encouragement for firms to invest in technology which is complementary to low skilled workers. This reduces the extent of skills biased technological progress in Europe compared to countries such as the US where such institutions are not so strong. The SBTC argument therefore can explain the differential rates in the shift of the relative labour demand curve across countries.

[3] This argument is also developed as a formal theoretical model of endogenous SBTC by Acemoglu (1998) and Acemoglu (2002)

International Trade

The theoretical underpinning of the international trade aspect of the debate around rising wage inequality is a Heckscher-Ohlin type model of trade, of the kind outlined by Wood (1995a).

The simplest version of this theory is a 2 x 2 x 2 model. It assumes two countries - one a developing country and one a developed country, two factors of production (skilled labour and unskilled labour), and two goods, one of which intensively uses skilled labour in its production and the other which intensively uses unskilled labour in its production. The example used by Wood is machinery (skilled) and apparel (unskilled).

The developed country has a larger relative endowment of skilled labour than the developing country, and therefore has a comparative advantage in the production of the skilled-labour intensive good and likewise the developing country has a comparative advantage in production of the unskilled-labour intensive good.

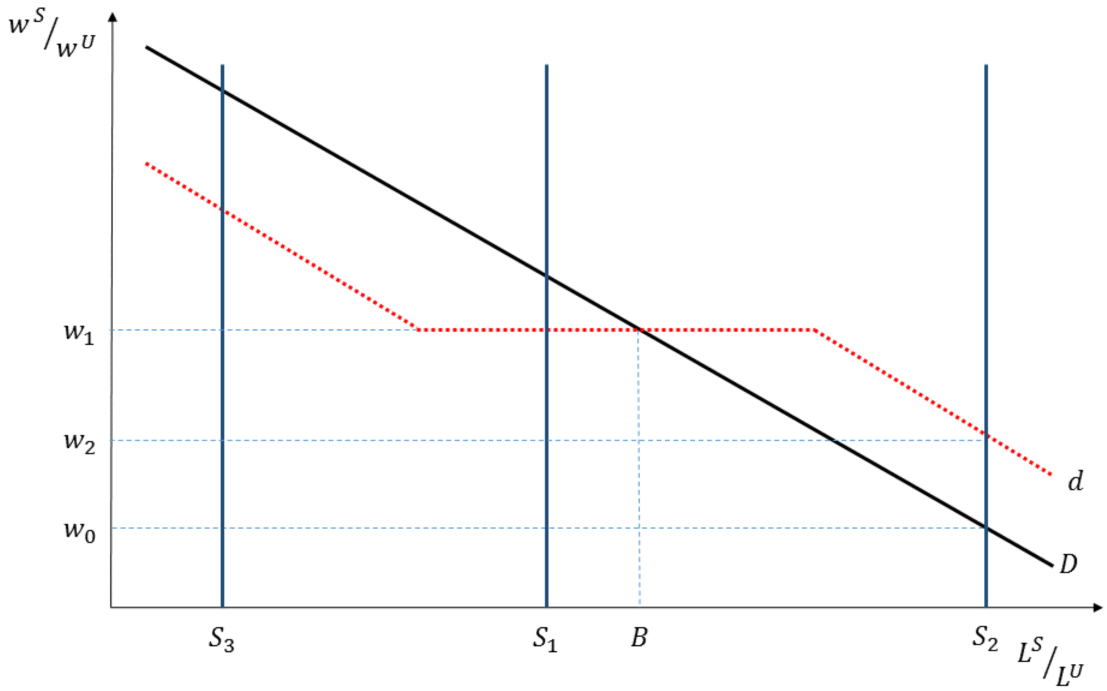
A result of the Heckscher-Ohlin model is that international trade and factor prices (in this case, the wages of the skilled and the unskilled) are linked through the changes in the prices of the finished products. This is called the Stolper-Samuelson theorem.

Under the Heckscher-Ohlin model assumptions (technology is given, perfect competition, constant returns to scale) there are two ways through which the domestic producer prices of the two goods can change. The first is a reduction in trade barriers. Tariffs and other barriers to trade keep the price of goods lower in the country which has a comparative advantage in their production. Removal of these barriers should reduce the price differences between countries.

The second way prices can change in this model is a change in the relative supplies of skilled and unskilled labour. If there was an increase in unskilled labour in the developing country, production and exports of the unskilled-labour intensive good would increase, therefore driving down the price of the good worldwide.

Leamer (1994) and Wood (1995a) present a supply and demand model to show the effects

Figure 3.3: **Effect of Different Trade Regimes on Wages**



of price changes on relative wages depending on the trade situation of the country. This model is illustrated in Figure 3.3. In the case where trade barriers are high the demand curve is given by the straight downward sloping curve d. Relative labour supply is perfectly inelastic. If a country's endowment of skilled labour is relatively low compared to unskilled labour, the supply curve will be at S_3 and the relative wage is high.

Demand curve d represents a country without trade barriers. The infinitely elastic section of the demand curve is a range where changes in the composition of labour supply do not affect world prices and therefore do not affect the wage structure. Shifts in relative labour supply only affect the composition of trade and output, not relative wages. For countries on this section of the relative demand curve trade is diversified - a mixture of low and high skilled-intensive production.

A country operating on one of the downward sloping parts of demand curve d specialises in trade according to the relative endowments of skilled and unskilled labour - at S_3 in unskilled-intensive products and at S_1 in skilled-intensive products. Where trade is specialised, changes in domestic labour supply will affect relative wages. Point *B* indicates the factor endowments - the factors being skilled and unskilled labour - at which a country which is open to trade will not actually do so. This is the intersection point of the demand curves for when the country is open to trade and when it has high trade barriers.

This framework can be used to compare the relative wages of skilled and unskilled labour under different regimes. To the left of point *B* a country which is open to trade with a relatively large endowment of unskilled labour will have a smaller relative wage than a country closed to trade or which has high trade barriers. Conversely, to the right of point *B*, a country has a relatively high endowment of skilled labour. In this case a country which is more open to trade has a higher relative skilled wage than one which is not.

More sophisticated theoretical models have since been developed in the trade literature to explain the link between trade liberalization and technology upgrading, for example by Bustos (2011a) who develops a heterogeneous firms model in which a reduction in tarrifs by trade partners induces incentives for firms to increase their productivity. In Bustos (2011b) this model is extended to one where there are skilled and unskilled labour in the economy.

In this model, simultaneous reduction in trade tariffs by two countries will increase the market share of high technology firms causing an increase in the relative demand for skills and consequently an increase in the skill premium. Trade liberalisation also makes high technology adoption profitable, incentivising more firms to invest in technology and consequently increasing the relative demand for skills. In this model trade therefore prompts SBTC

Borjas and Ramey (1994) use time series econometric techniques to examine the long run trend in the US wage structure over the 1964-1991 period (covering periods of both declining and increasing wage inequality). Two measures of wage inequality are used; the difference in mean log wages of college graduates and high school graduates, and college graduates and high school dropouts. They find that the only variable they consider which shares the same long run trend as their wage inequality measures is the durable goods trade deficit as a proportion of GDP.

Prior to 2005 estimates of the effects of trade flows on wages were obtained by Sachs and Shatz (1994) using the factor content method. An issue with the factor content method is non-competing imports. Estimates can be biased downwards because non-competing imports - imports of goods no longer produced in developed economies - will have their unskilled factor share over-stated because the higher level of wages in developed economies means if those goods were produced domestically, they would be produced under more capital-intensive production techniques.

Wood (1995a) compares the results of these estimates when controlling for this issue and finds the Sachs and Shatz (1994) estimates of the effect of trade on labour demand in manufacturing is downward biased compared to the Wood (1995b) estimates. Wood (1995b) found that trade reduced overall labour demand by 11% compared to no trade and the Sachs and Shatz (1994) figure is almost half of this. In both cases the fall in demand for unskilled labour was greater than that for skilled labour, but with very different magnitudes - respectively 1.9% and 22%. As well as increasing the estimated magnitude, the Wood (1995a) estimate suggests that the reduction is entirely due to reduction in demand for unskilled labour

Wood (1995a) argues that this 22% figure is still an understatement of the true impact of trade on relative labour demand because it ignores the contribution of trade to technological progress. It is also limited to the manufacturing sector and does not take into account the expansion of trade in services and growing demand from developing countries for skill-intensive services.

A number of other potential criticisms of this estimate are noted; they depend on assumed elasticities of substitution in production/consumption, and there are also several criticisms of the factor content approach in general. One of these criticisms is that in the Heckscher-Ohlin framework it is through product prices that trade affects wages, however there is less clear evidence from prices which is supportive of the trade explanation of the changing wage structure.

Sachs and Shatz (1996) highlight the arguments against international trade as providing anything more than a small role in the explanation in changing wage inequality. Their argument is that skills-biased technological change is a long term trend which pre-dates the rapid increases in US wage inequality, whereas the timing of increases in international trade correspond more closely to the increase in wage inequality. They do, however, conclude that there is no convincing empirical work on the role of trade in the increase in wage inequality in the US, but that theory and circumstantial evidence supports the link between the two.

Machin and Van Reenen (1998) investigate the potential role of international trade in explaining the changes in relative labour demand as an extension to their model looking at the SBTC explanation. They include a variable to measure import competition, which according to the trade argument more internationally competitive industries should experience larger changes in relative demand for skilled labour. In none of their specifications is their measure of import competition a significant explanatory factor of changing skill shares and the R&D coefficient is robust to the inclusion of this variable. Desjonqueres et al. (1999) also use this data with a primary focus on the international trade argument using a Heckscher-Ohlin trade model, however they fail to find any significant relationship between the proportion of skills and international trade for any country, except for the USA.

The standard model of the linkages between trade and wage inequality has testable implications for developing countries as well as developed countries. In developing countries - where unskilled labour is assumed to be relatively abundant - increasing trade with developed countries should result in a fall in wage inequality as the relative demand for unskilled labour increases. This did not, however, happen in the case of Mexico where wage inequality continued to increase despite trade liberalisation - Verhoogen (2008) - or in Brazil where the level of wage inequality remained roughly constant for a variety of measures of inequality over the period of trade liberalisation (Green et al. (2001)). In this latter case the skill premium is also examined, but the college premium is found to have increased rather than decreased (without having a significant impact on wage inequality). This is found to be due to an increase in the relative demand for skilled labour, potentially a result of SBTC.

Galiani and Sanguinetti (2003) also look at the effect of trade liberalisation on wage inequality in Latin America, focusing on the experience of Argentina. Their conclusion is that the increase in the skilled (or college) wage premium is positively correlated with import penetration, however only 15% of the increase in the skill premium can be explained by international trade. They therefore conclude that international trade is not one of the important causes of wage inequality growth in Argentina. Beyer et al. (1999) conclude that their empirical results for Chile are consistent with the Heckscher-Ohlin model; increasing openness to trade led to an increase in wage inequality.

Both technology and globalisation are deemed important factors in the change in the skill structure of UK manufacturing industries between 1982 and 1996 by Hijzen et al. (2005). They find that outsourcing increased from 33% to 40% of value added between 1984 and 1995 and that this has had a negative effect on the demand for unskilled labour. Their approach is to estimate cost-share equations for high skilled, semi-skilled, and unskilled labour (skill level being defined by occupational group). R & D is also found to have increased the demand for skilled labour.

In addition to the debate regarding the relative importance of the technology and trade arguments, foreign direct investment is considered by Taylor and Driffield (2005). They argue that the theoretical literature attempting to link inward FDI to wage inequality is ambiguous and models have been developed which lead to both positive and negative relationships between the two.

The paper hypothesises that increases in FDI will lead to technology spillovers which will influence domestic wage inequality. Using UK manufacturing data over the period 1983-1992 this paper estimates that 11% of the increase in wage inequality over this period can be explained by FDI.

Autor et al. (2013) examine the effects of trade and technology on the US economy between 1990 and 2007, although focussing on employment effects rather than wages. The focus of the international trade component is on exposure of US industries to imports from China and finds that greater exposure to trade from China results in reduced employment across all occupation groups in manufacturing.

The paper concludes that the growing impact of trade with China has increased the importance of the international trade effects on the labour market compared to the technological progress based arguments. This is particularly the case in manufacturing, as technological progress has shifted away from automation of production and towards computerisation in other industries.

Task-Biased Technological Change and Job Polarisation

More recently the literature has moved beyond the relatively simple SBTC theory. Goos and Manning (2007) presented the idea that technological change is not biased towards skills but towards tasks, developing the idea put forward in Autor et al. (2003) that technological change does not favour skilled jobs over unskilled, but non-routine tasks over routine.

This task-biased technological change (TBTC) affects jobs located in the middle of the wage distribution and so demand for workers with intermediate skills relative to low or high skills falls. This would be expected to have an effect of narrowing the wage gap between low and intermediate skilled workers while widening the wage gap between the intermediate and high skilled workers.

Job polarisation is also found to be occurring in Europe by Goos et al. (2009) - technological change favours non-routine tasks which has an adverse effect on the demand for labour in the middle of the wage distribution. The Lemieux (2008) paper considers the distinction between routine/non-routine and skilled/unskilled as the correct perspective from which to view the effects of technological change, but also suggests there is little direct empirical evidence on the contribution of this to wage inequality.

The Katz and Murphy (1992) analysis of US wage inequality is updated by Autor et al. (2008), updating the period studied from 1963-1987 to 1963-2005. They find that after 1992 there has been a significant slowdown in the growth of the relative demand for skilled labour, which they find to be inconsistent with a simple SBTC story given that computerisation continued at a rapid rate in the 1990s. They also find a divergence in the trends of within-group inequality, with inequality growing within the college educated group but levelling off or declining within the non-college educated group. This is taken to be a polarisation of wages which the Katz and Murphy (1992) CES two-factor model of the labour market cannot explain.

Autor et al. (2008) find more of a U-shaped relationship in the change in log wages by percentile for the period 1990-2000 than the monotonic relationship in the 1980s. This reflects a similar change in the relationship between share of employment and skill percentile across the two periods and is taken to be an indication that job polarisation began around this time, shifting the bias of technological change towards tasks rather than skills. They conclude from this that demand shifts have played a key role in the evolution of the wage distribution, although they also consider supply factors, institutions, and international trade all to be equally important.

The paper attempts to provide some evidence of the impact on wage inequality by regressing changes in wages between 1983 and 2002 within two-digit occupations on a quartic function of the average level of education within the occupation. The regression produces a u-shaped relationship, consistent with the occupations which are in the middle of the education distribution performing the worst. This paper only puts this result forward as indicative evidence of the effect of job polarisation on the change in the wage distribution, however, and argues that detailed decompositions are still required to assess the exact role of this possible explanation on wage inequality.

The impact of job polarisation on the UK labour market is considered by Holmes (2010) using two waves of the National Child Development Study. The conclusion of the paper on the effect on the wage distribution is that the changes could also reflect changes in the skill distribution and returns to education. It is also acknowledged, however, that the nature of the data could introduce bias into the calculation of the wage distributions by studying a single cohort which may not generalise to the population as a whole.

Holmes and Mayhew (2012) also consider whether job polarisation in the UK has translated into polarisation of the wage distribution. Using Family Expenditures Survey data between 1987 and 2001 they show that there was limited polarisation of wages in the UK wage distribution, only occuring below the 10th percentile. They conclude that the polarisation that has occurred is due more to supply factors (educational attainment) and labour market policies than to shifts in the demand for non-routine tasks. Their conclusion is also that the effect of polarisation has been more in terms of job titles than earnings, with good non-routine jobs beginning to appear in the middle of the distribution as the supply of graduate labour and variability at the top of the distribution increasing.

Shierholz et al. (2013) also examine the role of TBTC in explaining patterns of wage inequality. They conclude that there is no causal relationship between the two, and that the tasks based explanation cannot explain trends in wages since the 1980s, arguing that the decline of middle-wage jobs and growth of high-wage jobs is a phenomenon that predates the increases in wage inequality beginning in the 1970s. The consistency of this trend in job quality is also contrary to the changes in the nature of wage inequality over the same period.

3.2.2 Supply-Side Effects on Wage Inequality

Katz and Murphy (1992) consider supply-side factors and highlight the puzzle of rising wage inequality in conjunction with increasing wage differentials. Over the 1963-1987 period they find that the share of those with 13 to 15 and more than 16 years of education in the US labour force increased while the share of those with less education fell. Breaking this down into sub-periods, they find that the fastest increase in the supply of skilled labour (defined as college graduates) occured when the college premium was declining.

They conclude that within-group inequality increased as well as education differentials, however these phenomena did not occur simultaneously and so were likely to be distinct processes. The changing age structure of the US economy during the period studied (the entry of the "baby boom" generation into the labour market) had the impact of widening experience differentials.

Juhn et al. (1993) give some insight into the role of the supply side of the labour market using the same decomposition technique that is adopted by this chapter. Their approach is to decompose changes in the coefficients, distribution of covariates, and distribution of residuals between two OLS wage equations estimated as functions of education dummies, a quartic function in experience, and region dummies. This decomposition (as will be explained in greater detail later in the chapter) is able to distinguish between composition, between-group, and within-group effects.

They find that between 1964 and 1988 the biggest contributor to changing US male wage inequality is the increase in within-group inequality which when broken down into the

90-50 and 50-10 differentials is a much larger component of the change in the 50-10 differential than the 90-50, thus the rise in top-level inequality can be explained by observable human capital factors to a greater extent than the rise in bottom-level inequality. Within-group inequality is important in both parts of the distribution, however. The next most important component of the decomposition is the increase in skill prices, consistent with the rapid increase in the relative demand for skills over this period.

An alternative approach to decomposing changes in wage distributions is developed by Lemieux (2002) whose conclusions for the change in male wage inequality in the US are similar to those of Juhn et al. (1993). The finding of this paper is that throughout the 1980s the change in the skill premium or returns to education accounted for over half of the change in inequality, with within-group effects amounting to around 40% of the decomposition and leaving a negligible effect of the composition of the labour force. This increase in wage inequality within human capital groups is interpreted as increasing returns to unmeasured skills. These conclusions are based on a similar empirical model of wages as estimated by Juhn et al. (1993), with a regression including age, education, marital status, and ethnicity.

Lemieux (2008) attempts to explain changes in the nature of wage inequality in the US since the late 1990s and argues that unlike during the 1980s inequality growth was concentrated in the top of the wage distribution. Amongst other explanations of the change in wage inequality, the paper presents a possible relationship between human capital and wage inequality.

$$w_{it} = \alpha_t a_i + (\beta_t b_i)S_i + (\gamma_t c_i)X_i + e_{it} \tag{3.3}$$

In the random coefficients model represented by equation 3.3 the human capital pricing equation consists of individual heterogeneity terms b_i and c_i which affect the individual returns to, respectively, schooling (S_i) and experience (X_i). a_i is unobserved ability. Within this framework the variance of wages is given by:

$$Var(w_{it}|S_i, X_i) = \alpha_t^2 \sigma_a^2 + (\beta_t^2 \sigma_b^2)S_i^2 + (\gamma_t^2 \sigma_c^2)X_i + \sigma_t^2 \tag{3.4}$$

The part of this variance which is given by education shows that the variance will be larger for more educated workers and rising returns to education will increase the variance in wage for more educated more than it will for less educated workers. Rising returns to schooling can therefore explain increases in both between and within-group wage inequality.

Autor et al. (2008) find the changing composition of the labour force to be a relatively unimportant factor in the growth of residual wage inequality between 1973 and 2005 in the US. While it is a contributory factor, rising within-group inequality was found to be more important. After 1989 however, the composition effect is positive while the within-group effect is negative (and larger) for the bottom of the wage distribution, showing that within-group effects account for the net decline in the 50-10 differential for the US after the 1980s, but that changes in the composition of the labour force prevented this effect from being greater.

Their findings contradict those of Lemieux (2006) who finds that composition effects can explain all of the change in wage inequality during this period, however that paper only considered overall inequality while Autor et al. (2008) breaks down the analysis into the effects of the top and bottom of the wage distribution by considering the 90-50 and 50-10 differentials. They argue that because composition over explains one phenomenon and under explains the other, it appears to be a good fit to the behaviour of overall inequality when aggregated but cannot satisfactorily explain either upper or lower tail inequality, which is important given the differing behaviour of the two.

3.2.3 Labour Market Institutions

Labour market institutions are another potential explanation for changes in wage inequality. Two main labour market institutions which may have influenced the level of wage dispersion in the UK are trade unions and the national minimum wage (NMW) introduced in 1999.

Dickens and Manning (2004) conclude that the effect of the introduction of the NMW had a negligible effect on wage inequality (in contrast to findings in the US literature, where the minimum wage is found to have important effects e.g. DiNardo et al. (1996). It was found that the NMW only affected the wages of those directly impacted by it, with little or no effects at the 10th percentile and higher (this also contrasts with the US, where spillover effects of changes in the real minimum wage have been found to be relatively large). The effects were also found to be very short term, mostly occurring within the first two months of the NMW's introduction.

The decline of trade union power throughout the 1980's and 1990's is considered to be an important factor in explaining the growth in UK wage inequality during this period. Machin (1996) finds that union decline can explain around 20% of the rise in wage inequality, as well as important effects of incomes policies and Machin (1997) finds the weakening of both minimum wages[4] and trade unions throughout the 1990's to be an important explanation of the rise in UK wage inequality in this period.

Haskel (1999) also finds evidence in support of the decline of unionisation as a factor in explaining increasing wage inequality in the UK. In addition to the 50% of the increase in the manufacturing skilled premium he also attributes 16% of the increase to the decline of trade unions (and potentially more, which may have been picked up as a "small firm effect").

This effect of de-unionisation on wage inequality could at least in part be attributed to an indirect effect of SBTC. Acemoglu et al. (2001) argue that SBTC causes de-unionisation because it widens the productivity gap between skilled and unskilled labour and therefore increases the opportunity cost to skilled workers of working in a unionised firm/industry (i.e. the benefits of joining a unionised workplace may no longer offset the wage compression over workers with different skills, reducing the incentive of skilled workers to take jobs in unionised firms/industries).

Lemieux (2008) considers the role of labour market institutions. Relative wage gains in the US have been located increasingly in the top of the distribution, with the 90-50 percentile differential increasing in the 1990's while the 50-10 differential remained roughly

[4] As set by wage councils prior to their abolition in 1993 - wage councils set minimum wages for specific industries as opposed to the NMW which applies to all workers.

constant. This rules out factors such as the minimum wage in explaining recent inequality trends but not the role of institutional factors more broadly.

De-unionisation is considered a more attractive institutional explanation for increasing wage inequality because it can explain cross-country differences. Countries which experienced the sharpest increases in wage inequality (the UK and US) are also the ones experiencing the sharpest declines in unionisation. Pay-for-performance is another possible explanation for rising wage inequality, as it is most likely to be found in the top end of the distribution amongst senior managers and executives. Institutional changes are considered better able to explain the concentration of wage inequality growth within the top of the distribution compared to SBTC.

Unionisation changes are also considered by Western and Rosenfeld (2011). In the US between 1973 and 2007 unionisation fell by approximately 20% points for men and 10% points for women. Using a variance decomposition approach the paper attempts to estimate how much of the increase in US wage inequality can be explained by de-unionisation by holding the unionisation rate constant and comparing counterfactual wage distributions. They conclude that between a fifth and a third of rising male wage inequality in the US can be attributed to de-unionisation.

Summary

The determinants of wage inequality have received a lot of attention in the labour economics literature over the past 20 years. Demand-side factors have featured heavily in the literature, particularly in the debate between SBTC and international trade as explanations for the growth in wage inequality in the US and UK during the 1980's.

More recent research has distinguished the role of technological change as having a tasks or job bias rather than a skills bias on the demand for different types of labour. The empirical literature has so far not established a firm causal link between the job polarisation aspects of TBTC and the more recent patterns in wage inequality. In addition to the more commonly discussed demand-side factors, the supply side of the labour market has had an impact on wage inequality, with the changing labour force composition in terms of education and skills as well as changing wage distributions within education and experience groups playing a role.

As was found in the previous chapter for the UK, the US also experienced a change in the nature of wage inequality after the 1980's with a slowdown in the growth of inequality and a divergence of the evolution of the top and bottom of the wage distribution. This highlights the importance of not only explaining changes in overall inequality, but also finding the differential roles that these potential explanations have played in both parts of the wage distribution separately.

3.3 Methodology

This section describes the methodologies by which changes in wages can be decomposed and the particular approach taken in this study. It starts with the relatively simply Oaxaca-Blinder decomposition of the mean. A more sophisticated methodology for decomposing changes in the whole distribution of wages which is a generalisation of the Oaxaca-Blinder mean decomposition was developed by Juhn et al. (1993) is also discussed in detail. It is this latter approach which is utilised in this chapter.

3.3.1 Oaxaca-Blinder Decomposition

The decomposition of the mean is performed using the technique developed by Oaxaca (1973) and Blinder (1973). This is based on a standard OLS regression model of a dependent variable y as a function of independent variables x for individual i at time t:

$$y_{it} = x_{it}'\beta_t + u_{it} \tag{3.5}$$

Taking the mean of equation 3.5 relates the mean of the dependent variable to the mean of the independent variables in period t. Taking the mean of the equation for another period

s and subtracting this from the equation in period t yields an equation for the change in the mean of the dependent variable between periods t and s:

$$\bar{y}_t - \bar{y}_s = \bar{x}_t(\beta_t - \beta_s) + (\bar{x}_t - \bar{x}_s)\beta_s \tag{3.6}$$

In equation 3.6 the first term on the right hand side represents the effect of the change in the coefficients. The second term isolates the effect on changes in the mean value of the independent variables. Under the OLS assumption that $E(u_{it}|x_{it}) = 0$ for all periods t the residuals have no effect on the change in the mean of the dependent variable.

In the context of a simple human capital model of wages (i.e. log wages modelled as a function of education and experience) the coefficients effect isolates the impact of the change in the returns to human capital over time on wages. The effect of the change in the mean of the independent variables is the impact of changes in the mean level, or quantity, of human capital.

3.3.2 Juhn, Murphy, and Pierce Decomposition

Juhn et al. (1993) - denoted JMP hereafter - develop a generalisation of the Oaxaca-Blinder decomposition by which the entire wage distribution can be decomposed, and the change in any distributional statistic of interest can be split into the effects of quantities, prices, and unmeasured price and quantities (residuals). The decomposition is based on an OLS regression model for two mutually exclusive groups (in this case time periods) 1 and 2, as in the following equations:

$$y_1 = x_1\beta_1 + u_1 \tag{3.7}$$

$$y_2 = x_2\beta_2 + u_2 \tag{3.8}$$

In these models y_j is the outcome variable for group j, x_j is a vector of quantities of observed variables, β_j is the corresponding vector of observed prices/coefficients and u_j is the regression residual - the unobserved component of the outcome variable. Corresponding to these two models, the cumulative distribution functions for the residuals are also defined:

$$p_{i1} = F_1(u_{i1}|x_{i1}) \tag{3.9}$$

$$p_{i2} = F_2(u_{i2}|x_{i2}) \tag{3.10}$$

Figure 3.4 illustrates that $F()$ shows the rank - p - of the residual - u - in the distribution. The residuals can therefore be expressed as the inverse cumulative distribution function of p.

Decomposing the distribution into price, quantity, and unobserved effects entails using a reference model and isolating the three effects seperately. $F(.)$ and b (without subscripts) are used to define, respectively, the reference cumulative distribution of the residuals and the reference coefficients. The reference model in this application is the period 1 model.

Equations 3.11 and 3.12 give the value of the outcome variable for the two groups when the coefficients and residual distributions are fixed at their reference model values i.e. using the coefficients and residuals for the period 1 regression. Only the quantities differ between the two models. A comparison of the distributions generated by these two equations would therefore isolate the effect that the differing distributions of the independent variables in the model has on a given statistic of interest.

$$y_{i1}^1 = x_{i1}\beta_1 + F_1^{-1}(p_{i1}|x_{i1}) \tag{3.11}$$

$$y_{i2}^1 = x_{i2}\beta_1 + F_1^{-1}(p_{i2}|x_{i2}) \tag{3.12}$$

Equations 3.13 and 3.14 give the value of the outcome variable for the two groups when the residual distributions are fixed at the reference model values. Quantities and coefficients are both allowed to vary between the two groups. If for a chosen statistic of interest these two distributions were compared the result would be the effect of the different quantities and different coefficients on that statistic. Deducting the quantity effect calculated from equations 3.11 and 3.12 isolates the effect of differences in coefficients between the two groups.

$$y_{i1}^{2} = x_{i1}\beta_1 + F_1^{-1}(p_{i1}|x_{i1}) \tag{3.13}$$

$$y_{i2}^{2} = x_{i2}\beta_2 + F_1^{-1}(p_{i2}|x_{i2}) \tag{3.14}$$

Equations 3.15 and 3.16 give the value of the outcome variable for the two groups when the coefficients, residual distributions, and quantities are all allowed to vary between the two models. This is the case of the two models estimated separately with no reference model components as in equations 3.7 and 3.8, therefore simply returning the observed values of the dependent variable. Removing the effect of differing coefficients and distribution of independent variables from this isolates the effect of different residual distributions.

$$y_{i1}^{3} = x_{i1}\beta_1 + F_1^{-1}(p_{i1}|x_{i1}) \tag{3.15}$$

$$y_{i2}^{3} = x_{i2}\beta_2 + F_2^{-1}(p_{i2}|x_{i2}) \tag{3.16}$$

Using the mean - μ - as an example (which can be replaced with any chosen distributional statistic of interest in the analysis), the full JMP decomposition can therefore be written as follows:

$$\underbrace{\mu_1 - \mu_2}_{\text{Total}} = \underbrace{([\mu_1^1 - \mu_2^1])}_{\text{Quantities}} + \underbrace{([\mu_1^2 - \mu_2^2] - [\mu_1^1 - \mu_2^1])}_{\text{Prices}} + \underbrace{([\mu_1^3 - \mu_2^3] - [\mu_1^2 - \mu_2^2])}_{\text{Unobservables}} \tag{3.17}$$

Equation 3.17 breaks down the difference in a distributional statistic between the two groups into three components. The first term on the right hand side corresponds to the difference in equations 3.11 and 3.12 and therefore indicates the difference in the two groups which is due to differing quantities.

The second term takes the difference between equations 3.13 and 3.14 - the difference between the groups when both observable prices and observable quantities differ between the two groups. It then deducts the first term in order to isolate the pure price effect.

The final term in turn takes the difference between equations 3.15 and 3.16 - where all the components differ between the two groups. Deducting the second term (to hold price and quantity differences constant) from this isolates the contribution of the difference in the distribution of residuals, or the unmeasured prices and quantities. In this example the third term should be equal to zero as the mean should not depend on the residuals which have an expectation of zero. For other statistics it is likely that the distribution of residuals will play a role in explaining changes in the overall distribution.

In the analysis which follows the unobservables component represents "within-group" effects. These are within-group effects as they represent changes in inequality in the residuals i.e. differences in wages which remain once the human capital endowments of the individuals are controlled for. The price component represents "between-group" effects as these are the coefficients, and show how wages vary between different groups defined by the human capital variables. The quantity effect then represents compositional differences - changes in wage inequality which occur because of the changing proportions of individuals in different human capital groups. For example, an increasing proportion of individuals in groups with greater within-group inequality will increase the level of overall inequality, holding both within-group and between-group inequality constant.

3.3.3 Empirical Approach

The approach of this paper is to estimate JMP decompositions as outlined in the previous section. The aim is to decompose the change over time in the wage distribution into the effects of observed prices, observed quantities, and unobservables. The time period studied here is 1997-2012. This time period is chosen so as to be comparable to the analysis of the previous chapter. The decomposition is based on the following regression model estimated by OLS.

$$log(w_i) = X'\beta + \varepsilon_i \tag{3.18}$$

In equation 3.18 $log(w_i)$ is the natural logarithm of the hourly wage, X is a vector of human capital variables - education and experience - and β the corresponding vector of coefficients and ε_i is the error term, assumed to be normally distributed with an expectation of zero. These chosen functional forms are typical of the kind that have been estimated in the decomposition literature, for example Lemieux (2002) estimates an OLS regression using education dummies, years of schooling, a quartic in experience, marital status, and ethnicity in his decomposition using US data.

These decompositions are estimated using the *jmpierce* command in Stata. In order to perform statistical inference on the results, this program is bootstrapped with 500 replications for each model. As the decomposition involves two cross sectional regressions, each year is treated as a separate stratum and the bootstrap samples are drawn independently from both strata.

The overall period studied is 1997-2012. Regression models are estimated for each annual cross section and a decomposition between 1997 and each year from 1998-2012 is estimated and the results presented graphically. Quantitative results are presented for the overall period and two sub-periods. The sub-periods chosen are 1997-2005 and 2005-2012. These are analysed separately because the graphical results in Section 3.5 suggest a structural break in the evolution of wage inequality around this point which is of interest to decompose independently.

The main statistics of interest that are decomposed are the mean and measures of inequality. The main inequality measure considered is the 90-10 log wage differential. In order to independently analyse the top and bottom of the distribution the 90-50 and 50-10 differentials are also included.

3.4 Data

3.4.1 Dataset

This paper draws upon the UK's Labour Force Survey (LFS). The LFS is a nationally representative survey of the UK population which has been conducted on a quarterly basis since 1992. Sampling for the LFS is stratified rather than random and therefore the data includes sampling weights to ensure that statistics can be calculated which are representative of the population. The LFS is utilised as opposed to the Annual Survey of Hours and Earnings (ASHE) because the latter does not contain the required independent variables for the analysis.

The LFS information is gathered through responses by the individual or a proxy respondent on that individual's behalf. Each respondent is retained within the sample for five quarters with the sample staggered such that each quarter contains respondents in their first, second, third, fourth, or final wave of participation in the survey.

There is, therefore, a panel element to the data. This panel element to the data does not have any bearing on the methodological approach of this study as the quarterly data are pooled into years which are treated as repeated cross sections. The first quarters of 2001, 2004, and 2005 are excluded. This is because the earnings variable is not available in the 2001 first quarter, and the highest qualification variable is not available in the 2004 first quarter. Although these variables are referred to in the LFS documentation they are not provided in the respective datasets. The change from seasonal to calender quarters for the survey impacted the highest qualification variable - 30% of the observations do not have a response for this variable and this affects the data for the first quarter of 2005.

Table 3.1: OLS Log Wage Regressions 2005

	All 2005	Q1	Q2	Q3	Q4
Postgraduate	0.614***	0.0482*	0.801***	0.826***	0.791***
	(0.0113)	(0.0215)	(0.0208)	(0.0184)	(0.0220)
1st Degree	0.600***	0.756***	0.721***	0.732***	0.707***
	(0.00889)	(0.0203)	(0.0174)	(0.0165)	(0.0171)
Higher Education	0.408***	0.498***	0.472***	0.522***	0.458***
	(0.00890)	(0.0207)	(0.0166)	(0.0164)	(0.0171)
A Levels	0.256***	0.369***	0.321***	0.345***	0.316***
	(0.00778)	(0.0178)	(0.0146)	(0.0143)	(0.0148)
GCSE A*-C / O Levels	0.0832***	0.175***	0.146***	0.173***	0.164***
	(0.00781)	(0.0180)	(0.0148)	(0.0140)	(0.0149)
Other Qualification	0.0566***	0.149***	0.117***	0.151***	0.122***
	(0.00874)	(0.0206)	(0.0163)	(0.0159)	(0.0168)
Experience	0.0356***	0.0359***	0.0361***	0.0368***	0.0341***
	(0.000589)	(0.00126)	(0.00111)	(0.00112)	(0.00119)
Constant	1.770***	1.659***	1.688***	1.658***	1.713***
	(0.00913)	(0.0207)	(0.0174)	(0.0165)	(0.0180)
R^2	0.247	0.271	0.271	0.278	0.242
Observations	50502	9668	13602	13968	13264

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.1 shows a regression of the log wage on education dummies (with no qualifications as the omitted category) and experience for the year 2005. The regression using just the first quarter of 2005 clearly differs from those using quarters 2, 3, and 4. The clearest difference is in the coefficient for having a postgraduate degree. Not only does this coefficient differ significantly and substantially from the other quarters but it also has an interpretation inconsistent with the other quarters and with economic theory. As the highest level of education possible it should be associated with the highest wage relative to someone with no qualifications. In quarter 1 a postgraduate degree is associated with a 5% higher wage than someone with no qualifications. This is compared to someone whose highest qualification is GCSE grade A*-C level who earn an 18% higher wage.

As the income questions (i.e. including wages) are only asked in the first and fifth wave of participation in the survey each individual will only appear once in any given year when only observations for which wage data are available are included in the estimation sample. Each observation can therefore be treated as independent in the pooled annual cross sections.

The analysis focuses on full time workers, both male and female, and observations are included only if both alternative measures of the wage considered are available - one calculated using the individual's usual weekly hours and one calculated using the actual hours worked in the reference week. This gives a sample over the period considered (1997-2012) of 585,536.

Dependent Variable

The dependent variable is the natural logarithm of the individual's hourly wage. Since not all individuals are paid a set hourly wage[5], this figure is calculated for all individuals as their gross weekly earnings divided by total weekly hours worked. This measure of log wages is adjusted for inflation using the retail prices index (RPI).

There is potential for the results to be sensitive to the hours measure chosen. The LFS data allows for three potential hours totals; hours excluding any overtime, basic hours plus paid overtime, and basic hours plus paid and unpaid overtime. These totals can either be applied to actual hours (the actual hours worked in the reference week) or the individual's stated usual hours. This gives a potential 6 different measures which could be used to get an estimate of hourly wages.

For the main analysis, the measure used will be total (basic plus paid and unpaid overtime) usual hours. The sensitivity of the results to this particular choice is examined more closely in the analysis section. As can be seen in Table 3.2 the use of usual hours gives a lower estimate of the wage than with actual hours but the mean follows the same trend over time. There is, however, potential for other distributional statistics to be impacted on more seriously by the choice between the two measures.

[5] and those who are paid an hourly wage are disproportionately located in the bottom of the wage distribution

Table 3.2: Descriptive Statistics - Sample Means

	1997	2002	2005	2007	2012
Log Hourly (Usual) Wage	2.21	2.36	2.41	2.40	2.37
Log Hourly (Actual) Wage	2.28	2.43	2.46	2.46	2.42
Independent Variables					
Postgraduate Degree	0.04	0.05	0.07	0.08	0.09
1st Degree	0.11	0.13	0.15	0.16	0.21
Higher Education	0.10	0.10	0.11	0.11	0.11
A Levels	0.23	0.24	0.24	0.23	0.23
GCSE A*-C / O Levels	0.24	0.23	0.24	0.23	0.22
Other Qualification	0.15	0.13	0.12	0.12	0.08
No Qualifications	0.13	0.11	0.09	0.09	0.05
Experience	21.86	22.85	23.57	23.72	24.22
Male	0.49	0.49	0.48	0.48	0.48
Observations	68106	65149	42831	56277	44704

Independent Variables

The key independent variables are the human capital variables. The main variables in the standard human capital model are education and experience. These are measured in the LFS by a continuous variable experience, and 7 education dummy variables with no qualifications representing the base category. The experience variable (more precisely, *potential* labour market experience) is calculated as the individual's age minus the age they left full time education.

3.4.2 Descriptive Statistics

Figure 3.5 shows the change in real log wages at each percentile of the distribution for all workers over 1997-2012 . As the figure shows, over the whole period real log wages increased at each point in the distribution. The downward sloping portion of the line further indicates that the largest increases in real wages were obtained at the bottom end of the distribution and generally suggests decreases in wage inequality in this part of the distribution. This increase in wages at the bottom of the distribution is partly attributable to the minimum wage which was introduced in this period. The U shaped curve however suggests that inequality at the top end of the distribution increased. This highlights the importance of analysing both halves of the distribution independently in addition to the overall distribution.

The distribution of educational attainment has changed to reflect greater participation in higher education. This is illustrated in Figure 3.6. The proportion of individuals whose highest qualification is a degree has increased by approximately 10 percentage points and those with a postgraduate degree by 5 percentage points. The proportion of individuals whose highest qualification is an A level or equivalent has declined slightly over this period . Meanwhile there have also been slight declines in those whose highest qualification is a GCSE (both A*-C grades and D-G grades) and the proportion of those with no qualifications has fallen by around 5 percentage points.

The distribution of labour market experience has also shifted to indicate greater levels of human capital as shown in Figure 3.7 and the descriptive statistics given in Table 3.2. Between 1997 and 2007 the distribution became distinctly bimodal but with a larger proportion of the density accounted for by those with more than 20 years of experience in 2007. The 2012 distribution looks similar to that of 2007 but shifted to the right. It can be seen in Table 3.2 that the average level of experience has consistently increased since 1997.

Figure 3.8 gives an illustration of how the changes in inequality suggested by Figure 3.5 break down into within and between group changes. These two groups are a "more" experienced (21-40 years) and "less" (1-20 years) experienced group.

Both groups show the U shaped relationship between position in the wage distribution and the change in real log wage over the 1997-2012 period shown in Figure 3.5. Within group inequality has fallen in the bottom half of both distributions (more so in the less experienced group) and has increased in the top half. The between group comparison appears to show decreasing inequality - at almost all points in the respective distributions, real wages have grown faster for the less experienced group therefore closing the gap between the two. The mean wage differential between the two groups has fallen from 0.147 log points in 1997 to 0.091 in 2012.

A more detailed breakdown of the inequality change of the less experienced group into further groups defined by highest level of education is provided in Figure 3.9. Amongst the less educated groups - GCSE's and no qualifications - within group inequality has fallen, and more so in the bottom end of the distribution than the top. This also appears to hold true (although less obviously) for those with A Levels. There appears to have been slight increases in inequality for postgraduates and those with first degrees.

Looking at the case between groups potentially explains the U shaped relationship found in Figure 3.8. Wages for those with no qualifications have grown the fastest up to the median of each respective distribution which can explain the compression of the bottom half of the overall distribution of this experience group, and across the entire distributions faster than any group except postgraduates. Meanwhile at the top end of the distribution, growth in real wages for postgraduates has been consistently faster than for those with only a first degree (for this group the growth in real wages was negative).

For the less experienced group both within and between group comparisons suggest increasing inequality at the top end of the distribution, and similarly at the bottom end of the distribution both the within and between group comparisons are suggestive of decreasing inequality.

It is difficult to draw meaningful conclusions from this descriptive analysis alone even using a limited number of education categories and one experience group, and the conclusions which can be drawn may not generalise. This highlights the usefulness of the more formal decomposition approach to assessing the role of between-group and within-group effects in the changes in wage inequality.

3.5 Analysis

3.5.1 OLS Regression Results

Table 3.3 reports the results of the OLS regressions[6] corresponding to equation 3.18. The columns report, respectively, results for cross sectional regressions estimated for 1997, 2002, 2005, 2007, and 2012

Each regression produces results consistent with a basic human capital model. All coefficients on the education dummies are positive, reflecting the fact that individuals with education of any level would be expected to earn a higher wage than an individual with no qualifications. The magnitude of the coefficients also make sense, indicating that higher quality qualifications result in a higher expected wage.

The coefficients on the experience variables are also as would be expected. All coefficients on age are positive and all coefficients on age squared are negative. The simplified nature of the econometric specification of the human capital model means the returns to education reported here are overestimated i.e. they do not account for selection into education by those with greater ability and would consequently have been expected to earn more than those who choose not to undertake further non-compulsory education even without having undertaken the additional education themselves.

All estimated coefficients are significant at the 5% level at least and in most cases even at the 0.1% level using standard errors robust to heteroscedasticity. The R^2 values for each model suggest this specification can explain between 25% and 30% of the cross-sectional variation in log wages.

The columns of Table 3.4 correspond to those of Table 3.3 but for females. These results are again as would be expected from a regression model of this type and produce similar R^2 values to the male regressions.

[6] Reported coefficients are limited to the training dummy, the experience and experience squared variables and the education dummies

Table 3.3: OLS Log Wage Regression Results - Males

	1997	2002	2005	2007	2012
Postgraduate	0.801***	0.804***	0.757***	0.829***	0.822***
	(0.0165)	(0.0138)	(0.0172)	(0.0151)	(0.0184)
1st Degree	0.771***	0.747***	0.697***	0.712***	0.705***
	(0.0122)	(0.0117)	(0.0145)	(0.0137)	(0.0162)
Higher Education	0.519***	0.475***	0.476***	0.491***	0.490***
	(0.0127)	(0.0121)	(0.0146)	(0.0143)	(0.0173)
A Levels	0.318***	0.300***	0.301***	0.335***	0.332***
	(0.0102)	(0.00961)	(0.0118)	(0.0118)	(0.0150)
GCSE A*-C / O Levels	0.235***	0.217***	0.180***	0.222***	0.215***
	(0.0115)	(0.0107)	(0.0130)	(0.0131)	(0.0155)
Other Qualification	0.111***	0.106***	0.120***	0.142***	0.0900***
	(0.0114)	(0.0115)	(0.0137)	(0.0134)	(0.0166)
Experience	0.106***	0.0862***	0.0942***	0.0900***	0.0867***
	(0.00325)	(0.00312)	(0.00382)	(0.00346)	(0.00393)
Experience Sq/100	-0.431***	-0.330***	-0.385***	-0.365***	-0.328***
	(0.0250)	(0.0234)	(0.0282)	(0.0260)	(0.0280)
R^2	0.296	0.295	0.290	0.271	0.272
Observations	32068	30170	19561	25808	20294

Standard errors in parentheses

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

Table 3.4: OLS Log Wage Regression Results - Females

	1997	2002	2005	2007	2012
Postgraduate	0.872***	0.817***	0.828***	0.800***	0.828***
	(0.0151)	(0.0129)	(0.0151)	(0.0129)	(0.0156)
1st Degree	0.785***	0.743***	0.727***	0.706***	0.662***
	(0.0109)	(0.0103)	(0.0124)	(0.0111)	(0.0144)
Higher Education	0.596***	0.525***	0.512***	0.489***	0.472***
	(0.0100)	(0.00965)	(0.0120)	(0.0111)	(0.0147)
A Levels	0.316***	0.306***	0.295***	0.293***	0.280***
	(0.00945)	(0.00919)	(0.0113)	(0.0103)	(0.0137)
GCSE A*-C / O Levels	0.235***	0.212***	0.190***	0.184***	0.178***
	(0.00814)	(0.00799)	(0.0102)	(0.00934)	(0.0131)
Other Qualification	0.128***	0.130***	0.129***	0.143***	0.0792***
	(0.00882)	(0.00895)	(0.0120)	(0.0111)	(0.0147)
Experience	0.0942***	0.0818***	0.0830***	0.0767***	0.0676***
	(0.00321)	(0.00307)	(0.00379)	(0.00321)	(0.00377)
Experience Sq/100	-0.502***	-0.429***	-0.413***	-0.385***	-0.290***
	(0.0246)	(0.0231)	(0.0288)	(0.0231)	(0.0288)
R^2	0.254	0.264	0.282	0.256	0.263
Observations	32737	31829	21273	27798	22318

Standard errors in parentheses

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

3.5.2 JMP Decomposition Results

This section presents the results of the JMP decompositions. Appendix 3A contains figures allowing for a visual analysis of the decompositions of the mean and percentile differentials to complement the quantitative analysis presented here.

Full period Analysis

Quantitative results including bootstrap standard errors of the estimates for males are presented for the 1997-2012 decomposition in Table 3.5.

The results of the mean decomposition for males are illustrated in Figure 3.10. The top left panel shows the change in the mean relative to 1997 for each year up to 2012. The remaining panels then respectively show the contribution of the quantity, price (or returns), and unobservables effects to the decomposition.

Until 2005 the effect of prices grows along with the total change in the mean and is clearly the dominant component of the decomposition up to this point. After 2005 the role of prices becomes less important until by 2012 almost the entirety of the change in the mean wage since 1997 is attributable to the quantity effect, accounting for 0.103 of the 0.113 increase in mean log real wages. These results suggest that until 2005 the rising mean wage was predominantly due to increases in the return to human capital, complemented by the shifts in the distribution of human capital illustrated in Figures 3.6 and 3.7. The levelling off and decrease in mean wages is attributable to the decrease in the price effect relative to 2005 due to declining labour demand impacting on the real returns to human capital due to the Great Recession.

The overall growth in wages over the 1997-2012 period is therefore almost completely due to the shift in the human capital distribution, with real prices almost unchanged from 1997 levels. A major factor in this result is the decline in real wages since the onset of the Great Recession - had the human capital distribution remained fixed at its 1997 level, these results suggest the real mean log wage in 2012 would be no different from its 1997 level. The effect of the unobservables in explaining the change in the mean is statistically

Table 3.5: JMP Decomposition: Males 1997-2012

	T	Q	P	U
Mean	0.113***	0.103***	0.010*	0.000**
	(0.005)	(0.003)	(0.005)	(0.000)
Standard Deviation	-0.016*	-0.001	-0.010***	-0.005
	(0.006)	(0.001)	(0.002)	(0.006)
5th Percentile	0.192***	0.174***	0.018*	0.000
	(0.014)	(0.009)	(0.008)	(0.007)
10th Percentile	0.109***	0.095***	0.022***	-0.008
	(0.007)	(0.007)	(0.006)	(0.004)
50th Percentile	0.086***	0.082***	0.011*	-0.007**
	(0.007)	(0.005)	(0.005)	(0.002)
90th Percentile	0.127***	0.117***	-0.001	0.012**
	(0.008)	(0.007)	(0.006)	(0.004)
95th Percentile	0.171***	0.162***	-0.004	0.012*
	(0.013)	(0.009)	(0.007)	(0.006)
90-10 Percentile Differential	0.018	0.022*	-0.023**	0.019**
	(0.011)	(0.009)	(0.007)	(0.007)
90-50 Percentile Differential	0.041***	0.035***	-0.012**	0.019***
	(0.009)	(0.008)	(0.004)	(0.004)
50-10 Percentile Differential	-0.023**	-0.013	-0.011*	0.001
	(0.009)	(0.008)	(0.005)	(0.005)

Standard errors in parentheses

T=Total, Q=Quantity, P=Price, U=Unobservable

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

significant, however the effect is zero when rounding to three decimal places and so has no economic significance as can be seen in the bottom-right panel of figure 3.10.

Figures 3.11 to 3.13 show the decompositions for the 90-10, 90-50, and 50-10 differentials respectively. The 90-10 differential initially falls between 1997 and a minimum point reached in 2005. This is due to a negative price and unobservable effect which is offset slightly by a positive quantity effect. The magnitude of the price effect diminishes after this point but remains consistently negative and is significant in 2012. The positive effect of prices on the mean log wage but negative effect on wage inequality suggests rising returns to human capital across the wage distribution but faster for those with relatively little human capital.

The overall rise in the 90-10 differential by 2012 is due to the complementary effects of quantities and unobservables. This suggests overall increases in within group inequality and a shift in the human capital distribution towards those groups with higher and/or growing within group inequality. Both within-group and between-group effects are clearly therefore playing a role in the change in wage inequality. The change in the 90-10 differential is, however, not significant.

Breaking down the analysis of the whole wage distribution reveals differences in the mechanisms by which inequality has changed in the bottom and the top of the distribution. The 90-50 differential is consistently greater than it was in 1997 and the 50-10 differential is consistently lower. The 50-10 differential, similar to the 90-10, reaches a minimum point relative to 1997 in 2005 and thereafter increases. Overall 90-10 inequality fell until 2005 because the magnitude of the falling 50-10 differential offset that of the rising 90-50 differential. After 2005 these positions reversed, leading to the overall increase in the 90-10.

The quantity effect is the major component of the changes in the 90-50 differential, accounting for 0.035 of the 0.041 increase. This is complemented by the unobservables but offset by the price effect (as in the case of the 90-10). The quantity and price effects account for most of the overall change in the 50-10 differential, offset slightly by a positive unobservables effect. Only the price effect is significant, however.

The quantity effect on inequality in both sides of the distribution reflect the implied shifts in between group inequality suggested by Figures 3.8 and 3.9. Faster wage growth of the unqualified compared to those with GCSEs, and of those with GCSEs compared to A Levels suggest this compression of the bottom end of the wage distribution. Likewise, at the top end of the distribution, postgraduate degree holders experienced faster wage growth than those who hold only an undergraduate degree.

The price effect on inequality is consistently negative for each of the three wage differentials. By 2012 in each case, as with the mean, the price effect appears to be of little or no importance in explaining the change over time relative to the other components, with the exception of the 50-10 differential. Changing prices of human capital had a positive effect on average wages and a negative one on each inequality measure initially (up to 2005). By 2012 the price effect is reduced in magnitude but negative and significant for all inequality measures.

The price effect is the only significant component of the decomposition of the change in the 50-10 differential. For the 90/10 and 90/50 differentials each component of the decomposition is statistically significant.

The overall increase in wage inequality appears therefore to be explainable mostly in terms of within group inequality for males. The competing effects of changes in the distribution of human capital and the returns to human capital render the between-group effect small. In the distribution breakdown however the distribution of human capital is the most important component of both the changes in the 90-50 and 50-10 differentials. The opposing signs of these two changes means that they offset each other in the 90-10 differential decomposition. The change in the 50/10 differential is explained completely by human capital factors.

Table 3.6 presents the results of the decomposition for females. The results of the mean decomposition for females are qualitatively similar to the findings for males. Mean wages increased significantly (and more than for males) primarily due to the price effect until 2005, after which the price of human capital appeared to fall again and by 2012 quantities account for 0.140 of the 0.186 log point increase in the mean wage for females i.e. increasing average wages are due to a greater proportion of females having higher levels

Table 3.6: **JMP Decomposition: Females 1997-2012**

	T	Q	P	U
Mean	0.186***	0.140***	0.046***	0.000**
	(0.004)	(0.003)	(0.004)	(0.000)
Standard Deviation	-0.026***	0.012***	-0.016***	-0.021***
	(0.005)	(0.001)	(0.002)	(0.005)
5th Percentile	0.261***	0.174***	0.069***	0.017*
	(0.007)	(0.008)	(0.006)	(0.007)
10th Percentile	0.218***	0.133***	0.069***	0.017***
	(0.004)	(0.005)	(0.005)	(0.005)
50th Percentile	0.163***	0.124***	0.051***	-0.012***
	(0.009)	(0.007)	(0.005)	(0.002)
90th Percentile	0.185***	0.169***	0.019***	-0.002
	(0.009)	(0.007)	(0.006)	(0.004)
95th Percentile	0.199***	0.176***	0.021**	0.002
	(0.009)	(0.008)	(0.006)	(0.005)
90-10 Percentile Differential	-0.033***	0.036***	-0.050***	-0.019**
	(0.009)	(0.008)	(0.007)	(0.007)
90-50 Percentile Differential	0.022*	0.044***	-0.032***	0.009*
	(0.010)	(0.009)	(0.005)	(0.004)
50-10 Percentile Differential	-0.055***	-0.008	-0.018***	-0.028***
	(0.009)	(0.009)	(0.004)	(0.005)

Standard errors in parentheses
T=Total, Q=Quantity, P=Price, U=Unobservable
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

of human capital in 2012.

The 90-10 differential decreased significantly between 1997 and 2012 by 0.033 as Table 3.6 indicates. The effect of prices on wage inequality is consistently negative over time for each of three measures of inequality. Also similar to the male case, the quantity and unobservables effects are positive for the 90/50 differential. The results of the 90-50 differential for females look qualitatively similar to the results for males, with an overall increase driven by quantities and unobservables.

The change in the 50-10 differential is also similar to the male case but the change is larger in magnitude than the 90/50 differential. Each component of the this decomposition is negative. Table 3.6 shows that the unobservable effect explains around half of the decrease in the 50-10 differential. The price component complements this but is smaller in magnitude. The quantity effect is the most minor component of the decomposition and is insignificant.

Sub-period Analysis

These results so far suggest that it would be of interest to break down the period of analysis around 2005. In each of the statistics considered so far, given that this is where in each case the price effect reaches its peak (in explaining the mean) or trough (in explaining inequality). These results are presented quantitatively in Tables 3.8 and 3.9 for the 1997-2005 and 2005-2012 periods respectively for males. Tables 3.10 and 3.11 repeat this analysis for females.

For males in the 1997-2005 period, the rise in mean wages was due more to changes in the price of human capital though the positive contribution of changes in quantities of human capital is also strongly significant.

The 90-10 differential decreased significantly and this was due mainly to the price effect complemented by the unobservables. These two factors jointly over-explain the decrease and are offset by a positive quantity effect.

The decrease in the 90-10 differential is driven entirely by a fall in lower-end wage inequality, the 50-10 differential falls significantly and by much more than the 90-50 differential increases (which was insignificant). Each component of the decomposition in the 50-10 complement each other. Unobservables account for the major component of the decrease with a significant contribution from the price effect as well. The quantity effect is not significant.

In the 2005-2012 period the fall in mean log wages is statistically significant and driven by a negative price effect. Continuing shifts in the human capital distribution towards higher average amounts of human capital results in a significant positive quantity effect which is outweighed by the price effect. This qualitative result is found at each percentile of the distribution except for the 95th percentile which increased (though insignificantly)

The overall increase in the 90-10 differential is due to the increase of 0.077 in this latter period more than offsetting the decrease of 0.059 in the period before. The unobservables effect is still the most important component of the decomposition in the 2005-2012 period, explaining around three quarters of the increase in wage inequality. The price effects complement the unobservables but the quantity effects counter it for each of the differentials. All of the effects are significant except for the quantity effect for the 50-10 differential.

For females in the 1997-2005 period, as for males, the price effect was the major contributor to increasing mean wages. Wage inequality decreased, driven by the bottom half of the distribution. Another similarity with the male decompositions for this period is that the 90/50 differential did not change significantly. This rise in the 90-50 differential is explained by the quantity and unobservable effects, though only the quantity effect is significant. Offsetting this to an extent is the price effect, accounting for the insignificant overall change.

The 1997-2005 sub-period analysis gives the same pattern of results for both males and females in terms of the signs of the effects and in which effects are significant.

As with males the 50-10 differential decrease is due to all three components of the decomposition with unobservables accounting for the largest component and the quantity effect being significant. The 90-10 differential case is also identical to that of males with negative price and unobservable effects outweighing a positive (although in this case, significant) quantity effect.

The 2005-2012 period also looks very similar for females as it did for males. Mean log wages fell significantly because of a negative price effect outweighing a significant quantity effect. Negative price effects also dominated positive quantity effects at each different percentile of the female wage distribution and overall wages fell by more at the bottom of the distribution.

Wage inequality for females in this period increased by all three measures but the change in the 90-50 differential is insignificant. The increase in 90-10 wage inequality is statistically significant and is explainable in terms of the quantity effect and the unobservables which are both positive and significant. A significant negative quantity effect lessened the impact of these two factors.

In both the male and female cases, the significant and negative influence of the unobservables on the 50-10 differential in the 1997-2005 period may be a result of the introduction of the NMW in 1999. The lack of a significant effect of the unobservables in the 2005-2012 period for females and a positive effect for males would suggest that this influence was limited to a static effect when the minimum wage was introduced, with no long term effects.

3.5.3 Interpretation and Discussion of the Results

The overall results for males support the initial hypothesis. Increasing attainment of higher education in the 1997-2012 period was accompanied by a negative effect on between group wage inequality as would be expected given the declining skill premium. The effect on within-group inequality was positive and the impact of increasing the proportion of skilled labour (the composition effect) was also positive.

This effect differs across the distribution. This pattern is reflected in the top half of the distribution, which saw a significant increase in wage inequality due to positive within-group and and composition effects, also experiencing a negative effect on between-group inequality.

With skilled labour being defined as anyone with university level education and the expansion of the proportion of the labour force composed of both first degrees and postgraduate degrees it makes sense that the hypothesised effect which is found for overall inequality would occur primarily in the section of the wage distribution above the median.

Table 3.7 shows the changes in wage inequality within education and experience groups. High education is defined as anyone with a university level education, medium education is anyone with any qualification below university level, and low education is defined as

Table 3.7: Change in the log 90/10 Wage Differential by Education/Experience Group

Education Level:		High			Medium			Low	
Years of Experience:	0-9	10-19	20+	1-10	10-20	20+	1-10	10-20	20+
AGGREGATE	0.056	0.094	0.154	-0.258	-0.090	-0.115	-0.371	-0.246	-0.181
INDUSTRY									
Agriculture	0.408	0.370	0.408	-0.912	0.285	-0.006	-1.291	-0.546	0.020
Manufacturing	0.005	0.166	0.097	-0.184	-0.093	0.005	-0.239	-0.265	-0.143
Construction	0.073	0.270	0.525	-0.294	0.011	-0.008	-0.352	0.202	0.278
Wholesale/Retail	-0.170	-0.162	-0.045	-0.203	-0.169	-0.176	-0.304	-0.414	-0.294
Transport and Comms	-0.202	0.046	-0.074	-0.205	0.120	0.109	-0.625	-0.355	-0.021
Finance	-0.088	0.125	0.009	0.012	-0.050	-0.055	-0.148	-0.536	-0.291
Other Services	0.073	0.021	0.115	-0.369	-0.151	-0.128	0.356	0.179	-0.123
OCCUPATION									
High Skilled	0.030	0.030	0.116	-0.118	0.004	-0.008	1.456	0.144	0.017
Low Skilled	-0.106	-0.272	-0.119	-0.270	-0.190	-0.183	-0.416	-0.290	-0.193

no qualifications. The figures show that wage inequality within groups is only growing (at the aggregate level) for graduates, and this pattern is broadly found for most of the disaggregated industry groups.

The occupation groups are defined as in the previous chapter; SOC major groups 1-3 comprise high skilled occupations while the remaining groups comprise low skilled occupations. High skilled occupations experienced rising within-group inequality regardless of education/experience level (with the exception of medium educated workers with more than 20 years of experience) whereas the low skilled occupations had the opposite.

These figures support the idea that as participation in higher education increases the consequent widening of the ability distribution amongst university graduates increases inequality amongst this group. The results of the decomposition indicate that this effect is greater than the effect of reduced inequality within the groups of less educated workers as the net effect is an increase in within-group wage inequality.

The bottom half of the male wage distribution does not conform to this pattern, with a fall in wage inequality to be explained by the decomposition. The only significant effect in this case is a decline in between group wage inequality.

One explanation for this could be the effect of job polarisation. As the demand for intermediate skilled routine tasks falls the relative intermediate to low skilled wage would also be expected fall, which would explain the compression of the bottom half of the wage distribution.

Job polarisation would be expected to have a positive between-group effect on the top of the distribution as the relative demand for high over intermediate skills increases. The fact that this is not observed suggests that the growth in the relative supply of highly skilled workers outpaced the growth in relative demand implied by polarisation.

The introduction of the NMW in 1999 could also be playing a role. As an effective minimum wage will push up wages at the bottom of the distribution, this will also have a compression effect on the bottom end of the wage distribution by narrowing the gap between the average wages of the lowest skilled and the median worker.

The sub-period analysis suggests that there was some effect of the NMW, as the decline in lower level wage inequality was restricted to the earlier 1997-2005 period which could indicate an effect of the NMW on its introduction which did not persist. This is consistent with the literature which has suggested that the impact of the minumum wage was short term. In the latter period inequality grew significantly throughout the wage distribution for males.

Both within-group and between-group inequality significantly declined at the bottom of the distribution in the 1997-2005 period, consistent with the NMW increasing the average wage of the lowest skilled relative to other workers and also the price floor reducing the potential for dispersion in wages amongst the lowest skilled.

In the 2005-2012 period inequality significantly increased throughout the distribution of male wages. There appear to be no composition or between-inequality effects in this case, as only the within-group inequality effect is significant for any of the inequality changes. The results therefore continue to conform partially to the hypothesised effects of increasing relative skilled labour supply but without the expected composition and between-group effects.

Female wage inequality at the bottom of the distribution went through the same process as the male wage distribution, with the effects in each decomposition being identical in terms of significance and relative importance (with the exception of the insignificant within-group inequality effect in the 2005-2012 period decomposition). The overall fall in wage inequality at the bottom of the distribution over the whole period occured in the 1997-2005 period due to both declining within and between-group inequality.

The top half of the distribution also behaved in a similar manner to the male wage distribution, with the results again being consistent with the hypothesis stated in the introduction that growth in relative skilled labour supply reduced between-group wage inequality, increased within-group wage inequality, and a positive composition effect.

Unlike in the male wage distribution, however, overall inequality fell in the female wage distribution between 1997 and 2012. Despite the similar patterns in the inequality in the two halves of the distribution the difference is clearly driven by the within-group inequality effects. For females, this is negative and significant for the 50/10 differential in the 1997-2012 period but insignificant for males. The positive within-group inequality effect in the top of the distribution is also weaker for females than for males.

The result of this is a decline in within-group inequality for females as opposed to the increase for males. This decline in the within-group inequality is limited to the 1997-2005 period and so as discussed above, this could be a minimum wage effect which had a much a stronger impact on female wage inequality than male.

The results of the 2005-2012 sub-period analysis for females does not conform to the hypothesised effects of increasing relative labour supply. The negative composition effect and positive between-group inequality effect contradict the hypothesised effects. This may be an impact of the Great Recession, with demand for skilled female labour falling less than the demand for less skilled labour. This would increase the relative demand for skilled labour and put upward pressure on the skill premium and between-group inequality.

3.5.4 Robustness Checks

The results presented so far are subjected to robustness checks to take account of uncertainty due to the nature of the data. These uncertainties are around the construction of the log wage variable used in the analysis and potential measurement error in the wage variable. All of the results tables for the robustness checks can be found in Appendix 3B.

Payslip data

The first source of uncertainty that is subjected to robustness checks is the accuracy of the self-reported gross earnings of the individual. The LFS contains a variable which indicates if any documentation was used by the individual to report their earnings - either a pay slip, bank/ building society details, or some other source. The results obtained in the main part of the analysis are compared to the same results obtained just from those who provided payslip data[7]. It is only possible to make the comparison with the sub-sample who used payslips to provide information for the wage variable for the period 2005-2012 due to the timing of this variable becoming available in the LFS (the third quarter of 1998).

Tables 3.13 and 3.14 show the results of the decomposition using only the payslip data for the period 2005-2012 for males and females respectively.

Comparing Tables 3.13 and 3.9 reveals some differences but qualitatively the results are very similar. The mean still falls with a stronger negative price effect than positive quantity effect and this pattern holds throughout the distribution with the lower percentiles falling by more than the higher percentiles. The interpretation of the decompositions of the inequality measures still holds but the magnitudes of the inequality increases have diminished. Overall inequality increased due mostly to the unobservables effect.

The elements of the decomposition have also been reduced in significance with only the

[7] In what follows, the term "payslip data" refers to the sub-sample of individuals who used either their pay slip or bank/building society details to provide the information about earnings.

unobservable effect for the 90-10 and 50-10 differential being significant at the 5% level. The unobservables remain the main component of the decomposition for the inequality measures.

The results for females are similar and obtained by comparing Tables 3.14 and 3.11. The conclusions and inference around the mean are qualitatively the same as the full sample case but there are some notable differences when it comes to interpreting the inequality measures. The increase in the 90-10 and 50-10 differentials and their components are now not significant. For the 90-10 differential the unobservables effect is the major component of the decomposition and is complemented by the quantity effect (though this is insignificant). The price effect is negative but also insignificant.

Most of the difference between the full and payslip samples for males is the loss or weakening of significance of results. For females only the unobservables effect on the 90-10 differential remains significant when restricting the sample to those who used payslip information. For both genders, components of the decomposition change sign.

This difference in results is likely due to the problem of reduced sample size which is severe when restricting the sample in this way, the proportion of individuals in the pooled 2005 and 2012 data who used payslip details to provide income information is only 20%. Selection of the individuals who use payslip information is also likely to be systematic and therefore influencing these results.

The selection issue is that unobservable characteristics of individuals which are correlated with their education levels are also likely to be correlated with the propensity to use a payslip to give income information. More highly educated individuals are likely to be better organised and have ready access to their payslips and may also be more likely/willing to want to give an accurate answer to questions in the survey.

Construction of the wage variable

The other source of uncertainty in the data examined is the way in which the wage variable is constructed. The LFS provides two main measures of hours; usual hours - the hours measure used to define wages in the main analysis - and actual hours. Usual hours are the total hours an individual works in a typical week whereas actual hours are the hours the individual actually worked in the reference week of the survey.

Arguments can be made for the use of both of these measures; using actual hours will give a precise value (assuming no measurement error) for the hours the individual worked in the reference week. Usual hours on the other hand will give an indication of the individual's average working week which may be a better measure if the reference week was atypical for that worker (and if the reference week was similar to an average week the two measures should not differ).

Table 3.15 shows the same results as the decomposition in Table 3.5 - for males over the 1997-2012 period - using actual hours to define the wage rather than usual. The results for the mean hold - a large quantity effect explains all of the change in real wages - however there is also a negative price effect which is significant and offsets the total change in the mean. This is also found throughout the wage distribution although the price effect is not significant at the 5th and 50th percentiles.

In examining the total changes of each percentile an obvious difference between these results and the main analysis is observed - the U shaped relationship between the percentile and the change in the wage seen in Table 3.5 is not repeated for this wage measure; while real wages still increase throughout the distribution the magnitude of the increase monotonically declines, indicating decreasing wage inequality by each of the three differentials.

This result is found, contradicting the results of the main analysis where the 50-10 differential decreased and the 90-50 differential increased by a larger amount leading to overall rising wage inequality. In this case all three differentials decline, with 90% of the fall in the 90-10 differential attributable to the decline in the 50-10 differential. None of these changes are, however, significant.

Comparing Table 3.16 to Table 3.6 gives a comparison between the different hours measures for females. The insignificant increase in wage inequality measured by the 90-10 differential initially found becomes a significant decrease. The observed components of the decomposition remain similar in size and magnitude with prices and unobservables driving the changes in the 90-10 and 50-10 differential. The mean, similarly to males, has a significant negative price effect when using actual hours.

The main difference between the results of analysing these two wage measures is a substantial change in the decomposition mainly in the top half of the wage distribution. Inequality is found to decrease insignificantly rather than increase significantly and lead to an overall increase in wage inequality. The difference between the two hours measures is much greater for males and females.

Why do the hours measures give different results?

As the results are sensitive to this choice of how the dependent variable is constructed the issue is examined more closely using a variable constructed as the ratio of usual hours to actual hours. Table 3.17 shows the results of logit models estimated for the entire sample to model the probability that an individual's reported usual hours are equal to reported actual hours (which is the case for 328,060 observations out of 582,487 (or 56% of the sample). These probability models are estimated as a function of the human capital variables in the wage equations on which the decomposition is based plus a series of time dummies.

The results in column one are for the probability that the hours ratio is equal to one (the two measures are equivalent), column two models the probability that the ratio is greater than or equal to one (so usual hours are greater than or equal to actual hours). The results reported in column one indicate that individuals with more levels of human capital, or the higher skilled, are less likely to have their actual hours equal to their usual hours. All coefficients are highly significant and negative (except the experience squared term) and the education dummy coefficients monotonically increase in magnitude as the education level relative to no qualifications increases.

As these individuals are higher earners it points to these individuals as driving the difference between the decomposition results when a different hours measure is used to calculate the wage. The second column tells a similar story to column one but shows that not only are actual and usual hours more likely to differ between workers with higher levels of human capital but actual hours are increasingly likely to be larger than usual hours.

An intuitive explanation for this would be that individuals in highly paid jobs are less routine in terms of the hours worked on a week by week basis. This would make actual hours worked on a weekly basis more volatile for these types of workers and usual hours are then a reflection of the average week. If the individual worked an abnormally large number of hours in the reference week their average hourly pay will be understated. As the measure of usual hours implies a longer time horizon over which the individual considers their work pattern, this measure is likely to reduce the impact of isolated weeks with abnormally long hours worked and better reflect a "typical" working week.

The results of Tables 3.18 and 3.19 re-estimate the decomposition for males and females respectively, including only wage observations for the 56% of the sample for whom usual equal actual hours. Bearing in mind the results of the logit models, this means higher earners will be disproportionately under-represented in these results. For males, comparing Table 3.18 to 3.15 (actual hours full sample) and 3.5 (usual hours full sample) reveals that this sub-sample yields results more in common with the full sample where usual hours is used to define the wage variable.

The U shaped relationship between the change in the real log wage and the position in the distribution found for usual hours is again found here, rather than the strictly downward sloping relationship given by actual hours. In this case, however, the change in the 90-10 differential is negative but still insignificant.

In examining the elements of the decomposition for the three percentile differentials, the signs for each element is the same for this sub-sample as it is for the usual hours case. The only exceptions to this are the quantity and unobservable effects for the 50-10 differential, however as in the usual hours case both are insignificant. In this instance the overall changes in the differentials are all insignificant, with the 90-50 and 50-10 differential changes having fallen in magnitude but are all of the same sign as in the results for usual hours.

These results suggest that it may be more reliable to interpret the results of the main analysis based on usual hours rather than actual hours. When restricting the sample to those observations where actual and usual hours are the same, the results more closely resemble the full sample usual hours case than the actual hours case. The differences between the actual and usual hours results seem to be driven by a tendency for reported actual hours to over-state usual hours which is disproportionately located within the top of the wage distribution.

3.6 Summary and Conclusions

The aim of this chapter was to examine the change over time in the UK wage distribution within a human capital framework. This was undertaken using a decomposition analysis in order to investigate the role of the supply side of the labour market in recent trends in wage inequality. The hypothesis being investigated was that shifts in the relative supply of labour caused a decline in between-group inequality

The decomposition was also able to give an insight into changes in the level of wages as well as inequality. The increase in average wages between 1997 and 2012 for both males and females is attributable almost entirely to shifts in the human capital distribution. Had this remained at its 1997 level mean wages would not have significantly changed. Overall real wage growth is therefore a consequence of the changing skill composition of the workforce. Given the timing of the decline in the impact of the price of human capital and its equivalent impact on both males and females, the neutral effects of prices over the whole period is interpretable as a consequence of falling labour demand due to the Great Recession.

For both males and females, inequality grew significantly within the top of the distribution but declined significantly within the bottom of the distribution. This contributed towards a positive but insignificant change in wage inequality for males and significant decline in wage inequality for females. Changes in the price of human capital over time have had a negative impact on the level of wage inequality throughout the distribution for both males and females via a decline in between-group inequality, as would be expected given the declining skill premium.

This decline in the skill premium has, however, been accompanied by upward pressure on wage inequality from the supply side of the labour market. The positive composition effect suggests that shifts in the skill distribution have increased the proportion of workers in skill groups with higher levels of inequality and the positive change in within-group inequality suggests that this increase in educational attainment has expanded those wage distributions further. The overall results are therefore consistent with the initial hypothesis.

Two distinct periods can be identified during which inequality behaved differently. Up to 2005 wage inequality fell for both males and females driven predominantly by the bottom end of the distribution. In each case the unobservable within-group inequality effect was the strongest component. In this period the 90-50 differential did not change significantly for either gender. This is interpreted of a strong effect of the NMW around the period of its introduction in 1999 which narrowed the between-group inequality in the bottom of the wage distribution and also compressed within-group inequality amongst the lowest skilled workers.

After 2005 wage inequality increased again with falling human capital prices accounting for the fall in average wages and affecting the bottom of the distribution more than the top - a reversal of the role played by the price effect pre 2005. The increase in inequality for males by all three inequality measures is due mostly to the within-group inequality effects. Similarly for females, all three inequality measures increased between 2005 and 2012 due primarily to within-group effects.

The robustness of these results is an issue. In particular the way in which the hours variable is constructed has a significant impact on the analysis of changes in inequality at the top of the wage distribution. The results for the bottom of the distribution are much more robust to this, with significantly falling wage inequality over the 1997-2012 period for both males and females but driven by different factors for both. There may also be a problem in the change in the response rate to the LFS over time. Figure 3.18 illustrates this by plotting the number of observations in each year over time, displaying a very clear downward trend. Systematic attrition rates of particular subgroups may influence the results of analysis of trends over time as in this chapter.

Chapter Appendices

3.A Chapter 3 Figures

Figure 3.4: Residual Cumulative Distribution Function

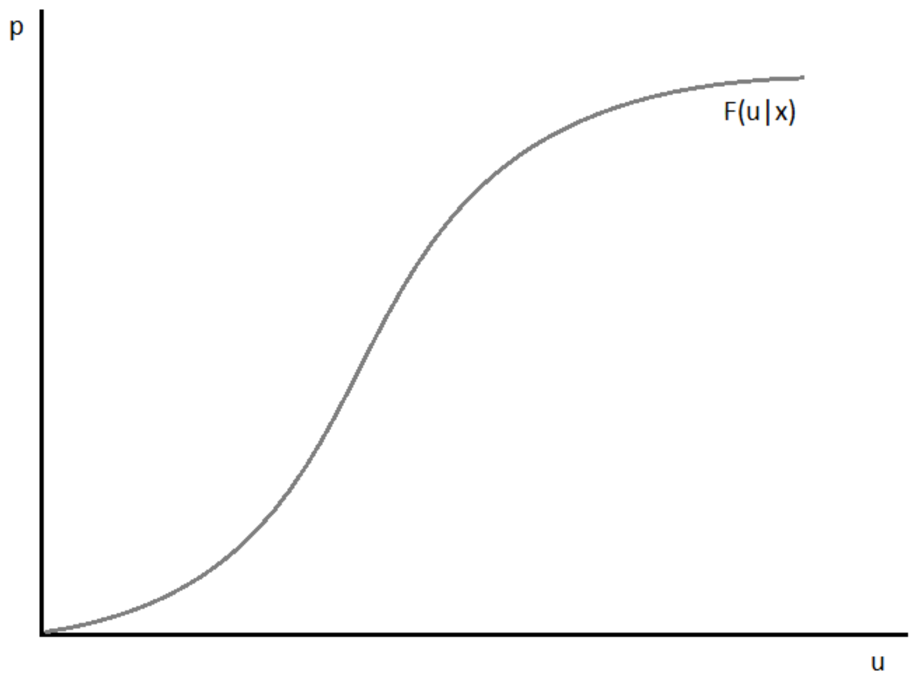


Figure 3.5: Change in Real Log Wages by Percentile 1997-2012

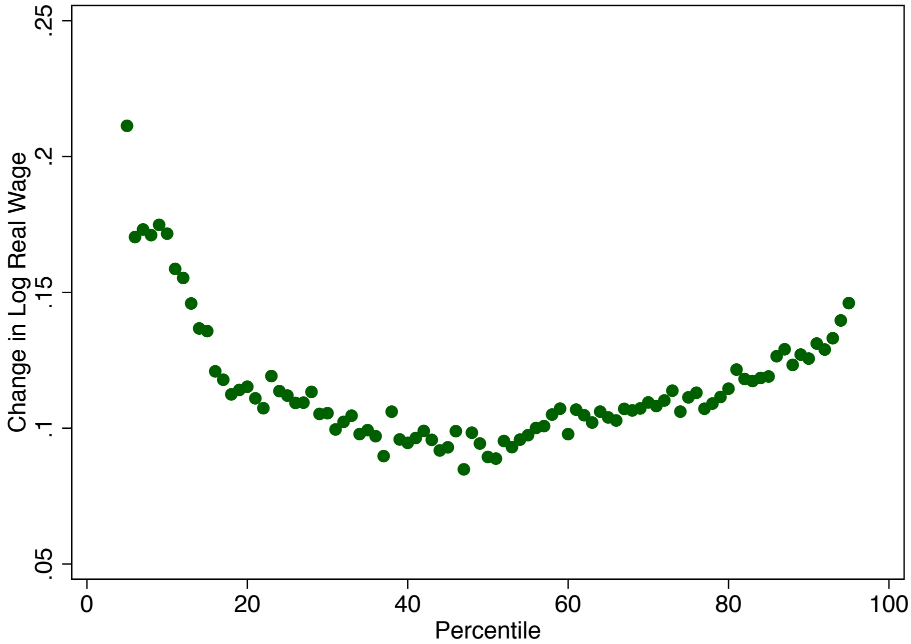


Figure 3.6: Change in Educational Attainment

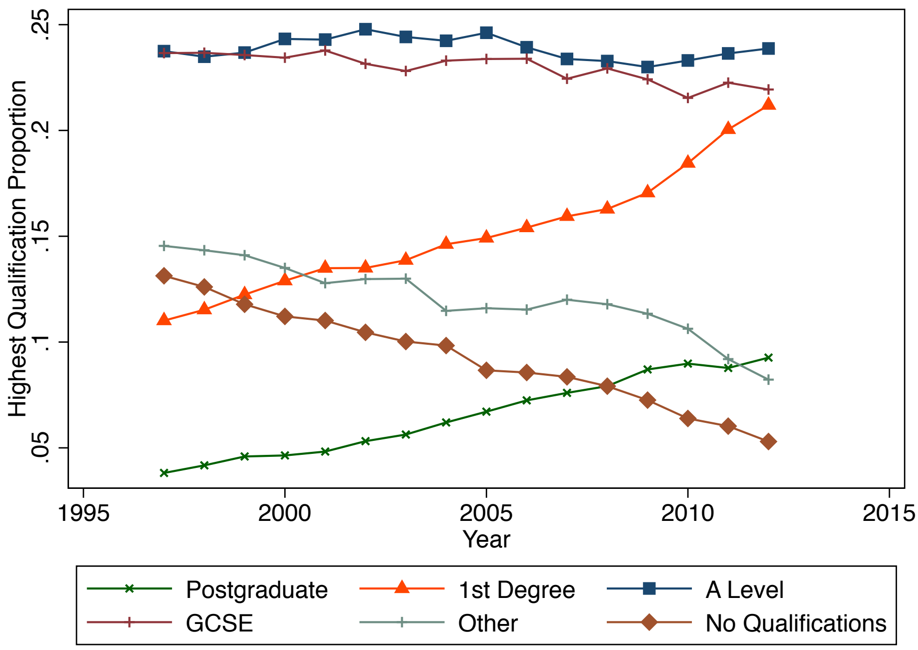


Figure 3.7: Experience Distributions

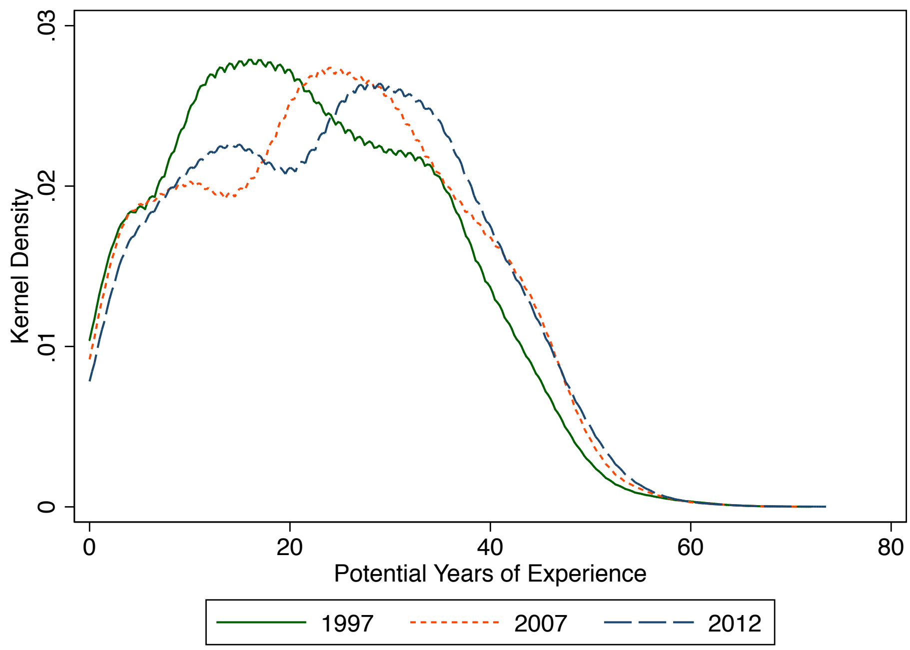


Figure 3.8: Change in Real Log Wages by Experience Groups 1997-2012

Figure 3.9: **Change in Real Log Wages by Education for the Less Experienced Group 1997-2012**

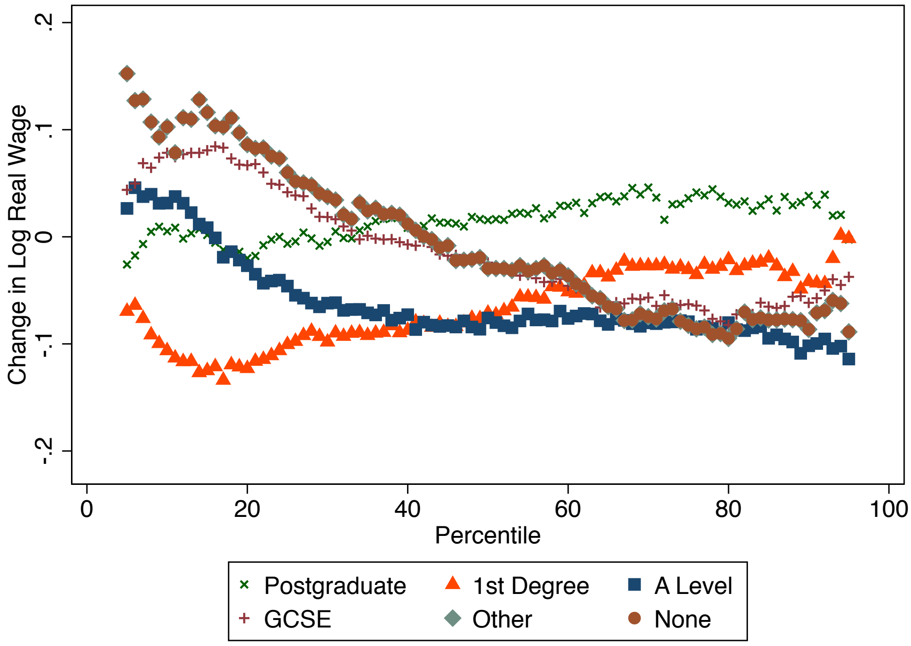


Figure 3.10: **JMP Mean Decomposition: Male**

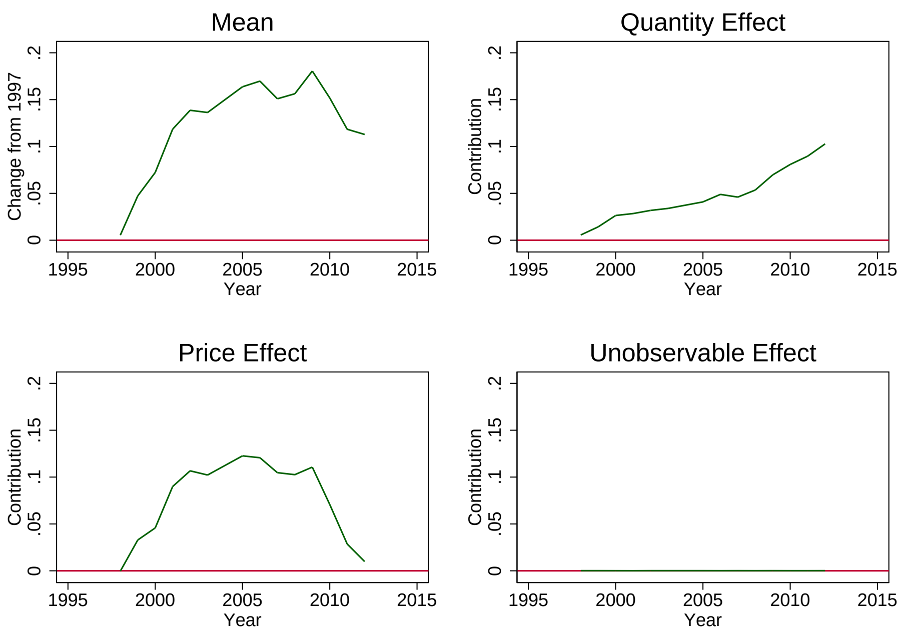


Figure 3.11: **JMP 90-10 Differential Decomposition: Male**

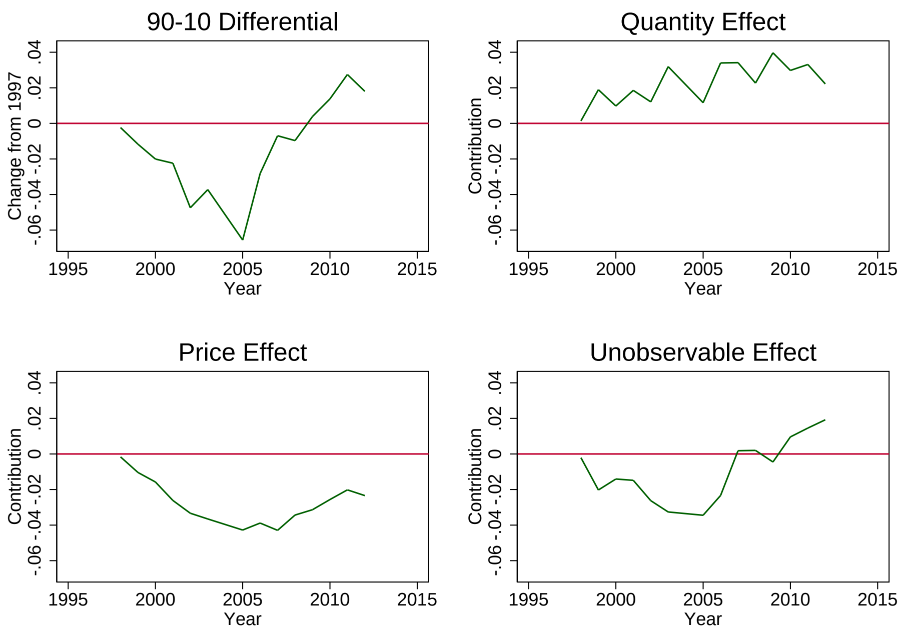


Figure 3.12: **JMP 90-50 Differential Decomposition: Male**

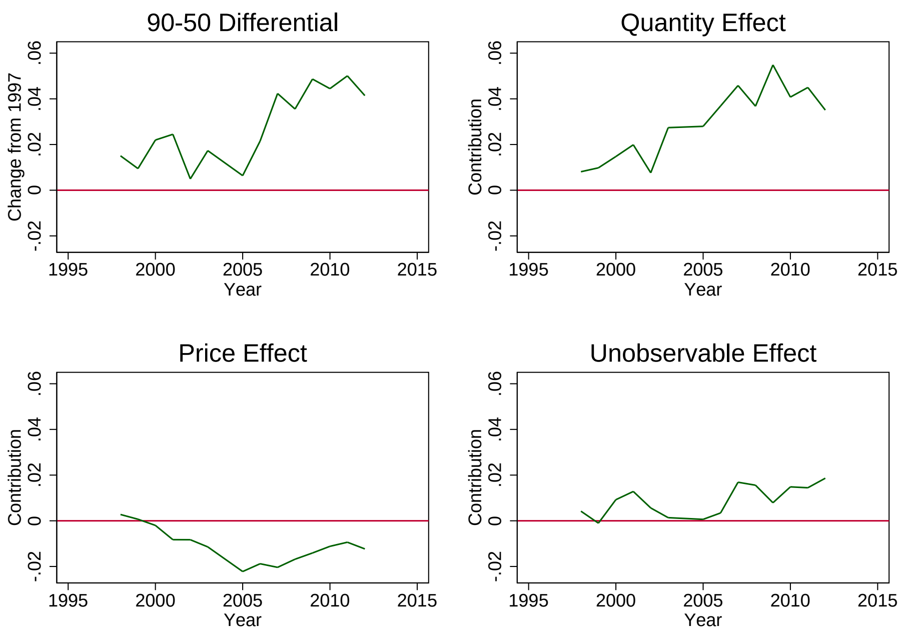


Figure 3.13: JMP 50-10 Differential Decomposition: Male

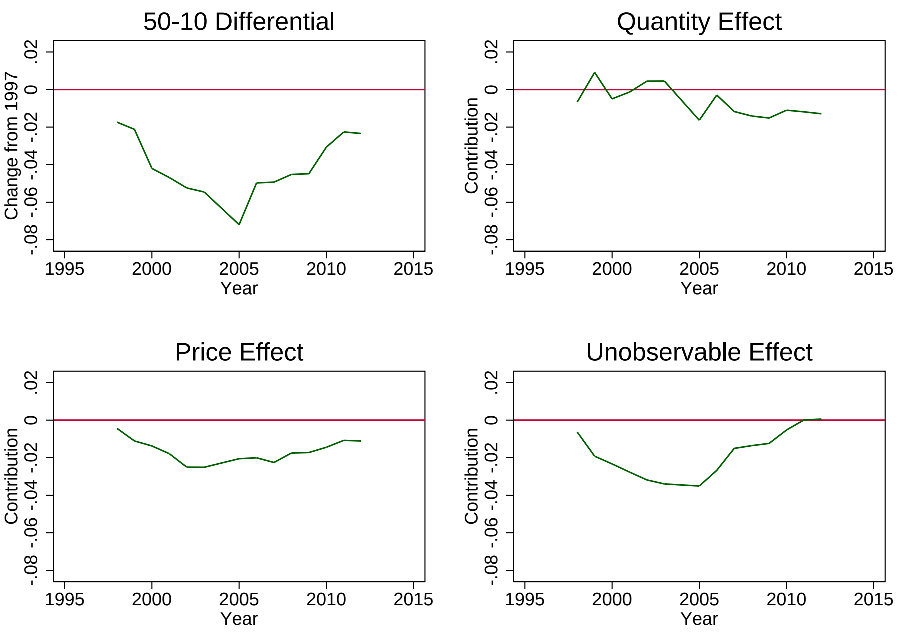


Figure 3.14: JMP Mean Decomposition: Female

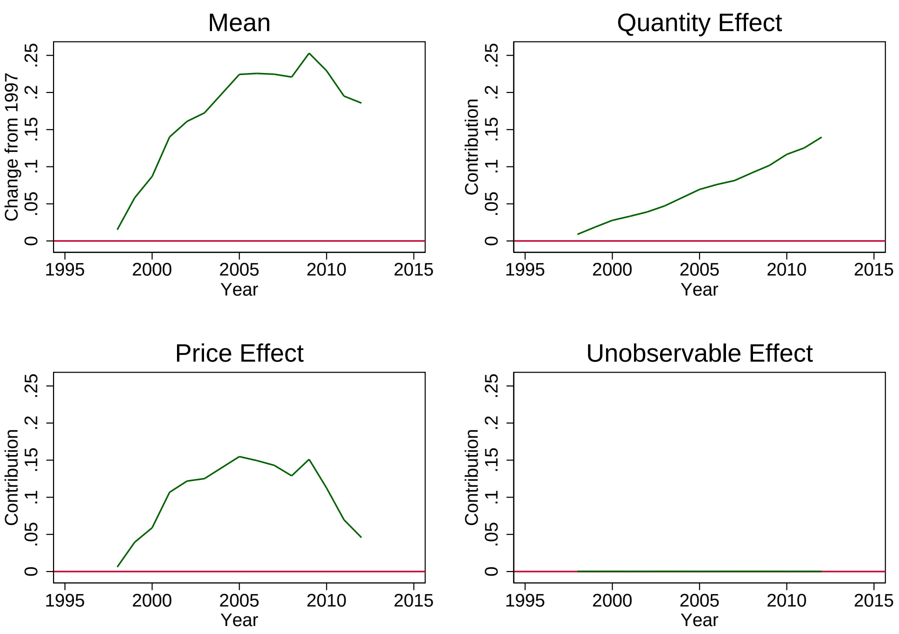


Figure 3.15: **JMP 90-10 Differential Decomposition: Female**

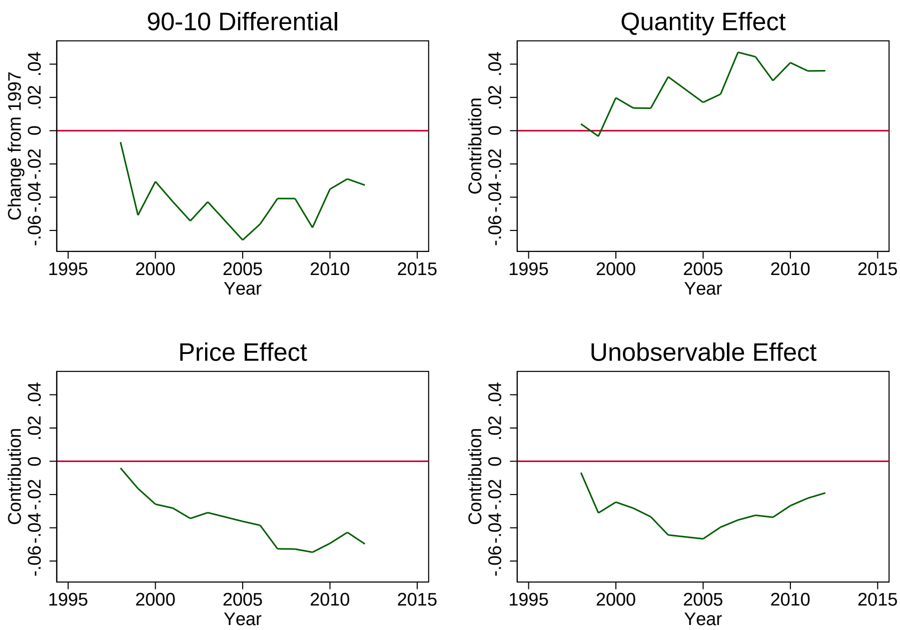


Figure 3.16: **JMP 90-50 Differential Decomposition: Female**

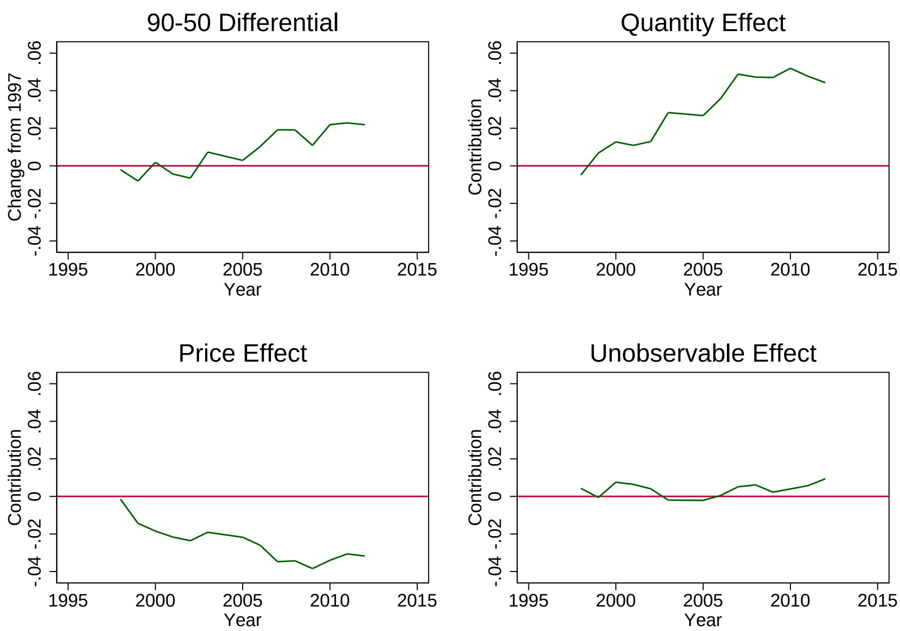


Figure 3.17: JMP 50-10 Differential Decomposition: Female

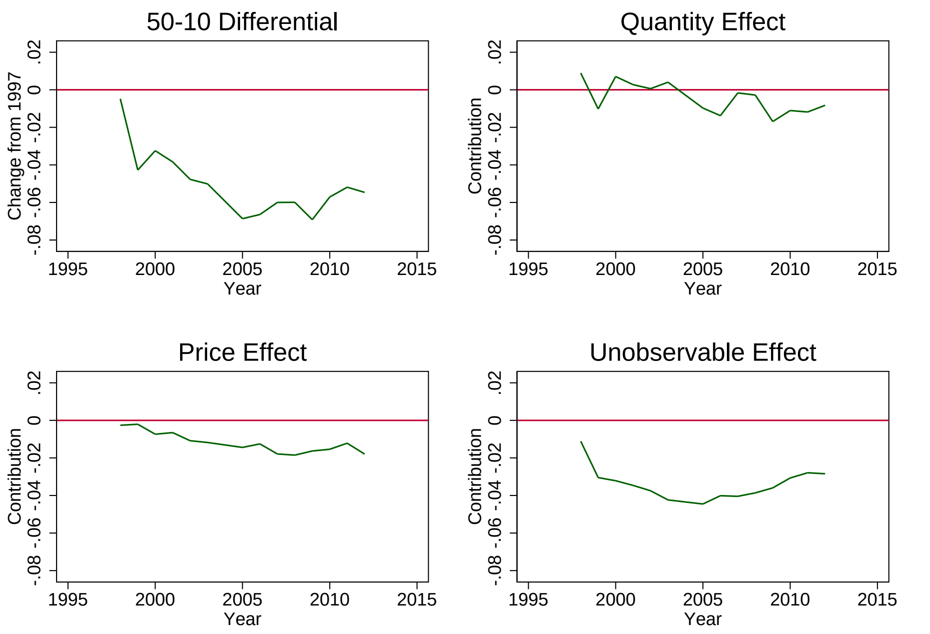
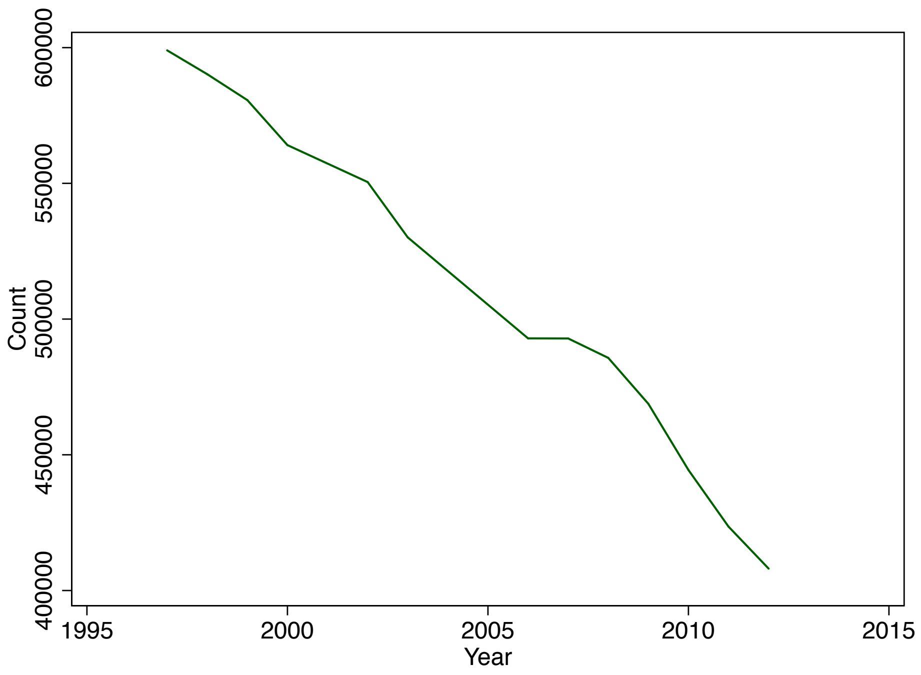


Figure 3.18: Observations in the LFS over time



3.B Chapter 3 Tables

Table 3.8: JMP Decomposition: Males 1997-2005

	T	Q	P	U
Mean	0.161***	0.044***	0.118***	0.000***
	(0.005)	(0.002)	(0.004)	(0.000)
Standard Deviation	-0.043***	0.009***	-0.027***	-0.025***
	(0.006)	(0.001)	(0.002)	(0.006)
5th Percentile	0.267***	0.076***	0.166***	0.024**
	(0.013)	(0.007)	(0.007)	(0.008)
10th Percentile	0.197***	0.031***	0.151***	0.016***
	(0.008)	(0.006)	(0.005)	(0.004)
50th Percentile	0.133***	0.023***	0.122***	-0.011***
	(0.007)	(0.004)	(0.005)	(0.002)
90th Percentile	0.138***	0.066***	0.076***	-0.004
	(0.006)	(0.005)	(0.005)	(0.004)
95th Percentile	0.149***	0.080***	0.073***	-0.005
	(0.011)	(0.008)	(0.007)	(0.007)
90-10 Percentile Differential	-0.059***	0.036***	-0.074***	-0.020**
	(0.009)	(0.008)	(0.007)	(0.007)
90-50 Percentile Differential	0.005	0.043***	-0.045***	0.007
	(0.008)	(0.007)	(0.004)	(0.004)
50-10 Percentile Differential	-0.064***	-0.007	-0.029***	-0.027***
	(0.008)	(0.006)	(0.004)	(0.005)

Standard errors in parentheses

T=Total, Q=Quantity, P=Price, U=Unobservable

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

Table 3.9: JMP Decomposition: Males 2005-2012

	T	Q	P	U
Mean	-0.051***	0.051***	-0.103***	0.000***
	(0.006)	(0.003)	(0.005)	(0.000)
Standard Deviation	0.027***	-0.001	0.005	0.023***
	(0.007)	(0.002)	(0.003)	(0.007)
5th Percentile	-0.086***	0.078***	-0.119***	-0.044***
	(0.010)	(0.010)	(0.007)	(0.007)
10th Percentile	-0.095***	0.049***	-0.109***	-0.035***
	(0.007)	(0.007)	(0.006)	(0.005)
50th Percentile	-0.046***	0.052***	-0.103***	0.005
	(0.008)	(0.005)	(0.005)	(0.003)
90th Percentile	-0.011	0.052***	-0.095***	0.031***
	(0.009)	(0.007)	(0.007)	(0.006)
95th Percentile	0.021	0.083***	-0.091***	0.028***
	(0.014)	(0.010)	(0.008)	(0.008)
90-10 Percentile Differential	0.084***	0.003	0.014	0.066***
	(0.011)	(0.009)	(0.008)	(0.009)
90-50 Percentile Differential	0.035***	0.000	0.009	0.026***
	(0.010)	(0.009)	(0.006)	(0.007)
50-10 Percentile Differential	0.049***	0.003	0.006	0.040***
	(0.008)	(0.009)	(0.005)	(0.006)

Standard errors in parentheses
T=Total, Q=Quantity, P=Price, U=Unobservable
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.10: JMP Decomposition: Females 1997-2005

	T	Q	P	U
Mean	0.220***	0.063***	0.157***	0.000***
	(0.004)	(0.002)	(0.004)	(0.000)
Standard Deviation	-0.040***	0.015***	-0.024***	-0.030***
	(0.005)	(0.001)	(0.002)	(0.004)
5th Percentile	0.305***	0.080***	0.189***	0.036***
	(0.010)	(0.007)	(0.006)	(0.007)
10th Percentile	0.267***	0.050***	0.192***	0.025***
	(0.006)	(0.004)	(0.005)	(0.004)
50th Percentile	0.196***	0.043***	0.166***	-0.013***
	(0.006)	(0.004)	(0.004)	(0.002)
90th Percentile	0.205***	0.101***	0.113***	-0.009**
	(0.006)	(0.005)	(0.005)	(0.003)
95th Percentile	0.216***	0.110***	0.112***	-0.006
	(0.009)	(0.007)	(0.006)	(0.005)
90-10 Percentile Differential	-0.062***	0.050***	-0.079***	-0.033***
	(0.009)	(0.006)	(0.006)	(0.006)
90-50 Percentile Differential	0.009	0.058***	-0.053***	0.004
	(0.007)	(0.006)	(0.005)	(0.004)
50-10 Percentile Differential	-0.071***	-0.007	-0.026***	-0.038***
	(0.007)	(0.006)	(0.003)	(0.005)

Standard errors in parentheses

T=Total, Q=Quantity, P=Price, U=Unobservable

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

Table 3.11: JMP Decomposition: Females 2005-2012

	T	Q	P	U
Mean	-0.035***	0.061***	-0.096***	0.000**
	(0.005)	(0.003)	(0.004)	(0.000)
Standard Deviation	0.014**	-0.007***	0.012***	0.009*
	(0.005)	(0.001)	(0.003)	(0.004)
5th Percentile	-0.044***	0.082***	-0.109***	-0.017*
	(0.009)	(0.008)	(0.006)	(0.006)
10th Percentile	-0.049***	0.075***	-0.115***	-0.009*
	(0.005)	(0.005)	(0.006)	(0.004)
50th Percentile	-0.032***	0.062***	-0.095***	0.000
	(0.008)	(0.007)	(0.005)	(0.002)
90th Percentile	-0.020*	0.044***	-0.071***	0.008
	(0.008)	(0.007)	(0.006)	(0.004)
95th Percentile	-0.017	0.037***	-0.063***	0.009
	(0.012)	(0.008)	(0.008)	(0.007)
90-10 Percentile Differential	0.029**	-0.031***	0.043***	0.017*
	(0.009)	(0.009)	(0.009)	(0.008)
90-50 Percentile Differential	0.013	-0.019*	0.024***	0.007
	(0.010)	(0.009)	(0.006)	(0.005)
50-10 Percentile Differential	0.017*	-0.012	0.020***	0.009
	(0.008)	(0.009)	(0.005)	(0.005)

Standard errors in parentheses
T=Total, Q=Quantity, P=Price, U=Unobservable
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.12: Percentage Change in Employment by Education/Experience Group

Education:		High			Medium			Low	
Years of Experience:	0-9	10-19	20+	1-10	10-20	20+	1-10	10-20	20+
INDUSTRY	4.304	4.701	6.246	-2.246	-8.175	3.602	-0.553	-1.041	-6.058
Agriculture	0.007	0.029	0.053	-0.075	-0.183	-0.023	-0.013	-0.028	-0.116
Manufacturing	-0.231	0.042	0.195	-1.721	-2.914	-2.118	-0.244	-0.408	-1.995
Construction	0.118	0.114	0.219	0.092	-0.233	0.361	-0.051	-0.057	-0.126
Wholesale/Retail	0.912	0.382	0.504	0.035	-1.285	0.941	-0.105	-0.247	-1.385
Transport and Comms	0.690	0.797	0.648	-0.245	-0.508	0.764	-0.006	-0.066	-0.187
Finance	0.272	0.410	0.214	-0.432	-0.704	-0.003	-0.004	-0.004	-0.106
Other Services	2.521	2.933	4.404	0.081	-2.353	3.656	-0.131	-0.235	-2.154
OCCUPATION									
High Skilled	2.504	3.643	4.819	-0.613	-2.311	1.031	-0.014	-0.058	-0.469
Low Skilled	1.800	1.058	1.427	-1.633	-5.864	2.572	-0.540	-0.983	-5.590

Table 3.13: **JMP Decomposition: Males 2005-2012 - Payslip Sub-sample**

	T	Q	P	U
Mean	-0.089***	0.029***	-0.118***	0.001**
	(0.012)	(0.006)	(0.011)	(0.000)
Standard Deviation	0.015	-0.004	0.002	0.016
	(0.015)	(0.003)	(0.006)	(0.013)
5th Percentile	-0.072***	0.086***	-0.126***	-0.032*
	(0.016)	(0.017)	(0.017)	(0.014)
10th Percentile	-0.103***	0.041**	-0.118***	-0.027*
	(0.016)	(0.014)	(0.016)	(0.011)
50th Percentile	-0.099***	0.013	-0.117***	0.005
	(0.015)	(0.011)	(0.012)	(0.005)
90th Percentile	-0.053**	0.034*	-0.107***	0.020*
	(0.018)	(0.015)	(0.017)	(0.009)
95th Percentile	-0.052*	0.029	-0.110***	0.029
	(0.025)	(0.020)	(0.019)	(0.016)
90-10 Percentile Differential	0.050*	-0.007	0.011	0.047**
	(0.023)	(0.021)	(0.021)	(0.017)
90-50 Percentile Differential	0.046*	0.021	0.010	0.015
	(0.020)	(0.019)	(0.015)	(0.010)
50-10 Percentile Differential	0.005	-0.028	0.001	0.032*
	(0.019)	(0.017)	(0.012)	(0.013)

Standard errors in parentheses

T=Total, Q=Quantity, P=Price, U=Unobservable

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

Table 3.14: **JMP Decomposition: Females 2005-2012 - Payslip Sub-sample**

	T	Q	P	U
Mean	-0.079***	0.058***	-0.137***	0.001***
	(0.011)	(0.006)	(0.009)	(0.000)
Standard Deviation	0.025*	0.005**	-0.005	0.025**
	(0.010)	(0.002)	(0.004)	(0.009)
5th Percentile	-0.129***	0.045**	-0.133***	-0.041***
	(0.017)	(0.015)	(0.012)	(0.013)
10th Percentile	-0.074***	0.065***	-0.129***	-0.011
	(0.011)	(0.010)	(0.011)	(0.008)
50th Percentile	-0.070***	0.057***	-0.134***	0.006
	(0.013)	(0.010)	(0.010)	(0.005)
90th Percentile	-0.055**	0.076***	-0.153***	0.022*
	(0.017)	(0.012)	(0.013)	(0.009)
95th Percentile	-0.048*	0.079***	-0.155***	0.028*
	(0.023)	(0.017)	(0.015)	(0.011)
90-10 Percentile Differential	0.020	0.011	-0.024	0.032*
	(0.020)	(0.014)	(0.015)	(0.015)
90-50 Percentile Differential	0.015	0.019	-0.019	0.015
	(0.018)	(0.016)	(0.012)	(0.010)
50-10 Percentile Differential	0.004	-0.008	-0.005	0.017
	(0.014)	(0.014)	(0.008)	(0.009)

Standard errors in parentheses

T=Total, Q=Quantity, P=Price, U=Unobservable

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

Table 3.15: **JMP Decomposition: Males 1997-2012 - Actual Hours**

	T	Q	P	U
Mean	0.090***	0.109***	-0.019***	-0.000
	(0.006)	(0.003)	(0.005)	(0.000)
Standard Deviation	-0.019**	0.001	-0.006*	-0.014
	(0.007)	(0.001)	(0.003)	(0.007)
5th Percentile	0.135***	0.158***	-0.012	-0.011
	(0.012)	(0.009)	(0.008)	(0.008)
10th Percentile	0.093***	0.118***	-0.019**	-0.005
	(0.008)	(0.006)	(0.007)	(0.005)
50th Percentile	0.085***	0.091***	-0.010	0.004
	(0.008)	(0.005)	(0.006)	(0.003)
90th Percentile	0.083***	0.127***	-0.032***	-0.011
	(0.011)	(0.007)	(0.008)	(0.006)
95th Percentile	0.065***	0.137***	-0.036***	-0.037***
	(0.014)	(0.009)	(0.009)	(0.010)
90-10 Percentile Differential	-0.010	0.009	-0.013	-0.006
	(0.013)	(0.009)	(0.009)	(0.010)
90-50 Percentile Differential	-0.001	0.036***	-0.022***	-0.015*
	(0.011)	(0.008)	(0.006)	(0.007)
50-10 Percentile Differential	-0.009	-0.027***	0.009	0.010
	(0.009)	(0.008)	(0.006)	(0.006)

Standard errors in parentheses
T=Total, Q=Quantity, P=Price, U=Unobservable
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.16: JMP Decomposition: Females 1997-2012 - Actual Hours

	T	Q	P	U
Mean	0.129***	0.142***	-0.013*	-0.000
	(0.006)	(0.004)	(0.006)	(0.000)
Standard Deviation	-0.033***	0.004**	-0.009**	-0.028***
	(0.008)	(0.001)	(0.003)	(0.007)
5th Percentile	0.188***	0.155***	0.010	0.023**
	(0.011)	(0.009)	(0.009)	(0.008)
10th Percentile	0.144***	0.129***	0.003	0.012*
	(0.007)	(0.007)	(0.008)	(0.005)
50th Percentile	0.116***	0.137***	-0.016**	-0.006
	(0.008)	(0.007)	(0.006)	(0.003)
90th Percentile	0.107***	0.142***	-0.022*	-0.013*
	(0.011)	(0.008)	(0.009)	(0.006)
95th Percentile	0.136***	0.178***	-0.017	-0.025*
	(0.022)	(0.014)	(0.011)	(0.011)
90-10 Percentile Differential	-0.036**	0.013	-0.024*	-0.025*
	(0.013)	(0.010)	(0.010)	(0.010)
90-50 Percentile Differential	-0.009	0.005	-0.006	-0.007
	(0.012)	(0.010)	(0.007)	(0.007)
50-10 Percentile Differential	-0.028**	0.008	-0.018**	-0.018**
	(0.009)	(0.009)	(0.006)	(0.006)

Standard errors in parentheses

T=Total, Q=Quantity, P=Price, U=Unobservable

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

Table 3.17: Logit Models: Probability Usual = Actual Hours

	Usual = Actual	Usual $\geq$ Actual
Postgraduate Degree	-0.548***	-0.560***
	(0.0142)	(0.0211)
1st Degree	-0.545***	-0.486***
	(0.0120)	(0.0185)
Higher Education	-0.518***	-0.471***
	(0.0127)	(0.0193)
A Levels	-0.459***	-0.430***
	(0.0111)	(0.0173)
GCSE A*-C / O Levels	-0.323***	-0.292***
	(0.0114)	(0.0179)
GCSE D-G / CSE's	-0.316***	-0.242***
	(0.0178)	(0.0273)
Other Qualification	-0.273***	-0.294***
	(0.0132)	(0.0204)
Experience	-0.0258***	-0.0339***
	(0.000793)	(0.00120)
Experience Sq/100	0.0507***	0.0588***
	(0.00169)	(0.00254)
Training	-0.201***	-0.193***
	(0.00715)	(0.00996)
Observations	582487	582487

Standard errors in parentheses

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

Table 3.18: **JMP Decomposition: Males 1997-2012 - Usual = Actual**

	T	Q	P	U
Mean	0.142***	0.110***	0.032***	0.000**
	(0.007)	(0.005)	(0.006)	(0.000)
Standard Deviation	-0.038***	0.000	-0.017***	-0.021*
	(0.009)	(0.002)	(0.004)	(0.008)
5th Percentile	0.254***	0.182***	0.054***	0.017
	(0.022)	(0.013)	(0.011)	(0.011)
10th Percentile	0.155***	0.099***	0.056***	-0.000
	(0.008)	(0.008)	(0.009)	(0.005)
50th Percentile	0.124***	0.101***	0.033***	-0.010**
	(0.009)	(0.007)	(0.007)	(0.003)
90th Percentile	0.145***	0.138***	0.007	0.001
	(0.014)	(0.011)	(0.008)	(0.006)
95th Percentile	0.160***	0.156***	0.006	-0.002
	(0.016)	(0.012)	(0.009)	(0.008)
90-10 Percentile Differential	-0.010	0.039**	-0.049***	0.001
	(0.016)	(0.013)	(0.011)	(0.010)
90-50 Percentile Differential	0.021	0.036**	-0.026***	0.011
	(0.015)	(0.012)	(0.007)	(0.007)
50-10 Percentile Differential	-0.031**	0.003	-0.023**	-0.010
	(0.010)	(0.010)	(0.007)	(0.006)

Standard errors in parentheses

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

T=Total, Q=Quantity, P=Price, U=Unobservable

Table 3.19: JMP Decomposition: Females 1997-2012 - Usual = Actual

	T	Q	P	U
Mean	0.221***	0.149***	0.071***	0.000***
	(0.006)	(0.004)	(0.006)	(0.000)
Standard Deviation	-0.022***	0.014***	-0.011***	-0.025***
	(0.006)	(0.002)	(0.003)	(0.006)
5th Percentile	0.301***	0.184***	0.092***	0.025*
	(0.012)	(0.011)	(0.009)	(0.010)
10th Percentile	0.232***	0.136***	0.085***	0.012*
	(0.006)	(0.008)	(0.008)	(0.005)
50th Percentile	0.191***	0.140***	0.068***	-0.017***
	(0.007)	(0.005)	(0.006)	(0.004)
90th Percentile	0.218***	0.184***	0.044***	-0.011*
	(0.009)	(0.007)	(0.007)	(0.005)
95th Percentile	0.222***	0.172***	0.048***	0.003
	(0.015)	(0.010)	(0.008)	(0.007)
90-10 Percentile Differential	-0.015	0.048***	-0.040***	-0.023**
	(0.010)	(0.009)	(0.009)	(0.008)
90-50 Percentile Differential	0.026**	0.045***	-0.024***	0.006
	(0.010)	(0.008)	(0.007)	(0.007)
50-10 Percentile Differential	-0.041***	0.004	-0.016***	-0.029***
	(0.008)	(0.008)	(0.005)	(0.007)

Standard errors in parentheses

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

T=Total, Q=Quantity, P=Price, U=Unobservable

Chapter 4 Wage Inequality and Firm Performance

4.1 Introduction

The purpose of this chapter is to investigate the impact of wage dispersion on firm performance. The aim is to exploit the availability of two large datasets which contain the largest quantity of detailed information about individual wages and firm characteristics in the UK - respectively the New Earnings Survey (NES) and the Annual Respondents Database (ARD).

There exists a body of empirical literature which has researched this relationship but there are relatively few applications to UK data which is partially due to data limitations. One notable paper which has examined the issue for the UK is Beaumont and Harris (2003) which uses the ARD to examine the relationship between pay dispersion and performance. The data used in their study is, however, from the period 1978-1995 and so relatively outdated now. This is because their measure of pay dispersion (the ratio of non-manual to manual wages) which is obtained from the ARD is only available in the years examined in their paper. Analyses using more up to date data require the matching in of other data sources from which pay dispersion measures need to be calculated. This is the contribution of this study.

Another contribution of this study is that it examines the UK economy more widely. The Beaumont and Harris (2003) paper looks specifically at five detailed manufacturing industries. Another advantage which is obtained by using more recent ARD data is that it now samples firms from eight broadly defined industries, of which manufacturing is only one (and the only one until the mid 1990's). Sectors which are sampled in more recent data include services, property, catering, construction, wholesale, retail, and motor vehicles in addition to manufacturing.

Using data from the Labour Force Survey, Figure 4.1 shows the change over time in the relative size of a number of industries in the UK by employment from 1997 to 2012. Two clear trends can be identified from this figure, the increase in the employment share of the service sector (by approximately 15 percentage points) and the simultaneous decline of manufacturing by around 10 percentage points. Throughout this period the service sector has accounted for a much larger share of employment than manufacturing and this gap has widened, with wholesale/retail distribution and catering accounting for a slightly larger share of employment than manufacturing by the end of the period.

This highlights the need for an analysis of the relationship between pay inequality and firm performance which is wider in scope than an analysis focused on manufacturing firms. While manufacturing is still a substantial component of the UK economy it accounts for less than a fifth of total employment.

This chapter extends analysis beyond the manufacturing sector by including firms from other industries in the analysis as well as estimates performed separately by industrial sector to examine the effects of industry heterogeneity on the relationship between pay inequality and performance.

The rest of this chapter is arranged as follows; sections 4.2 and 4.3 respectively outline the theoretical and empirical contributions to the dispersion-performance literature to date. Section 4.4 provides an overview of the relevant datasets used in this analysis and provides summary and descriptive statistics, Section 4.5 outlines the methodological approach of this study, Section 4.6 presents the results of the analysis, and Section 4.7 presents conclusions.

4.2 Theoretical Literature

The theoretical literature consists of contradictory predictions in terms of the expected relationship between pay differentials and firm performance. An influential paper is Akerlof and Yellen (1990) which proposed the fair wage hypothesis and is a basis for establishing a negative relationship between pay differentials and firm performance.

The fair wage hypothesis is underpinned by the following assumed relationship:

$$e_i = min(\frac{w_i}{w_i^*}, 1) \tag{4.1}$$

In equation 4.1 each worker type i provides full effort e (normalised to be equal to one) if they are paid the fair wage $w*$. Otherwise effort provided will be a fraction of the maximum in proportion to how much less than the fair wage they are paid. Wages paid must therefore be on the fair wage constraint to elicit maximum effort from workers.

The results of the model can be summarised in Figure 4.2. This diagram represents the market for unskilled labour[1]. The wage of the unskilled is on the vertical axis and their employment on the horizontal axis.

The vertical dashed line labeled L^S represents full employment and the line labeled L^D is the demand curve for unskilled labour. The line labeled FWC is the "fair wage constraint". The slope is given by the relative weight that individuals place on the wages of others (in this case, the skilled workers) compared to the market clearing wage when deciding what the fair wage is. The unskilled workers are paid their fair wage w^f which is in excess of the market clearing wage w^* and therefore generates unemployment (which is the outcome of interest in the Akerlof and Yellen (1990) paper, not the wage distribution) of low skilled workers of $L^S - L^f$.

This model provides a theoretical basis for arguing that greater wage inequality will reduce firm performance. If firms do not pay a fair wage then individuals will supply less effort, therefore damaging firm performance. This is contingent upon workers taking the wages of others into account in determining what the fair wage should be.

In the extreme case that only the market clearing wage is given any importance, the FWC is vertical at L^S and the wage paid is the market clearing wage. In this case, changes in pay differentials will not impact on worker effort and performance. The greater is the

[1] The model uses two types of labour, skilled and unskilled, the skilled are paid their market clearing wage and are fully employed in this model

weight put on fairness considerations, the higher the unskilled wage must be relative to the skilled wage and the more compressed the wage distribution must therefore be to elicit maximum effort.

Although this paper was originally developed to explain unemployment, it provides an implicit link between the dispersion of pay and firm performance (through effects on effort elicitation) and has been used as a basis in the empirical literature for arguing that greater wage inequality may damage firm performance.

Levine (1991) also theoretically models a positive relationship between greater wage equality and firm performance. Cohesiveness in firms can be achieved with a more compressed wage structure and cohesiveness will lead to greater productivity in firms where the performance of individual workers can affect each other. If firms have to pay higher wages to its high skilled workers (because they possess a particularly high level of skills, have bargaining power, or for efficiency wage reasons such as monitoring, turnover etc.) cohesiveness concerns will necessitate that low skilled workers are paid a relatively high wage as well.

The main strand of literature which argues for a different relationship is tournament theory, which developed from Lazear and Rosen (1981). In these types of models pay differentials act as an incentive towards increased worker effort, since each worker has a probability of winning the "prize" through promotion or a bonus or other type of incentive pay. Increased effort improves the probability of winning the tournament and the larger the pay differential, the greater the expected value of winning the tournament.

The basic theory can be illustrated using the following model. Assuming a risk neutral utility function:

$$U = U(w - c(e)) = w - c(e) \tag{4.2}$$

Where w is the wage and e is worker effort. e gives the worker disutility via the cost function $c(e)$. Assume there are two possible wages that the individual could earn: w_1 is the wage earned if the worker wins the tournament; and w_2 is the wage earned if the worker loses the tournament. w_1 exceeds w_2 and could be interpreted as the basic wage plus a performance related bonus, with w_2 representing the basic wage. The worker has a probability p of winning the tournament, which is endogenous to the level of effort and denoted $p(e)$.

The cost function is assumed to have the properties $c'(e) > 0, c''(e) > 0$. The first and second derivatives are both positive indicating that the cost of effort is increasing in effort and the marginal cost is also increasing in the level of effort. The probability function has the property $p'(e) > 0, p''(e) < 0$. The probability of winning the tournament is increasing in effort but at a decreasing rate. The expected utility function is given by:

$$E(u) = p(e)[w_1 - c(e)] + (1 - p(e))[w_2 - c(e)] \tag{4.3}$$

This simplifies to:

$$E(U) = p(e)[w_1 - w_2] - c(e) + w_2 \tag{4.4}$$

Differentiating equation (4.4) with respect to effort and equating this to zero gives the utility maximisation condition where the marginal benefit of effort is equated to its marginal cost:

$$p'(e)[w_1 - w_2] = c'(e) \tag{4.5}$$

Equation (4.5) illustrates the relationship between wage differentials and worker performance. The differential is given by the term $w_1 - w_2$. If the wage earned by the tournament winners relative to the losers increases this would raise the marginal benefit of effort above that of the marginal cost. In this case utility maximising individuals increase their effort. This establishes a link between wage inequality and firm performance that suggests reducing wage compression will incentivise additional effort from workers and therefore increased firm performance in aggregate.

Lazear (1989) presents a model similar in nature to the tournament theory model in Lazear and Rosen (1981). This model incorporates worker cohesion into the incentive framework thereby extending the basic model - workers facing a tournament for a higher wage or promotion may choose to increase their chances of success not by increasing their own effort, but by actively sabotaging the output of others (if possible).

The effect of this would be for wage inequality to reduce firm performance. This is opposite to the incentives of the basic tournament theory framework which predicts increasing the wage differential will increase incentives for the players to win. In the basic model, the only way in which workers could increase their chances of winning is by supplying extra effort, therefore unambiguously raising firm performance. This assumes that there is not an output maximising level of effort beyond which increased effort is counter-productive. Introducing the ability for workers to influence each others' output into the model introduces a perverse incentive - the greater potential reward for the winner may motivate acts of sabotage which reduce firm performance.

When both workers and the firm optimise, net output is lower when sabotage is possible than when it is not. Effort is also lower when sabotage is a possibility. The optimal wage dispersion is larger when sabotage is not possible. This is a key result of the analysis - that it is profit maximising to have more equitable pay when workers have the ability to influence each others' output. If sabotage is possible higher wage inequality will have a detrimental effect on performance.

The more the workforce is composed of "doves" in the terminology of this paper (employees who exhibit cooperative behaviour rather than attempt to sabotage each other - described as "hawks") the more effective a dispersed wage structure will be at enhancing performance. Firms can sort between workers at the hiring stage and set an appropriate compensation scheme for the workforce composition.

Acts of worker sabotage are most likely to be a problem at the top end of the wage distribution, as it is those jobs highest in the corporate hierarchy which have higher rates of competitive individuals (this can be explained as those who are the most competitive amongst those lowest in the hierarchy are most likely to win the tournaments which allow them to rise to the higher levels of the hierarchy). This suggests that wage compression within the top of the wage distribution will have positive effects on firm performance.

4.3 Empirical Literature

This section presents a review of the literature which has attempted to estimate the impact of wage inequality on firm performance.

The empirical literature discussed here (as relates to firms) is summarised in Table 4.9. A wide variety of measures of wage dispersion have been used, such as the coefficient of variation and the standard deviation of pay. Several papers also emphasise the difference between dispersion in raw wages and the wage dispersion which is left unexplained by worker characteristics. These papers calculate inequality measures from residual wages instead of (or complementary to) measures from raw wages. Similarly there is variety in the measure of firm performance used, with the most common being gross value added or profits per employee.

Most of the papers mentioned here have found positive relationships between wage inequality and performance and so are more supportive of the competition theory rather than fairness theory. There are, however, some exceptions which have found negative relationships, as well as some which have found no significant relationship between wage inequality and firm performance at all.

Some of the empirical work which has examined the relationship between dispersion in wages and firm performance has come from applications to sport. Data on pay and performance of sports teams are particularly useful in testing the predictions of tournament theory.

Berri and Jewell (2004) study the effect of increasing wage inequality in the National Basketball Association (NBA) on the performance of US basketball teams. "Firm" performance in this case is measured as the team winning percentage. A fixed effects model was used to estimate the effect of changes in a team's relative wage disparity between seasons on the change in the teams winning percentage between seasons (estimated over six seasons of data). Controlling for factors such as player ability and coaching quality, this study finds no significant effect of team wage dispersion on team performance. A similar result is obtained by Langelett (2005), also for the NBA, using an OLS model in levels rather than first differences.

The evidence from sport is, however, difficult to generalise to firm performance, as sports players represent a particularly specialised labour market. It does, however, give an indications of possible relationships which may exist between pay and performance in the wider economy.

An early paper which analysed the relationship between pay dispersion and performance of the firm is that of Leonard (1990). This paper focuses on executive and managerial pay rather than the workforce as a whole. Using data from a sample of US firms the paper estimates firm performance regressions (measured as the return on equity - ROE) as a function of variables designed to capture the incentive pay and hierarchical structure of the firm as well as the standard deviation of pay.

The coefficient on standard deviation of pay is positive for the mean ROE regression and negative (but insignificant) for a change in ROE regression estimated on data from 1981 and 1985. This result suggests that higher wage dispersion firms perform better, in line with the competition theory rather than fairness, but that wage dispersion levels do not impact the longer term evolution of firm performance.

Winter-Ebmer and Zweimuller (1999) analyse the issue using a panel dataset of Austrian firms covering the period 1975-1991. The total sample consists of 130 firms observed for at least four periods in the time considered. The approach is to estimate Tobit regression models (to account for top-coding in the wage data) of the log monthly wage for each firm-year pair.

The tobit model is estimated separately for each annual cross section and each firm is shown in equation 4.6 below for the wage of individual i. X is a vector of individual level control variables including age, age squared, tenure, nationality, and a blue-collar worker dummy.

$$ln(w_i) = \alpha + X_i'\beta + \varepsilon_i \tag{4.6}$$

The standard error of the regression is taken as the measure of wage inequality accounting for observable differences. These wage inequality estimates are then included in regressions modelling the performance (y) of firm j at time t as a function of wage dispersion. This model is shown in equation 4.7 which accounts for firm fixed effects (α_j) and additional controls Z_{jt} including log firm size, proportion of blue collar workers, the proportion of female workers, and the proportion of workers in different age bands.

$$ln(y_{jt}) = \alpha_j + Z_{jt}'\beta + \zeta_{jt} \tag{4.7}$$

A major weakness of this study is its lack of a direct measurement of firm performance. The wage level is used as a proxy for productivity. Under the assumption that individuals are paid their marginal product, the wage level represents the efficiency of the firm. In the absence of a direct measure of productivity, this is the measure of performance used in their study.

The relationship between pay dispersion and performance itself is examined using an OLS regression separately for blue and white collar workers. The specification includes the wage dispersion measure and its square, workforce composition and log firm size. Another issue with this study is that investment and/or capital stock are not controlled for. The conclusions drawn from the OLS results are that both white and blue collar workers exhibit behaviour closer to the tournament theory type predictions - a positive association between dispersion in pay and performance, however this relationship is non-monotonic, and too high a level of wage inequality can have a detrimental effect.

Fixed effects results with a squared term to capture non-linearities suggest a U shaped relationship between inequality and performance for blue collar workers but the coefficients are statistically insignificant. Fixed effects results for white collar workers suggest a positive and significant relationship between inequality and performance with a negative but insignificant coefficient on the squared term. Group (industry) means regressions produce a significant inverse U relationship for both white and blue collar workers.

When the analysis is repeated for inequality calculated for male employees only, both the fixed effects and group means regressions for both type of workers return a positive coefficient on inequality and a negative coefficient on its square. In the case of blue collar workers each of these coefficients are insignificant. Overall, this paper produces no evidence in support of the fairness hypothesis.

Hibbs and Locking (2000) examine the relationship between wage dispersion and firm performance in Sweden. Contrary to the fairness argument, wage leveling in Sweden led (by general presumption) to a reduction in the productivity of labour. Since this compression in the wage distribution was caused by a strong centralised trade union movement (rather than firm decisions) it is considered that this may have been the objective of the unions - to achieve a trade-off between efficiency and a more compressed wage distribution.

Their empirical model to estimate the relationship between dispersion and performance is given by equation (4.8):

$$ln(Q) = ln[Ef(\sigma^2(w))F(.)] \tag{4.8}$$

In this setup $F(.)$ is a standard production function (i.e. with labour and capital as inputs and a technology parameter). $Ef()$ denotes some impact of the wage distribution on output of the firm for a given set of inputs. The main results of this paper are based on a Cobb-Douglas specification for $F(.)$ but results are reported to be similar for other functional forms such as translog and constant elasticity of substitution production functions.

The independent variables in their regressions are the real prices of labour and capital services, real value added, a one period lag of labour, and a time trend. Value added appears on both sides of the regression and is therefore treated endogenously. The measure of wage dispersion used in the regression is the squared coefficient of variation and the instruments used for the endogenous value added term on the right hand side of the regression are lagged output and external demand for Swedish tradables given by imports for OECD countries. Plant and industry level regressions are estimated by OLS.

The results of the paper find no support for the "fair wage" view of the relationship between pay dispersion and performance. The conclusion is that the reductions in the variance of wages in Sweden from the 1960's to the 1980's reduced the growth of labour productivity in Swedish firms.

Beaumont and Harris (2003) examine the relationship between firm performance and wage differentials in the UK using the Annual Respondents Database. They use plant level measures of both performance (measured as gross value added per worker) and wage differentials (the ratio of the average non manual to manual labour costs). The functional form is a double logarithmic specification and equations are estimated separately for five major UK manufacturing industries; pharmaceuticals, electronic data processing, motor vehicles and engines, aerospace, and miscellaneous foods.

Other variables included in the model are capital stock, employment, the ratio of non-manual to manual employees, dummies indicating UK or US ownership of the firm, the age of the plant, and time and regional dummies. An extended form of the model where the wage differential variable is interacted with a dummy variable for if the plant has more than 250 employees is also estimated. As in Hibbs and Locking (2000) the dependent variable is real gross value added per worker.

The estimation technique used is the Arellano and Bond (1991) GMM estimator in order to allow for a first order autoregressive process in the dependent variable and also to control for endogeneity in the productivity, employment, capital, and wage differential variables.

The results show that in four of the five industries (pharmaceuticals being the exception) wage dispersion was associated with significantly higher plant productivity with elasticities ranging from 0.05 to 0.45. In pharmaceuticals a significant negative elasticity was found of 0.30. Unlike the previous studies there is therefore some support for the fairness hypothesis in these results, however manufacturing as a whole (as represented by the five specific manufacturing industries in this paper) conforms more to the competition hypothesis.

When interacting the wage differential variable with foreign ownership and firm size dummies important additional effects were found, with a negative coefficient found for UK owned large firms. Foreign owned large firms therefore gain greater productivity increases when increasing wage dispersion.

Lallemand et al. (2004) employ an identical methodology to the Winter-Ebmer and Zweimuller (1999) approach - a wage equation is estimated to derive a measure of residual wage inequality which is then used as an independent variable in a firm performance regression. Measures of overall wage dispersion such as the standard deviation, coefficient of variation, and maximum to minimum wage ratio are also used.

In the firm performance regression wage dispersion is instrumented for in a two-stage least squares (2SLS) estimator by the intra-firm standard deviation of income tax on earnings excluding bonuses. This is instrument is used because it is assumed to be uncorrelated with firm profits but highly correlated with wage dispersion.

Their sample is of Belgian private sector firms which have at least 200 employees. This paper explicitly recognises the endogeneity between firm performance and wage dispersion, arguing for example that firms which perform better may pay higher bonuses which leads to greater wage inequality. This necessitates the use of instrumental variables.

The key improvement to this paper over the Winter-Ebmer and Zweimuller (1999) paper is that it utilises their methodology with a more direct measure of firm performance as the dependent variable - the log of gross profits per worker. It also reports results for four different measures of pay dispersion. In both the OLS and the 2SLS estimates the coefficients for all four specifications of wage inequality are positive and significant at the 5% level. The coefficients are also larger in the 2SLS specifications than the OLS ones. The conclusion from these baseline results is therefore that there is no evidence to support the fairness hypothesis.

The wage inequality variables are interacted with a dummy variable equal to one if the workforce is composed of more than 50% white collar workers to test for workforce composition effects and the results show that for all wage inequality measures the magnitude of the relationship between inequality and performance is lower for firms with a greater white collar worker intensity. Possible explanations for this are that piece rates are used more frequently with blue collar worker intensive firms and it is also more difficult to monitor white collar workers.

The effect of monitoring is also examined using a dummy variable interaction, this time equal to one if the share of supervisors in the total workforce is less than 20%. Results indicate that the elasticity of performance to wage inequality is significantly higher in firms with a high degree of monitoring.

Heyman (2005) directly tests four predictions of tournament theory: a positive relationship between wage inequality and firm performance; a positive relationship between the number of contestants in a tournament and wage inequality; a positive relationship between product market volatility and wage inequality; a convex relationship between wages and position in the corporate hierarchy. Matched employer-employee Swedish data in 1991 and 1995 are used.

The main measure of wage dispersion is the variance of log wage regression residuals (where the wage is estimated as a function of gender, education, labour market experience and its square, and tenure). Other measures of wages used are the coefficient of variation and the difference between the log 90th and 10th percentiles of raw wages.

The main findings are that residual wage inequality has a positive effect on firm performance (which is here measured as profits per employee). This is found for both the workforce as a whole and amongst managers. This finding is qualitatively robust to estimates from OLS, first difference, random effects, and instrumental variables regressions. The result is also robust to inclusion of large firms (larger than 50 employees) only, although the coefficients on wage inequality increase in magnitude. These regressions restricted to the large firms sample are unreported in the paper.

The effect of wage dispersion on firm performance is estimated for a cross section of German manufacturing firms by Jirjahn and Kraft (2007). Using OLS firm productivity (the log of gross value added per 1,000 employees) is modelled as a function of wage inequality (the percentage difference between the highest effective hourly wage of a skilled blue collar worker and the lowest effective hourly wage of an unskilled blue collar worker) and a variety of firm level controls. Baseline results suggest an increase in wage inequality of 1% leads to a 0.46% increase in productivity in a model where wage inequality is interacted with other variables such as the existence of a collective agreement for wages, a tenure variable, managerial profit sharing, and piece rates. In the model with no interactions the effect of wage inequality is insignificant.

The presence of work councils and collective bargaining reduces this effect significantly, respectively to 0.15% and 0.18%. This result makes sense in that firms with stronger central bargaining over wages will face greater resistance to widening pay differentials and limit the potential benefit this could have on performance. Conversely there is a positive effect of individual piece rates which increases the effect of wage dispersion to 0.73%. Group piece rates have an even stronger impact, increasing the effect to 0.94%.

The results of this paper are therefore broadly in line with the rest of the literature in obtaining positive effects of wage dispersion on firm performance from OLS estimates, as well as positive effects for blue collar workers and manufacturing firms. This paper does not, however, use any of the more sophisticated estimators such as fixed effects which the literature has shown to impact results substantially. This is due to a lack of panel data in this instance.

Martins (2008) uses a large dataset of Portuguese firms which also contains detailed information on employees, including pay. This paper is motivated by the need to control for unobserved worker heterogeneity in determining wages as previous papers implicitly assume that the wage residuals from regressions controlling for human capital are a good indicator for the dispersion of pay determined by firms' wage setting policies.

It is argued that unobservable differences between workers such as school quality and innate ability also play a large role in explaining wage determination. Without controlling for all of these factors, higher wage differentials in some firms or industries may just be a reflection of higher dispersion in unobserved human capital.

The econometric approach taken is to estimate a log wage regression with worker and firm fixed effects and education, experience, tenure, and gender as control variables. Pay dispersion is calculated from the residuals of this regression as the difference of the 90th and 10th percentiles and the standard deviation. this first stage regression model is:

$$log(w_{it}) = X_{it}'\beta + \alpha_i + \psi_{j(i,t)} + \varepsilon_{it} \tag{4.9}$$

In equation 4.9 w_{it} is the wage of individual i at time t, X_{it} is the vector of independent variables, and α_i is an individual fixed effect. $\psi_{j(i,t)}$ is a firm fixed effect for the firm j that the individual works in at time t. The ε_{it} is the idiosyncratic error term.

The second stage of the analysis is a firm performance equation estimated as a function of the pay dispersion calculated from the residuals of the first stage regression, worker composition characteristics by average gender, schooling, tenure, and experience. Time dummies, firm size and equity per worker are also included along with firm fixed effects. The dependent variable is measured as log sales per worker. The second stage estimating equation is:

$$log(y_{jt}) = \lambda\hat{\sigma}_{jt} + Z_{jt}'\delta + \theta_j + \tau_t + \zeta_{jt} \tag{4.10}$$

in equation 4.10 y_{jt} denotes the measure of performance for firm j at time t. The $\hat{\sigma}_{jt}$ is the main variable of interest - the firm level wage dispersion calculated from the predicted residuals obtained from estimates of equation 4.9. The dispersion-performance relationship is measured by the parameter λ. The Z_{jt} is a vector of firm characteristics, θ_j captures the firm fixed effects, τ_t is a set of time dummies, and ζ_{jt} is the error term.

The results indicate a positive relationship between wage premium dispersion and firm performance when estimating by pooled OLS. When accounting for unobserved firm heterogeneity with a fixed effects model the effect is negative and statistically significant. A one standard deviation increase in wage inequality is associated with an 18% reduction in firm performance. The results of this paper are therefore supportive of the fairness hypothesis.

The difference between the OLS and fixed effects can be explained as the difference between within-firm and between-firm effects. The OLS results show between-firm differences in the relationship between wage inequality and firm performance. An OLS regression predicts a positive relationship because individuals select into firms based on the observed wage distribution - higher ability workers who are prepared to exert effort to move up the hierarchy will select into firms with wider wage distributions as there is a greater potential gain from doing so. These firms will therefore be more productive, hence a positive relationship.

The within-firm estimator gives the opposite result - a negative relationship. This is because a widening of the wage distribution over time within firms is perceived as unfair, or conversely a compression of the wage distribution is perceived as fair. Fairness considerations will lead to a reduction in effort supplied as the wage distribution widens and consequently firm productivity declines, producing the observed negative effect.

Grund and Westergaard-Nielsen (2008) examine not only wage dispersion but "wage increase" dispersion. In addition to dispersion in the wage distribution which may impact firm performance it is argued that dispersion in wage increases will also impact on performance. Their data is a matched employer-employee dataset which has information on Danish private sector firms and their employees and can be tracked over time in a panel. For each year, firms are only included if there are at least 20 employees so that the calculated wage dispersion measures are meaningful.

The key variables are the firm performance and wage measures. The wage is measured as hourly gross wages and the dispersion measure of wage increases (the ratio of the individual's wage in time t divided by the wage in time $t-1$) is the coefficient of variation - the standard deviation divided by the mean. The square of the wage dispersion measure is also used to look for potential non-linear effects. The dependent variable, firm performance, is measured as gross value added per employee.

Other independent variables included in the regressions are; percentage blue collar workers, percentage female, mean workforce age and age dispersion (measured also using the coefficient of variation). The empirical approach to estimating these regressions is pooled OLS and fixed effects models to control for unobserved firm heterogeneity.

Their results indicate a statistically insignificant relationship between wage dispersion and firm performance. The OLS model predicts an inverse U shaped relationship between wage level dispersion and labour productivity but the model accounting for firm fixed effects reveals no significant relationship (on aggregate). The models estimated for wage growth dispersion give different results. Both the OLS and fixed effects models give a statistically significant U shaped relationship between dispersion and performance. The negative relationship (or the fairness effect) affects 98% of the firms in the sample and the remaining 2% lie on the upward sloping portion of the curve (where the competition effect dominates).

The paper therefore concludes the fairness effect to be more important in general than the competition effect. Its key finding is that it may not be the wage distribution itself which engenders feelings of unfairness and in turn directly affects productivity but marginal changes to the wage distribution. Marginal increases in dispersion of the wage distribution will, in general, reduce performance. The explanation for this is that each firm has an equilibrium wage distribution which is accepted as fair by employees on the basis of differences in human capital. Any change to that wage distribution is therefore perceived of as unfair.

Esteves and Martins (2008) analyse Brazilian data to determine whether firm performance is driven by tournaments or fairness. Their data is a census of establishments with over 30 employees and a random sample of smaller firms. They use a variety of econometric techniques including OLS, quantile regression, 2SLS, fixed effects, and fixed effects 2SLS. With their data they also distinguish between manufacturing firms and service sector firms.

A distinction is made between conditional and unconditional wage inequality and unconditional measures used are the standard deviation, coefficient of variation, and minimum to maximum wage ratio. The conditional measure of wage dispersion is the standard error of a wage regression. The logarithm of value added is used as the dependent variable in the firm performance regressions.

Results across the cross sectional regression techniques predict a positive relationship between pay dispersion and performance, with the quantile regression models indicating a stronger relationship in more efficient firms. When using fixed effects, the effect for services is found to be negative but coefficients for both manufacturing and services are insignificantly different from zero. In the fixed effects IV approach both manufacturing and services coefficients are positive but only the one for services is significant. Esteves and Martins (2008) therefore concludes there is no evidence to support the fairness hypothesis. The weaker effect of wage inequality on performance in the services sector relative to manufacturing is interpreted in the Lazear (1989) context; i.e. in services there may be a larger share of non-cooperative workers who may compete with their workers through sabotage, therefore necessitating a degree of wage compression.

In summary, there are a variety of ways in which the relationship between wage inequality and firm performance has been estimated. Commonly used measures of firm performance are profits or gross value added (Hibbs and Locking (2000), Beaumont and Harris (2003), Lallemand et al. (2004), Heyman (2005), Esteves and Martins (2008), and Grund and Westergaard-Nielsen (2008)) and in this chapter gross value added is the measure which will be used. A variety of measures of wage inequality have also been used. A commonly used measure is the standard deviation (Leonard (1990), Lallemand et al. (2004), Martins (2008), and Esteves and Martins (2008)) which will also be utilised in this chapter in addition to the log of the 90/10, 90/50, and 50/10 percentile differentials to investigate the possibility of the effect differing across the wage distribution.

Another finding in the literature review is the large range of methodologies which have been used to estimate this relationship. All papers make use of a baseline OLS regression model but fixed effects estimators in particular have also been commonly used. This can potentially lead to substantial differences in results, such as OLS results returning positive coefficients but fixed effects returning negative coefficients as in Martins (2008). Notably, only one paper - Beaumont and Harris (2003) - takes advantage of the availability of panel data to estimate a dynamic model allowing for dependence over time in firm performance. The GMM approaches of Arellano and Bond (1991) and Blundell and Bond (1998) allow for dynamic specifications, endogenous variables, and unobserved firm heterogeneity to be handled in a single framework. This chapter makes use of a variety of estimators ranging from the simple OLS regression model to the dynamic system GMM estimator and compares and contrasts the results.

4.4 Data

This chapter makes use of three datasets; the New Earnings Survey, the Annual Respondents Database, and the Capital Stock Dataset. These three datasets are each discussed in turn in this section. The combined dataset used in the analysis is obtained by matching these three together. The Capital Stock Dataset and Annual Respondents Database can be matched on a one for one basis while the New Earnings Survey is matched at industry level using SIC codes.

Limitations to the available data with which the research question of this chapter is addressed requires the assumption that industry level wage inequality is a proxy for firm level inequality. This is because the firm level data in the ARD does not provide information at the employee level which would be required to calculate firm level wage inequality measures.

Smaller industries are likely to have less variation in the level of inequality between firms, for example because of reduced variation in firm size and therefore the size of corporate hierarchies. This will improve the likelihood that the industry level of inequality will provide a reasonable proxy for firm level inequality. The wage inequality measures are therefore calculated for as disaggregated a level as possible. This poses a problem in that these smaller industries will, by definition, be less well represented in the NES data from which the wage inequality measures are constructed.

The results of this chapter could be interpreted more directly as the impact of industry wage inequality on firm performance, however the previous theoretical and empirical literature relate inequality to performance at the firm level. In order to fit in with this literature the interpretation of the industry level inequality measures as a proxy for wage inequality is therefore more appropriate. Given the constraints in the data this is the best that can be achieved and the results will be considered in light of this potentially strong assumption.

4.4.1 New Earnings Survey

The data on wage inequality are obtained from the New Earnings Survey (NES). The NES is a 1% random sample of UK employees who earn above the income tax threshold conducted annually. The sample is determined by the employees' national insurance number, therefore the data is a panel as the same individuals are included each year provided they are still employed and earning a sufficient amount to be sampled.

The wage measure used is the log hourly wage calculated as the natural logarithm of gross pay divided by total hours. Observations are included in the analysis if the individual works a single job, is paid a full adult rate, and earnings are unaffected by absence.

Wage inequality is calculated at industry level. This differs from previous studies which calculate inequality at the firm level - which is the ideal level, however it is not possible with the data used in this study. Industry is defined using the four digit level of the standard industrial classification of 1992 (SIC-92).Wage inequality is calculated by the difference between the 90th percentile and 10th percentile of the log hourly wage, equivalently the log of the ratio of the 90th percentile of the wage distribution to the 10th, for each industry in each year. Equivalent to the 90-10 differential, the 90-50 and 50-10 differentials are also computed. Other wage inequality measures calculated are the standard deviation and coefficient of variation.

These measures of wage inequality are also calculated from log wage residuals as well as the wage itself. This follows the approaches of several papers discussed previously which argued that observed and unobserved worker heterogeneity should be controlled for in the measure of pay dispersion used. Any wage differentials used in the pay-performance regressions can then be interpreted as reflecting demand-side factors assuming that all supply side factors have been accounted for in the regression model (either as one of the observed variables or included in the heterogeneity term).

The residuals are obtained from individual level log wage equations (which will be explained in more detail in the methodology section) estimated from the NES data using age and occupation as explanatory variables. Ideally, measures of human capital such as education and experience, as are standard variables in empirical wage equations, would be used, however these are the only variables present in the NES which are also consistently available throughout the sample.

There is an issue that some industries may not have sufficient observations in the NES to obtain reliable estimates of wage inequality - for example an industry with only two observations in a particular year cannot produce a meaningful value for the 90-10, 90-50, and 50-10 differentials. A threshold of 20 observations is therefore used to determine the adequacy of the inequality measure from this industry.

Industries are retained at the 4 digit SIC-92 level if they contain at least 20 wage observations in each year. To minimise the loss of information which the omission of industries entails, those industries which do not have sufficient observations at the 4 digit level are merged together with other industries which belong to the same 3 digit industry. Figure 4.3 illustrates the process.

In Figure 4.3 there are 7 four digit industries and two three digit industries. Each of the four digit industries belongs to one of the three digit industries. The shaded industries 1, 4, and 5 indicate industries for which there are a sufficient number of observations already to calculate a reliable measure of wage inequality. Industries 2 and 3 do not have sufficient observations by themselves to calculate a reliable measure of wage inequality so these two are merged together as they both belong to three digit industry A.

This creates a set of three digit industries which are composed of four digit industries which did not have sufficient observations by themselves to calculate a time series of wage inequality measures for. For the subset of artificially constructed three digit industries which still do not consistently have sufficient observations for a series of inequality the process is repeated, merging three digit industries together to the two digit level.

Table 4.1 shows the result of this process in the NES data. The final column in this table shows the proportion of the four digit industries which are included in the analysis at each level of the standard industrial classification. At the four digit level, 425 of the 729 total industries consistently have sufficient observations to calculate wage inequality measures for each year which represents 58% of the industries in NES. Using the threshold of 20 observations and only using the 4 digit level of the standard industrial classification to

Table 4.1: Industry Classification

Digit	Consistently < 20	Consistently ⩾ 20	Intermittent	Total	% Industries Retained	Cumulative % Retained
4	154	472	131	757	62.35%	62.35%
3	8	93	30	131	70.99%	89.08%
2	4	4	19	27	14.81%	90.70%
1	0	3	5	8	37.50%	94.19%

match to the ARD therefore only allows less than two thirds of the industries to be used in the analysis.

Aggregating the industries which cannot be used at the 4 digit level to the 3 digit level results in 131 potential 3 digit industries of which 85, or 65%, are suitable for use in the analysis. This increases the total proportion of all 4 digit industries included in the analysis (whether at the 4 or 3 digit level) to 85%. Continuing this procedure to obtain more industries at the 2 digit and finally the 1 digit level results in 95.5% of the industries in NES being available to the analysis. The industries still excluded at this stage are primarily from the agriculture, forestry, and fishing industries.

4.4.2 Annual Respondents Database

Firm level data are obtained from the Annual Respondents Database (ARD). The ARD is the largest survey of business micro-data in the UK, containing a variety of firm characteristic variables. Overviews of the ARD are given by Oulton (1997) and Griffith (1999).

The ARD is a stratified random sample of UK establishments. Griffith (1999) illustrates how the sampling frame changed between 1970 and 1995. The sampling frame is biased towards larger establishments and this has become increasingly more so over time. Between 1972 and 1977 all establishments with 20 or more employees were included. From 1978-1979 this was reduced to all establishments with 50 or more employees and half of establishments with 20-49 employees. This continued to change until 1993-1995 when all establishments with more than 100 employees were included, half of establishments with 50-99, and one in five establishments with 20-49 employees. Table 4.10 in the appendix summarizes the changing ARD sampling frame over time.

Data are available at the local unit (plant), reporting unit, enterprise, and enterprise group level. A local unit is a plant or single geographic location but which may not be able to provide all of the information required by the survey. Reporting units are units large enough to provide the full information requested in the survey. Reporting units are not economic units because they are not standardised in anyway - a firm may be entirely represented as one reporting unit or it may be represented by several reporting units. Reporting unit level data are therefore not meaningful for analysis, they are therefore aggregated to enterprise level.

The dependent variable is performance and there are a number of variables in the ARD which can be used to measure this. The main variable utilised here, following the literature, is gross value added. Each of these measures is divided by employment so that firm performance is measured per worker. The ARD also provides all firm level characteristics to be included in the firm performance regressions. Prominent variables included are the factors of production - labour and capital. A major disadvantage of the ARD is that it does not contain information on the capital stock, only capital expenditures.

Estimates of capital stock provided separately by the ONS are therefore used to supplement the ARD data. The level of capital stock is integral to economic models of firm production but information on this is not directly available in the ARD. The Capital Stock Dataset is derived from the investment data in the ARD and is provided by a dataset created by the ONS specifically for the purpose of deriving capital stock data at the reporting unit level. The process of deriving the capital stock from the ARD is described in detail in Martin (2002)

The capital stock is calculated using the perpetual inventory method (PIM). This is performed at the reporting unit level and uses the investment data in the ARD. This is summarised in equation 4.11.

$$K_{ijt} = K_{ij,t-1}(1-\delta) + I_{ijt} \tag{4.11}$$

The capital stock K for reporting unit i in industry j at time t is calculated as investment I_{ijt} plus the capital stock from the period before multiplied by a depreciation term determined by δ. These depreciation rates differ across three types of asset; buildings, plants and machinery, and vehicles and so the capital stock of each type of asset is calculated individually. The overall capital stock is then the summation of these three individual capital stocks.

The annual depreciation rates for the three types of capital are those used by the ONS for calculating sectoral aggregates (Martin (2002)). These are 6% for plant and machinery, 2% for buildings, and 20% for vehicles. It could be argued that these may be unrealistic depreciation rates. For example 6% for plant and machinery might be considered too low as machinery might be expected to depreciate at a much faster rate relative to buildings as implied here. As these rates have already been applied to the dataset they cannot be changed and therefore the capital stock used in the analysis is subject to the assumptions made when these depreciation rates were applied.

Other explanatory variables included in the regressions are a dummy for UK ownership and time dummies. The dataset also consists of dummy variables indicating the broad sector of the enterprise; catering, construction, motors, wholesale, retail, services, property, and manufacturing. These variables are used to estimate firm performance regressions separately by sector.

As the ARD is a census of large firms and a sample of smaller firms the sample is biased towards larger firms. As the estimated models include the variable which determines the sampling frame (employment) the regression models do not need to be weighted [Cameron and Trivedi (2010) p113]. All descriptive statistics do need to be weighted however.

Within the ARD dataset there is a database containing (limited) information about all firms in the sampling frame whether or not they are selected - including employment and a dummy to indicate whether or not the firm was selected in that year. Firms are grouped into eight size bands by employment and each individual weight is calculated as the inverse probability that the establishment was selected. These weights are then matched into the main ARD response dataset for those which were selected.

Figure 4.4 shows the distributions of key variables. The log of gross value added, capital stock, and labour follow approximately normal looking symmetric distributions. The change over time in gross value added, capital stock, and labour are shown in Figures 4.7 to 4.9 for five of the sectors (with wholesale and retail combined into one). They show that manufacturing/production is the largest sector by gross value added followed by services, wholesale and retail, and construction.

In terms of inputs, the services sector is larger in 2004 than production having overtaken it in size in terms of both capital stock and labour during this period. The relative decline of production compared to services is also apparent in terms of value added - total log GVA has been declining for production but increasing for services.

4.4.3 Matched Dataset

The matched dataset uses the period 1997 - 2004. This period is chosen for a number of reasons. The SIC codes in both the NES and the ARD are consistent with SIC-92 throughout this period, this period in the ARD contains the required information for more sectors (not just manufacturing) starting in 1997, and the capital stock data are available up to 2004. This gives an unbalanced panel of eight years worth of data.

Observations are then retained for enterprises which are observed in each of the eight years covered by the sample period. This is because the nature of the ARD (random sampling of smaller firms) is such that a comparison of pooled OLS results with results obtained from panel data estimators will be based on substantially different estimation samples. An enterprise is retained if observed for the full eight year time horizon to allow estimation of dynamic models using a comparable sample. As the estimators for these models include lagged dependent variables and further lags as instruments, using firms observed in each available time period ensures that the same set of enterprises is used when utilising different panel data techniques and examining different lag structures.

As the ARD is a census of large firms and a random sample of smaller firms in any given year it is important to note that restricting the sample in this way introduces a selection issue and further biases the estimation sample towards the larger firms. The results of the analysis will consequently reflect the larger firms rather than the full population of firms. Restricting the estimation sample in this way is, however, necessary to maintain comparability between models as previously discussed. The analysis includes regression models present weighted and unweighted results in order to show the impact of this large-firm bias.

Table 4.2 provides some descriptive statistics for the main variables of interest. As the sample is likely to be large enterprise biased due to including only those which appear in each of the eight years a concern is that small firms may not be represented, however as can be seen from Figure 4.4 the bottom end of the distribution of labour is represented in the sample.

Figure 4.5 shows how wage inequality is distributed for the three percentile differential measures calculated from the fixed effects residuals. The 90/50 and 50/10 differentials are similarly distributed around a mode of approximately 0.1 with a substantial positive skew. The 90/10 differential is distributed with a mode of around 0.2 and, as it is composed of the other two, is more dispersed. It also has a substantial positive skew.

Summary statistics for the standard deviation measure of wage inequality are shown in Table 4.2. This measure is shown calculated from the residuals of the fixed effects log wage regression (the main measure used in the analysis), it is also shown calculated from the pooled OLS residuals of the same regression model, and also from the raw wage measure. The distributions of each measure are also shown in Figure 4.6.

Inequality calculated from the fixed effects has the smallest mean and mode and is also the least dispersed. Moving from fixed effects to pooled OLS residuals both the mean and standard deviation of wage inequality increase and again when comparing OLS residuals to raw wages. As is the case for the percentile differentials, each of these three measures of the standard deviation has a positive skew.

4.5 Methodology

The methodological approach of this study is in two parts. The first part involves the derivation of inequality measures from the NES and matching this into the ARD data. The

Table 4.2: Descriptive Statistics

Variable		Mean	Std. Dev.	Observations
Log(GVA per Worker)	overall	3.669	1.011	N = 17319
	between		1.029	n = 2340
	within		0.439	T-bar = 7.40128
UK Ownership	overall	0.505	0.5	N = 18916
	between		0.417	n = 2411
	within		0.278	T-bar = 7.84571
Log(Labour)	overall	6.125	1.303	N = 18903
	between		1.27	n = 2406
	within		0.335	T-bar = 7.85661
Log(Capital)	overall	10.547	1.806	N = 18847
	between		1.776	n = 2399
	within		0.345	T-bar = 7.85619
Log(Capital per Worker)	overall	4.423	1.407	N = 18847
	between		1.354	n = 2399
	within		0.373	T-bar = 7.85619
Std. Dev (Fixed Effects)	overall	0.118	0.035	N = 18935
	between		0.022	n = 2412
	within		0.027	T-bar = 7.85033
Std. Dev (OLS)	overall	0.325	0.058	N = 18935
	between		0.045	n = 2412
	within		0.036	T-bar = 7.85033
Std. Dev (Raw Wages)	overall	0.454	0.085	N = 18935
	between		0.075	n = 2412
	within		0.041	T-bar = 7.85033

second stage involves the estimation of firm performance models including a measure of pay dispersion to examine the causal relationship between industry level wage inequality and enterprise performance.

The first stage involves the calculation of measures of wage inequality. The approach in this stage closely follows that of Martins (2008). The overall wage inequality measures are simply calculated from the sample statistics by industry and year. The residual wage inequality measures are estimated as the residuals from the following equation:

$$ln(wage)_{it} = \alpha + \beta_1 age_{it} + \beta_2 age_{it}^2 + \beta_3 Occ_{it} + \beta_4 Reg_{it} + \beta_5 t + u_i + \varepsilon_{it} \qquad (4.12)$$

The *Occ* term is a vector of dummy variables indicating the individual's occupation at the two digit level, *Reg* is a vector of 9 regional dummies and *t* is a vector of time dummies. The occupational dummies in particular add a large number of regressors to the model but also improve the precision of the predicted wage and the large sample size of the NES can support the cost in terms of degrees of freedom. This equation is estimated by individual fixed effects in order to account for time invariant unobserved heterogeneity.

As the standard occupational classification changes throughout the NES sample these fixed effects regressions are estimated separately for each distinct period within which the occupational codes are consistent - prior to 2002 using SOC-90 and for 2002 and after using SOC-2000.

The feature of interest from these regressions is the term ε_{it} - the random error component. The rest of the regression is composed of the part of the wage which can be explained by observables and the individual fixed effect. Residual wage inequality measures are calculated from predictions of this term - $\hat{\varepsilon}_{it}$.

Inequality in the wage residuals is interpreted as a measure of unfairness as it represents differences in wages amongst homogeneous workers i.e. differences which remain once observed and unobserved heterogeneity are both accounted for. According to the fairness theory a higher degree of dispersion in wages amongst equivalent workers is expected to reduce firm performance. For this reason measures of wage inequality calculated from the residuals rather than raw wages are more appropriate in this context.

Having matched the information obtained from the NES data to the ARD the remainder of the methodology relates to estimating regression models with the aim of obtaining estimates of the elasticity relating pay dispersion to firm performance. The basic model to be estimated is given by equation 4.13.

$$log(y)_{ejt} = \alpha + \beta_1 \hat{\sigma}^{w}_{jt} + \beta_2 log(k_{ejt}) + \beta_3' X_{ejt} + v_{ejt} \tag{4.13}$$

In this equation $log(y_{ejt})$ is the log of gross value added per worker of enterprise e in industry j at time t. k is capital stock per worker, and X is a vector of additional control variables - sector dummies, time dummies, and a dummy variable indicating UK ownership. v_{ejt} is the error term. The main coefficient of interest is β_1 - the coefficient on the wage dispersion variable denoted σ^{w}_{jt}. Only subscripts j and t apply to this variable as it is only observed at the industry level and over time, hence standard errors need to be clustered at the industry level.

$$log(y)_{ejt} = \alpha + \beta_1 \sigma^{w}_{jt} + \beta_2 log(k_{ejt}) + \beta_3' X_{ejt} + \delta'(S_{ejt} * \sigma^{w}_{jt}) + v_{ejt} \tag{4.14}$$

Equation 4.14 shows an extended version of the model in equation 4.13 with an extra vector of variables. This additional variable is an interaction between the sector dummies (contained in X_{ejt}) with the wage dispersion variable. The corresponding coefficient vector δ allows estimates of the relationship between pay dispersion and performance in individual sectors to be obtained in addition to the aggregate level measure obtained from equation 4.13.

The percentile differentials of the log wage residuals are equivalent to the log of the ratio of the 90th and 10th percentile of wage residuals. The estimated parameter for these variables can therefore be calculated as an elasticity - the proportionate change in firm performance which results from a 1% point increase in the ratio of the 90th percentile to the 10th of the residual wage distribution. The coefficient for the standard deviation is interpreted as the proportionate change in wage inequality for a one standard deviation increase in wage dispersion.

These equations are estimated initially by pooled OLS as a baseline. It is also important to control for unobservable firm characteristics which may influence performance. The longitudinal nature of the ARD data is such that the panel data techniques previously described can be used to account for these issues. Standard fixed effects and random effects models are considered.

Due to the issue of endogeneity first difference IV equations are also estimated. Within this framework the issue of endogeneity can be addressed whilst continuing to account for unobserved heterogeneity by using the fixed effects transformation. There are two main issues which may cause endogeneity in this model.

The first of these issues is input bias. As well as output depending on the level of inputs the relationship is likely to work in reverse. Firms react to productivity shocks by increasing or reducing output which in turn respectively increases or decreases the demand for labour and/or capital services. To the extent that the estimated model does not capture productivity shocks to output there is an endogeneity problem in the labour and capital variables which consequently need to be instrumented.

The second source of endogeneity is more important in this case because it affects the main independent variable of interest. As explained by Esteves and Martins (2008) if rent sharing with workers occurs disproportionately throughout the wage distribution (because, for example, higher skilled workers have greater bargaining power) then an exogenous shock to productivity will impact the wage distribution i.e. there is a reverse relationship whereby increased firm performance increases wage inequality. This means the wage dispersion variable may also be endogenous.

Estimates of the parameters of the model may still be inconsistent in the IV fixed effects/first difference analyses due to the omission of appropriate lags of the dependent variable.

The difference GMM estimator uses lagged levels of variables as instruments for the first differences of endogenous variables and the full system GMM estimator additionally uses lagged differences as instruments for the endogenous variables in levels. Exogenous variables are used as their own instruments.

The parameter estimates - $\hat{\beta}$ - are short run effects of the covariates on the dependent variable, the dynamic model can be used to obtain long run effects as well.

4.6 Analysis

4.6.1 Log Wage Equations

Table 4.3 shows the results of the first stage regressions of log wages. Columns 1 and 2 respectively show the pooled OLS regressions, one for each distinct period covered by the two different occupational classifications (1997-2001 and 2002-2004). Each specification includes age and its square, regional dummies, 2 digit SOC occupational dummies, and year dummies. Columns 3 and 4 are estimated using the same data as the columns 1 and 2 respectively but are estimated using individual fixed effects.

The coefficients for age and age squared are highly significant and have the expected sign (positive and negative respectively) indicating decreasing returns to labour market experience - for which age is a proxy. The overall R squared are quite high in the OLS results ranging between approximately 0.55 and 0.60 between the two periods but decrease in the fixed effects estimates. The between and within R squared available from the fixed effects result suggest that this model performs better at explaining between-individual variation in wages rather than within-individual variation over time.

The inequality measures used in the main analysis are calculated from the residuals of the fixed effects regressions. Alternative measures are calculated from the pooled OLS residuals as well as the raw age measures as a robustness check.

The change over time in the average level of residual wage inequality for each sector is shown in Figure 4.10. The series is discontinuous between 2001 and 2002 as the residuals are based on two separate regressions. The overall change in residual wage inequality over this period has been a decline (despite being a period of increasing overall wage

Table 4.3: Log Wage Regressions

	OLS (97-01)	OLS (02-04)	FE (97-01)	FE (02-04)
Age	0.0425***	0.0396***	0.0367***	0.0544***
	(0.000)	(0.000)	(0.000)	(0.000)
Age Sq/100	-0.0475***	-0.0453***	-0.0378***	-0.0621***
	(0.000)	(0.000)	(0.000)	(0.000)
North-East	-0.0226***	-0.0248***	-0.0129	0.0132*
	(0.000)	(0.000)	(0.105)	(0.019)
North-West	0.00508*	-0.00045	-0.0172**	0.00367
	(0.023)	(0.788)	(0.002)	(0.356)
Yorkshire	-0.0142***	-0.0201***	-0.0355***	-0.00665
	(0.000)	(0.000)	(0.000)	(0.114)
East Midlands	-0.0191***	-0.0275***	-0.0234***	-0.00747
	(0.000)	(0.000)	(0.000)	(0.088)
West Midlands	-0.00506*	-0.00743***	-0.0144*	0.0165***
	-(0.033)	(0.000)	(0.014)	(0.000)
Southwest	-0.00567*	-0.0184***	-0.0175**	-0.00867*
	(0.019)	(0.000)	(0.002)	(0.042)
East	0.0414***	0.0263***	-0.00708	0.00725
	(0.000)	(0.000)	(0.207)	(0.069)
London	0.251***	0.205***	0.0332***	0.0645***
	(0.000)	(0.000)	(0.000)	(0.000)
Southeast	0.0799***	0.0543***	0.0055	0.0225***
	(0.000)	(0.000)	(0.278)	(0.000)
Occupation Dummies	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
Observations	410,222	670,253	410,222	670,253
Overall R Squared	0.555	0.602	0.38	0.437
Between R Squared			0.395	0.446
Within R Squared			0.0514	0.138

inequality), particularly sharp between 2001 and 2004 following a decline/recovery between 1997 and 2001. This pattern in residual wage inequality over time is shared by each of the sectors. The relative ranking of the sectors has remained the same - with manufacturing being a relatively low inequality sector and services being relatively high inequality.

4.6.2 Enterprise Performance Equations

The second stage regressions are reported in Tables 4.4 and 4.5. Each regression reported is the aggregate level main effects model i.e. does not include sector dummy interactions. The former table reports coefficients from a variety of techniques used to estimate the same model of performance. These techniques are, from left to right; OLS, random effects, first differences, fixed effects, and IV fixed effects. The OLS results are presented for different functional forms in the first three columns, respectively including no additional dummy variables, then adding in sector dummies, and in the third column adding time dummies. Each of the reported models uses the standard deviation of log wage residuals as the measure of wage inequality.

Table 4.4: Enterprise Performance Regressions

	OLS (1)	OLS (2)	OLS (3)	RE	FD	FE	IV-FE
Log Capital per Worker	0.289***	0.320***	0.320***	0.316***	0.458***	0.304***	0.211***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Standard Deviation	-0.960***	0.524**	0.625**	-0.317*	-0.0275	-0.359*	-0.217
	(0.000)	(0.007)	(0.004)	(0.028)	(0.843)	(0.013)	(0.155)
UK Owned		0.0899***	0.0913***	0.0225	0.0134	0.00434	-0.00996
		(0.000)	(0.000)	(0.063)	(0.304)	(0.730)	(0.483)
Sector Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	No	No	Yes	Yes	Yes	Yes	Yes
Observations	17,655	17,071	17,071	17,071	14,358	17,071	14,752

P values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results look sensible with respect to the coefficient on the input factor of production. In all regressions, the coefficient for capital per worker is positive and highly significant at conventional levels. The OLS results also suggest a positive and significant effect of wage inequality on firm performance and also that UK owned firms are significantly more productive. The wage inequality measure has a significant effect on enterprise performance in each of the three OLS estimates, the inclusion of sector dummies in the second column changes the sign from negative to positive and the additional inclusion of time dummies increases the magnitude from 0.524 to 0.625.

This positive effect of UK ownership is contrary to the findings of Harris (2002) and Harris and Robinson (2003) who find foreign owned plants perform better in the UK than domestically owned ones. Harris and Robinson (2002) also find that manufacturing plants acquired by foreign firms performed better than those acquired by UK firms. This could be due to a selection issue; the size bias introduced into the sample by the imposed requirement that the enterprises be consistently observed for the full period is likely to have disproportionately removed UK owned firms. The effect of UK ownership is, however, insignificant with all panel data estimators.

The remaining columns of Table 4.4 present the results of the panel data estimators. The use of the panel data estimators substantially alter the results of the enterprise performance models compared to the pooled OLS specifications. The coefficient on log capital per worker in the random effects regression (0.316) is similar to the OLS results (0.320), however the first difference estimator produces a much higher coefficient of 0.458. The coefficient on log capital per worker from the fixed effects estimates is similar to the random effects coefficient but is much lower at 0.211 with the IV fixed effects although still positive and significant. The standard deviation is negative and significant at the 5% level in both random effects and fixed effects estimates but not for first differences or IV fixed effects.

Table 4.5 shows results of the same models as in Table 4.4 estimated by GMM and including lags of the dependent variable as regressors. The coefficients reported are those on the standard deviation, UK ownership, capital, and the lagged dependent variable. One lag of the dependent variable was judged to be appropriate and as the p values indicate, the lag of log GVA per worker has positive and significant coefficients in all six estimated models.

The difference between each of the models is the lag structure used in the instruments.

Table 4.5: Enterprise Performance Regressions - System GMM

	AB (1)	AB (2)	AB (3)	AB (4)	AB (5)	AB (6)
Log Capital per Worker	0.187***	0.119***	0.121***	0.121***	0.120***	0.349***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Standard Deviation	0.225	-0.026	0.013	0.013	0.001	0.035
	(0.147)	(0.865)	(0.934)	(0.934)	(0.996)	(0.838)
UK Owned	0.0234	0.0179	0.0203*	0.0203*	0.0196*	0.0234
	(0.071)	(0.062)	(0.035)	(0.035)	(0.042)	(0.089)
Log(GVA) t-1	0.533***	0.777***	0.775***	0.775***	0.777***	0.606***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Hansen Test P Value	0.000	0.056	0.093	0.158	0.171	0.253
Instruments	26	25	22	23	24	25
Firms (n)	2,233	2,233	2,233	2,233	2,233	2,233
Observations (n*T)	14,202	14,202	14,202	14,202	14,202	14,202

P values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A variety of specifications were tested in order to find the appropriate model to use to estimate the dispersion-performance relationship. The differences between these models can be seen in the number of instruments which is reported for each model. An appropriate model minimises the number of instruments used to avoid the problem of weak instruments. As can be seen only models AB(4), AB(5) and AB(6) have a p value for the Hansen test sufficiently high as to fail to reject the null hypothesis of valid over-identifying restrictions.

The chosen specification is that of AB(6). This specification passes the Hansen test with the highest p value and uses 25 instruments (or 32 in the sectoral level models, with each of the seven exogenous sectoral interactions used as their own instrument).

The results include a positive but insignificant effect of wage inequality on enterprise performance in all GMM estimates, with the exception of AB(2) where it is negative but still insignificant. The coefficients on capital per worker are all positive and significant. The coefficients on the lagged dependent variable suggests significant persistence in GVA per worker over time with a coefficient of over 0.5, which is evidence of the appropriateness of the dynamic specification.

4.6.3 Dispersion-Performance Relationship

Aggregate Level

Table 4.6 shows the estimated effect of each of the four wage dispersion measures as estimated by OLS, fixed effects, first differences, IV fixed effects, IV first differences, and system GMM. Random effects results are not reported as the existence of a correlation between the unobserved heterogeneity and the observed independent variables means the random effects assumption is violated and the estimates are therefore inconsistent.

The results generally indicate that there is no significant relationship between wage inequality and performance. There are some significant effects to be observed at the aggregate level, however these are not consistent enough across estimators as to be convincing that the few significant coefficients obtained are robust.

Focussing on the first seven rows of the results table (the final three rows relate to alternative specifications which are used as robustness checks), there are no significant coefficients for the 90/10 differential or for the standard deviation and consequently no evidence that overall wage inequality has an impact on firm performance.

Each of the OLS estimates suggest that the impact of wage inequality is positive but only the effect of the 90/50 differential has a significant effect. The significance of the 90/50 differential is also found in the fixed effects and IV fixed effects results, although with substantially reduced coefficients. The only significant results found for the aggregate case are also obtained by the fixed effects and IV fixed effects estimators which in both cases is a negative coefficient for the 50/10 differential.

The fixed effects results therefore provide some evidence in support of the fairness hypothesis. This evidence is, however, limited to the bottom of the wage distribution with no significant effects of inequality in the residual wage distribution as a whole.

There are no significant coefficients when accounting for persistence in the dependent variable over time. Both the short and long run estimated effects of wage inequality on firm performance are highly insignificant. The system GMM estimator therefore provides

Table 4.6: Aggregate Level Inequality-Performance Coefficients

	Log 90/10	Log 90/50	Log 50/10	Std. Dev.
OLS	1.435	2.437*	0.833	0.625
	(0.213)	(0.027)	(0.618)	(0.571)
N=16,735				
Fixed Effects	-0.138	0.314*	-0.678*	-0.359
	(0.405)	(0.032)	(0.007)	(0.106)
N=16,735				
First Differences	-0.060	0.163	-0.345	-0.028
	(0.705)	(0.145)	(0.216)	(0.852)
N=14,110				
IV Fixed Effects	-0.102	0.326*	-0.582*	-0.196
	(0.571)	(0.049)	(0.026)	(0.342)
N=14,335				
IV First Differences	-0.175	0.074	-0.435	0.027
	(0.367)	(0.587)	(0.200)	(0.876)
N = 11,963				
GMM (Short Run)	0.183	0.410	-0.097	0.034
	(0.630)	(0.225)	(0.850)	(0.927)
N=14,202				
GMM (Long Run)	0.466	1.033	-0.247	0.088
	(0.606)	(0.148)	(0.852)	(0.926)
N=14,202				
GMM (Short Run - Weighted)	0.171	0.158	0.191	-0.501
	(0.571)	(0.754)	(0.656)	(0.391)
N=14,202				
GMM (Short Run - Pooled OLS Residuals)	0.173	0.205	0.182	0.435*
	(0.114)	(0.191)	(0.173)	(0.043)
N=14,202				
GMM (Short Run - Raw Wages)	0.175*	0.155**	0.250	0.456**
	(0.03)	(0.009)	(0.259)	(0.009)
N=14,202				

P values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

no evidence in favour of any relationship between wage inequality and firm performance. While the lack of consistency achieved in the results across the estimators already suggests that the few significant results obtained are not robust, the GMM approach is the preferred estimator and definitively finds no evidence of a relationship.

The results presented here indicate that there is no significant relationship to be found between wage inequality and firm performance at the aggregate level.

Sectoral Level

This section presents the results of the sectoral level breakdown of the relationship between pay dispersion and firm performance. Tables 4.7 and 4.8 display the short and long run coefficients from the system GMM estimator, the preferred estimator. The results for each of the other estimators can be found in Appendix 4B.

The short run effects presented in Table 4.7 consist of only two significant coefficients, both for the 90/50 differential in the production and construction sectors. Table 4.8 shows that there are no significant long run effects at all. Comparing these results to those of the other estimators reveals that again, as in the aggregate level analysis, the inconsistency in the significance of the results makes the existence of any significant effects found unpersuasive.

Based on the OLS results there is particularly strong evidence of a positive relationship between dispersion and performance in the production/manufacturing sector. All four coefficients are significant at the 5% level and the 90/10 and 90/50 differentials are significant at the 1% level.

The magnitudes suggest a strong relationship with each elasticity being greater than one, indicating an elastic rather than inelastic relationship between dispersion and performance. As in the aggregate case, this effect again is strongest at the top of the residual wage distribution rather than the bottom when estimated by OLS.

Similar conclusions can be drawn from the retail sector coefficients. All four coefficients are significant at the 5% level and the 90/10 differential is significant at the 1% level as

Table 4.7: System GMM: Short Run Inequality-Performance Coefficients

	Log 90/10	Log 90/50	Log 50/10	Std. Dev.
Production	0.443	0.584*	0.334	0.277
	(0.108)	(0.020)	(0.277)	(0.544)
Services	0.518	1.084	0.178	0.488
	(0.642)	(0.410)	(0.902)	(0.787)
Wholesale	-1.689	-1.009	-3.121	-1.043
	(0.374)	(0.390)	(0.384)	(0.321)
Retail	0.364	0.531	0.061	0.055
	(0.335)	(0.141)	(0.921)	(0.921)
Motors	1.242	1.839	0.907	-0.933
	(0.641)	(0.397)	(0.861)	(0.856)
Construction	0.581	1.173*	-0.411	-0.524
	(0.232)	(0.043)	(0.515)	(0.274)
Property	-0.649	-1.654	-0.189	-1.069
	(0.828)	(0.699)	(0.965)	(0.719)
Catering	-1.497	-1.224	-1.666	-2.628
	(0.385)	(0.441)	(0.436)	(0.118)
Observations	14,202	14,202	14,202	14,202

P values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

in the production sector. The relative magnitudes are even larger than those found for the production sector.

The motor vehicles sector also produces significant results, in this case just for the 90/10 and 90/50 differentials which are highly significant. The magnitudes are larger than in retail with the 90/50 differential having a more than threefold impact on enterprise performance and the 90/10 differential elasticity which is also of substantial magnitude at 2.60.

All other estimated coefficients are insignificant with services, wholesale, construction, property, and catering all providing no significant coefficients for any of the inequality measures considered.

Table 4.8: System GMM: Long Run Inequality-Performance Coefficients

	Log 90/10	Log 90/50	Log 50/10	Std. Dev.
Production	1.58	1.618	1.516	1.966
	(0.143)	(0.101)	(0.279)	(0.122)
Services	1.698	2.403	1.268	2.299
	(0.325)	(0.215)	(0.594)	(0.380)
Wholesale	-1.802	-0.886	-3.981	-0.121
	(0.566)	(0.666)	(0.494)	(0.950)
Retail	1.455	1.534	1.082	1.616
	(0.195)	(0.154)	(0.494)	(0.211)
Motors	2.848	3.59	2.427	0.052
	(0.520)	(0.320)	(0.775)	(0.995)
Construction	1.8	2.542	0.331	0.699
	(0.158)	(0.061)	(0.840)	(0.575)
Property	-0.152	-1.9	0.684	-0.163
	(0.975)	(0.779)	(0.922)	(0.973)
Catering	-2.374	-1.923	-2.651	-4.156
	(0.395)	(0.449)	(0.444)	(0.129)
Observations	14,202	14,202	14,202	14,202

P values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

These findings do not all hold when compared to the fixed effects results. The production section coefficients all become insignificant compared to the OLS results with the only 90/50 differential maintaining a significant effect. As in the aggregate case the magnitude of this coefficient is substantially reduced.

By comparison with the OLS results, the conclusions drawn for the retail sector change completely. All coefficients are now negative and each of these elasticities and the effect of the standard deviation are all insignificant.

The service sector yields a relatively elastic and negative dispersion-performance relationship for the 50/10 differential but no other inequality measure yields a significant effect at the 5% level. The effect of the 90/50 differential is positive but highly insignificant with a p value of 0.60.

The motor vehicles sector, which produced some positive and significant elasticities in the OLS estimates, still returns significant results for the 90/10 and 90/50 differentials in the fixed effects analysis. These estimates are reduced in magnitude but still exceed unity. The wholesale, construction, property, and catering sectors continue to produce insignificant results as in the pooled OLS estimates.

In these fixed effects results all significant elasticities are positive with the exception of those for the services sector. Accounting for unobserved firm fixed effects produces some limited evidence in favour of the fairness hypothesis at the sectoral level, but only in the services sector.

Similar again to the aggregate level results, the IV fixed effects estimator produces results which are similar to those from standard fixed effects. These are, however, not consistent in terms of which effects are found to be significant. The standard deviation becomes significant for the catering sector and the 90/10 and 90/50 differentials become insignificant for, respectively, the motor vehicles and production sectors.

First difference results again produce different significant estimates (except for the motor vehicles sector results, which are similar in magnitude as well as significance to the fixed effects results). Only the 90/10 differential for the motor vehicles sector and the 90/50 differential for the retail, construction, and motor vehicles sectors are significant at the 5% level in the first difference estimates and are all positive.

The IV first difference results are not consistent with standard first differences in terms of the significance of effects. The 90/50 differential is positive and significant in both cases but this is the only consistency between the two results. All other effects which were significant when estimated with first differences are insignificant with the IV first differences estimator. The 90/50 differential has a significant negative coefficient with IV first differences which was insignificant in the standard first difference results.

4.6.4 Robustness Checks

This section discusses the results of robustness checks which show that the conclusion of no significant results using the preferred estimator (system GMM) is not a consequence of model specification.

Non-linearities

The presence of non-linearities in the dispersion-performance relationship is examined by including the square of the wage inequality measure in the baseline regression model and also interacting this squared term with the sector dummies in order to allow the nature of the non-linearity to differ by sector. Use of the squared term allows the effect of wage inequality on firm performance to depend on the level of wage inequality itself when partially differentiating the firm performance equation with respect to wage inequality.

The models estimated are extended versions of the baseline models given in equations 4.13 (the aggregate model) and 4.14 (the sector level model) respectively:

$$log(y)_{ejt} = \alpha + \beta_1 \sigma_{jt} + \beta_2 \sigma_{jt}^2 + \gamma' X_{ejt} + v_{ejt} \tag{4.15}$$

$$log(y)_{ijt} = \alpha + \beta_1 \sigma_{jt} + \beta_2 \sigma_{jt}^2 + \delta_1'(S_{ejt} * \sigma_{jt}) + \delta_2'(S_{ejt} * \sigma_{jt}^2) + \gamma' X_{ejt} + v_{ejt} \tag{4.16}$$

In equations 4.15 and 4.16 the matrix X consists of all independent variables estimated in the baseline models with the exception of the wage inequality measure. Partially differentiating these models with respect to the wage inequality variable yields:

$$\frac{\mathrm{dlog(y)_{ejt}}}{\mathrm{d}\sigma_{\mathrm{jt}}} = \beta_1 + 2\beta_2 \sigma_{jt} \tag{4.17}$$

$$\frac{\mathrm{dlog(y)_{ejt}}}{\mathrm{d}\sigma_{\mathrm{jt}}} = \beta_1 + 2\beta_2\sigma_{jt} + \delta_1' S_{ejt} + 2\delta_2' S_{ejt}\sigma_{jt} \tag{4.18}$$

Equations 4.17 and 4.18 show how the effect of wage dispersion on performance can vary by the level of wage dispersion itself at both the aggregate and sectoral level in these models. Adding the extra terms to capture the non-linearities in the relationship to the model and estimating by system GMM yields no significant aggregate or sectoral level results.

Weighted Regressions

Due to the nature of the sampling of establishments for the ARD and the way the estimation sample for this analysis has been chosen, this section presents the results of the analysis when using sampling weights. Contained within the ARD is a database of each unit which could have been sampled which also contains the number of employees. This is used to calculate for each year and within 8 size bands the probability that an enterprise was selected. The weight is calculated as the inverse of this probability, giving relatively more weight to the smaller enterprises.

The 7th row in Table 4.6 shows the aggregate level results equivalent to those in the 5th row (the short run effects estimated by system GMM) when using weights to account for the large firm bias.

Although the coefficients change when using weights, none are significant. Table 4.16 shows the results of weighting the regression at the sectoral level and the same result holds - weighting the regressions produces entirely insignificant results.

Alternative Wage Inequality Measures

The final two rows of Table 4.6 and Tables 4.17 and 4.18 show the results of calculating alternative measures of wage inequality - one from the residuals of the pooled OLS log wage regression (i.e. corresponding to the first two columns of Table 4.3), and one from the raw wages themselves rather than residuals.

The results are again reported for the system GMM estimates of the short run effects for the purpose of comparison with the preferred estimator from the main analysis.

There is slightly stronger evidence of a relationship between wage inequality and firm performance when using the pooled OLS residuals than the fixed effects residuals, but this is still limited to two significant coefficients at the sectoral level and one at the aggregate level (which is only marginally significant at the 5% level and not at the 1% level). There is therefore still little persuasive evidence of a link between residual wage inequality and firm performance.

The results for raw wages suggest some relationship between inequality and performance. At the aggregate level all measures of wage inequality yield a positive and significant coefficient except for the 50/10 differential. At the sectoral level three significant coefficients are also found for the production sector (the exception being the 90/50 differential) and a significant effect of the standard deviation for the catering sector.

These robustness checks have shown that the insignificance of the results are not due to the particular specification chosen with an allowance for non-linearities in the inequality-performance relationship, weighting to correct for large firm bias, and the calculation of an alternative measure of residual wage inequality all resulting in largely insignificant results as in the main analysis.

Raw, as opposed to residual, wage inequality produces significant results at the aggregate level and in the production sector, but the other sector remain insignificant.

4.7 Summary and Conclusions

This chapter has provided evidence on the relationship between firm performance and wage inequality. It aimed to improve on existing evidence on this issue for the UK by considering a range of wage inequality measures and econometric techniques as well as expanding the scope of the analysis to sectors other than manufacturing.

The analysis presented here has shown that selecting the appropriate estimator is important in determining the overall result. Many of the previous studies which have addressed the same issue have not used a system GMM approach despite the persistence in firm productivity.

The results are mixed and sensitive to the estimator used but with the preferred estimator there is no evidence found for the fairness hypothesis. Depending on the wage measure used there is either no effect to be found at either the aggregate or the sectoral level, or the results suggest a positive relationship between wage inequality and firm performance.

A reason for the lack of evidence on a significant relationship between wage inequality and firm performance could be that industry level wage inequality is a poor proxy for firm wage inequality. This will be the case if there is large variation in inequality at the firm level which cannot be represented by an industry level aggregate. This violates the assumption which was imposed on the empirical approach.

The lack of significant results makes sense if the effects are interpreted directly as the effects of industry level wage inequality on firm performance, rather than treating the industry level measures as proxies for firm level measures of inequality. In this case the lack of relationship between the two can be explained as employees having no knowledge of industry level wage inequality, and even if this was not the case individuals are less likely to respond to changes in inequality within the industry rather than changes in inequality within their own firm.

Despite these limitations this analysis provides new insight into the relationship between wage inequality and firm performance in the UK by building on previous work. An improvement to this work could be made by using firm level wage inequality in the estimated models, however there is no dataset currently available in the UK with the required level of detail for such an improvement to be made.

Chapter Appendices

4.A Chapter 4 Figures

Figure 4.1: Distribution of Employment in the UK by Industry

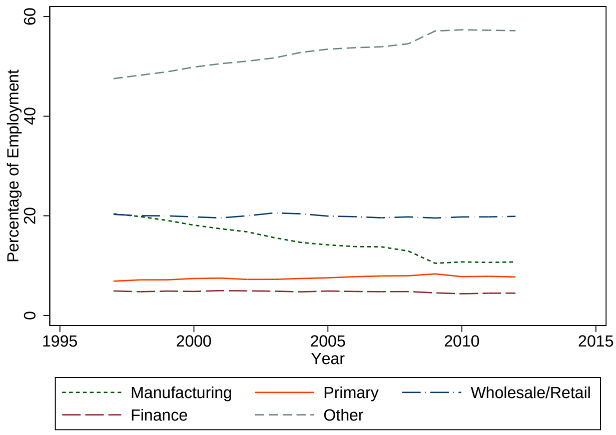


Figure 4.2: Low Skilled Labour in the Akerlof-Yellen Fair Wage Model

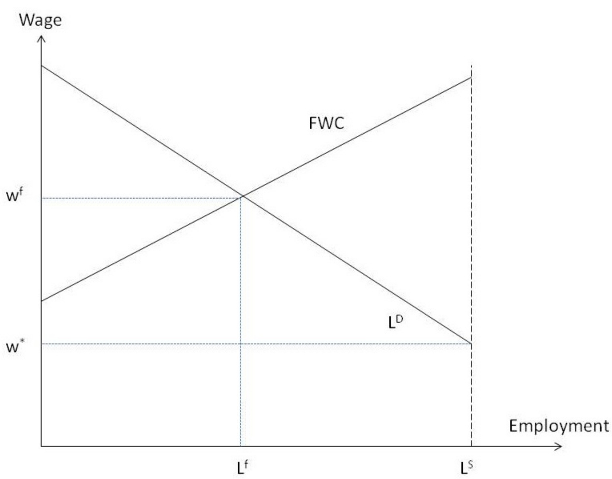


Figure 4.3: Industry Classifications Example

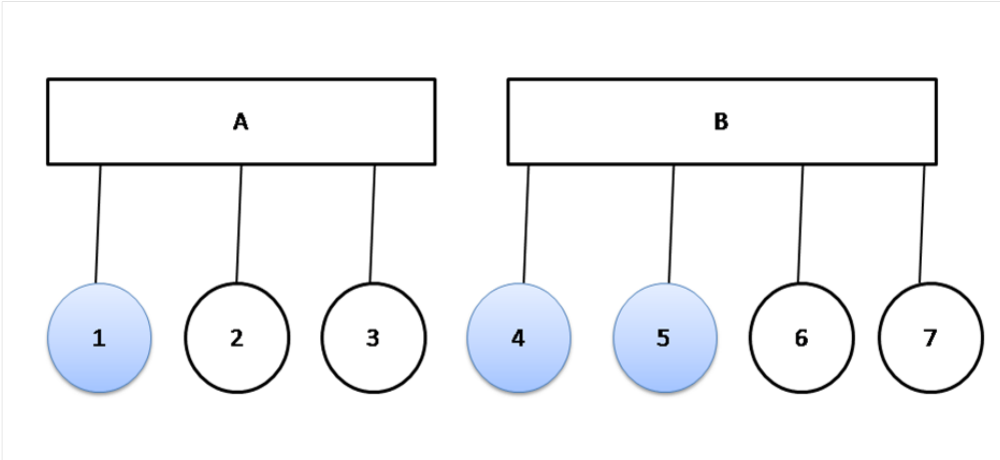


Figure 4.4: Distributions of Value Added, Labour, and Capital

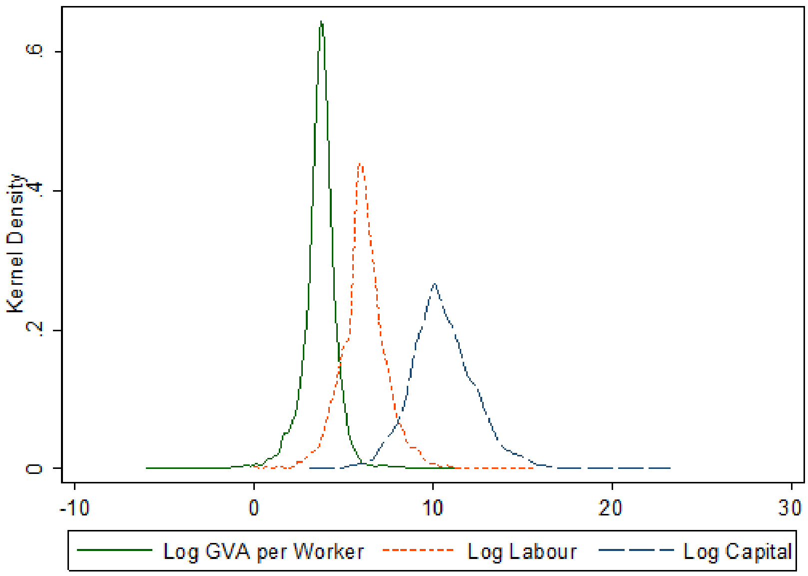


Figure 4.5: **Distribution of Percentile Differentials**

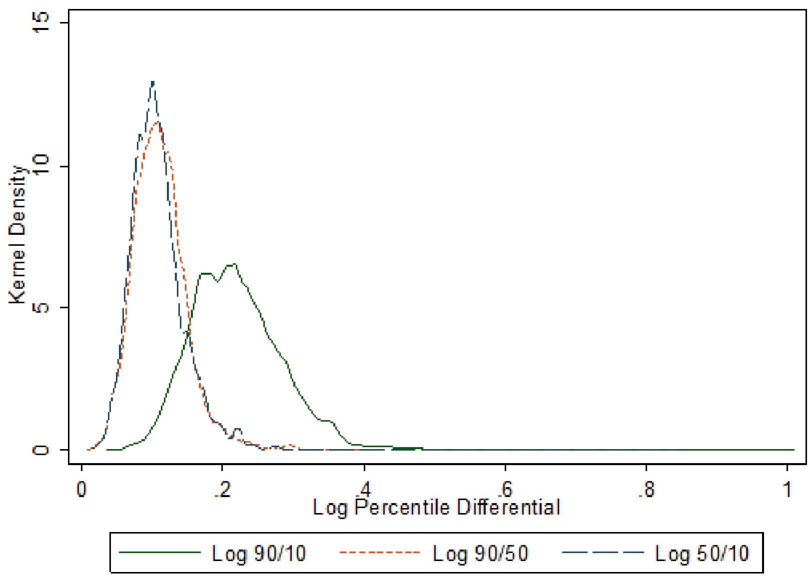


Figure 4.6: **Distribution of Standard Deviation**

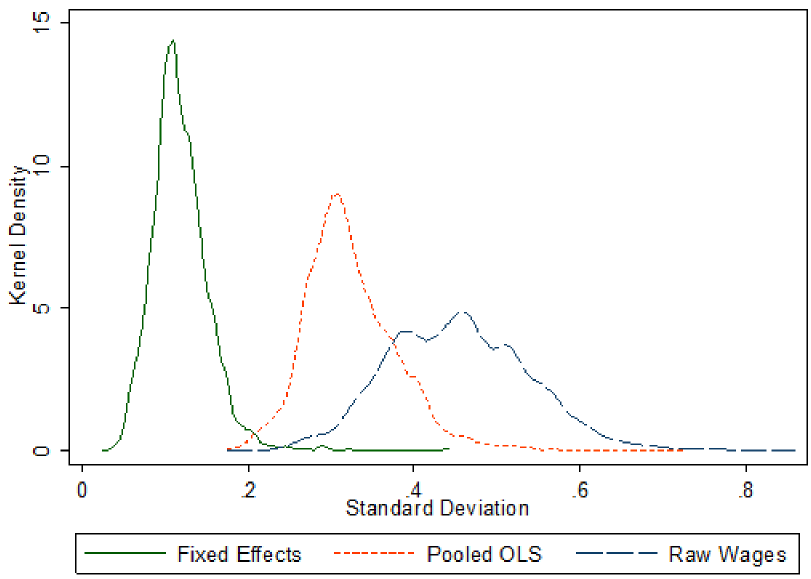


Figure 4.7: Log Total Gross Value Added by Sector

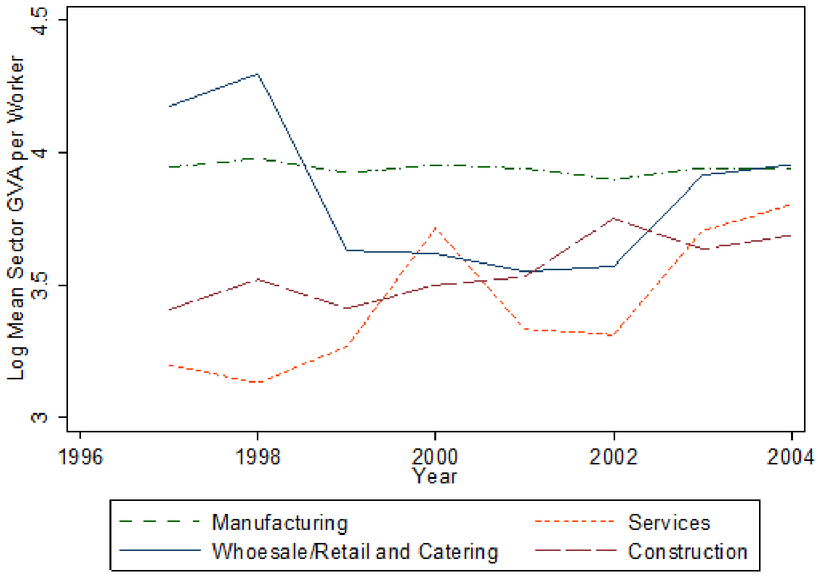


Figure 4.8: Log Total Capital Stock by Sector

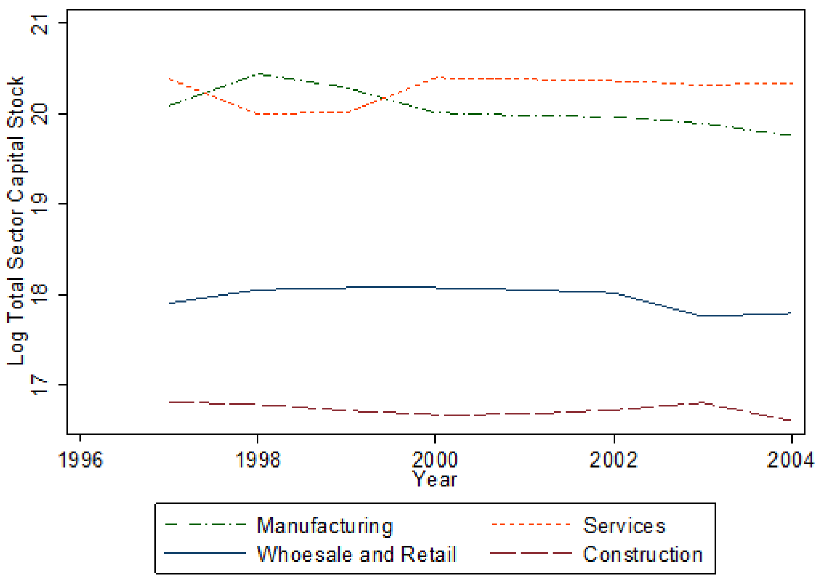


Figure 4.9: Log Total Labour by Sector

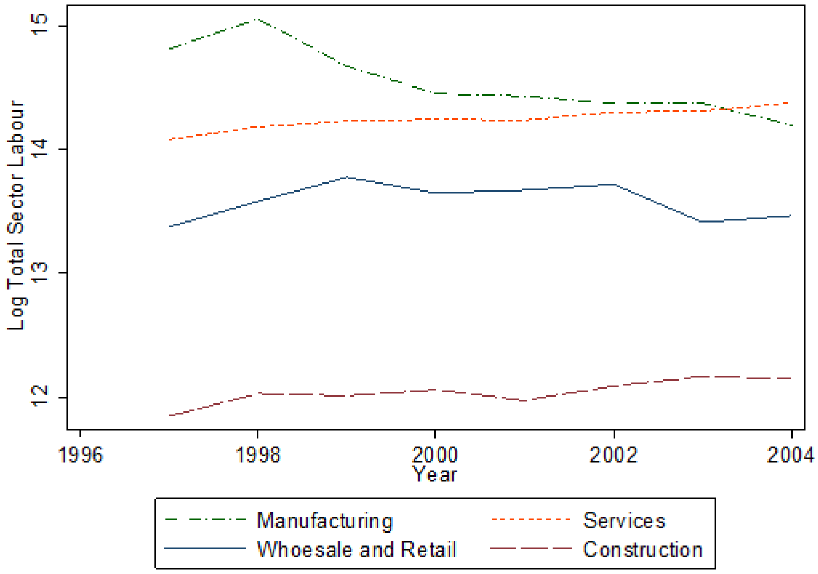
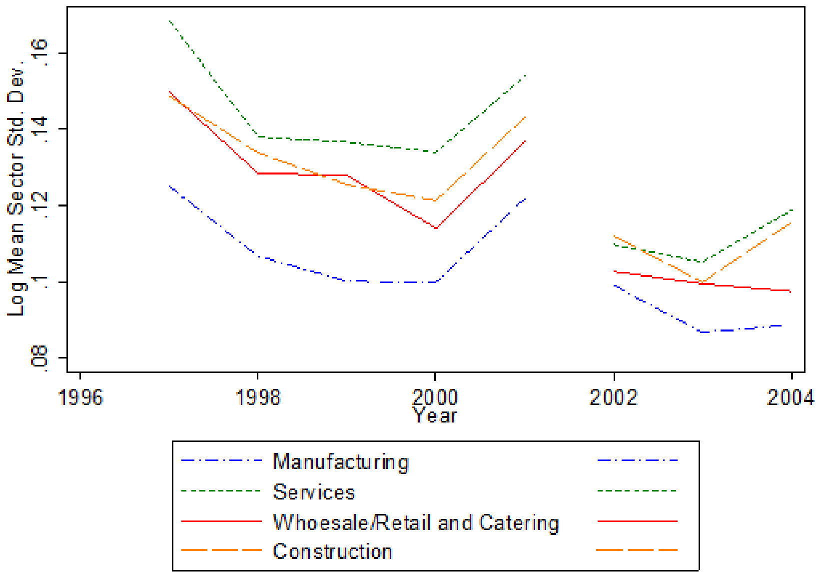


Figure 4.10: Average Wage Inequality by Sector



4.B Chapter 4 Tables

Table 4.9: Wage Inequality and Firm Performance Literature Summary

Author	Methodology	Data	Key Variables	Results
Leonard (1990)	OLS regression in levels and differences	US firm data for 1981 and 1985. A survey of managerial and executive compensation.	*Firm Performance*: Return on Equity *Dispersion*: Standard Deviation of Pay	No significant effect of standard deviation of pay on performance
Winter-Ebmer and Zweimuller (1999)	Pooled OLS and Fixed Effects	Panel of Austrian Firms 1975-1991	*Firm Performance*: Total Wage Level *Dispersion*: Standard Error of a Tobit regression model of wages	Positive relationship between wage dispersion and performance but an inverse U shaped relationship for white collar workers
Hibbs and Locking (2000)	Pooled OLS	Swedish plant and industry level data 1964 - 1993	*Firm Performance*: Log Real Value Added per Worker *Dispersion*: Squared coefficient of variation	No support for the "fair wage" hypothesis predictions - decreasing variance in wages is associated with a decrease in labour productivity
Beaumont and Harris (2003)	Arellano-Bond GMM estimator	UK plant level data - Annual Respondents Database. Five UK manufacturing industries	*Firm Performance*: Log Real Value Added per Worker *Dispersion*: Ratio of non-manual to manual labour costs	Positive relationship between dispersion and performance for 4 of the 5 industries, negative for the 5th. Elasticities are significantly smaller for UK owned firms
Lallemand et al. (2004)	OLS and 2SLS	Belgian private sector firms with at least 200 employees	*Firm Performance*: Log Gross Profits per Worker *Dispersion*: standard deviation, coefficient of variation, maximum to minimum wage ratio	Positive and significant coefficients on the wage dispersion variables, larger in magnitude in the 2SLS models. There is therefore no evidence to support the fair wage hypothesis predictions.
Heyman (2005)	OLS, 2SLS, First Differences, Random Effects	Swedish firm data 1991, 1995	*Firm Performance*: Log Gross Profits per Worker *Dispersion*: Variance of log wage residuals, coefficient of variation and 90-10 percentile differential of raw wages	Residual wage inequality has a positive effect on firm performance when inequality is measured for the workforce as a whole and just amongst managers

Table 4.9 (continued): Wage Inequality and Firm Performance Literature Summary

Author	Methodology	Data	Key Variables	Results
Martins (2008)	OLS, Fixed Effects	Census of Firms in Portugal 1991-2000 (including only firms with at least 20 employees)	*Firm Performance*: Total Sales per Worker *Dispersion*: Standard deviation of log wage residuals, 90-10 percentile differential of log wage residuals	OLS results suggest a positive and significant relationship between wage inequality and firm performance but when accounting for firm heterogeneity with fixed effects the relationship is found to be negative and significant.
Jirjahn and Kraft (2007)	OLS	German manufacturing firms.	*Firm Performance*: Gross Value Added per Employee *Dispersion*: Percentage difference in highest hourly wage of a skilled blue collar worker and the lowest hourly wage of an unskilled blue collar worker	Positive effect of wage dispersion on firm performance.
Esteves and Martins (2008)	OLS, 2SLS, Quantile Regression, Fixed Effects, IV Fixed Effects	Brazilian manufacturing and service sector establishments.	*Firm Performance*: Gross Value Added per Employee *Dispersion*: Coefficient of variation, Standard Deviation, Min-Max ratio, Standard error of wage regression	Positive relationship between pay and performance found for most specifications, with a few exceptions all are significant. No evidence in support of the fairness hypothesis.
Grund and Westergaard-Nielsen (2008)	OLS, Fixed Effects	Matched Employer-Employee data from Denmark - private sector firms with at least 20 employees.	*Firm Performance*: Gross Value Added per Employee *Dispersion*: Coefficient of variation	A statistically insignificant relationship between wage dispersion and firm performance is found. The OLS results give an inverse U shaped relationship but this effect becomes insignificant when using fixed effects. There is a U shaped relationship between wage growth dispersion and performance with 98% of firms in the sample located on the downward sloping portion of the relationship.

Table 4.10: ARD Sampling Frame

Sample Period	Establishment Size	Sampling Proportion
1970-1971	Under 25	0
	25 or more	All
1972-1977	Under 20	0
	20 or more	All
1978-1979	Under 20	0
	20-49	0.5
	50 or more	All
1980-1983	Under 20	0
	20-49	0.25
	50-99	0.5
	100 or more	All
1984	Under 20	0
	20-49	0.5
	50 or more	All
1985-1988	Under 20	0
	20-49	0.25
	50-99	0.5
	100 or more	All
1989	Under 20	0
	20-49	0.5
	50 or more	All
1990-1994	Under 20	0
	20-49	0.25
	50-99	0.5
	100 or more	All
1995-1997	Under 10	0.2
	10-49	0.25
	50-99	0.5
	100-199	0.75
	200 or more	All
1998 onwards	Under 10	0.25
	10-99	0.5
	100-249	All or 0.5 (industry dependent)
	250 or more	All

Table 4.11: Sector Level Pooled OLS Inequality-Performance Coefficients

	Log 90/10	Log 90/50	Log 50/10	Std. Dev.
Production	1.454**	1.929***	1.311*	1.097*
	(0.003)	(0.000)	(0.034)	(0.043)
Services	1.723	4.103	0.764	0.037
	(0.437)	(0.163)	(0.809)	(0.992)
Wholesale	-0.513	-0.767	-1.409	-1.478
	(0.573)	(0.553)	(0.293)	(0.240)
Retail	2.040**	2.883*	1.992*	2.274*
	(0.001)	(0.000)	(0.027)	(0.024)
Motors	2.603***	3.521**	2.509	0.321
	(0.000)	(0.001)	(0.080)	(0.897)
Construction	0.621	1.199	-0.741	-1.229
	(0.445)	(0.099)	(0.431)	(0.104)
Property	-0.435	0.544	-2.298	7.184
	(0.820)	(0.733)	(0.579)	(0.200)
Catering	0.673	0.96	0.123	-1.661
	(0.408)	(0.521)	(0.906)	(0.223)
Observations	16,735	16,735	16,735	16,735

P values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.12: Sector Level Fixed Effects Inequality-Performance Coefficients

	Log 90/10	Log 90/50	Log 50/10	Std. Dev.
Production	0.162	0.49**	-0.058	0.136
	(0.249)	(0.004)	(0.792)	(0.315)
Services	-0.451	0.116	-1.229**	-1.14
	(0.148)	(0.788)	(0.006)	(0.097)
Wholesale	-0.675	-0.455	-1.45	-0.936
	(0.398)	(0.576)	(0.301)	(0.248)
Retail	-0.046	0.494	-0.57	-0.49
	(0.910)	(0.268)	(0.418)	(0.490)
Motors	1.287**	2.026**	1.157	-2.303
	(0.035)	(0.005)	(0.147)	(0.338)
Construction	-0.519	-0.05	-1.171	-1.309
	(0.248)	(0.919)	(0.097)	(0.135)
Property	-1.2	-0.127	-2.964	-1.147
	(0.443)	(0.954)	(0.107)	(0.762)
Catering	-0.744	-0.958	-0.97	-1.885
	(0.334)	(0.360)	(0.371)	(0.037)
Observations	16,735	16,735	16,735	16,735

P values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.13: Sector Level IV Fixed Effects Inequality-Performance Coefficients

	Log 90/10	Log 90/50	Log 50/10	Std. Dev.
Production	0.141	0.44	-0.011	0.197
	(0.295)	(0.012)	(0.959)	(0.116)
Services	-0.281	0.243	-0.895*	-0.562
	(0.330)	(0.542)	(0.025)	(0.390)
Wholesale	-1.839	-1.139	-3.626	-1.575
	(0.133)	(0.229)	(0.115)	(0.130)
Retail	0.122	0.491	-0.154	-0.055
	(0.732)	(0.232)	(0.781)	(0.897)
Motors	1.394	2.574**	0.503	-2.368
	(0.061)	(0.002)	(0.588)	(0.313)
Construction	-0.398	0.303	-1.291	-0.845
	(0.386)	(0.546)	(0.064)	(0.343)
Property	-1.004	-0.066	-3.848	-1.903
	(0.426)	(0.957)	(0.137)	(0.477)
Catering	-0.907	-0.942	-0.856	-2.38*
	(0.303)	(0.372)	(0.458)	(0.019)
J-Test P Value	0.648	0.702	0.657	0.626
Observations	14,335	14,335	14,335	14,335

P values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.14: Sector Level First Difference Inequality-Performance Coefficients

	Log 90/10	Log 90/50	Log 50/10	Std. Dev.
Production	0.114	0.204	0.047	0.196
	(0.338)	(0.147)	(0.800)	(0.192)
Services	-0.147	0.071	-0.482	-0.304
	(0.332)	(0.712)	(0.054)	(0.360)
Wholesale	-1.482	-0.667	-2.999	-0.682
	(0.322)	(0.466)	(0.251)	(0.482)
Retail	0.132	0.736*	-0.592	-0.017
	(0.670)	(0.026)	(0.271)	(0.979)
Motors	1.16*	2.108**	0.42	0.394
	(0.021)	(0.006)	(0.738)	(0.889)
Construction	0.206	0.471*	-0.142	0.24
	(0.598)	(0.024)	(0.814)	(0.584)
Property	-1.223	-1.595	-1.785	-2.071
	(0.216)	(0.206)	(0.240)	(0.231)
Catering	-0.578	-1.059	-0.167	-1.349
	(0.453)	(0.218)	(0.873)	(0.068)
Observations	14,110	14,110	14,110	14,110

P values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.15: **Sector Level IV First Difference Inequality-Performance Coefficients**

	Log 90/10	Log 90/50	Log 50/10	Std. Dev.
Production	0.026	0.114	0.094	0.229
	(0.847)	(0.502)	(0.665)	(0.223)
Services	-0.212	0.193	-0.642	-0.127
	(0.344)	(0.482)	(0.069)	(0.782)
Wholesale	-2.55	-1.374	-4.363	-0.726
	(0.194)	(0.202)	(0.192)	(0.544)
Retail	-0.205	0.007	-0.327	-0.139
	(0.604)	(0.987)	(0.570)	(0.821)
Motors	0.403	1.242	-0.165	-2.11
	(0.544)	(0.117)	(0.929)	(0.479)
Construction	0.172	0.888*	-0.561	0.405
	(0.703)	(0.021)	(0.295)	(0.521)
Property	-1.906	-3.233	-1.512	-2.854
	(0.081)	(0.112)	(0.200)	(0.412)
Catering	-1.135	-1.755*	0.237	-1.009
	(0.238)	(0.029)	(0.853)	(0.427)
J-Test P Value	0.260	0.263	0.265	0.259
Observations	11,963	11,963	11,963	11,963

P values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.16: Sector Level Dynamic Model: Short Run (Weighted)

	Log 90/10	Log 90/50	Log 50/10	Std. Dev.
Production	0.37	0.494	0.441	-0.015
	(0.210)	(0.220)	(0.301)	(0.979)
Services	0.433	0.944	0.297	0.482
	(0.582)	(0.376)	(0.773)	(0.747)
Wholesale	-2.037	-2.922	-1.565	-3.387
	(0.357)	(0.490)	(0.737)	(0.380)
Retail	0.303	0.65	-0.113	0.148
	(0.500)	(0.268)	(0.867)	(0.838)
Motors	-3.597	-5.523	-4.019	-7.584
	(0.373)	(0.339)	(0.487)	(0.150)
Construction	0.378	1.402	-1.18	-0.541
	(0.543)	(0.321)	(0.443)	(0.640)
Property	-3.768	-5.185	-6.408	-6.882
	(0.416)	(0.335)	(0.530)	(0.369)
Catering	0.014	1.428	-1.385	-5.476
	(0.994)	(0.350)	(0.458)	(0.268)
Observations	14,202	14,202	14,202	14,202

P values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.17: Sector Level Dynamic Model: Short Run (Pooled OLS Residuals)

	Log 90/10	Log 90/50	Log 50/10	Std. Dev.
Production	0.162	0.229	0.089	0.332
	(0.179)	(0.101)	(0.579)	(0.210)
Services	0.899*	1.303	1.148	2.010*
	(0.049)	(0.063)	(0.057)	(0.033)
Wholesale	-0.161	-0.644	0.748	0.121
	(0.766)	(0.410)	(0.106)	(0.865)
Retail	-0.021	-0.231	0.105	0.153
	(0.842)	(0.569)	(0.494)	(0.674)
Motors	-0.216	0.052	-0.802	-1.253
	(0.764)	(0.948)	(0.320)	(0.436)
Construction	-0.1	0.276	-0.613	-0.472
	(0.798)	(0.636)	(0.129)	(0.432)
Property	1.163	1.226	1.896	1.549
	(0.240)	(0.437)	(0.235)	(0.468)
Catering	-0.338	0.093	-0.768	0.161
	(0.533)	(0.803)	(0.423)	(0.851)
Observations	14,202	14,202	14,202	14,202

P values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.18: Sector Level Dynamic Model: Short Run (Raw Wages)

	Log 90/10	Log 90/50	Log 50/10	Std. Dev.
Production	0.155*	0.101	0.335*	0.391*
	(0.029)	(0.175)	(0.011)	(0.030)
Services	0.41	0.567	0.356	1.348
	(0.390)	(0.066)	(0.682)	(0.210)
Wholesale	0.212	0.343	0.144	0.493
	(0.342)	(0.265)	(0.706)	(0.480)
Retail	0.047	-0.07	0.478	-0.188
	(0.740)	(0.676)	(0.183)	(0.720)
Motors	0.06	-0.056	0.525	-0.757
	(0.918)	(0.921)	(0.758)	(0.541)
Construction	0.458	0.251	1.418	0.876
	(0.392)	(0.631)	(0.159)	(0.495)
Property	-0.212	-1.096	0.413	-1.946
	(0.706)	(0.481)	(0.632)	(0.335)
Catering	0.367	0.183	0.841	0.938*
	(0.095)	(0.654)	(0.242)	(0.006)
Observations	14,202	14,202	14,202	14,202

P values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 5 Conclusions

The aim of this thesis has been to examine aspects of wage inequality in the UK. The thesis has made three empirical contributions to the literature in this area. The first contribution, which is the subject of chapter 2, is to give an overview of the recent changes in wage inequality in the UK as a whole and putting this in context of the longer term trends in wage inequality since the 1970's. Chapter 3 presents the second contribution; to decompose the more recent changes in wage inequality identified in the first piece of work to examine the factors which have driven these changes in wage inequality. Chapter 4 provides the final contribution which is to add to the literature relating wage inequality to the performance of firms. All of these contributions are empirical in nature and use UK micro-data.

5.1 Summary of the Thesis

Chapter 2 provides an analysis of the trends in UK wage inequality over the period 1975-2011. The aim is to identify changes in wage inequality for the UK as a whole and also for disaggregated sections of the economy by industry, occupation, public/private sector, and gender. This is performed by estimating the parameters of distributions for annual cross sections of wage data and calculating measures of wage inequality from the parameter estimates. The advantage of this technique is that it provides a unified framework for calculating any measure of wage inequality for which expressions have been derived as functions of the distribution of parameters, which also allows standard errors to be estimated.

This approach has previously been most commonly applied to estimating distributions of household income. This thesis contributes to the literature by applying the approach to

UK wages over a long time horizon, using the recent availability of the NES and ASHE datasets which provide the high quality of wage data required for this type of analysis. The Dagum distribution was judged to be the appropriate distribution to model the wage distribution as a whole, while the Pareto distribution was used to model the upper tail of the distribution to facilitate an analysis of wage inequality amongst the highest earners.

This chapter produces a number of interesting results. At the aggregate level, wage inequality has increased significantly between 1997 and 2011, but when comparing this to the earlier of experience of the UK economy using the NES data, this rate of increase has slowed down substantially. The slowdown in wage inequality growth compared to the 1980's appears to be at least partially due to compression in the bottom of the distribution, however the growth in extreme (top 10%) wage inequality has also slowed down compared to this earlier period and so this also plays a role in explaining the slowdown.

At the sub-group level, the increase in wage inequality has been markedly faster in the finance industry than in any other sub-group breakdown of the economy. When controlling for other factors, the finance sector is the factor with the strongest influence on wage inequality in the top 5% of the wage distribution in 2011.

Other results in this chapter include the consistency of greater wage inequality in the private sector compared to the public sector. This finding is robust to the measure of wage inequality considered and controlling for other factors in the inter-quantile and Pareto regressions. Controlling for other factors, wage inequality is higher for males than females and has become even more so between 1997 and 2011. The largest difference in wage inequality for the whole distribution is between the high skilled and low skilled occupations.

The second contribution made by this thesis to the literature is the decomposition analysis of the change in the UK wage distribution presented in chapter 3. The aim is to identify whether changes in UK wage inequality are due to within-group or between-group shifts in wage inequality and relates this to a human capital model of wages. The approach is to estimate wage equations by OLS where log wages are related to education and labour market experience. The decomposition technique then allows changes in wage inequality to be divided amongst "price" (or returns to human capital) effects, "quantity" (or the distribution of human capital) effects, and residual effects.

The results of this chapter found different trends in inequality for males and females, with the change in inequality for males in particular showing a break around 2005. This corresponds with the findings of the previous chapter for overall wage inequality using the same dataset. For both males and females the overall change in wage inequality was predominantly determined by within-group changes in wage inequality

Changes in wage inequality were predominantly driven by the bottom end of the distribution during the decline in inequality observed for males until 2005. This, along with the dominance of the unobservables effect in the decomposition, suggests that the introduction of the National Minimum Wage in 1999 played some role in this. After 2005, the increase in wage inequality was predominantly driven by the top of the wage distribution, with the within-group effects still dominating the decomposition.

Chapter 4 provides an analysis of the relationship between wage inequality and the performance of UK enterprises. There has been little work on this area for the UK, with the exception of Beaumont and Harris (2003). This chapter attempts to build on their work by using more recent ARD data than that used in their study, enabling sectoral level differences to be analysed. Furthermore, the chapter is able to construct different measures of inequality, also considering residual wage inequality (calculated from the residuals of wage regression models rather than raw wages) following the work of Martins (2008) using Portuguese data.

The final results indicated that there was no significant relationship between wage inequality and the performance of UK enterprises in either the long or short run when estimated by system GMM at the aggregate level. Some short run significant effects are found at the sectoral level, both of which are positive and associated with inequality within the top of the residual wage distribution. These are, however, not robust to weighting the model to account for the large establishment bias in the sample selection.

The previous literature has used different techniques to account for various issues with the equation to be estimated, these include endogeneity of factor inputs in the production function and the level of wage inequality, unobserved firm heterogeneity, and dynamic effects in the dependent variable. Due to this breadth of econometric issues and estimators which have been used to deal with this issues, this chapter has presented results from a range of estimators in order to assess the sensitivity of the results obtained.

The conclusions drawn regarding the relationship between inequality and performance are sensitive to the estimator used. A standard OLS regression produces more significant results than the other estimators which are also typically larger in magnitude. Use of panel data estimators by comparison illustrate the importance of accounting for unobserved enterprise heterogeneity, with results changing substantially from the OLS estimates. There are also differences between fixed effects and first difference estimators.

5.2 Potential for Further Research

The findings in this thesis present a number possibilities for future research. The second chapter begins to model the parameters of distributions as functions of individual level variables in order to assess changes in inequality within sub-groups while controlling for other factors. An extension to this work could be to model these distribution parameters as a function of macroeconomic variables which could provide insight into how macroeconomic policy could potentially be utilised to influence the growth in wage inequality.

The findings presented in chapter 3 gave some insight into how human capital has played a role in the changes in wage inequality between 1997 and 2012. The results of this analysis suggested an important role of within-education/experience group effects on wage inequality, with shifts in the demand for labour within industries towards more human capital. An extension of the decomposition analysis would therefore be to account for industry effects in the regression model. Also, the findings of this chapter are based on LFS data. As this dataset provided a different picture of how wage inequality has changed since 1997 than the NES/ASHE data in chapter 2 it would be of interest to replicate the analysis presented in chapter 3 using the ASHE data in order to see how this impacts on the decomposition. The LFS was chosen because of the availability of human capital data (education and experience). Using the ASHE data to perform the decomposition analysis would require the use of proxies for these variables.

Future research could consider the other potential consequences of wage inequality. In addition to the possible impact on firms, wage inequality is likely to affect individuals. Further research could examine the impact of wage dispersion on individual well-being.

The findings from chapter 4 indicate a clear need for further work on the issue of the effects of wage inequality on firm performance. The lack of strong robust evidence of a relationship between residual wage inequality - or "fairness" and performance is likely due to the inadequacy of industry level wage inequality as a proxy for firm level wage inequality. Ideally, data would be available at the individual employee level within firms in order to obtain reliable measures of wage inequality within firms. For the UK however, such detailed data do not currently exist.

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