UK wage inequality: An industry and regional perspective

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ABSTRACT This paper looks at male wage inequality in the United Kingdom across industries and regions over a fifteen year period. After controlling for the heterogeneity of productivity characteristics across the population, that part of wage inequality which cannot be explained by observable worker characteristics is examined. This is undertaken at both the industry and regional level to assess the key themes dominate in the literature capable of explaining within-group wage inequality, namely: technology; globalisation; female participation; immigration; shifts in the supply of relative education across cohorts; and falling unionisation.

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1. Introduction.

The literature on wage inequality has identified a number of distinct trends. In particular the overall increase in wage inequality consists of two distinct phenomena. Firstly, there has been a noticeable increase in the returns to education and experience (Juhn *et al*, 1993 for the USA; and Schmitt, 1995; Machin, 1996 for the UK). Secondly, there has been a dramatic rise in wage inequality within groups, known as within-group wage inequality, the so-called increase in the returns to unobserved skills. In particular UK wage inequality occurring within age and experience groups increased by 23% from 1979 to 1993 (Machin, 1996). This paper focuses exclusively upon the increase in the returns to unobserved skills and attempts to explain what may have caused this over and above observable worker characteristics. Since skill is not directly observable[1] this paper follows others in the literature (see Juhn *et al*, 1993; Machin, 1996;; Katz and Autor, 1999; Bernard and Jensen, 2000; and Acemoglu, 2002) and calculates the returns to skill as the residual from a standard wage regression. A full explanation for changes in wage inequality needs to account not only for changes in the returns to observable skill measures but also for the large changes in within-group wage inequality.

Explanations for the large increases in within-group wage inequality are generally seen as a relative demand shift in favour of skilled labour (Katz and Autor, 1999). More recently evidence has pointed to relative supply shifts with a fall in the growth rate of educational attainment amongst cohorts born after the 1950s (Card and Lemieux, 2000). Apart from the forces of demand and supply a weakening of institutional frameworks which aids lower paid workers could also explain within-group inequality (Machin, 1996). After controlling for observable skills which have the potential to cause wage

[1] Typically economists have used occupation, education or years of schooling to proxy skills. However, there is no general consensus as to how skills should be measured. Moreover, employers themselves do not perceive skill shortages in a uniform way (Green *et al*, 1998).

differentials across workers, this paper tests explanations which are consistent with wage inequality occurring within groups. In particular these explanations are: skill-biased technological change; globalisation; increasing female participation; immigration; changes in the relative supply of education across cohorts; and falling union power. The contributions this paper makes are:

(i) wage inequality is considered after controls have been made for observable skills in the form of education and occupation for each industry and region, known as residual or within-group wage inequality. This is deemed important in so far as previous studies typically take a measure of wage inequality to be a ratio of one decile to another or the standard deviation of wages. However, such an approach assumes a homogeneous distribution of productivity characteristics. Moreover, Acemoglu (2002); Levy and Murnane (1992) in their widely cited survey of the literature concluded that the most important unresolved puzzle concerned the growing trend in residual wage inequality;

(ii) to examine a number of industries including the Service sector – this adds to the existing literature which is predominantly for the Manufacturing sector only or for the UK as a whole (Machin, 1996; Gosling *et al*, 2000);

(iii) to investigate how within-group wage inequality has evolved across regions. At present there is an absence of empirical evidence on UK regional wage inequality. This is somewhat of a surprise given the well documented North-South divide in wages Blackaby and Manning (1990); and Cabinet Office (1999). Moreover, Duranton and Monastiriotis (2000) find evidence of a North-South divide in UK wage inequality where the gap has increased over time[2];

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[2] The existence of a North-South divide suggests that regional labour markets operate in isolation with limited mobility across regions. This is consistent with recent research where in a typical year less than 2% of the work force change region (McCormick, 1997). Furthermore, estimates show (not included, available upon request) the existence of different education premia across regions in any year plus their persistence over time. This suggests that regional labour markets do not adjust even in the long run to equate the returns to education - which is what one would expect if there was perfect mobility between regions.

(iv) to assess any remaining inequality at the industry and regional level in terms of technological change, trade intensity, female participation, immigration, falling relative supply of education across cohorts and falling union power. This occurs in a multivariate framework, previous work has typically considered only one or two of the explanations at once – not all simultaneously (the analysis of Canadian wage inequality by MacPhail, 2000 is an exception). Following from points (ii) and (iii) above the argument herein is that any theory of the rise in wage inequality in the UK as a whole should also be capable of explaining any heterogeneity which exists across industries and regions.

The following section discusses in more detail those factors which have the potential to explain within-group wage inequality. Section 3 introduces the empirical methodology, and section 4 considers the data required to undertake the analysis. First stage results are given in Section 5, followed by the second stage analysis to test the potential causes of within-group wage inequality at the both the industry and regional level in Section 6.

2. Explanations of within-group wage inequality.

A number of explanations exist which are consistent with increasing wage inequality occurring within groups. The two most common are skill-biased technological change and the growth in international trade. One of the major theoretical arguments for rising wage inequality is that technological change has favoured the skilled worker.

The evidence that skill-biased technological change has increased demand in favour of skilled labour is twofold, both indirect and direct. Indirect evidence has relied upon residual wage inequality from standard earnings functions, whilst direct evidence is based upon correlation's between wage differentials and indicators of technological progress. The indirect evidence is open to criticism since empirically technical change is typically defined to be the amount of change in relative wages that cannot be explained by observable characteristics, that is the residual. More recently direct evidence has provided a link between indicators of technology, such as computer use or research and development intensity, and wage inequality (Krueger, 1993; Autor *et al*, 1998; and Machin and Van Reenen, 1998).

Globalisation arguments suggest that developed countries have become increasingly open to competition from lower wage developing economies. Consequently, firms have taken the opportunity to gain from these lower costs by substituting unskilled intensive production abroad. A number of authors have recently argued that such outsourcing is important in explaining wage inequality (Wood, 1994, 1998; Anderton and Brenton, 1999; and Feenstra and Hanson, 1999).

Less common explanations apparent in the literature which focus on market forces, are the role of female participation and immigration. Both of these factors may increase the supply of relatively low skilled labour, and thus drive down the wages of low skilled workers. However, this is unlikely given the fact that the supply of skilled labour has increased (Schmitt, 1995), aided by female participation (Harkness, 1996) and immigration (Bell, 1997) where both groups have become more skilled over time. Alternatively, the impact of both changing female participation rates, and immigration is largely dependent upon the degree of substitutability for low skilled males. For example, if females or immigrants are substitutes to low skilled workers, then a rise in the supply of either leads to a fall in the demand for the lower skilled (Topel, 1997).

Another possible cause of increasing inequality has only recently received attention – changing inter cohort skills over time (Card and Lemieux, 2000). This argument rests on the fact that the gap between highly educated and lower educated men has increased drastically over the past three decades, but at the same time the gap for older males has remained nearly constant. Cohorts born in the first half of the twentieth century had a steady increase in educational attainment offsetting rising demand for higher skilled labour. However, this trend was reversed by the early 1950s and cohorts entering the labour market at this time experienced slowdowns in the rate of growth of educational attainment. In terms of demand and supply analysis this means that not only may the relative demand for highly skilled labour have increased – possibly caused by the above factors (resulting in higher skilled wages), but as new cohorts entered the labour market, with falling rates of skill acquisitions, the relative supply of skilled labour may have fallen exacerbating the increase in wage inequality. Both Card and Lemieux (2000) looking at three countries including the UK, and Gosling *et al.* (2000) for the UK find that changing education patterns across cohorts over time have had a large impact upon wage inequality.

Aside from market force explanations, other authors have stressed the importance of labour market institutions, in particular trade unions, in shaping the way labour markets have responded to these changes in demand and supply (Freeman, 1993; Gosling and Machin, 1995; and Machin, 1997). Market force explanations can explain many of the similarities in the development of the wage structure, but are less illuminating when attempting to explain international differences (Katz *et al.*, 1995; Gottschalk and Smeeding, 1997). Following the same logic, different degrees of erosion of union power across industries and regions over time may account for some of the trend in wage inequality, and potential differences.

Having introduced the theories which can explain within-group wage inequality the following section outlines the empirical model used to control for the heterogeneity of productivity characteristics amongst the population and assess the competing claims capable of explaining any remaining inequality. This is undertaken in an attempt to explain the unresolved puzzle of residual or within-group wage inequality (Levy and Murnane, 1992).

3. Empirical Methodology.

The empirical approach takes place in two distinct stages. Initially, a standard wage equation is estimated pooled across individuals and estimated across three time periods 1981-85, 1986-90 and 1991-95 using micro data based upon the individual to control for differences across the population in experience, education, occupation, regional location, industry affiliation and time – all of which may influence wages. This enables wage inequality to be split into within-group and between-group components, following Juhn *et al.* (1993), Bernard and Jensen (2000)[3,4]. The reason the wage equation is estimated across three pooled time periods is to allow for time varying returns to human capital controls, as in Katz and Autor (1999), Bernard and Jensen (2000)[5]. In the second step aggregate industry (regional) data is used to proxy those factors introduced in section 2, in an attempt to explain the trend in within-group wage inequality over time.

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[3] Note that traditionally the residual from a standard wage equation was seen as indirect evidence of skill-biased technological change (Katz and Autor, 1999). However there is no reason why the other factors mentioned in section 2 couldn't also explain part of the remaining residual, see Bernard and Jensen (2000) – interpreted in the literature as unobservable skills.

[4] Only the former is considered in this paper, since the majority of inequality both in the UK and the USA is unexplained by between-group components (i.e. observable characteristics), Gosling *et al*, (2000); Schmitt (1995); and Katz *et al*, (1995. Taylor (2002) examines how technology and trade may have influenced between-group determinants specifically educational and occupational returns.

[5] Another way to obtain industry (regional) residuals allowing for time varying returns would have been to estimate industry and regional specific equations for each year. This was tried initially and the trend in each inequality measure was largely unaffected (as found by Bernard and Jensen, 2000 for the USA). However, using this approach the sample sizes are small between 135 and 1,250 observations for industry equations and 90 to 565 observations for the regional equations. Consequently the degree of confidence one can have in the point estimates is limited. The approach used here follows Bernard and Jensen (2000) and Katz and Autor (1999), where the former recover time and region specific measures of within-group wage inequality from a pooled wage equation across three distinct time periods.

A two stage approach is adopted for a number of reasons. Firstly, including industry or regional proxies for the explanations of within-group wage inequality into a standard wage equation could result in aggregation bias where estimates are downwardly biased (Moulton, 1990). Blackaby and Murphy (1991), looking at wages across regions, use a two stage approach for the same reason. Secondly, even if the standard errors of the regression are corrected for aggregation bias, including proxies for technological change etc., in a wage equation tells us nothing about wage inequality, since the independent variable is the log wage level not an inequality measure – the focus of analysis in the paper i.e. the second moment of the residual. In other words the key thing of interest is any remaining inequality known as residual or within-group wage inequality which is largely unexplained by observable individual characteristics (Levy and Murnane, 1992; Gosling *et al.*, 2000; and Acemoglu, 2002). Thus a two stage methodology is adopted following Bernard and Jensen (2000) for the USA, where residual wage inequality is found after human capital controls and then regressed against its possible determinants.

3.1 Obtaining a measure of within-group wage inequality.

One problem with existing studies is that the measure of inequality used is typically a ratio of one relatively skilled group to a less skilled group, this raises the issue that any inference about the determinants of inequality assumes an equal distribution of human capital characteristics amongst groups of individuals. However, this is unlikely, and the approach taken compensates for the heterogeneity of productivity characteristics by deriving a measure of within-group wage inequality by industry and region. Thus initially a standard wage equation is estimated across individuals i over time t as follows:

$$\mathrm{Log}(\mathrm{Wages})_{it} = a + \boldsymbol{X}_{it} d_t + e_{it} \qquad (1)$$

where $e_{it} \sim IID\left(0, s^2\right)$. As mentioned above equation 1 is estimated across three time periods, where $t = 1981\text{-}85$, $t = 1986\text{-}90$ and $t = 1991\text{-}95$, thus allowing d_t to vary across the three periods (although the coefficient remains fixed within each period – as in Katz and Autor, 1999; and Bernard and Jensen, 2000). Equation 1 is estimated for white male head of households, in full time employment who are born in the UK. Individual human capital characteristics are given in the matrix ***X***, specifically experience, education, occupation, interactions between education, occupation and experience, plus controls for regional location, industry affiliation and time. Under such a scenario within-group wage inequality can be seen as the variance of the residual from the regression (Juhn *et al*, 1993). Then a wider dispersion of the residuals shows greater wage inequality occurring within-groups. Such inequality is important to understand, as the majority of wage inequality occurred within narrowly defined groups in the UK – Gosling *et al.* (2000). The interpretation given to the residual e_{it} from an equation based upon the above, is that after controlling for human capital endowments, occupation, regional location, industry and time remaining inequality can be referred to as within-group wage inequality.

3.2 Explaining trends in within-group wage inequality.

The second stage of the analysis considers the possible sources of within-group wage inequality (introduced in section 2) over time across industries and regions. To do this industry, region and time specific measures of within-group wage inequality are derived from the residuals in equation 1. The general format for estimating is:

$$\left(\hat{s}_e\right)_{gt} = \sqrt{\sum_{i=1}^{n}\left[\left(\hat{e}_i - \hat{\bar{e}}\right)^2 / (n-k)\right]_{gt}} = g + \boldsymbol{Z}_{gt}p + n_{gt} \qquad (2)$$

where, $\left(\hat{s}_e\right)$ is the standard deviation of the residual from equation 1 and $n_{gt} \sim IID\left(0, s^2\right)$. The subscript g represents that the regression is estimated either across industries or regions, pooled over t periods[6]. The matrix Z includes proxies for technological change, globalisation, female participation, immigration, cohort skills and union strength. Comparing estimates, the $\hat{p}$'s, on each of these proxies provides a simultaneous test of which factor is most important in explaining any remaining wage inequality. In terms of the expected direction of influence, both technology and trade intensity have increased over time (increasing demand for skilled labour), as has female participation and immigration (either increasing the supply of low skilled labour, or acting as substitutes for low skilled males) and so it is expected that for each influence $p > 0$. Conversely, a fall in the degree of unionisation is hypothesised to cause greater inequality as wage floors are eroded, and cohort education suggests slowdowns in the rate of growth of educational attainment again implying $p < 0$. The following section introduces the data used in equation 1 to control for observable worker characteristics and the proxies employed to explain within-group wage inequality in equation 2.

4. Data.

The first step of the analysis based upon equation 1, above, requires information on the individual, whilst for the second step more aggregated data at the industrial and regional level is required to gain measures of market forces and institutional changes. Specific factors controlled for in equation 1 are experience, highest educational qualification[7,8], occupation[9], regional location, industry and time. The data source used to

[6] Note that although it would have been possible to split the analysis into industries by region the cell sizes would have been small, but more importantly it would not have been possible to find proxies in the second stage that differ by industry and region. Consequently, the analysis considers industry and regional wage dispersion separately, following Bernard and Jensen (2000).

[7] Following Blackaby *et al.* (1997) the educational dummies were constructed as (1) Degree, including first and higher degrees; (2) Higher Vocational education; (3) A levels; (4) O levels; (5) Apprenticeships; (6) Other groups (i.e. a catch all category). The reference category is individuals with no qualifications.

[8] Education captures demand shifts better than years of schooling, Schmitt (1995), and recent research has shown that education captures demand changes better than occupation, Riley and

estimate equation 1 is the General Household Survey (GHS) which is a continuous survey of cross sections based upon individuals within the sample household. Six industries are derived over the period – Energy, Gas and Water; Manufacturing; Other Manufacturing; Construction; Transport and Communication; and Services. Although the GHS has ten industrial sectors it was only possible to gain a measure of technological change for the six defined sectors. Ten regions are considered over time: North; York & Humberside; North West; East Midlands; West Midlands; East Anglia; South East; South West; Wales and Scotland.

The more aggregated data used in the second stage of the analysis are required at the industry and regional level in order to proxy for the factors capable of explaining within-group wage inequality (introduced in section 2). The following describes the data used first at the industry level and secondly for the regional analysis.

4.1 Industry level data.

The analysis of six industries over a fifteen year period provides 90 observations when pooled. On the demand side technological shocks are proxied by research and development intensity for each industry. This is defined as research and development expenditure as a proportion of value added, using data from the OECD ANBERD data base and OECD STAN data base respectively – with all expenditure data deflated to 1981 prices. Globalisation in the tradable sector was proxied by trade intensity, defined as import expenditure as a proportion of value added. The source of the trade expenditure data was also the OECD STAN data base – again all expenditure data was deflated to 1981 prices.

Young (1999). Consequently, education is an important variable to have when identifying the impact of technology and trade (possible demand shifters) upon returns to observable skills.

[9] Occupational categories are given as: Professional, Management, Non-manual, Skilled manual, and Unskilled manual. The latter group is the reference category.

Immigration and female participation by industry were derived from the GHS, and calculated as those individuals born outside the United Kingdom (female) who were in employment (defined as working more than one hour per week) as a ratio to total industry employment size. For the supply side, following Card and Lemieux (2000), four cohorts are constructed, for those individuals born 1950-54, 1955-59, 1960-64 and 1965-1969. Aggregate supply effects are given by the ratio between high skilled (defined as degree holders) and lower skilled workers (defined as A level and O level holders) over time, given as (S_t/U_t). Similarly, age-group specific effects are defined as the relative supply of higher skilled labour in cohort j at time t, given by (S_{jt}/U_{jt}). Because relative supplies of higher skilled labour have not grown at a constant rate the following indicator of aggregate and age-specific effects (see Card and Lemieux, 2000) varies over time $Log(S_{jt}/U_{jt}) - Log(S_t/U_t)$. For the industry measure of relative supply of skills across cohorts the difference between age-specific and aggregate effects was calculated in the pooled sample and then recovered for each time period and industry and weighted across cohorts.

To try to gain a measure of union strength proved to be a relatively more difficult task than at first sight. Because union data is not available for one digit industries over the entire period the number of workers involved in strikes was used to proxy union strength. Information on strikes is available from the International Labour Organisation. At the economy wide level the trend in union membership/density is closely related to that of strikes over time, see Machin (1997).

4.2 Regional level data.

The estimation period of equation 2 across the ten regions was the same as at the industry level 1981 to 1995 giving 150 observations when pooled. Unfortunately, to gain a measure of technological change using R&D data was not possible, since the Office for National Statistics only started to collect this information post 1992. In order to try to gain a proxy for technological change the ratio of non-manual to manual labour was used obtained from the New Earnings Survey – consistent with previous research (Leslie and Pu, 1996; Lucifora, 1999; and MacPhail, 2000). Globalisation was considered to have the same impact across regions (basically this is because it is not possible to obtain a measure of globalisation at the regional level), also it is unlikely different regions experience varying degrees of openness to trade – and was defined as above, deflated to 1981 prices.

Immigration and female participation by region were derived from the General Household Survey, and calculated as those individuals born outside the United Kingdom (female) who were in employment (defined as working more than one hour per week) as a ratio to total regional employment size. For the regional measure of the relative supply of skills across cohorts the method used was as discussed above, with the difference between age-specific and aggregate effects calculated in the pooled sample and then recovered for each time period and region and weighted across cohorts. As with the industry level data trade union density or membership was not available consistently over the time period. In an attempt to proxy trade union strength the number of days lost through strikes for each region was used, based upon data from Regional Trends.

Summary statistics of the industry and regional level data used in the second stage of the empirical analysis are shown in Table A1 in the appendix. The table also shows the trend in each variable over the period 1981 to 1995 as increasing "+" or decreasing "-".

5. Wage equations, within-group industry and regional inequality.

Equation 1 is estimated across individuals and time split into three periods. The sample is restricted to white male head of households only, aged between 16 and 65, who are employed (not self employed), have only one job and are of UK origin. Pooling the data in this manner from 1981 to 1995 yields 45,550 observations, which when split into the three time periods 1981-85, 1986-90 and 1991-95 yields 17,071, 14,592 and 13,887 observations respectively. Table 1 below shows the results of estimating equation 1 across the three periods, all of which include experience in a quartic, observable measures of skill based upon education and occupational dummies, regional, industry and time controls, plus interactions between education and occupation, and between experience and observable skills. The specification used is very similar Katz and Autor (1999) for the USA.

<<TABLE 1 HERE>>

Clearly, the well-known patterns to returns to observable skills are evident in these regressions. In the first period 1981-85 the return to men with a degree relative to an unqualified individual was 0.502 log points or 65%[10] in levels, this fell during the second period to 42% before returning to 65% by the final period. Across each of the education categories the same pattern is evident – a fall in returns to education from the early 1980's to the late 1980's followed by a subsequent increase in the 1990's. Considering returns to occupations, excluding professionals and skilled manuals, each occupational group experienced increasing returns period on period, with managers having the greatest returns relative to unskilled manuals.

Tables 2 and 3 below show within-group wage inequality decomposed over time into industry specific measures. Clearly, within-group wage inequality has increased in each industry over the period 1981 to 1995. What is evident from Table 2 is that usually the Services experienced higher within-group inequality than Manufacturing and in any

[10] $\left(\exp^{d} - 1\right) \times 100$ where d is the return.

one year residual inequality in Manufacturing was never the largest in magnitude when compared to other industries. Table 3 shows the percentage change across each of the

<<TABLE 2 HERE>>

three periods in within-group inequality as well as changes in overall inequality (measured by the standard deviation of log wages). Again considering any one period the largest percentage increases in inequality, both overall and within-group, were not witnessed in the Manufacturing sector. The evidence from Tables 2 and 3 make it imperative that

<<TABLE 3 HERE>>

industries other than just Manufacturing or economy wages are considered since it is here that the level and increase in returns to unobserved skills has been the most rampant.

As with the industry level findings each region experienced different levels and trends in wage inequality after controls have been implemented for observable worker characteristics, as shown in Tables 4 and 5 below. Clearly, in almost all regions across the three time periods residual inequality increased, Table 5. Interestingly, in 1981 the

<<TABLES 4 AND 5 HERE>>

Midlands had the lowest levels of inequality, Table 4, yet by 1985 experienced large increases, averaging 35%, Table 5. By the 1990's York & Humberside and the South East had the greatest inequality although actual growth between 1991-95 was markedly different between the two regions at 16% and 3% respectively.

The results from the first stage have clearly indicated that heterogeneity exists across industries and regions, shown not only by changes in within-group inequality but also by the overall variance of wages. The question that arises from the first stage results of equation 1 (as Levy and Murnane, 1992 concluded), is what lies behind the increases in within-group wage inequality at the industry and regional level? The following section provides an insight to this.

6. Explaining within-group wage inequality.

Having discussed the results from the first step of the empirical process, and found that each industry experienced different trends in wage inequality (after human capital controls), the following looks at the results from the second stage of the empirical approach. Equation 2 is estimated across industries and then by regions.

6.1 Industry analysis.

The industry results are shown in Tables 6 to 8 below. In each of the tables apart from the final column univariate regressions of equation 2 are shown based upon regressing within-group industry inequality against each potential determinant one at a time. All estimates based upon fixed effects with robust standard errors[11]. Alternate columns control for time effects i.e. any unobserved aggregate trending variable could be driving both the LHS and RHS variables, as such it is important to know just how robust and sensitive the results are to time controls. Across all industries, Table 6, technological

<<TABLE 6 HERE>>

change is insignificant and explains less than 2% of the variation in inequality heterogeneity across industries and time. The impact of trade again explains around 2% of total variation in inequality, but is only significant in the absence of time controls. Our measure of de-unionisation proxied by strike data accounts for around 5% of the variation in the pooled estimation and is robust to time effects. Changing inter cohort skills over time, shown in the fourth column, indicate that new cohorts entering the labour market have experienced slower growth rates in skills, resulting in shifts to the relative supply curve detrimental to lower skilled males – thus adding to increasing inequality and the effects of relative demand shifts. Cohort effects not only have the

[11] Pooled estimation in first differences did not yield different conclusions to those below.

largest coefficient in magnitude when comparing each of the univariate regressions but also explain 36% of the variation of residual inequality across industries and time. Columns 5 and 6 consider the impact of supply side pressures upon residual inequality in the form of female participation and immigration. The coefficients are positive and remain significant in the event of time controls. This suggests that increasing female participation and immigration over time has adversely influenced inequality, either because females/immigrants are substitutes for low skilled males or because they are higher skill endowed than lower skilled males. The argument that females/immigrants are becoming more skilled over time relative to lower skilled males, and so are possible substitutes to lower skilled males, is more appealing, since this is consistent with the findings of Harkness (1996) for females and Bell (1997) for immigrants[12]. The final column of Table 6 considers a multivariate specification with all our potential variables. In the absence of time controls around 47% of the variation is explained, with the largest and significant coefficients being for cohort effects, trade and females. However, only cohort effects and female participation are robust to time controls.

The results in Tables 7 and 8 further the analysis by considering the influence of potential explanations for different industrial sectors, Manufacturing and Non-Manufacturing (defined as Energy, Gas and Water; Construction; Transport and Communication; and Services) respectively. Technology effects both in univariate and multivariate analysis are only significant in the presence of time controls and in Manufacturing, Table 7, with a coefficient of 0.06. Hence a one percentage point rise in R&D intensity increases wage inequality by around 0.06 percentage point, similar in magnitude to the effect found by Machin (1996). Technology has a positive coefficient, which indicates skill bias, as expected theoretically. That is, as wage inequality and

[12] Bell (1997) found that the gap between the educational attainment of immigrants and native males in the UK has grown in favour of immigrants over the period 1973 to 1992, i.e. successive cohorts of immigrants are more educated than native UK males.

technological development increased over the period a positive association between the two is indicative of technology favouring higher skilled workers[13].

<<TABLES 7 AND 8 HERE>>

Of the univariate regessions in Manufacturing union change and cohort effects explain the largest percentage of variation in inequality at 43% and 32% respectively, and both effects are robust to time controls. Conversely in Non-Manufacturing industries, Table 8, in the absence of time controls the largest explanatory power comes from cohort effects and female participation at 39% and 13%. Interestingly, the univariate regressions show a role for immigration outside of Manufacturing.

Considering the multivariate results across the sector split, in Manufacturing the only significant impacts come from trade and technology both robust to time controls, entering with the expected sign suggested an increase in demand for skilled labour. The largest coefficient is associated with trade intensity, outweighing the technology coefficient by over four times. There is some disagreement in the literature about whether technology or trade is the most important factor in causing increasing demand for skilled workers and consequently greater wage inequality (Machin and Van Reenen, 1998; Wood, 1994, 1998; Anderton and Brenton, 1999 and Feenstra and Hanson, 1999). The results for the Manufacturing sector that trade has a larger impact than technology, comes down in favour of the trade theory rationale backing the findings of Wood (1994, 1998); and Anderton and Brenton (1999) for the UK. However, although it is common in the literature to distinguish between technology and trade effects, Levy and Murnane (1992), it is possible that the trade variable could be accounting for the importation of

[13] However, causality may not run from technology to wage differentials, but rather from wages to technology. Hence, if workers who use new technology are better paid, is it because they are more able, or is it due to the fact that the new technology increases their productivity? Indeed, evidence for the USA does suggest that the former is true (Doms et al, 1997). Moreover, Caselli and Coleman (2001) find that higher levels of human capital (the more able) are associated with computer adoption across 89 countries (both OECD and non OECD) from 1970 to 1990.

new capital equipment i.e. technology. Furthermore, Coe and Helpman (1995) model trade as a means to the adoption of R&D undertaken in other countries. Acemoglu (2002) also argues that international trade may cause a change in the path of technological progress. Indeed a combination of increased openness to international trade coupled with endogenous technological change can give rise to accelerating skill biased technological change. As such, although it is common to discriminate between technology and trade, it is possible that increased international trade is a route for technological progress and so the distinction between what are often seen as main competing hypotheses capable of explaining rising wage inequality is perhaps somewhat blurred.

It is noticeable that in the multivariate analysis controlling for all possible causes of residual inequality simultaneously the coefficient on cohort effects becomes insignificant in Manufacturing. In comparison in Non-Manufacturing industries the largest and significant coefficients are from cohort effects and female participation, both robust to time controls – there is no role for technological change.

The analysis of Tables 6 to 8 has shown that there is a role for supply side pressures in explaining within-group wage inequality, although technology and trade are important in Manufacturing (as commonly found in the literature). However, cohort effects, which indicate changing patterns of skills by year of birth over time, when significant explain large proportions of remaining inequality in comparison to other potential candidates. The significance of cohort effects in explaining unobserved returns to skills is consistent with other work for the UK, Card and Lemieux (2000), and Gosling et al. (2000). Due to the magnitude of inequality outside of Manufacturing and the fact that the potential causes play a different role across sectors, it seems imperative that industries other than solely Manufacturing or economy wide wages are considered. Each potential explanation also has the expected sign of correlation with residual inequality where significant in the univariate and multivariate results.

Having considered the impact of market forces and institutional changes upon within-group industry wage inequality the following investigates their potential effects upon the evolution of within-group regional wage inequality across deciles – this is something which for the UK has been unexplored.

6.2 Regional analysis.

The regional results are shown in Tables 9 to 12 below, where in each of the tables apart from the final column univariate regressions of equation 2 are shown based upon regressing within-group regional inequality against each potential determinant one at a time. As with the industry level results all estimates based upon fixed effects with robust standard errors and alternate columns of the tables control for aggregate time effects. Table 9, below, shows estimates of equation 2 across all ten regions.

<<TABLE 9 HERE>>

The importance of institutions upon inequality is consistent with the findings of Blackaby and Murphy (1991), where unionisation influences regional wages, but this is not robust to time controls, suggesting that the prior significance of unions was due almost entirely to its aggregate trend movements and not due to variation across regions. Only immigration is insignificant in the univariate regressions and all other explanations of residual inequality, with the exception of unions, are robust to time controls. Female participation explains the largest proportion of the variation in inequality across regions and time at 57%. In the final column of Table 9 the largest coefficients in magnitude are trade and technology intensity – female participation is driven to insignificance when entered simultaneously with other controls.

Tables 10 and 11, below, consider the impact of each potential factor in the North and South of the UK separately – where the North is defined as: North; York & Humberside; North West; and Scotland. The reason for doing this is that given evidence that there may well be a 'North-South' divide in economic fortunes, Blackaby and Manning (1990); and Duranton and Monastiriotis (2000), it seems logical that the causes

<<TABLES 10 AND 11 HERE>>

of inequality may differ across the two regions. Indeed this is what the evidence in Tables 10 and 11 suggests. In the univariate results technology intensity explains the largest percentage of variation in the North at 60%, whilst in the South it is female participation at 61%. Furthermore, considering the multivariate specifications, for the North of the economy trade has a role to play and is the only significant coefficient in the presence of time controls. Noticeably, technology effects are only significant in the South and the impact of unions is small and insignificant when time controls are entered.

The major noticeable difference between the North and South is that there is a role for supply side pressures in the South with female participation being significant even in the presence of time controls. In terms of the magnitude of the coefficients female participation is the dominate cause of residual inequality in the South. The finding of the significance of female participation in explaining inequality is also consistent with the results of Monastiriotis (2000). As with the industry level results both the univariate and multivariate analysis show correctly signed coefficients.

One could argue that regional residual wage inequality could be influenced by de-industrialisation that is the changing structure of industry employment within regions[14]. Increased wage inequality is a possible outcome of de-industrialisation as workers shift from the relatively high wages of manufacturing to lower paid jobs in the service sector,

[14] Note that de-industrialisation causes between industry demand shifts and so wasn't considered in the industry analysis since this hypothesis isn't capable of explaining rising inequality within industries.

see Harrison and Bluestone (1990); Wood(1994, 1998). In order to investigate whether this affects the regional results gained so far the proportion of manufacturing employment to total employment across regions and time is included as a control in estimating equation 2. The results are shown in Table 12, below.

<<TABLE 12 HERE>>

The first two columns of Table 12 show univariate and multivariate results across all regions, whilst columns 3 and 4 give corresponding results for the North and the final two columns results for the South. What is clear from Table 12 is that where significant in the univariate regressions (without time controls) de-industrialisation can only explain around 4½% of the variation in residual regional inequality – small in comparison to other effects – see above. Across all regions including a proxy for de-industrialisation in the multivariate analysis doesn't change the fact that trade and technology intensity have the largest effects upon residual inequality, although the technology effect is driven to insignificance in the presence of time controls. Although significant in the univariate analysis of the South included along side other controls de-industrialisation is insignificant and doesn't change the rankings found in Table 11. However, de-industrialisation does have an impact in the North, where Table 10 reported only trade having an effect in the presence of other competing theories. Interestingly though, the main effects upon residual inequality now come from cohort education and unions, although both are outweighed by the coefficient on de-industrialisation.

The impact of de-industrialisation in the North is perhaps not surprising given the fact that the demand for labour has shifted from industries located in the North, which were predominantly manufacturing, and relocated in the South in service orientated industries, Jackman and Savouri (1999). For example, over the period 1979 to 1989 the share of manufacturing employment fell from: 30.7% to 23.5% in the North; 33.1% to 24.3% in York & Humberside; 33.7% to 25.3% in the North West; and 26.8%

to 19.3% in Scotland. Furthermore, Bernard and Jensen (2000) using geographic variation across US states also find that regions which have experienced large falls in manufacturing employment are strongly correlated with increasing residual wage inequality.

7. Conclusions.

The argument in this paper is that the majority of previous research on UK wage inequality has ignored the heterogeneity of observable worker characteristics across the population, and the heterogeneity of inequality movements across industries and regions. In order to investigate these issues initially a measure of inequality was gained by industry and region from 1981 to 1995 conditional upon controls for the heterogeneity of productivity characteristics amongst individuals, known as within-group or residual wage inequality. Secondly, the trend in within-group wage inequality across industries and regions was considered. Moreover, the potential influences upon the trend in within-group wage inequality, identified from the literature, were tested simultaneously. The two stage approach followed Bernard and Jensen (2000) to focus explicitly upon what may have caused rising residual wage inequality, something largely unexplained in the literature (Levy and Murnane, 1992; Gosling *et al*, 2000; and Acemoglu, 20002) and unexplored in the UK. The results have: (i) shown rising residual inequality is evident everywhere, although can be explained by different sources due to the heterogeneity of inequality across industries and regions; (ii) shown it is imperative to examine industries other than Manufacturing; and (iii) exhibited a role for supply side effects – specifically changing inter cohort skills over time and female participation.

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Table 1: First stage results

	PERIOD 1 1981-85	PERIOD 2 1986-90	PERIOD 3 1991-95
Experience	0.0174 (5.21)	0.0209 (9.84)	0.0746 (9.67)
Experience^2	-0.0003 (3.12)	-0.0003 (9.66)	-0.0035 (6.32)
Experience^3	$-5.11e^{-6}$ (10.59)	$-4.92e^{-6}$ (9.21)	0.0001 (4.92)
Experience^4	$5.44e^{-8}$ (2.26)	$3.93e^{-8}$ (9.31)	$-6.85e^{-7}$ (4.59)
Degree	0.5019 (13.59)	0.3490 (9.81)	0.5010 (11.48)
Higher Vocational	0.3079 (9.51)	0.2154 (7.18)	0.2457 (6.20)
A level	0.2588 (8.87)	0.1203 (3.78)	0.2334 (6.23)
O level	0.1668 (6.32)	0.0916 (3.51)	0.1235 (3.69)
Apprenticeship	0.0401 (1.15)	0.0113 (0.29)	-0.1096 (1.18)
Other	0.2649 (7.26)	0.0975 (3.55)	0.1284 (3.24)
Professional	0.2374 (5.07)	0.2078 (6.41)	0.2615 (6.25)
Manager	0.3079 (8.76)	0.3182 (11.88)	0.3795 (10.84)
Non-manual	0.0873 (2.78)	0.1197 (4.85)	0.2118 (6.54)
Skilled manual	0.1442 (5.22)	0.0624 (2.93)	0.0997 (3.57)
Education×Experience [6]	Yes**		
Occupation×Experience [4]	Yes**		
Education×Occupation [24]	Yes**		
Regional controls [10]	Yes**		
Industry controls [9]	Yes**		
Time controls [4]	Yes**		
Observations	17,071	14,592	13,887
Adjusted R Squared	0.4590	0.4024	0.2723

** Jointly significant at the 1% level. [.] number of dummy categories.

Table 2: Trends in within-group (residual) industry inequality

	1981	1985	1990	1995
Energy, Gas & Water	0.2659	0.2864	0.3467	0.5053
Manufacturing	0.2705	0.3489	0.3198	0.4318
Other Manufacturing	0.2899	0.3824	0.3878	0.4438
Construction	0.3115	0.3424	0.3727	0.4549
Transport & Communication	0.2949	0.4147	0.3244	0.4709
Services	0.3413	0.3712	0.3919	0.4936

Table 3: Changes in overall wage inequality (wage levels) and within-group (residual) industry inequality

	1981-85		1986-90		1991-95	
	Wages	Residual	Wages	Residual	Wages	Residual
Energy, Gas & Water	2%	8%	7%	19%	24%	45%
Manufacturing	16%	29%	4%	7%	10%	21%
Other Manufacturing	24%	32%	12%	8%	6%	3%
Construction	9%	10%	17%	20%	-5%	-9%
Transport & Communication	36%	41%	3%	9%	7%	8%
Services	9%	9%	9%	7%	1%	2%

Table 4: Trends in within-group (residual) regional inequality

	1981	1985	1990	1995
North	0.2865	0.3234	0.3333	0.4419
York & Humberside	0.2994	0.3548	0.3734	0.5158
North West	0.2772	0.3432	0.3655	0.4508
East Midlands	0.2686	0.3747	0.3596	0.4403
West Midlands	0.2756	0.3588	0.3568	0.4518
East Anglia	0.3314	0.3034	0.3790	0.4738
South East	0.3428	0.4014	0.3686	0.5040
South West	0.3316	0.3522	0.3667	0.4019
Wales	0.3027	0.3473	0.3522	0.4248
Scotland	0.3123	0.4102	0.3362	0.4964

Table 5: Changes in overall wage inequality (wage levels) and within-group (residual) regional inequality

	1981-85		1986-90		1991-95	
	Wages	Residual	Wages	Residual	Wages	Residual
North	18%	13%	9%	12%	6%	-1%
York & Humberside	6%	19%	14%	16%	10%	16%
North West	22%	24%	12%	5%	-1%	-7%
East Midlands	37%	40%	15%	14%	-5%	3%
West Midlands	10%	30%	31%	30%	7%	9%
East Anglia	-8%	-8%	17%	18%	13%	16%
South East	11%	17%	6%	0%	-2%	3%
South West	11%	6%	4%	3%	-17%	-13%
Wales	5%	15%	4%	7%	4%	18%
Scotland	19%	31%	26%	21%	4%	16%

Table 6: All industries

	1		2		3		4		5		6		7	
Technology intensity	-0.007 (0.78)	-0.004 (0.56)											-0.005 (0.81)	-0.003 (0.74)
Trade intensity			0.159 (2.01)	-0.013 (0.25)									0.121 (1.88)	0.034 (0.64)
Unions					-0.011 (3.01)	-0.005 (1.84)							-0.009 (2.69)	-0.001 (0.03)
Cohort education							-0.233 (6.91)	-0.174 (5.23)					-0.149 (3.79)	-0.151 (3.94)
Female participation									0.045 (3.37)	0.034 (3.49)			0.049 (3.43)	0.024 (2.05)
Immigration											0.051 (2.51)	0.037 (2.74)	0.020 (1.16)	0.012 (0.81)
Time dummies	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**
Observations	90													
Adjusted R Squared	0.018	0.749	0.016	0.742	0.045	0.769	0.360	0.693	0.120	0.806	0.082	0.785	0.469	0.731

Table 7: Manufacturing industries

	1		2		3		4		5		6		7	
Technology intensity	-0.009 (1.06)	0.009 (2.01)											-0.024 (0.90)	0.060 (1.77)
Trade intensity			0.067 (1.33)	-0.039 (1.10)									0.193 (2.07)	0.258 (2.46)
Unions					-0.026 (4.55)	-0.010 (1.76)							-0.026 (2.69)	0.017 (0.87)
Cohort education							-0.170 (3.61)	-0.188 (3.89)					-0.022 (0.37)	-0.084 (1.21)
Female participation									0.045 (2.38)	0.039 (2.08)			-0.047 (0.51)	-0.012 (0.11)
Immigration											-0.039 (0.65)	0.061 (1.21)	0.044 (0.87)	-0.006 (0.08)
Time dummies	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**
Observations	30													
Adjusted R Squared	0.039	0.851	0.059	0.823	0.425	0.842	0.318	0.788	0.064	0.853	0.015	0.826	0.660	0.895

Table 8: Non-Manufacturing industries

	1		2		3		4		5		6	
Technology intensity	-0.006	-0.001									-0.039	-0.001
	(0.47)	(0.03)									(0.54)	(0.17)
Unions			-0.004	-0.006							-0.006	0.001
			(0.98)	(2.16)							(1.47)	(0.35)
Cohort education					-0.267	-0.171					-0.202	-0.151
					(5.97)	(3.39)					(3.74)	(2.58)
Female participation							0.045	0.033			0.039	0.017
							(2.94)	(2.60)			(2.30)	(2.12)
Immigration									0.061	0.035	0.012	0.012
									(2.61)	(2.16)	(0.57)	(0.66)
Time dummies	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**
Observations	60											
Adjusted R Squared	0.008	0.747	0.012	0.802	0.387	0.687	0.130	0.818	0.116	0.796	0.453	0.725

Table 9: All regions

	1		2		3		4		5		6		7	
Technology intensity	0.211 (9.50)	0.041 (2.08)											0.095 (3.96)	0.045 (1.92)
Trade intensity			0.444 (12.2)	0.070 (23.7)									0.141 (2.08)	0.187 (2.08)
Unions					-0.036 (13.4)	-0.001 (0.25)							-0.018 (5.18)	-0.004 (0.78)
Cohort education							-0.186 (7.53)	-0.114 (5.82)					-0.019 (0.77)	-0.011 (0.46)
Female participation									0.960 (14.1)	0.328 (2.01)			0.197 (1.30)	0.246 (1.42)
Immigration											0.007 (0.89)	0.001 (0.13)	0.013 (2.21)	-0.006 (1.07)
Time dummies	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**
Observations	150													
Adjusted R Squared	0.343	0.799	0.501	0.786	0.524	0.786	0.279	0.716	0.573	0.797	0.006	0.786	0.680	0.806

Table 10: The North

	1		2		3		4		5		6		7	
Technology intensity	0.358 (9.36)	0.086 (2.26)											0.222 (2.87)	0.036 (0.65)
Trade intensity			0.472 (7.84)	0.068 (18.8)									0.213 (1.67)	0.185 (2.57)
Unions					-0.037 (8.48)	-0.016 (2.63)							-0.012 (1.63)	-0.009 (1.19)
Cohort education							-0.275 (6.39)	-0.203 (5.74)					0.027 (0.44)	-0.059 (1.37)
Female participation									1.001 (8.01)	0.279 (1.29)			-0.251 (0.88)	0.191 (0.77)
Immigration											0.017 (1.21)	0.009 (1.78)	-0.007 (0.71)	0.001 (0.06)
Time dummies	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**
Observations	60													
Adjusted R Squared	0.602	0.903	0.514	0.891	0.554	0.906	0.413	0.839	0.526	0.897	0.025	0.899	0.689	0.913

Table 11: The South

	1		2		3		4		5		6		7	
Technology intensity	0.195 (6.99)	0.034 (1.34)											0.082 (3.42)	0.059 (2.36)
Trade intensity			0.426 (9.43)	0.318 (6.34)									0.076 (0.97)	0.069 (0.53)
Unions					-0.036 (10.7)	-0.034 (0.46)							-0.016 (4.14)	-0.009 (1.42)
Cohort education							-0.148 (5.06)	-0.087 (3.68)					-0.029 (1.11)	-0.011 (0.37)
Female participation									0.939 (11.8)	0.450 (1.80)			0.408 (2.39)	0.427 (1.73)
Immigration											0.002 (0.18)	-0.002 (0.19)	0.018 (2.71)	0.014 (2.08)
Time dummies	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**
Observations	90													
Adjusted R Squared	0.280	0.768	0.493	0.752	0.502	0.749	0.221	0.684	0.611	0.772	0.001	0.752	0.716	0.793

Table 12: The role of de-industrialisation

	ALL REGIONS				THE NORTH				THE SOUTH			
	1		2		3		4		5		6	
De-industrialisation	-0.135	-0.081	-0.048	-0.057	-0.151	-0.041	-0.072	-0.096	-0.126	-0.101	-0.011	-0.036
	(2.65)	(2.53)	(1.86)	(1.93)	(1.63)	(1.69)	(2.11)	(2.33)	(2.10)	(2.52)	(0.28)	(0.87)
Technology intensity			0.079	0.030			0.183	0.028			0.079	0.049
			(3.11)	(1.36)			(2.16)	(0.46)			(3.02)	(1.77)
Trade intensity			0.141	0.188			0.191	0.166			0.078	0.099
			(2.10)	(2.19)			(1.69)	(1.47)			(0.98)	(0.73)
Unions			-0.019	-0.006			-0.014	-0.014			-0.017	-0.009
			(5.40)	(1.18)			(1.79)	(1.78)			(4.09)	(1.35)
Cohort education			-0.014	-0.017			-0.039	-0.079			-0.028	-0.006
			(0.54)	(0.73)			(0.64)	(1.86)			(1.05)	(0.21)
Female participation			0.187	0.222			-0.194	0.281			0.398	0.353
			(1.25)	(1.37)			(0.67)	(1.18)			(2.28)	(2.34)
Immigration			0.011	0.003			-0.002	0.007			0.017	0.011
			(1.88)	(0.55)			(0.19)	(0.98)			(2.46)	(1.58)
Time dummies	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**	No	Yes**
Observations	150				60				90			
Adjusted R Squared	0.046	0.667	0.684	0.812	0.044	0.729	0.696	0.923	0.048	0.665	0.716	0.795

Table A1: Summary statistics

	MEAN	STANDARD DEVIATION	MAX	MIN	TREND
<u>Across Industries</u>					
Residual inequality	0.373	0.076	0.588	0.256	+
Technology (R&D expenditure/value added)	2.139	3.291	10.182	0.012	+
Trade (import expenditure/value added)	32.099	47.404	82.743	0	+
Unions (000's workers involved in strikes)	104.165	151.803	709.001	0	-
Female participation (females in >1hr/employment)	26.567	15.753	59.060	7.660	+
Immigrants (those born outside UK >1hr/employment)	6.096	1.982	10.820	1.120	+
Cohort education	0.315	0.035	0.389	0.133	-
<u>Across Regions</u>					
Residual inequality	0.381	0.078	0.627	0.264	+
Technology (non-manual/manual)	68.238	26.346	88.085	57.143	+
Trade (import expenditure/value added)	31.079	10.404	85.012	70.562	+
Unions (days lost through strikes)	230	297	1209	2	-
Female participation (females in >1hr/employment)	46.002	2.861	51.96	40.712	+
Immigrants (those born outside UK >1hr/employment)	6.049	5.08	21.66	0.33	+
Cohort education	0.450	0.311	0.715	0.051	-