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Discussion paper

The Evolution of Inequality in Productivity and Wages: Panel Data Evidence

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The Evolution of Inequality in Productivity and Wages: Panel Data Evidence

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Abstract

There has been a remarkable increase in wage inequality in the US, UK and many other countries over the past three decades. A significant part of this appears to be *within* observable groups (such as age-gender-skill cells). A generally untested implication of many theories rationalizing the growth of within-group inequality is that firm-level productivity dispersion should also have increased. Since the relevant data do not exist in the US we utilize a UK longitudinal panel dataset covering the manufacturing and non-manufacturing sectors since the early 1980s. We find evidence that productivity inequality has increased. Existing studies have underestimated this phenomenon because they use manufacturing data where which has shrunk rapidly. Most of the increase in individual wage inequality has occurred because of an increase in inequality between firms (and within industries). Increased productivity dispersion appears to be linked with new technologies as suggested by models such as Caselli (1999) and is not primarily due to an increase in transitory shocks, greater sorting or entry/exit dynamics.

Keywords: wage inequality, productivity dispersion, technology.

JEL: D24, J24, J31, O31

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I. Introduction

Wage inequality has increased substantially in the United States and the United Kingdom in the last thirty years. Acemoglu (2002) reports that the difference in wages earned by a worker in the 90th percentile of the wage distribution compared to a worker in the 10th percentile increased by 40% in the US from 1971 to 1995. For the UK, the 90-10 differential increased by 48% from 1975 to 2000 (see Machin, 2003; Machin and Van Reenen, 2007). Increases in within-group inequality, i.e. increases in inequality among observationally equivalent workers, account for a significant proportion of the rise¹.

Many theories have been proposed to explain the rise in wage inequality. These include demand-side explanations (trade with developing countries or technological change)², supply-side explanations (changes in the relative supply of highly-educated workers across cohorts)³ and institutions (decline in union power and/or the minimum wage⁴). Technology-based theories have proven popular in explaining the within group rise. They generally assume some type of labor market friction whereby workers' wages are linked with the productivity of the worker-firm match. Such effects arise naturally in search based models of equilibrium wage dispersion, but there are other theoretical foundations based on bargaining that

¹ Lemieux (2006) argues that the scale of this increase may have been exaggerated in some early studies due to compositional effect. Autor *et al.* (2005) still find a substantial within component especially in the upper tail of the distribution.

² See, among others, Machin and Van Reenen (1998) and Autor *et al.* (1998) for evidence that the rapid spread of computers has increased the demand for skills. See, among many others, Caselli (1999), Aghion *et al.* (2004) and Violante (2002) for models in which rapid technical change increases the demand for skills and causes a rise in inequality.

³ See Card and Lemieux, 2001.

⁴ Differences in labor market institutions are often proposed to explain cross-country inequality (e.g. Blau and Kahn, 1996). Unions have declined just about everywhere and in the US the real value of the minimum wage fell substantially until the mid 1990s (see, e.g., DiNardo *et al.*, 1996).

generate similar implications⁵. When a “general purpose technology” like information and communication technologies (ICT) becomes available, firms will adopt technologies at different rates and be successful to different degrees. This generates increased wage dispersion even for observationally identical workers (e.g. Violante, 2002; Aghion *et al.*, 2002, 2004). An under-appreciated implication of these models is that they imply that productivity dispersion between firms should also have risen.

Unfortunately, very little is known about the evolution of the productivity distribution. Wages are not a sufficient statistic for productivity once we move away from the simplest models of spot competition in labor markets. Some authors have examined in detail the determinants of the cross sectional distribution of productivity and others have decomposed aggregate productivity growth into incumbent firm productivity growth and reallocation effects driven by entry, exit and the relative growth of more productive firms. This literature strongly suggests that the between firm effects (ignored by representative agent models) are very important⁶. As useful as this literature is, however, it has generally focused on explaining the evolution of the first moment of the productivity distribution and has not focused on how the higher order moments of the productivity distribution have evolved over time. Understanding the dynamics of productivity dispersion is the main contribution of this paper.

Data constraints are an important reason why the changing productivity distribution is under-studied. In order to examine secular changes, a long time series

⁵ Mortensen (2003) and Postal-Viney and Robin (2003) contain theoretical models linking equilibrium wages with employer heterogeneity in productivity. They use these models to structurally estimate the cross sectional wage distribution in Denmark and France, respectively. Layard, Nickell and Jackman (2005) show how the link between workers wages and employer productivity can arise across a range of models – union bargaining, efficiency wage, rent-sharing and search-based.

⁶ For the cross sectional dispersion of productivity see among others Haltiwanger *et al.* (1999) for the U.S. and Martin (2004) for the UK. For decompositions of productivity changes see among others, Bailey *et al.* (1992), Olley and Pakes (1996) and Bartelsman *et al.* (2005).

of data is needed and firm-level data is usually only available for such periods on the manufacturing sector⁷. Since this sector only now employs about 14% of the British workforce and 13% of the American workforce, it is problematic to extrapolate to the whole economy from just manufacturing industries. It is particularly a problem for productivity analysis as the rapid decline in manufacturing in the OECD over the last three decades is partly due to increased competition from less developed countries with much lower labor costs. With heterogeneous firms, increases in competition will generally lower the productivity dispersion (see Syverson, 2004, for a model and empirical evidence confirming the importance of this intuition). Consequently, the existing studies of the change in productivity dispersion may have seriously underestimated the importance of the growth of productivity inequality. Although production data on non-manufacturing is available in the US in Compustat, this only includes firms listed on the Stock Market. Since most firms are private, an analysis of productivity inequality that ignored these unlisted firms is unconvincing⁸. The new US Longitudinal Business Database is available for non-manufacturing firms in the US, but it does not contain data on sales or capital (see Davis *et al.*, 2006).

To tackle these data constraints we use the UK as a test bed – wage inequality has risen rapidly since the early 1980s and we use a data source (FAME) covering listed and unlisted firms in both manufacturing and service sectors. This is an unbalanced panel and is available since the early 1980s.

Figure 5a shows the headline finding from this data where we look at the firm-specific distribution of labor productivity measured by value added per worker. We will discuss more data details later in the paper (e.g. see Table A1 for levels of

⁷ See Dunne *et al.* (2004) for the US and Haskel and Martin (2002) for the UK.

⁸ For example, several papers have argued that there is an increase in the dispersion of firm-specific shocks over time as the variation of firm sales growth in Compustat appears to have increased (e.g. Comin and Philippon, 2005). Unfortunately, this does not seem to be generally true across the US economy (see Davis *et al.*, 2006).

productivity dispersion). We consider the 10th, 50th and 90th percentiles of the log (labor productivity) distribution where we normalize these values to unity in 1984, so the lines show what has happened to growth at each of these percentiles. The data reveal a dramatic growth in the dispersion of productivity between firms. Productivity increased by 60 log points at the 90th percentile between 1984 and 2001 whereas it increased by only 20 log points at the 10th percentile (there was a growth of around 40 log points at the median). This is a substantial increase in productivity inequality and we investigate in detail the cause of this change in this paper. We report three major findings.

First, using individual and firm level data we find that the vast majority of the increase in individual wage inequality in the UK is a between-firm (rather than within-firm) phenomenon⁹. This implies that understanding the evolution of the between firm productivity distribution may be critical in understanding the between firm wage distribution and therefore the overall wage distribution (we also show that the correlation between wages and productivity has become more important over time). Furthermore, the vast majority of the growth of wage and productivity dispersion is within industries, suggesting industry level data on productivity and wages will not be able to identify the causes of the changes.

Second, we show that the increase in the productivity dispersion (as with the wage dispersion) is mainly in the service sector of the economy suggesting that the focus on manufacturing in the existing literature has indeed underestimated the rise of economy wide productivity inequality.

⁹ This is interesting as it suggests the media-grabbing attention attached to CEO pay relative to workers pay in the same firm may be misplaced, as the overall increase in inequality has relatively little to do with this. Nevertheless, we are not including many components of CEO remuneration such as share options that are important.

Third, we show that the increase in labor productivity dispersion is mainly driven by an increase in total factor productivity dispersion (rather than being due to just an increase in the dispersion of capital-labor ratios or greater sorting as in Kremer and Maskin, 1996). This suggests technological differences may be driving our results as suggested in the theories of in Caselli (1999) or Acemoglu *et al* (2001)¹⁰. We present some direct evidence in line with this idea by using ICT data to explain the increase in within industry productivity dispersion. We also examine (and reject) other possible explanations including increasing a greater incidence of transitory shocks, differential entry/exit rates, institutional changes and/or measurement error.

To our knowledge, there are only two studies that have looked at changes in productivity dispersion across many sectors. Dunne et al (2004) analyse changes in the distribution of firm productivity across US plants. They show that inequality of plant wages and productivity dispersion increased between 1975 and 1992 and much of this was a between-plant phenomenon (this is consistent with what we find below for the UK). Haskel and Martin (2002) examined changes in labor productivity in UK establishments (the Annual Business Inquiry Respondents' Database) and also found some increase in dispersion. We argue that since both of these earlier studies look only at the manufacturing sector they have seriously underestimated the magnitude of the change.

The paper is organised as follows. In Section 2, we briefly discuss the theoretical framework and Section 3 details the data sources we use. Section 4 describes the main results and Section 5 discusses what could explain the trends observed in the data. Section 6 offers some concluding comments.

¹⁰ Acemoglu *et al* (2001) present a model where skill biased technical change causes deunionization. This amplifies the direct effect of technology to further increase wage inequality. We investigate institutional change and unionisation directly in sub-section 5.4. and 5.5.

2. Theoretical framework

In this section, we use the papers by Caselli (1999) and Kremer and Maskin (1996) to generate some empirical predictions regarding the distribution of wages and productivity. Caselli (1999) models the impact of a technological “revolution” on the dispersion of wages and productivity. In the Caselli model, there is a distribution of worker types and machine types and operating a given type of machine requires a given type of skill. The cost of learning a skill varies across workers and is lower for more skilled workers and a technology is a combination of workers of type i who have the appropriate skills to operate machines of type i . A technological “revolution” occurs with the introduction of a new type of machine. Since workers of different abilities are distributed heterogeneously across firms and for each period firms consider as given the skill composition of their workforce, there will be differential adoption of new technology by firms. High-skill workers will tend to use the new technologies since it is less costly for them to acquire the new skills.

This model has at least three implications that are relevant for our empirical analysis. Firstly, we will expect increased wage dispersion between (and within) firms¹¹. Secondly, labor productivity (value added per worker) dispersion increases between firms due to the fact that more skilled workers are now more productive. Thirdly, since capital is also reallocated to its best use total factor productivity increases in firms that introduce a new technology so Total Factor Productivity (TFP) dispersion also rises.

It is worth noting that the Caselli model is different from a pure sorting model where between firm wage (and labor productivity) dispersion could rise because

¹¹ There are two effects in operation: a direct effect and an indirect effect. The wages of high-skill workers rise because they now operate on more productive machines (the direct effect). There is also a reallocation of capital away from old technologies towards new technologies, depressing the wages of the low skilled and benefiting the wages of the high skilled (the indirect effect).

“good” workers tend to cluster in one type of firm and “bad” workers cluster in another. Kremer and Maskin (1996) present an example of such a model that accounts for the simultaneous existence of increased wage inequality and increased segregation of workers by skill. They introduce a set of specific assumptions regarding the firm organisational structure: imperfect substitution of workers of different skills; complementarity of tasks within a plant, and differential effects of a worker skill depending on the task performed. Under this set of assumptions and further assuming a rise in the dispersion of skills across workers, Kremer and Maskin derive an equilibrium solution where low-skill workers are sorted in low-productivity plants and high-skill workers sorted in high-productivity plants (i.e. sorting or segregation). Therefore, if dispersion of skills has increased due to increased educational inequality for example, this could lead to increased sorting¹².

This model predicts an increase in the dispersion of wages across firms. There will also be an increase in the dispersion of labor productivity because skilled workers will be segregated into different firms. However, unlike technology-based models like Caselli’s, because increased wage and productivity dispersion is due to sorting there should be no effect on total factor productivity dispersion. We therefore look explicitly at TFP as well as labor productivity and wages to distinguish between the two approaches.

¹² In this model the degree of asymmetry/complementarity of tasks within a plant is crucial in shaping the distribution of workers across plants. The asymmetry of tasks in the production function favours cross-matching across workers (less segregation). Conversely, the complementarity of tasks favours self-matching (more segregation). Workers of different abilities will be cross-matched up to the point at which differences in skills or abilities are so great that segregation will be inevitable. If the distribution of skills is sufficiently compressed, cross-matching seems to be the most probable outcome. If the distribution of skills is dispersed, self-matching or sorting workers by skill will prevail. This gives some ambiguity to the predictions as although the level of educational achievement has risen over time, it is less clear whether educational inequality has risen.

3. Data description

All datasets are described in detail in the Appendix B. The main dataset we use is FAME (Financial Analysis Made Easy) which is a UK company-level panel data set available since 1982. In Britain, all incorporated companies are legally required to register their accounts at Companies' House and given a unique (VAT) registration number. Unlike the US, this includes not only companies listed on the Stock Exchange (which are held on databases such as COMPUSTAT) but also all *unlisted* companies. In 2003, we arranged a special purchase of this data with a private sector company that has converted this data into electronic form. This is unbalanced panel data and includes all firms that had exited the database prior to 2003 (by either bankruptcy or takeover)¹³.

In our main analysis, we drop some firms. In general, this could lead to selection bias causing us to find smaller or greater increases in inequality over time, we argue in Appendix B that these biases are not generally large by checking the sensitivity of the results to including the dropped observations and using complementary datasets (contrast Figures 5a and 5b to see that these exclusions have little effect on the overall trends). Firstly, we drop firms with less than ten employees because small firms are not required to report certain key variables we need for our analysis such as the wages bill. Secondly, we use the consolidated accounts of parent firms and drop the unconsolidated accounts of their subsidiaries. We would be double counting if we used both parents and subsidiaries. Because some subsidiaries are below ten employees, we would be missing parts of the economy if we just used subsidiaries. Thirdly, we start the sample in 1984 because sampling of FAME was not

¹³ Under UK law, firms are also required to report a great deal more accounting information on their wage bills than in the US (where declaration of staff expenses is a voluntary item). Because of this, we are able to construct measures of average firm wages that are unavailable for most firms in the US public accounts.

complete in the early 1980s. Finally, we generally drop certain sectors: agriculture, mining, utilities, health and education. We were concerned that these sectors were heavily influenced by state control for at least some of the sample period covered. We also drop the financial sector because of the well-known problems of measuring productivity in banking and insurance.

Our final sample we use contains about 11,000 firms a year between 1984 and 2001 (we cover about 13 million workers each year). We have information on a large number of variables. We use information on employment, capital, sales, total worker remuneration, gross profits and industry. Note that we do not have information on the demographics of the workforce or hours worked. But we investigate biases associated with this omission in sub-section 5.4.

The main measure we use for labor productivity is value added per worker, but we also consider using sales per worker as an alternative. Sales has the advantage that it is reported as a line item in the accounts, but the major disadvantage is that it will be influenced by the purchase of intermediate inputs, so “labor productivity” could rise simply because a firm was buying more materials per worker – this will particularly be a problem in the service sector. We also examine total factor productivity (TFP) calculated in various ways. The main way we calculate TFP is as a residual of outputs from weighted inputs, but we also consider estimating firm production functions and using the estimated parameters to construct TFP measures.

There are numerous well-known problems with measuring labor productivity and TFP. Some of these are discussed below (e.g. appropriate choice of weights). One issue is that the value added numerator is not measured in physical units so will reflect differential mark-ups among firms as well as physical productivity increases.

Thus, when we say productivity it is shorthand for “revenue productivity”¹⁴. This is still an interesting measure to look at as the ability of firms to sustain mark-ups is partly a reflection of product quality, and technological change may enable firms to improve quality (see Appendix B and Table A2 for an analysis of the changing variation in profitability). Undoubtedly, there are other sources of market power and the increased variation of market power could be a reason for increased measured productivity dispersion. We have reason to doubt this explanation, however, as competition has almost certainly increased over time in the UK due to waves of policy-driven liberalization and globalization of markets. Other things equal, this would lead to a reduction in productivity dispersion as the least efficient firms are driven from the market.

The second dataset we use is the New Earnings Survey (NES) data which give consistent information on individual wages, and covers one per cent of the entire UK working population (those whose National Insurance/Social Security numbers end in the same two digits, 14). We currently have access to data for all years between 1975 and 1999 in NES. We use annual gross pay as our measure of the wage in NES which matches most closely with FAME’s measure of annual staff costs. The FAME measure is higher on average because it includes the employers’ payroll taxes¹⁵.

¹⁴ We use an economy wide deflator, the Retail Price Index for value added. Industry-level deflators are available at a more disaggregated level for manufacturing and the results are robust to using these deflators. Industry-level deflators are not, however, available for the service sector (due to the difficulty of defining price). Since the comparison between manufacturing and services is important, we chose to report our main results using a common aggregate deflator.

¹⁵ In FAME, we cannot distinguish employers’ payroll tax costs from total annual staff costs. Employers National Insurance is a relatively small part of total wage costs so it is unlikely this could account for an increase in dispersion. Nevertheless, we investigate this issue by looking at demographics (gender, age, part-time proportion, etc.).

4. The evolution of the wage and productivity distribution

In this section we document the changes in wage (sub-section 4.1) and productivity (sub-section 4.2) dispersion. We then decompose the trends in sub-section 4.3.

4.1. Trends in Wage Dispersion

We begin by first examining wage trends with our data. Using individual data (NES) and firm level data (FAME), we compute log real annual wages for male workers aged 16-64. We compute values at the 90th, 50th (median) and 10th percentiles and normalise these to unity in 1984. The series therefore represent cumulative changes relative to the initial year, 1984¹⁶. We split the sample by manufacturing and private services. Looking at private services first in Figure 1, wages at the 90th percentile increased by about forty log points between 1984 and 1999. By contrast, the wage earned at the 10th percentile increased by only seventeen log points, thus generating an increase in the 90-10 differential of about twenty-three log points. The increase in inequality was stronger in the 1980s than in the 1990s. The picture does not fundamentally change when we restrict the sample to include only 16-64 full-time¹⁷ male workers or measure earnings using hourly instead of annual wages (we are using annual wages so that we can compare these with FAME). Figure 2 presents the equivalent changes for manufacturing. Although it is clear that wage inequality has also risen in this sector, the rise is much less dramatic than for services. Indeed, there is hardly any change at all in the 1990s. Studies focusing on manufacturing will therefore miss a large part of increased inequality.

Figures 3 and 4 present similar evidence on wage dispersion using the FAME firm-level data. Recall that we are examining the distribution in the average firm wage (rather than individual wage) in these diagrams. Wage dispersion has risen for both

¹⁶ See Gosling *et al* (2000) for similar analyses from earlier time periods in the UK.

¹⁷ As documented in Machin (2003), the NES data under-sample part-time low-wage individuals so focusing on full-time men eliminates a lot of this bias.

sectors, but again the rise is much stronger for services (Figure 3) than for manufacturing (Figure 4).

Although the trend analysis is interesting, the samples are somewhat different – the NES figures cover men and all firms whereas the FAME figures cover all workers and only firms with more than 10 employees. Below in sub-section 5.3 we match the samples more exactly to estimate how much of the overall changes in individual wage variation are due to an increase in inter-firm wage dispersion compared to the intra-firm wage dispersion.

4.2 Trends in the Productivity Dispersion

We discussed the change in the overall productivity distribution briefly in the Introduction (Figure 5a). As with the wage distribution there was a substantial secular increase in productivity inequality 1984-2001. For example, comparing the 1984 to 1989 average with the 1996 to 2001 average the 90-10 differential rose from 1.44 to 1.71. Essentially, this is the main new “stylized fact” of the paper. Note that Figure 5a “Whole Economy” is the entire raw FAME data before we exclude particular industries and size classes discussed in the data section. The pattern is remarkably similar to Figure 5b “manufacturing and services” which is the sample after these selections have been made.

In addition to the secular increase there is also an interesting cyclical pattern of productivity dispersion. There was an increase in productivity dispersion in the late 1980s followed by a reduction during the recession of the early 1990s. Afterwards, productivity dispersion continued to increase until at least the year 2000. This pattern is consistent with the idea of the “cleaning effect of recessions” (e.g. Caballero and Hammour, 1994). The least productive firms are more likely to exit an industry (see the analysis of entry/exit in sub-section 5.3 below) and this effect is likely to be

particularly strong during cyclical downturns. Consequently the productivity distribution is compressed due to a truncation of the left tail in the early 1990s. Note that this selection effects implies that macro-economists are probably *underestimating* the degree of pro-cyclicality of productivity over the business cycle.

Increases in productivity dispersion for the whole economy are largely driven by increases in private services (see Figure 6). Productivity dispersion across UK manufacturing firms has increased, but to a much more limited extent (see Figure 7). The service sector also displays a stronger cyclical component in the variation of productivity, decreasing very strongly in the early 1990s recession.

Overall, we find that the inter-firm productivity distribution has moved in a similar way to the inter-firm wage distribution over the last twenty years, suggesting that the two patterns may be linked. We explore this link in more detail in the next sub-section.

4.3 Decomposing trends in wage and productivity inequality

We first consider decomposing the overall increase in individual wage inequality into between firm and within firm components. We can further sub-divide the between firm component into a within and between industry component. We use comparable NES and FAME samples to accomplish this, so we restrict the NES sample in the same way we restricted the FAME sample (same industries, both male and female workers, both part-time and full-time workers, etc.).

Our decomposition methodology follows Davis and Haltiwanger (1991) and Dunne *et al.* (2004). We use the NES data to estimate the overall variation of individual log wages denoted $V(W^{NES})$, and the FAME data to estimate the variance of between firm ln(wages) denoted $V(W^{FAME})$. The within firm component denoted

\hat{V}_{WF} , is then the residual between the two series:

$$\hat{V}_{WF} = V(W^{NES}) - V(W^{FAME}) \quad (1)$$

Details and further discussion of the decomposition methodology are in Appendix A.

Figure 8 contains the first results of this decomposition. The bold line shows the total individual variation of $\ln(\text{wages})$ between 1984 and 1999 which has increased by about 16 log points. This trend is well documented in several papers. The dashed line shows the “between” component (the inter-firm wage variation) and the dotted line the within firm component (the difference between overall wage dispersion and the between firm dispersion) over the same period. Looking first at the cross section in the 1980s, about half of the variation in wages is attributable to the variation within firms and half is between firms. The interesting aspect, however, is in the time series. The trend increase in between-firm wage variation is similar to the trend increase in the overall variation of wages. In fact, the between firm component essentially accounts for just about all of the increase in the growth of aggregate inequality (the within firm increase rises a little in the second half of the 1990s, but is essentially flat).

Figure 9 takes this one stage further and decomposes the between firm variation into a between and within industry component. The between industry component has risen, but only by a minor amount. *In short, the dominant reason for the increase in wage inequality appears to be the growth of inequality between firms within industries.* This suggests that examining how firms’ productivity have changed over time could help account for the changing wage distribution as many of these recent theories by Caselli and others have suggested. Figures 10 through 13 show the breakdown between manufacturing and services to illustrate, as before, that the results are driven by the service sector.

We now turn to productivity again. Since productivity is a firm-level measure, we cannot look within firms, so our decompositions are into within and between industry components. We find a consistent picture that the increase in productivity inequality is a within industry phenomenon (Figure 14). There is only a small increase in the productivity dispersion between industries in services (Figure 15) and in manufacturing (Figure 16). One may be concerned that the industry decompositions are based on two digit sectors and this is too aggregated. We replicated the results on more finely disaggregated industries that lead to similar qualitative results¹⁸.

5. Explaining the rising dispersion of productivity

Our key finding is that there has been a secular increase in labor productivity dispersion in the UK. We now seek to explain this by first showing that this is not simply due to an increase in dispersion of factor inputs (sub-section 5.1), in transitory shocks (sub-section 5.2) or in entry/exit behaviour (sub-section 5.3). We then present some direct evidence in line with the idea that information technology has an important role to play (sub-section 5.4). We end with some international evidence (sub-section 5.5) and some evidence on magnitudes (sub-section 5.6).

5.1. Total Factor Productivity

The main theories of within group wage inequality emphasise that there has been some increase in the technological heterogeneity between firms over time. We would expect this to be reflected in differences in total factor productivity (TFP). Labor productivity differences could arise from TFP differences, but could also arise from increases in the dispersion of capital intensity (fixed capital per worker) between firms. Of course, some of this increased capital heterogeneity could reflect

¹⁸ There is a trade-off here as the cell size per industry year used to construct the variance components is obviously rather small when we go to more disaggregated industries.

experimentation with different technologies (such as ICT). However, we would still expect some TFP differences (recall the discussion of Caselli's model in Section 2). Theories of increased sorting (e.g. Kremer and Maskin, 1996), by contrast, do not have this implication.

We can construct TFP in a number of ways. The basic method is the difference between weighted inputs and outputs. Measured TFP (MTFP) for firm j at time t is:

$$MTFP = \ln Q_{jt} - \alpha_j \ln L_{jt} - (1 - \alpha_j) \ln K_{jt} \quad (2)$$

Where Q_{jt} denotes value added, α_j denotes the share of labor costs in output, L_{jt} denotes labor and K_{jt} denotes the capital stock. This is the simplest method to compute TFP. There are more sophisticated ways¹⁹ to compute the parameters α_j and to derive measures of TFP. We compute α_j as firm specific weights, i.e. α_j is measured as the ratio of total wage bill over value added at the firm level and averaged over 1984-2001²⁰.

We start with analyzing the dispersion of capital intensity (in Figure 17). Although this has indeed risen over the period, it cannot fully account for the increase in the productivity dispersion, as TFP has risen significantly over this period as well

¹⁹ Griffith *et al.* (2004) discuss the methods common in the growth accounting literature. Direct estimation of the production by the methods of inter alia Olley and Pakes (1996) and Blundell and Bond (1998) is another possibility.

²⁰ We also compared this with (i) imposing $\alpha_j = 0.7$, the typically value for labor's share used in the literature on productivity and (ii) estimating α_j as industry specific weights, i.e. α_j measured as the ratio of total wage bill over value added at the two or three digit industry level and averaged over the sample period. These produced similar results.

(see Figure 18). Comparing the evolution of labor productivity dispersion and TFP dispersion, we find that the two series follows each other very closely²¹.

Since the sorting models do not predict such as rise in TFP, we view this as giving some support for the technology-based explanations of Caselli (1999) and others.

5.2. Transitory Shocks

Statistically, a rise in the cross sectional dispersion of firm productivity could arise purely from an increase in the transitory productivity shocks hitting firms²². The environment may have become more volatile for firms due to globalization, liberalization of product markets and/or financial markets. Some analyses of listed US firms have claimed that the variance of firms' sales growth has increased over time²³. Since productivity tends to rise with positive demand shocks (see Figures 5a and 5b, for example), perhaps the increased variability of firm-demand then maybe this could account for the patterns in the data.

We analyze this hypothesis by looking at transition probability matrices of labor productivity, TFP, wages and profits. Our objective is to investigate whether increasing productivity dispersion over time simply reflects increasing firm mobility across points in the productivity distribution. We consider productivity deciles and construct transition probability rates for the distributions of labor productivity over the years 1986-2001. We compare transition probability rates between 1986/87 and 1988/89 (the "early period"), between 1992/93 and 1994/95 (the "middle period"),

²¹ Interestingly, between-industry effects are slightly more important in explaining variation in TFP than in labor productivity. While they explain 17% of the increase in labor productivity dispersion, they account for 25% of the variation in TFP.

²² Dickens (2000) or Blundell and Preston (1998) are examples showing that the increase in wage and income inequality are partially driven by increases in the transitory component.

²³ See the debate between Comin and Philippon (2005) and Davis *et al* (2006).

and between 1998/99 and 2000/01 (the “late period”)²⁴. We pool the data into two-year blocks and compute the transition probabilities between adjacent blocks of years. For example, in the early period we pool data for the same firms between 1986 and 1987 to calculate the firm’s position in the productivity distribution in “ t ”, and then do the same exercise for the firms in 1988 and 1989 ($t+1$). We then compare where firms in each decile of the distribution in t ended up in $t+1$ (including the state of exiting from the sample).

It can be misleading to compare transition probabilities rates at different points of the business cycle, because recession (expansion) years are characterised by an unusual number of firms exiting (entering) the market. Given our way of shaping the data, the early and late periods correspond to a roughly similar position in the business cycle. The middle and late 1980s were expansionary years as well as the middle and late 1990s. The early 1990s were recession years.

The results are summarized in Table 1 for the top and bottom deciles (the full matrices for labor productivity are in Table 2)²⁵. We focus on the probability that a firm stays in the same decile it began with, and measure a decrease in this probability as indicating a rise in mobility. Unsurprisingly, firms that start in the top decile of the productivity distribution tend to stay there. In the early period, for example, 60% of firms who were in the top decile of the productivity distribution were still in the top decile two years later. Similarly, 46% of the firms who began in the bottom decile of the productivity distribution were still there two years later (this underestimates the persistence because the least productive firms are disproportionately likely to exit the dataset as we show in Table 2). This is a much higher frequency than would be

²⁴ We pooled data in order to keep the cell sizes reasonably large for the decile analysis. Other grouping lead to similar findings.

²⁵ We condition on the sub-sample of firms that appear in two consecutive years.

expected by random fluctuations suggesting that productivity differences are persistent over time.

The key column for our purposes is column (4) of Table 1 that compares the early and late years (these are at similar points in the business cycle). There is a very small increase of firms at the bottom of the productivity distribution moving up: only 45% of firms in the bottom decile stayed there in the late period, a one-percentage point fall from the early period. Similarly, the most productive firms were two percentage points less likely to stay in the top decile in the late period relative to the early period (58% down from 60%). So mobility has increased, but only by a small amount.

The next rows of Table 1 perform the same exercise for TFP. For the least productive firms, there is an increase in mobility between the early and the late period. In the late period, 59% of the firms in the bottom decile of the productivity distribution were still there two years later (compared to 61% in the early period). However, the opposite is true for firms at the top: they show a decrease in mobility (50% up from 47%). As with labor productivity there is no sign of a large increase in mobility: although mobility rates have increased slightly for the bottom decile by two percentage points, they have *declined* at the top decile by three percentage points.

We also investigated transitions for average wages and productivity. Looking at average wages, we find some increase in mobility between the early and the late period. This is true for firms both at the top (six percentage points) and at the bottom (four percentage points) of the wage distribution. This finding is not surprising and is also consistent with the results obtained by Dickens (2000) and Blundell and Preston (1998). Looking at average profits, we find an increase in mobility at the top only,

with a decrease in mobility at the bottom. The decrease at the bottom (four percentage points) outweighs the increase at the top (two percentage points).

Overall, then it appears that there is no evidence of a substantial increase in the transitory productivity shocks facing firms, implying that this is not the main explanation for the increase in the cross-sectional productivity distribution.

Table 2 shows the transition matrices in full detail. Because we have many small firms there is a lot of exit²⁶, especially for the least productive firms. In the early period, for example, 30% of firms in the lowest productivity decile exited compared to 20% in the highest productivity decile. This pattern of greater exit probability for the less productive firms is unsurprising as is the greater level of exit during the middle period in the early 1990s when demand was low. This prompts the question of whether these differential exit and entry patterns explain the aggregate increase in productivity dispersion.

5.3. Exit and Entry of Firms

One possible explanation of the rise in productivity dispersion that we observe could be that there was a rise in productivity dispersion among entrants. If entry barriers have declined due to liberalization or improved access to finance, for example, then a wider variety of entrants could enter the market with higher levels of productivity dispersion than previous cohorts²⁷. In principle, incumbents could have no increase in dispersion.

We analyse cohorts of new entrants and incumbents for the early (1987-1989), middle (1993-1995) and late (1999-2001) periods. We then look at the evolution of

²⁶ Note that exit includes exits to bankruptcy as well as exits due to takeovers. Takeovers are less likely to be a signal of under-performance than bankruptcy.

²⁷ Of course, the tougher competition associated with lower entry barriers could reduce productivity dispersion if the least productive firms exit. Similarly, lower entry barriers may mean that less efficient forward looking firms rationally choose not to enter assuming they can observe their productivity in advance of entry.

the top half (90th-50th differential) and the bottom half (50th-10th differential) of the labor productivity distribution. Table 3 shows that entrants are indeed more dispersed in terms of productivity than incumbents. In the early period, for instance, dispersion in the top half of the distribution was 0.92 for entrants and 0.79 for incumbents. This pattern has also been found in similar datasets for other countries. There has not been an increase in aggregate entry rates, however, so this finding by itself could not account for the increase in aggregate productivity dispersion²⁸.

Looking at changes in the productivity dispersion of entrants between the early and late periods, we do see that there has been an increase: the differentials have increased by seventeen log points and thirty-one log points in the top half and bottom half, respectively. Nevertheless, we also see an increase in the productivity inequality of incumbents. Productivity inequality for the top half has increased at a similar rate for entrants and incumbents (0.17 vs. 0.15). More interestingly, the 50-10 has increased faster for entrants (0.31 vs. 0.11). So this suggests that increased heterogeneity of entrants may have some role to play in accounting for the increase in “lower tail” (but not upper tail) productivity inequality.

We also conduct a further check in Table 4. We exclude all entrants and exiters, and we look at the evolution of productivity dispersion for two balanced panels of “continuing” firms (i.e. those who were alive throughout the period 1984-2001 and those who were alive throughout the period 1990-2001). We find that there is an increase in productivity dispersion even among continuing firms, suggesting that entrants are *not* the only cause of the rise in productivity dispersion that we observe within the economy.

²⁸ The higher overall entry rates in the early period are due to the fact that there was strong cyclical growth in the late 1980s and much merger and acquisition activity.

5.4. The role of Information and Communication Technology (ICT) in explaining the growth in productivity dispersion within industries

In the previous sections we discussed and systematically eliminated alternative explanations for the rise in productivity dispersion within the UK economy (i.e., more sorting between firms, a rise in transitory shocks, and a rise in productivity dispersion among entrants). As a consequence, we consider technical progress the most likely cause and in this sub-section, we directly examine the role of ICT may have in explaining the growth in within-industry productivity dispersion.

ICT information at the firm level does not exist for a long enough time period to perform a micro-analysis (See Bloom, Sadun and Van Reenen, 2007, for a discussion). We can, however, evaluate the impact of ICT on within-industry productivity growth using the Bank of England Industry Dataset²⁹ (BEID) which contains information on ICT services, total capital services, hours of work, output, value added, etc. at the two-digit industry level.

We use FAME data to compute the between-firm dispersion of labor productivity. We measure this as the 90-10 differential in log (real value added per employee) within each industry and calculate the change between 1984-1988 and 1996-2000. We regress this long-difference change in productivity dispersion on the change in ICT intensity and various controls.

The first column of Table 5 simply presents the bivariate regression between the change in productivity dispersion and ICT intensity revealing a large and statistically significant coefficient on ICT. A 10% increase in the share of ICT capital in total capital services is associated with a 2.7% increase in the dispersion of labor productivity. Column (2) includes a dummy for the manufacturing sector. As we

²⁹ See Oulton and Srinivasan (2003). We thank Nick Oulton for making this data available to us.

would expect given the earlier analysis, the dummy is significantly negative indicating that even conditional on ICT the growth in productivity dispersion is lower in manufacturing. Column (3) includes additional controls for the growth of total capital services per hour, the growth of the proportion of workers with college degrees and the change in union density (the proportion of workers who are members of trade unions). Including these extra controls reduces the magnitude of the coefficient on ICT intensity, but it remains significant at the 5% level. The other variables take their expected signs. Capital intensity is positive and significant which is consistent with the idea that some technology is embodied in non-ICT capital. ICT capital growth could be reflecting the growth of skills, which is why we condition on human capital – the variable is positive and significant. Institutional explanations of the rise in inequality emphasize that union decline may allow low wage/low productivity firms to survive. The union coefficient is indeed negative but it is insignificantly different from zero.

We were concerned that the observed increase in dispersion may be due to the problem that hours are not available at the firm level. Increased dispersion of productivity could simply reflect increased dispersion of hours worked. To control for this we calculated the dispersion of hours worked in each industry using individual level data from the NES (in column (4)) and the Labor Force Survey (in column (5)). These variables were both insignificant and did not affect the coefficient on ICT intensity. We also included other demographic controls (female workers and part-time workers) as possible correlates with the increased use of ICT capital (and as factors that could affect labor productivity). Again, the ICT coefficient remains significant.

In summary, after controlling for various factors, the positive association between increases in productivity dispersion and changes in ICT intensity still holds.

The ICT variable is economically as well as statistically significant. ICT intensity has grown very rapidly over this period (from 3.4% of all capital services in 1984-1988 to 15% in 1996-2000). Given the estimated coefficient we can essentially account for *all* of the increase in productivity dispersion (0.266 points) by the increase in ICT intensity³⁰.

5.5. International Data

If the growth of productivity inequality was technology based we would expect to observe this in other countries. In particular, France and Norway where there has been little change in wage inequality (e.g. Machin and Van Reenen, 2007). Figure 19 shows us the situation in France between 1989 and 2000 (we chose these years because we have consistent data). Interestingly, like the UK, there has been a clear increase in the variation of productivity over this period. Note, however, the y-axis scale is much narrower than in previous graphs. Productivity has grown by about 10% for firms at the 90th decile and has fallen by 10% for firms at the lower decile. The median firm has experienced productivity growth of about 5%. This is in the same direction as the UK, but the rise in productivity dispersion has been less dramatic.

Figure 20 shows the situation in Norway in the 1995-2002 period (the only period for which we have value added per worker information in non-manufacturing as well as manufacturing). There has been a small growth in the 90-10 decile ratio over this period. Interestingly this increase is confined to the upper part of the

³⁰ See Table A2. $\ln(\text{ICT services/capital services})$ increased by 1.605 over this period so the implied “effect” is 0.37, more than 100% of the observed change.

distribution (the 90-50); the lower half of the distribution has shown some small decrease in inequality.

It is well known that inequality of wages in France and Norway has also grown more slowly than in the UK or US in the last 25 years. So although the increase in productivity dispersion is not unique to the UK, it seems more muted in countries where there has been a slower growth of wage inequality. This suggests that institutional factors may play a role in the change of productivity dispersion.

5.6. Quantification: How Important are the results for the wage distribution?

How important could the change in the structure be in explaining the change in the wage distribution? We have not yet written a formal general equilibrium model of the simultaneous determination of the wage and productivity distribution³¹ so all we can do is to give some intuition over the magnitudes. Appendix C gives a simple model that could help us estimate some of the magnitudes. The model assumes that productivity is driven by technological factors and that wages are determined by a mixture of human capital characteristics and firm characteristics. Our model allows us to estimate the impact of the changing productivity dispersion on wage dispersion as:

$$\beta^2 \frac{\Delta \text{var}\left(\ln \frac{Q}{L}\right)}{\Delta \text{var}(\ln W)} \quad (3)$$

Between 1984 and 2001 the variance of $\ln(\text{productivity})$ rose by 0.26 and the variance of firm $\ln(\text{wages})$ rose by 0.21. If we assume that $\beta = 0.3$ (e.g. Van Reenen, 1996) then this implies that 10% of the increase in the variance of inter-firm wages is accounted for by the variance of inter-firm productivity. Therefore, this still leaves a

³¹ See Klette and Kortum (2004) or Lentz and Mortensen (2005) for an attempt to do this in the cross section.

big residual for such factors as the increase in the return to observable skills (and possibly increased sorting). Nevertheless, the increased productivity dispersion is a significant part of the story.

Furthermore, there is some evidence that the between firm distribution of productivity could have become more important over time in accounting for the wage dispersion. Running wage regressions separately for different time periods reveals that β has been increasing over time. For example, Table 6 reports specifications of a regression of wages on productivity with controls for time dummies and industry effects. We estimate separately for an early period (1984-1989), a middle period (1990-1995) and a late period (1996-2001). The first column reports simple OLS, the second column adds a full set of fixed effects and the third column reports GMM “System” estimates in the manner of Blundell and Bond (1998). All results show an increase in the importance of the effect of productivity on wage. For examples in the GMM estimates the coefficient rises from 0.325 in the mid 1980s to 0.382 in the late 1990s. This suggests that firm heterogeneity has become more important in explaining the overall wage distribution.

Although this shows that firm heterogeneity remains important for the wage distribution, it is difficult to estimate how important this phenomenon is for the overall increase in inequality. As Appendix C shows, the effect will depend on such hard to measure things as the variation of human capital and the degree of worker-firm sorting (and the changes in these objects).

6. Conclusions

In this paper we have examined some evidence for the explanation of the growth of residual wage inequality. We have shown that a generally untested

implication of many technology-based theories of within group wage inequality is that there should be *an increase in the dispersion of productivity between firms*. We argue that existing studies will underestimate the importance of the growth of productivity inequality because they focus on the manufacturing sector that has experienced a surge of international competition truncating the lower tail of poorly performing firms and therefore compressing the (counterfactual) productivity distribution.

Using new panel data on UK firms over the 1984-2001 period we show that the substantial increase in individual wage inequality is mainly a between firm (rather than within firm or between industry) phenomenon. More importantly we show that there has been a substantial increase in the between firm productivity dispersion. The 90th percentile of the productivity distribution grew by 60 log points between 1984 and 2001 whereas the 10th percentile grew by only 20 log points. Furthermore, we show that the increase was driven by the private service sector – the growth of dispersion in the manufacturing sector was muted.

We examined several hypotheses that sought to explain the growth of the productivity dispersion. Overall, we conclude that the data gives some support for models along the lines of Caselli (1999) or Acemoglu *et al.* (2001). The diffusion of new technologies heterogeneously across firms has increased both the spread of productivity and the spread of wages. We found that those industries that had the most rapid increase in the use of ICT also had the most rapid increase in productivity dispersion.

We argued that increases in the dispersion of inputs (such as ordinary capital) could not fully account for this pattern as TFP dispersion has risen - which implies that increased sorting is unlikely to be the main cause of the change. In addition, the pattern was not due to an increase in transitory shocks as the transition matrices

appear to be relatively stable at the beginning and end of the period. Thirdly, we showed that increased dispersion amongst entrants was not the only cause of the increased productivity inequality as productivity inequality grew even among survivors.

The next steps in our analysis are to combine the information here with explicit measures of firm-level technology to test the theories more rigorously. Such data is available and is being constructed (Bloom *et al.*, 2007). We also need to use more of the data from other countries, especially matched worker-firm data where we can do more to control for worker heterogeneity. Moreover, we need to address whether institutional or trade explanations have any purchase on the data. Finally, a tighter match with the theory of equilibrium wage and productivity dispersion is also a pressing need (e.g. Klette and Kortum (2004) or Lentz and Mortensen (2005)). This research is in progress.

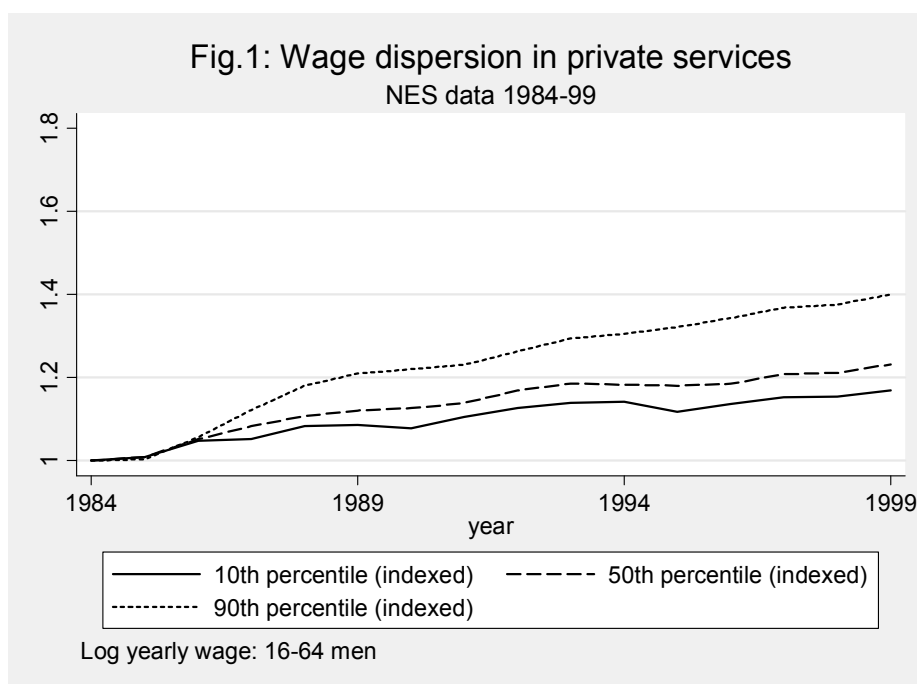
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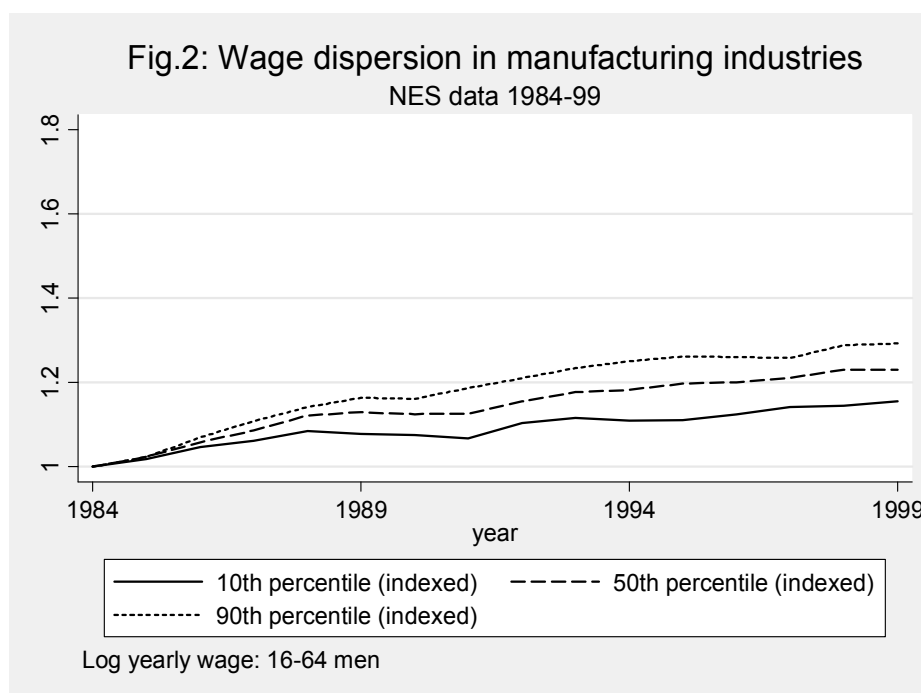
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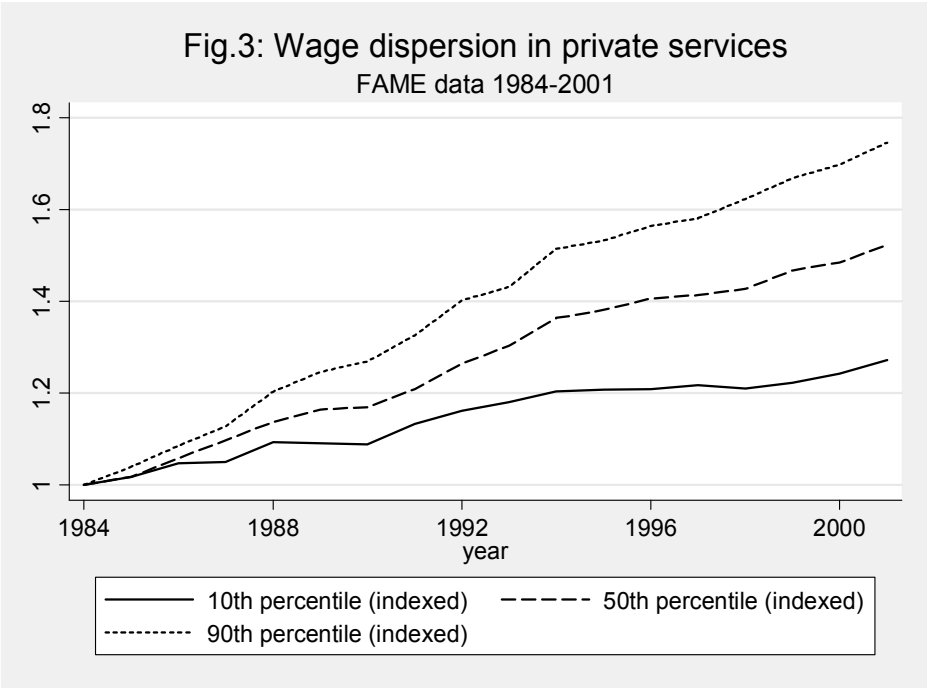
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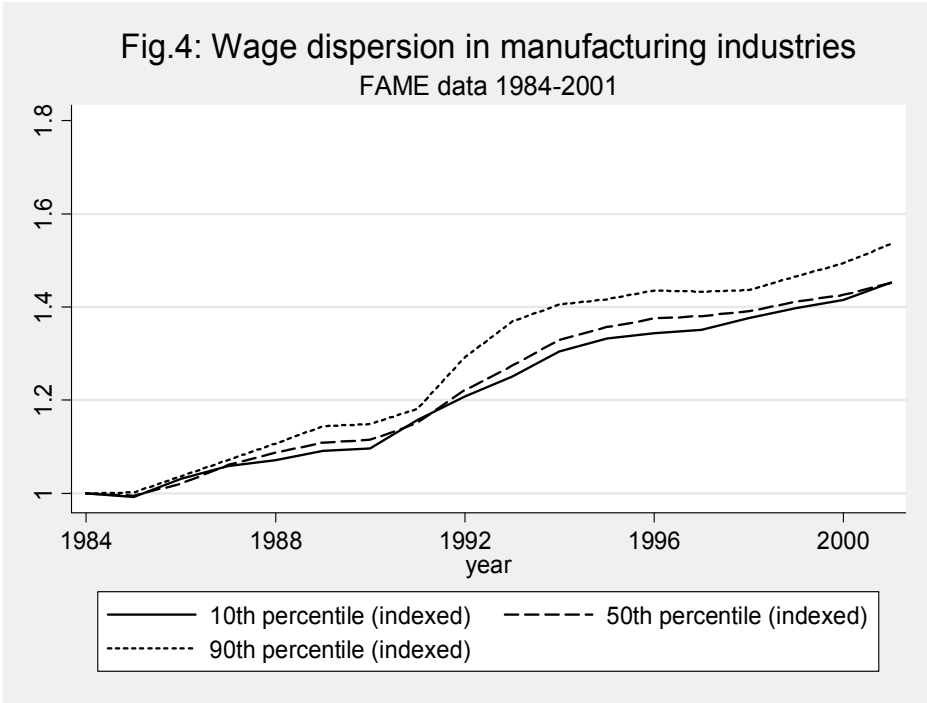
Source: New Earnings Survey Data, $\ln(\text{annual wages})$, men 16-65. Private Services only.



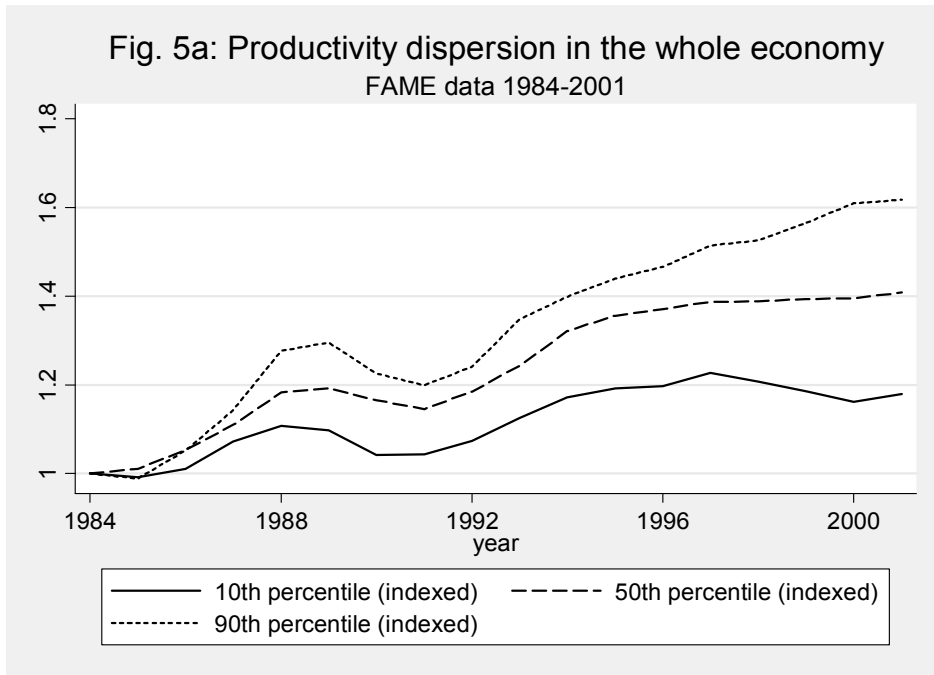
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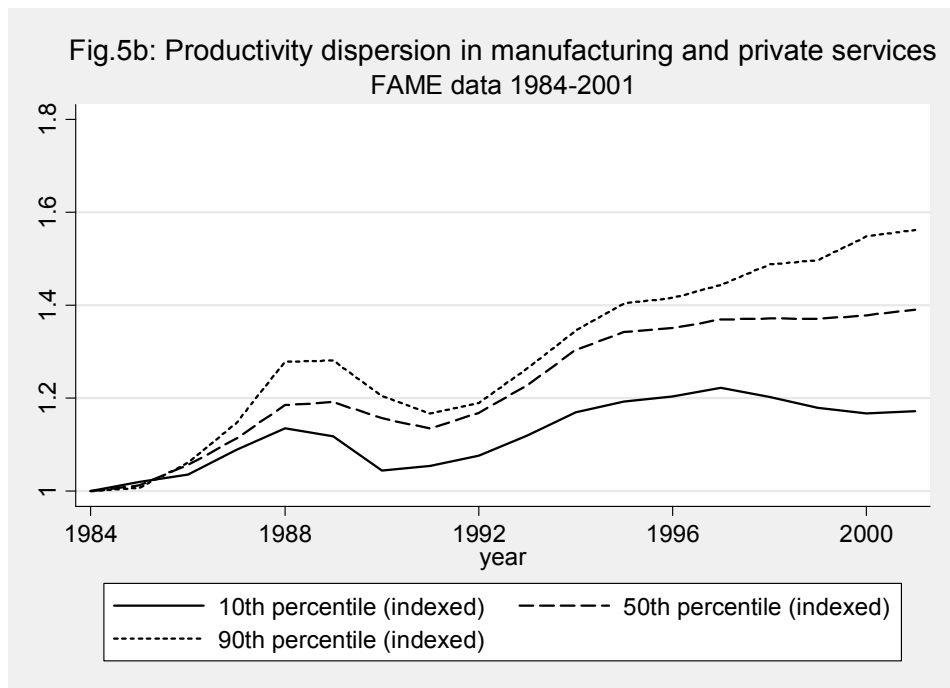
Source: FAME Company level data, ln(average annual wages).



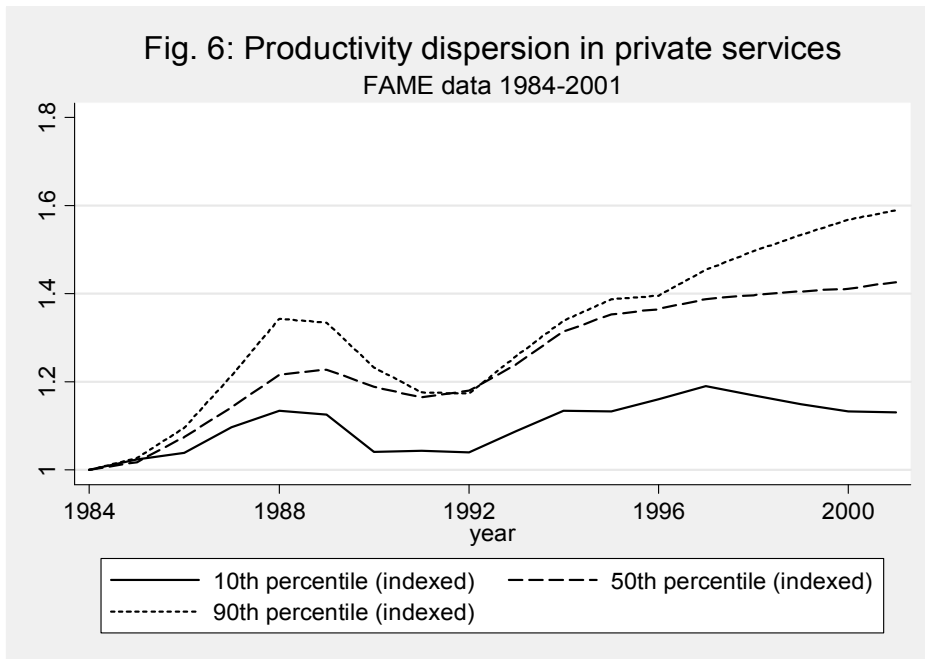
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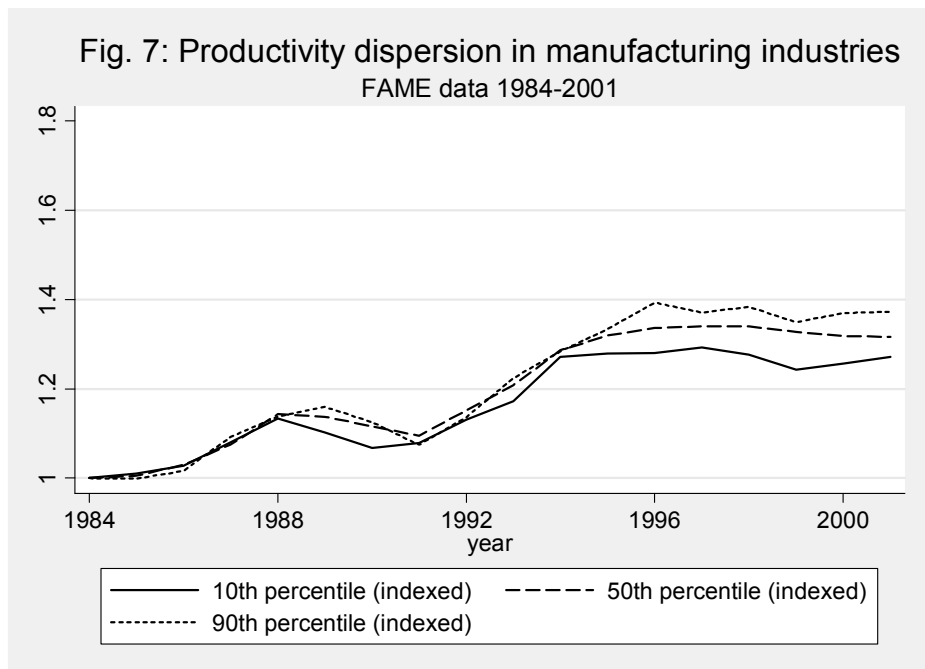
Source: FAME Company level data, $\ln(\text{value added per worker})$.



Source: FAME Company level data, $\ln(\text{value added per worker})$.

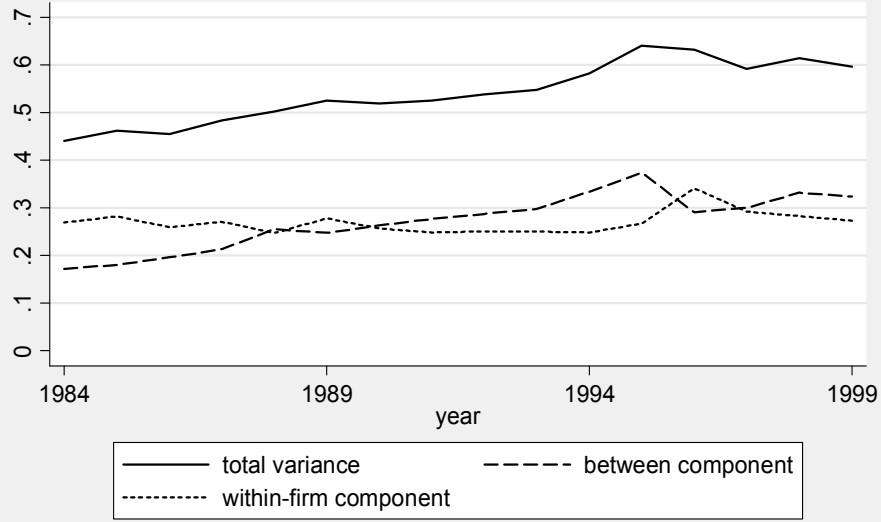


Source: FAME Company level data, $\ln(\text{value added per worker})$.



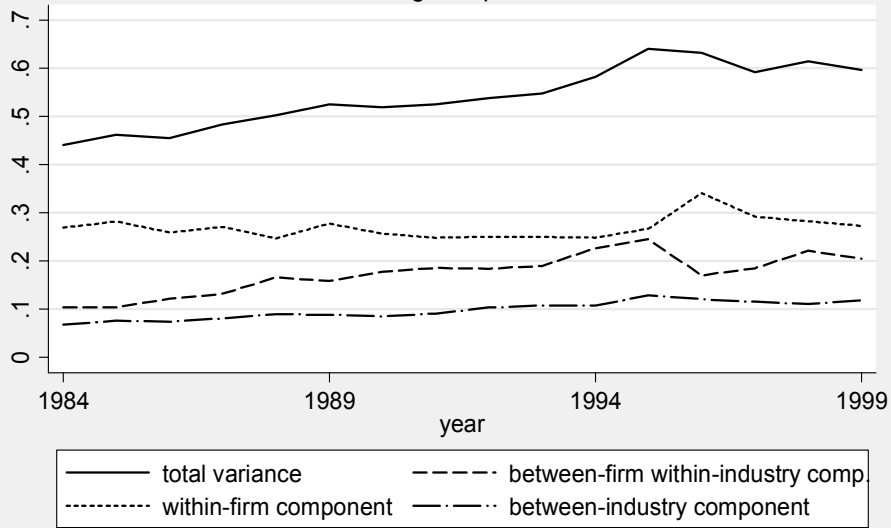
Source: FAME Company level data, $\ln(\text{value added per worker})$.

Fig.8: Decomposition of wage dispersion
Manufacturing and private services



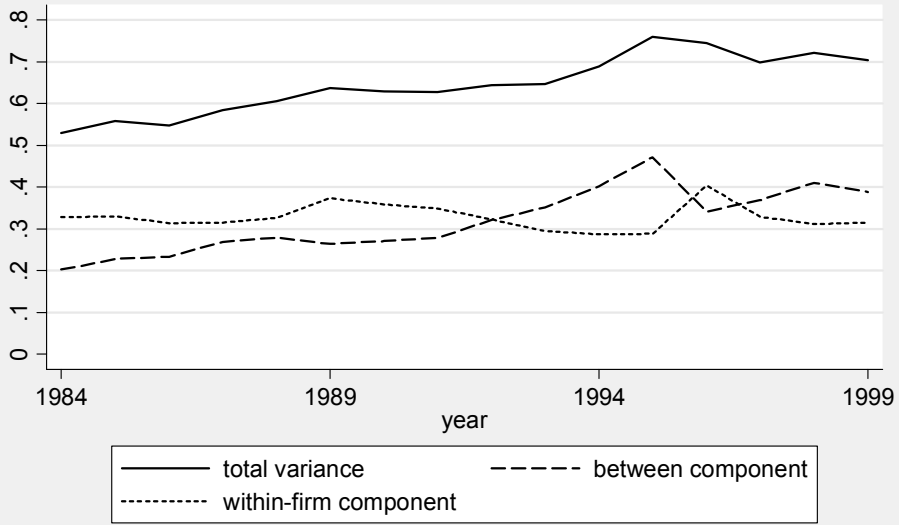
NES and FAME Datasets 1984-1999.

Fig.9: Decomposition of wage dispersion
Manufacturing and private services



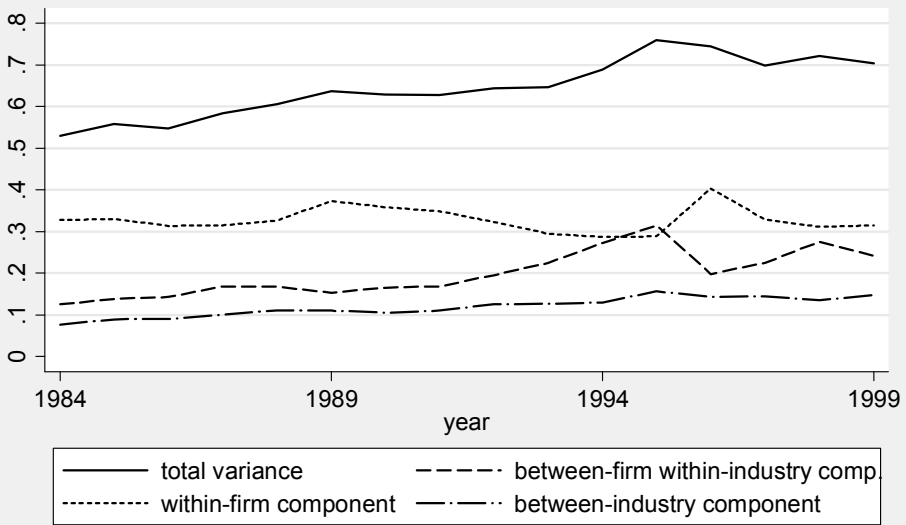
NES and FAME Datasets 1984-1999.

Fig.10: Decomposition of wage dispersion
Private services



NES and FAME Datasets 1984-1999.

Fig.11: Decomposition of wage dispersion
Private services



NES and FAME Datasets 1984-1999.

Fig.12: Decomposition of wage dispersion
Manufacturing industries

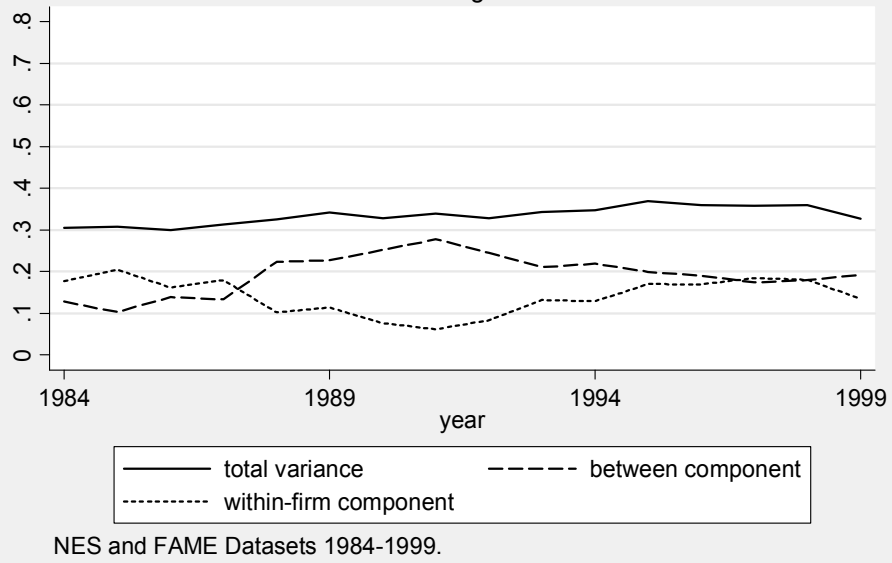


Fig.13: Decomposition of wage dispersion
Manufacturing industries

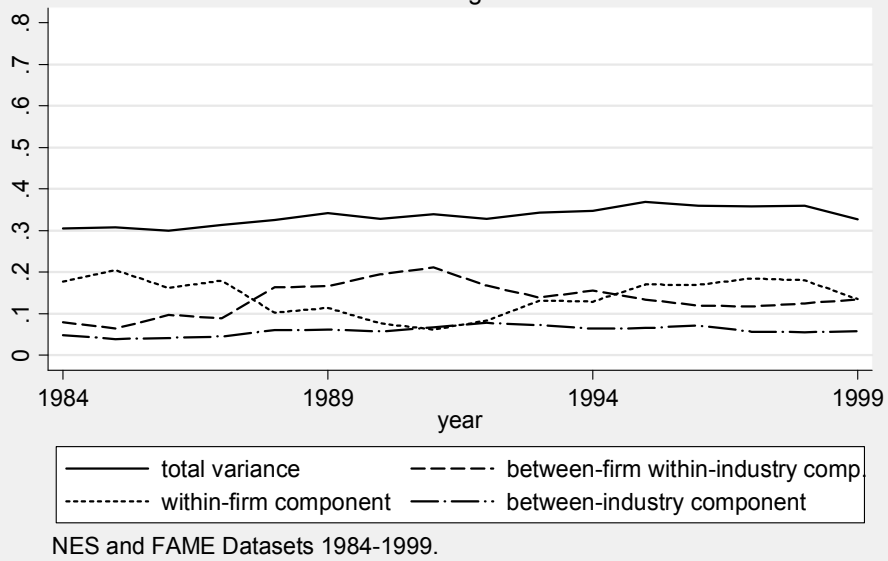


Fig.14: Decomposition of labour productivity dispersion
Manufacturing and private services

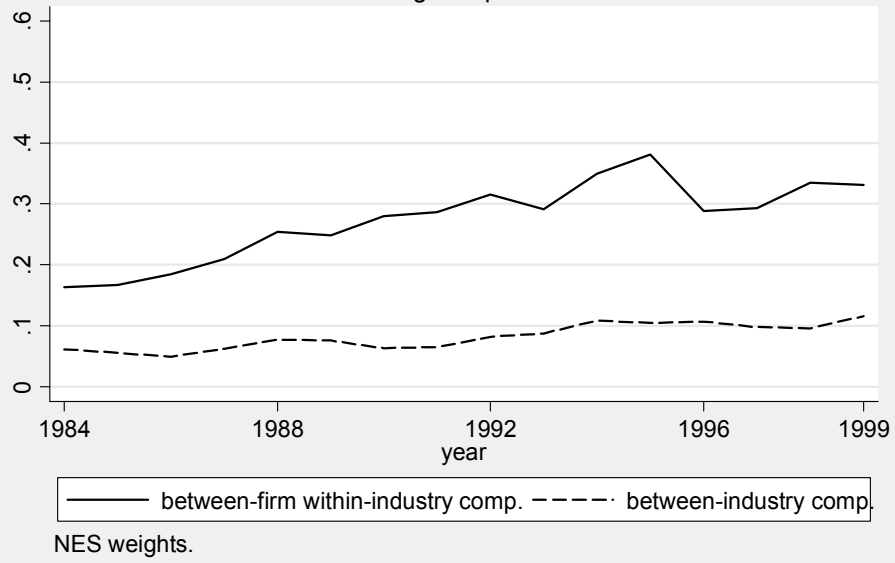


Fig.15: Decomposition of labour productivity dispersion
Private Services

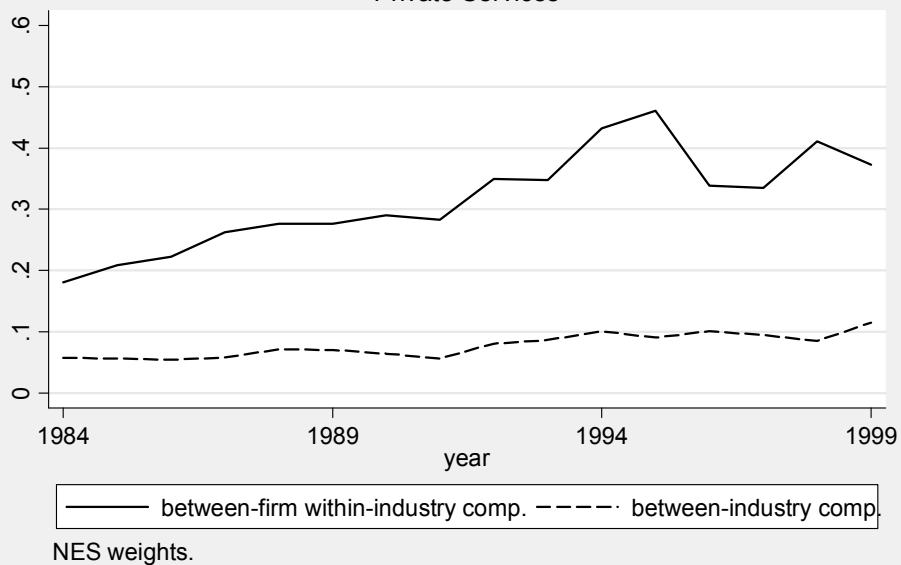


Fig.16: Decomposition of labour productivity dispersion
Manufacturing Industries

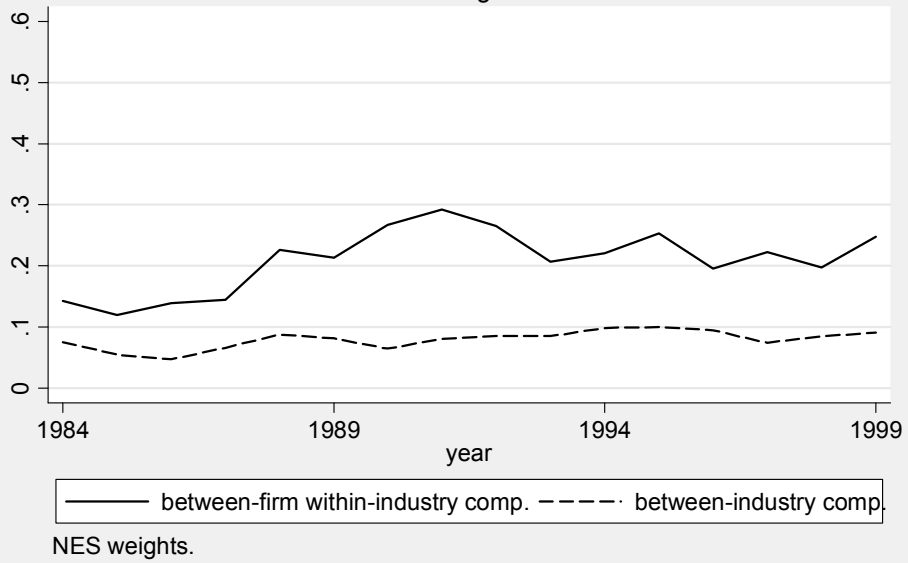
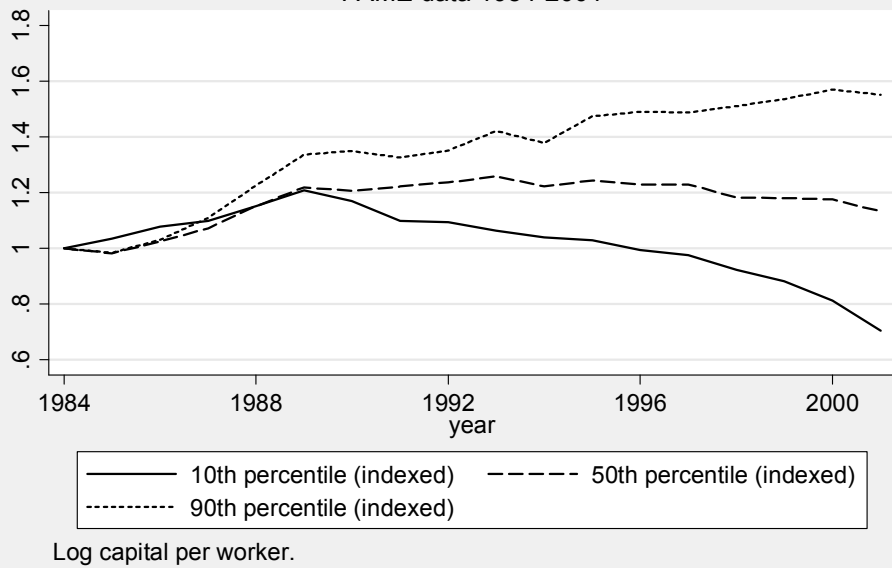


Fig. 17: Capital per worker dispersion in the whole economy
FAME data 1984-2001



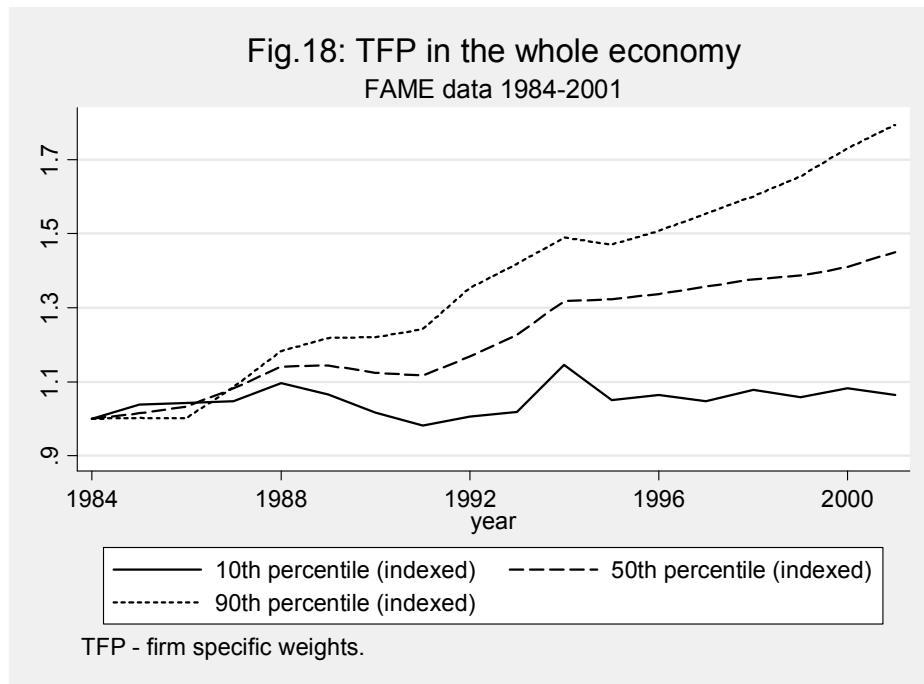
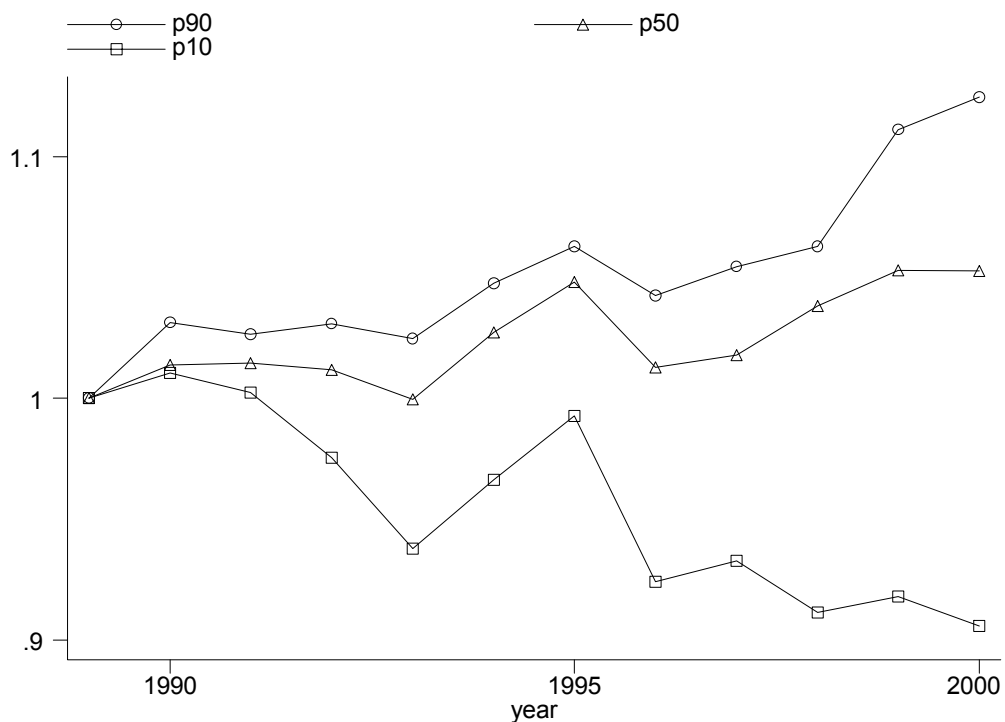
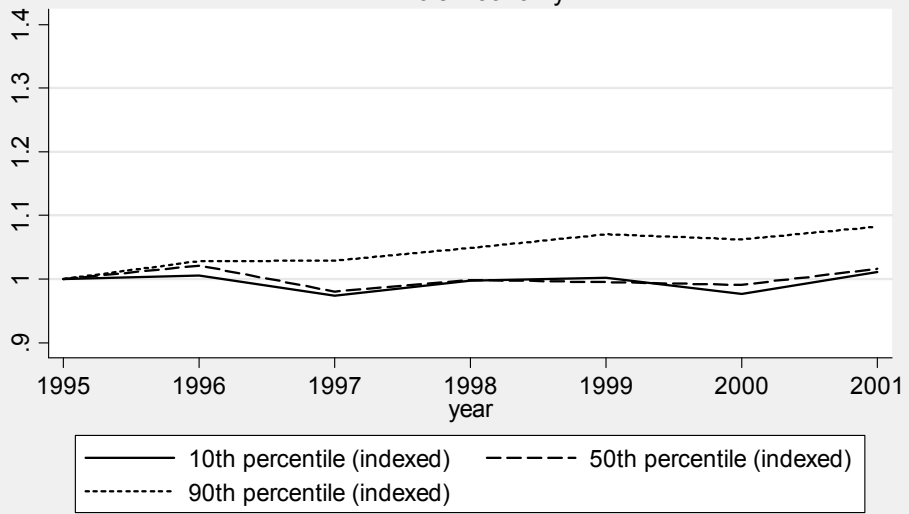


Figure 19: Change in French Productivity Dispersion (Value added per worker), whole economy, 1989-2000



Source: BRN Database

Fig.20: Change in Norwegian Firm Productivity Dispersion 1995-2001
Whole Economy



Source: REGN dataset.

Sample of firms with $emp \geq 10$; $\ln(va/emp)$.

Table 1: Transition probability matrices: summary of the results

	(1)	(2)	(3)	(4)	(5)
	<i>Early</i>	<i>Middle</i>	<i>Late</i>	<i>Total change</i>	<i>Δ Late to Middle</i>
	From 1986/87 to 1988/89	From 1992/93 to 1994/95	From 1998/99 to 2000/01	Δ (2000/01 - 1986/87)	Δ (2000/01 - 1992/93)
Labor Productivity					
1 st decile	0.60	0.48	0.58	-0.02	0.10
10 th decile	0.46	0.38	0.45	-0.01	0.07
TFP (α=firm weights)					
1 st decile	0.47	0.44	0.50	0.03	0.06
10 th decile	0.61	0.52	0.59	-0.02	0.07
Average Wage					
1 st decile	0.59	0.50	0.55	-0.04	0.05
10 th decile	0.60	0.52	0.56	-0.06	0.04
Average profits					
1 st decile	0.60	0.48	0.58	-0.02	0.08
10 th decile	0.25	0.19	0.29	0.04	0.06

Note: Labor Productivity is defined as log (real value added /employment). We compare the transitions between (two year) periods by decile (see Table 2 for the full matrix for labor productivity). For example, the element in the first row and column indicates that 60% of the firms who were in the top decile of productivity in the 1986-1987 period remained in the top decile in the 1988-1989 period. Column (4) is the absolute difference between columns (3) and (1). Column (5) is the absolute difference between columns (3) and (2).

Table 2: Three-Year Transition Rates: Labor Productivity

	State in 1988-89											
State	1 st	2 nd	3 rd	4 th	5 th	6 th	7 th	8 th	9 th	10 th	Exit	Obs.
86-87												
1 st	0.60	0.13	0.05	0.01	0.01	0	0	0.01	0	0	0.20	706
2 nd	0.10	0.38	0.18	0.06	0.03	0.02	0.01	0.01	0	0.01	0.20	706
3 rd	0.04	0.15	0.26	0.19	0.07	0.03	0.02	0.01	0.01	0.01	0.20	706
4 th	0.01	0.05	0.15	0.22	0.18	0.08	0.05	0.02	0.02	0.01	0.22	706
5 th	0.01	0.02	0.05	0.14	0.22	0.18	0.09	0.05	0.02	0.01	0.20	707
6 th	0	0.01	0.03	0.07	0.15	0.21	0.16	0.10	0.05	0.02	0.20	706
7 th	0	0.02	0.02	0.03	0.07	0.13	0.24	0.19	0.07	0.03	0.21	706
8 th	0.01	0	0.01	0.02	0.03	0.07	0.14	0.24	0.18	0.05	0.24	706
9 th	0	0	0.01	0.02	0.02	0.03	0.05	0.12	0.31	0.18	0.25	706
10 th	0.01	0	0.01	0.02	0.01	0.01	0.02	0.04	0.12	0.46	0.30	707
	State in 1994-95											
State	1 st	2 nd	3 rd	4 th	5 th	6 th	7 th	8 th	9 th	10 th	Exit	Obs.
92-93												
1 st	0.48	0.11	0.03	0.01	0	0	0	0	0	0.01	0.35	810
2 nd	0.13	0.32	0.15	0.06	0.02	0.01	0.01	0.01	0	0.01	0.28	809
3 rd	0.03	0.14	0.25	0.18	0.07	0.02	0.02	0.01	0.01	0	0.27	809
4 th	0.02	0.05	0.13	0.19	0.18	0.08	0.04	0.02	0.01	0.02	0.27	809
5 th	0.01	0.02	0.05	0.11	0.17	0.17	0.10	0.04	0.02	0.01	0.30	809
6 th	0	0.01	0.02	0.05	0.10	0.19	0.16	0.10	0.02	0.02	0.32	810
7 th	0	0.01	0.01	0.03	0.07	0.10	0.16	0.18	0.09	0.03	0.34	809
8 th	0	0	0.01	0.01	0.03	0.04	0.10	0.19	0.20	0.05	0.37	809
9 th	0	0.01	0	0.01	0.02	0.03	0.05	0.10	0.24	0.15	0.38	809
10 th	0	0.01	0.01	0.01	0.01	0.02	0.03	0.03	0.08	0.38	0.40	809
	State in 2000-01											
State	1 st	2 nd	3 rd	4 th	5 th	6 th	7 th	8 th	9 th	10 th	Exit	Obs.
98-99												
1 st	0.58	0.11	0.02	0.01	0.01	0	0	0	0	0	0.28	959
2 nd	0.11	0.36	0.16	0.04	0.03	0.01	0.01	0.01	0.01	0.01	0.26	959
3 rd	0.02	0.15	0.26	0.14	0.06	0.03	0.02	0.01	0.01	0.01	0.29	959
4 th	0	0.06	0.15	0.23	0.15	0.08	0.03	0.02	0.02	0.01	0.24	959
5 th	0.01	0.02	0.07	0.17	0.22	0.13	0.07	0.04	0.02	0.01	0.23	959
6 th	0	0.01	0.03	0.06	0.14	0.23	0.16	0.08	0.04	0.02	0.22	959
7 th	0	0.01	0.02	0.03	0.08	0.15	0.23	0.15	0.07	0.02	0.24	959
8 th	0	0.01	0.01	0.02	0.03	0.05	0.14	0.25	0.17	0.05	0.26	959
9 th	0.01	0.01	0.01	0.02	0.02	0.03	0.04	0.14	0.29	0.15	0.30	959
10 th	0	0	0.01	0.01	0.01	0.02	0.02	0.04	0.10	0.45	0.34	959

Notes: Labor Productivity is defined as log (real value added /employment). We compare the transitions between (two year) periods by decile (see Table 2 for the full matrix for labor productivity). For example, the element in the first row and column indicates that 60% of the firms who were in the top decile of productivity in the 1986-1987 period remained in the top decile in the 1988-1989 period. Column (4) is the absolute difference between columns (3) and (1). Column (5) is the absolute difference between columns (3) and (2).

Table 3: Labor productivity dispersion among entrants and incumbents

<i>Periods</i>	<i>Entrants</i>			<i>Incumbents</i>		
	90 th -50 th	50 th -10 th	Obs.	90 th -50 th	50 th -10 th	Obs
Early (1987-1989)	.92	.72	5585	.79	.60	7437
Middle (1993-1995)	.99	.82	5167	.84	.65	9764
Late (1999-2001)	1.09	1.03	4180	.94	.71	10367
Δ(1987-2001)	.17	.31		.15	.11	

Notes: 90th -50th = differential between the 90th and 50th percentile of the productivity distribution; 50th -10th = differential between the 50th and 10th percentile of the productivity distribution.

Table 4: Labor productivity dispersion – balanced panels

<i>Periods</i>	<i>Balanced panel, 1984-2001</i>			<i>Balanced panel, 1990-2001</i>		
	90 th -50 th	50 th -10 th	Median	90 th -50 th	50 th -10 th	Median
84-86	0.68	0.50	2.96			
87-89	0.68	0.53	3.09			
90-92	0.60	0.55	3.07	0.72	0.60	3.09
93-95	0.64	0.57	3.19	0.73	0.57	3.21
96-98	0.74	0.58	3.24	0.79	0.60	3.28
99-01	0.77	0.58	3.24	0.86	0.59	3.25
Δ(1984-2001)	0.09	0.08	0.28	0.14	-0.01	0.16

Notes: 90th -50th = differential between the 90th and 50th percentile of the productivity distribution; 50th -10th = differential between the 50th and 10th percentile of the productivity distribution. The balanced panel (1984-2001) contains 784 observations every year; the balanced panel (1990-2001) contains 2136 observations every year.

Table 5: The role of ICT in explaining the growth in within- industry productivity dispersion

Dep. Var.: Δ(Dispersion in labor productivity)	(1)	(2)	(3)	(4)	(5)
$\Delta \ln(\text{ICT services/total capital services})$	0.266*	0.311**	0.230**	0.232*	0.292**
	(0.143)	(0.147)	(0.117)	(0.124)	(0.136)
Manufacturing dummy		-0.356**	-0.166	-0.090	-0.141
		(0.154)	(0.133)	(0.186)	(0.167)
$\Delta \ln(\text{total capital services/hours})$			0.538*	0.403	0.184
			(0.319)	(0.273)	(0.317)
$\Delta(\text{proportion of workers with college degree})$			0.368**	0.375	0.517**
			(0.170)	(0.243)	(0.237)
$\Delta(\text{union density})$			-0.118	-0.282	-0.094
			(0.263)	(0.388)	(0.414)
$\Delta(\text{coefficient of variation in total actual hours of work - LFS})$				-0.357	
				(0.469)	
$\Delta(\text{coefficient of variation in hours of work - NES})$					-0.121
					(0.096)
$\Delta(\text{proportion of part-time workers})$				0.223	0.141
				(0.183)	(0.167)
$\Delta(\text{proportion of female workers})$				0.088	0.001
				(0.324)	(0.426)
R²	0.10	0.17	0.36	0.44	0.49
No. of observations	33	33	33	33	33

Notes: These are OLS regressions using the Bank of England Dataset. All variable are in “long differences” between 1984-88 and 1996-2000. The dependent variable, Dispersion in labor productivity, is the 90-10 of $\log(\text{value added per worker})$. Robust standard errors are in parentheses below coefficients.). Regressions weighted by the industry size. Robust standard errors are in parentheses below coefficients. (*): significant at the 10% level; (**): significant at the 5% level; (***): significant at the 1% level.

Table 6: Correlation between wage and labor productivity

	(1)	(2)	(3)
Firm Performance Variable	Ln(Value added per worker)	Ln(Value added per worker)	Ln(Value added per worker)
	OLS	Within Groups	GMM (Blundell-Bond, 1998)
Early (1984-89)	0.385*** (0.002)	0.240*** (0.002)	0.325*** (0.028)
Middle (1990-1995)	0.446*** (0.002)	0.259*** (0.002)	0.352*** (0.037)
Late (1996-2001)	0.491*** (0.002)	0.282*** (0.002)	0.382*** (0.032)
# of obs.	182,189	182,189	118,806

Notes: Standard errors are in parentheses below coefficients are robust to heteroskedacity and arbitrary serial correlation (i.e. clustered by firm). (*): significant at the 10% level; (**): significant at the 5% level; (***): significant at the 1% level. GMM in column (3) conditions on having at least four continuous time series observations. Instruments used are ln(value added per worker) lagged t-2 and t-3 in the differenced equation and Δ ln(value added per worker) lagged t-1 in the levels equations. All columns include a full set of time dummies. Columns (2) and (3) include firm fixed effects.

Appendix A: Variance decomposition of the between-firm component

Following Davis and Haltiwanger (1991) and Dunne *et al.* (2004), we decompose wage dispersion into between-firm and within-firm components. Our objective is to measure the contribution of the between and within components in explaining wage inequality.

Total variation in $W = \ln(\text{wages})$ across workers is defined as V and can be divided into a within firm (V_{WF}) and between firm (V_{BF}) component:

$$V = V_{WF} + V_{BF} \quad (\text{A1})$$

The between firm component can be further divided into a between industry (V_{BI}) and within industry (but between firm) component (V_{BFI}). This can be written:

$$V = V_{WF} + V_{BI} + V_{BFI} \quad (\text{A2})$$

More explicitly write the individual variance of wages as:

$$V = \sum_k \sum_j \sum_i (W_{ijk} - \bar{W})^2 = \sum_k \sum_j \sum_i [(W_{ijk} - W_{jk}) + (W_{jk} - \bar{W})]^2 \quad (\text{A3})$$

where W_{ijk} is the $\ln(\text{wage})$ for worker i at firm j in sector k , W_{jk} is the average $\ln(\text{wage})$ at firm j in sector k and \bar{W} is the mean wage across all workers in all firms and sectors.

Multiplying and dividing the first term of the right-hand side of equation (A3) by N_{jk} , (the total number of workers in firm j) and considering that the $\sum_i (W_{ijk} - \bar{W}) = N_{jk} (W_{jk} - \bar{W})$, equation (A3) becomes:

$$V = \sum_k \sum_j N_{jk} \sum_i \frac{(W_{ijk} - W_{jk})^2}{N_{jk}} + \sum_k \sum_j N_{jk} (W_{jk} - \bar{W})^2 \quad (\text{A4})$$

Equation (A4) can be written as:

$$V = \sum_k \sum_j N_{jk} V_{jk} + \sum_k \sum_j N_{jk} (W_{jk} - \bar{W})^2 \quad (\text{A5})$$

Dividing through by N , the total number of workers in the economy, we obtain the decomposition of overall variation into within firm (WF) and between-firm (BF) components:

$$V = \frac{1}{N} \sum_k \sum_j N_{jk} V_{jk} + \frac{1}{N} \sum_k \sum_j N_{jk} (W_{jk} - \bar{W})^2 \quad (\text{A6})$$

Define V_{WF} as the employee-weighted variance of mean wages within firms and V_{BF} denotes the employee-weighted variance of mean wages between firms.

$$V_{WF} = \left(\frac{1}{N} \right) \sum_k \sum_j N_{jk} V_{jk} \quad (\text{A7})$$

$$V_{BF} = \left(\frac{1}{N} \right) \sum_k \sum_j N_{jk} (W_{jk} - \bar{W})^2 \quad (\text{A8})$$

Substituting (A7) and (A8) into (A6) gives us equation (A1). It is straightforward to show how this can be further decomposed into an industry specific component.

The between-firm and within-firm variance terms in (A8) and (A7) cannot be isolated from individual surveys like the NES, although the NES does permit estimation of their sum, V . To isolate the components, we first calculate V_{BF} directly from the wage data in a firm-level database, FAME. We then estimate the within-firm

wage variance as a difference between total variance and the between-firm component using equation (A1)

$$\hat{V}_{WF} = V(W^{NES}) - V(W^{FAME}) \quad (\text{A9})$$

where $V(W^{NES})$ is the variance of measured wages in the NES and $V(W^{FAME})$ is the variance of wages in FAME. By applying this straightforward approach, we assume that there is no bias resulting from measurement error in the NES³².

³² Our approach of using equation (A8) to estimate within-firm variance of wages relies on the assumptions that the variance of measurement error in the NES wage observations and the covariance between true wage and the NES measurement error are negligible. Testing these assumptions requires both employer-reported and worker-reported wages for a sample of workers. Unfortunately, we do not have employer-employee linked data for the UK.

Appendix B: Data and additional results

B1. The Datasets used

Firm level dataset - FAME (Financial Analysis Made Easy)

This database consists of company account data for the United Kingdom as discussed in the main text. The main dataset we use is FAME (Financial Analysis Made Easy) which is a UK company-level panel data set available since 1982. In Britain, all incorporated companies are legally required to register their accounts at Companies House and given a unique registration number. Unlike the US, this includes not only companies listed on the Stock Exchange but also all unlisted companies. In 2003, we arranged a special purchase of this data with a private sector company (Jordan's) that has converted this data into electronic form³³. This is unbalanced panel data and includes all firms that had exited the database prior to 2003 (by either bankruptcy or takeover).

Under UK law, firms are also required to report a great deal more accounting information on their wage bills than in the US (where declaration of staff expenses is a voluntary item). Because of this, we are able to construct measures of average firm wages that are unavailable for most firms in the US public accounts.

We define average firm wage as the log ratio of total remuneration over the number of employees. We define labor productivity as log real value added per worker. Value added is calculated as the sum of gross profits before tax and staff expenses (see Griffith, Harrison and Van Reenen, 2006). We also consider a definition based on sales minus estimates of intermediate inputs.

We apply three different measures of total factor productivity (TFP): (1) TFP measured by the Solow residuals with fixed weights, (2) TFP measured by the Solow residuals with industry specific weights and (3) TFP measured by the Solow residuals with firm specific weights (this is the preferred measure used in the Figures). All financial variables are expressed in thousands of pounds sterling and deflated by the annual Retail Price Index (RPI).

We made the following selections in the main analysis (selection biases discussed below)

- We exclude firms whose main industry was in agriculture, fishing, mining, utilities, public administration, health, education, social work and finance (the “manufacturing and private services” sample).
- We keep consolidated company accounts data.
- We keep firms with at least 10 employees.

The final sample of firms contains information on about 11,000 companies each year between 1984 and 2001. The database provides detailed information on employment, tangible fixed assets, sales, gross profits, profits before tax and the industry in which the firm is operating (as well as many other items from the balance sheet).

In testing the incidence of transitory productivity shocks hitting firms (subsection 5.2) we compute transition probabilities matrices of labor productivity, TFP, average wage and average profits. We condition on the sub-sample of firms that also

³³ Bureau Van Dijk (BVD) supplied AMADEUS which contains FAME as a UK sub-component (licensed from Jordan's). Unfortunately only firms who died within the previous ten years are kept and AMADEUS was not very complete until around 1999. This is why we needed to deal directly with Jordan's and arrange a dump from their mainframe.

satisfy the conditions that we have labor productivity values in a two-year periods. The two-year periods are 1986/87 and 1988/89 (“the early period”), 1992/93 and 1994/95 (“the middle period”), 1998/99 and 2000/21 (“the late period”). The final sub-sample for the entry/exit analysis includes 7,062; 8,092 and 9,590 firms in the early, middle and late periods, respectively.

The New Earnings Survey (NES) is an employer reported survey, conducted in April each year, of employees in employment in the UK. The sample frame, based on national insurance (NI) numbers, covers roughly 1% of all employees – some 200,000 individuals each year between 1984 and 1999. Individuals can be matched across years by their National Insurance (NI) numbers to form a panel of employees in employment. Details on personal characteristics are limited, but there is a wealth of information on earnings, hours, industry, occupation, sector and region. We have access to the data for the years 1984 through 1999.

In order to compute our measure of gross annual pay, (1) we exclude Northern Ireland from our sample, thus concentrating on a sample for Great Britain; (2) we select 16-64 year old males and 16-59 year old females for which their pay and working hours are not affected by absence; (3) we compute gross annual pay by multiplying gross weekly pay by 52. Our sample consists of about 160,000 individuals each year. Wage variables are expressed in thousands of pounds sterling and deflated by the annual Retail Price Index (RPI).

Datastream contains company accounts data for UK firms listed on the stock exchange. We exclude firms operating in the financial sector (SIC80 code: 814-832). The sample at our disposal consists of about 1,350 firms each year between 1983 and 2001. We define average firm wage as real total remuneration per employee. We also define labor productivity as real value added per employee. We use the annual RPI as deflator.

Regnskapsstatistikk (REGN data) are the statistics of accounts for non-financial joint-stock companies prepared by Creditinform and Statistics Norway. The accounts statistics are from the enterprises’ financial statements submitted annually to the Register of Company Accounts in Brønnøysund and cover in principle the entire population of non-financial joint-stock companies. Data are available from 1992 but the sample is incomplete before 1995. By selecting companies with at least 10 employees, our sample consists of about 18,000 firms each year from 1995-2002. We define average firm wage as gross pay per employee. We also define labor productivity as log real value added per employee. We use the annual CPI as deflator.

Bank of England Industry Dataset (BEID). This is a two-digit industry level dataset covering all sectors of the economy. We drop public administration and defence so we are left with 33 sectors. (Results are robust to the exclusion of sectors 31 (Education) and 32 (Health and social work.)) It is based on National Accounts data from the Census. The ICT data is based on the supply and use tables. The full list of industries is contained in Table A2. Descriptive statistics of the BEID dataset matched to FAME are in Table A3.

B2. Robustness of the findings to sample selection and choice of productivity measure

In this sub-section we discuss the sensitivity of the findings to the sample selections (and other decisions) that we have made on FAME.

Industry Selection

We considered a sample with no exclusions based on industry (“whole sample”) as well as the main sample which drops various problematic sectors. These sectors are problematic either because they have been influenced by government control and/or because of difficulties in measuring productivity (financial services). The original data had some missing values on the industry codes of dissolved firms so we collected this information from other sources. Of the final sample, an average of 6% of firms (which represent 1% of aggregate employment) had missing values on industry codes (see Table A.4 for details).

To check the findings we contrast the dispersion trends for the “whole economy” sample with the “manufacturing and private services” sample. The levels of the firm and wage productivity distribution are given in Table A1 below. In Panel A we use the whole economy sample across all sectors and group years into an early (1984-89), middle (1990-95) and late (1996-2002) period. Mean real wages and real productivity grew at the 10th, median and 90th percentiles of the distribution. But inequality clearly grew too. The lower panel (B) shows the equivalent for the more restricted sample. Although there is less dispersion as a whole (as we would expect from drawing a more homogenous sample) the trends in inequality of wages and productivity are quite comparable to the larger sample. This similarity can also be seen from Figure 5a which contains the whole sample which is very similar to the trends when we drop the problematic industries (see Figure 5b).

Using sales per worker instead of value added per worker

Figure A1 uses sales per worker as an alternative measure of productivity to value added per head. Sales are a line item in the company accounts, but have the major disadvantage that they will be affected by intermediate materials. An increase in the intensity of material use will increase sales per worker even if value added per worker remains constant. This is particularly important in the retail and wholesale sectors where intermediates are a large share of revenue.

The variation of sales per worker has increased over this period, but not to the same extent as value added per worker. In particular the increase in inequality has come from an expansion of the 50-10 whereas the 90-50 has remained pretty constant. We conclude that it is important to look at value added as the distribution of intermediates has changed systematically over time.

Profit dispersion

A related concern of using value added is that the increase in value added dispersion is mechanical because value added is partly composed of the wage bill. Of course, it is quite possible for individual wage dispersion to rise and between firm wage dispersion to stay constant if the rise in wage inequality was entirely within firms. Nevertheless, it is useful to examine the other component of value added, gross profits directly to see if the variation in profits has risen. This is illustrated in Figure A2. We see that it is indeed the case that profit variability has raised substantially in

the data and the increase in productivity dispersion is driven by both an increase in the inter-firm wage and the inter-firm profit dispersion.

FAME Sampling Frame

Could our results be driven by some problem with the sampling structure of FAME? Although FAME is meant to be comprehensive, data errors cannot be ruled out as the data collectors did appear to become more efficient over time (we dropped the 1979-1983 data because the numbers of firms were too low to be representative of the cross section). The total number of firms in FAME rises over time, but this is also partly due to the booming business cycle after 1983. The fact that inequality rises consistently after 1987 when the number of FAME firms is very stable gives us confidence that this is not the case.

Nevertheless, we tested the “sample composition” hypothesis in several ways. First, we turned to an entirely separate database, Datastream. The Datastream On-line service includes only listed firms (like Compustat) but has been running since 1968 so is much better established. It is comparable to Compustat in the US. The disadvantage of Datastream, of course is that it does not include unlisted firms. Consequently, whereas we have 11,000 firms a year in FAME we have around 1,500 firms a year in Datastream.

Despite these limitations, we re-ran our analysis on the Datastream sample using the same variable and sample definitions as FAME. The results were similar, if not even stronger. Figure A3 gives the productivity dispersion graphs for the whole economy and is comparable with Figure 5 in the main text. The 90th percentile has increased value added per worker by 60 log points over this period, almost identical to FAME. This is all of the Datastream firms are contained in FAME and will generally be those at the top of the productivity distribution. By contrast, the 10th percentile has experienced almost no productivity growth. This is a larger increase in dispersion than we observed in FAME. It is consistent with the Davis, Haltiwanger, Jarmin and Miranda (2006) finding that listed firms in the US appear to be becoming more heterogeneous than unlisted firms (possibly due to greater turnover in the Stock Market as more volatile firms, such as biotechnology and software start-ups enter and exit).

When we split by sector, as usual we observe that the growth of inequality in the manufacturing sector (Figure A4) is much less than the growth of inequality in the services sector (Figure A5). Again, this is reassuring as it is consistent with the findings from the FAME database.

Firm Size

We drop firms with less than ten employees because sales and employment do not need to be reported for these firms under UK accounting regulations. This could cause various types of selection bias. One test of this concern is to compare the variance trends with the 90-10 Figures. The percentiles of the firm distribution treat each firm as a separate unweighted unit, so dropping the small firms potentially makes a large difference. The variance calculations, however, weight a firm’s productivity by its employment size. Since the firm size distribution is highly skewed the missing firms will only have a small weight in the overall productivity distribution so are unlikely to have much effect on the results.

As a second check on the sample composition of FAME we examined the changing size distribution by looking at employment. In 2002 the median firm had

150 employees in FAME. We plot out the 90-50 and 50-10 of the log (employment) distribution in FAME in Figure A6. There has been some decrease in the size distribution at the higher end – the 90-50 has fallen, but there has been some widening of the size distribution at the bottom end as the 50-10 has risen. Overall, the 90-10 is about the same at the end of the period (4.02) as it was at the beginning of the period (4.11). We conclude that the firm size distribution has not become systematically more unequal over this period. This suggests that the sampling frame has not changed in FAME in a systematic way that would necessarily imply more heterogeneity on all measures.

The lack of a trend in the size distribution also makes it unlikely that our results are due to changes in the degree of outsourcing by firms. A concern with using consolidated accounts is that firms may be focusing on smaller lines of business and outsourcing non-core functions. This would give the appearance of increased productivity dispersion even though all that is occurring is vertical fragmentation. The fact that the size distribution is reasonably stable makes this explanation unlikely.

Appendix C: Changes in the variance of wages and the role of firm productivity

Assume that wages are determined partially by the worker's value on the open labor market and partially by the performance of the firm that he or she is matched to. This type of equation is rationalised by a number of theoretical models of imperfect labor market competition (e.g. Mortensen, 2003; Layard *et al.*, 2005). The wage equation is assumed to be:

$$\ln W_t = \alpha_t \ln H_t + \beta_t \ln A_t = \alpha_t h_t + \beta_t a_t \quad (C1)$$

where W is the average wage in the firm, H is the competitive wage for the workers (which depends on human capital) and A is the performance (i.e. the productivity of the firm). Small case letters denotes natural logarithms. Theory restricts $0 \leq \beta_t, \alpha_t \leq 1$.

$$\frac{d}{dt}(\text{var}(w_t)) = \frac{d}{dt}(\alpha_t^2 \text{var}(h_t)) + \frac{d}{dt}(\beta_t^2 \text{var}(a_t)) + 2 \frac{d}{dt}(\alpha_t \beta_t \text{cov}(h_t, a_t)) \quad (C2)$$

$$\begin{aligned} \frac{d}{dt}(\text{var}(w_t)) = & \\ & \beta_t^2 \frac{d}{dt}(\text{var}(a_t)) + 2 \text{var}(a_t) \beta_t \frac{d\beta_t}{dt} \\ & + \alpha_t^2 \frac{d}{dt}(\text{var}(h_t)) + 2 \text{var}(h_t) \alpha_t \frac{d\alpha_t}{dt} \\ & + 2 \alpha_t \beta_t \frac{d \text{cov}(h_t, a_t)}{dt} + 2 \alpha_t \text{cov}(h_t, a_t) \frac{d\beta_t}{dt} + 2 \beta_t \text{cov}(h_t, a_t) \frac{d\alpha_t}{dt} \end{aligned} \quad (C3)$$

In discrete time this becomes

$$\begin{aligned} \Delta(\text{var}(w_t)) = & \\ & \beta_t^2 \Delta(\text{var}(a_t)) \\ & + 2 \text{var}(a_t) \beta_t \Delta \beta_t + \alpha_t^2 \Delta(\text{var}(h_t)) + 2 \text{var}(h_t) \alpha_t \Delta \alpha_t \\ & + 2 \alpha_t \beta_t \Delta \text{cov}(h_t, a_t) + 2 \alpha_t \text{cov}(h_t, a_t) \Delta \beta_t + 2 \beta_t \text{cov}(h_t, a_t) \Delta \alpha_t \end{aligned} \quad (C4)$$

So clearly, one way in which an increase in the productivity variation increases the wage dispersion is through the first term: $\beta_t^2 \Delta(\text{var}(a_t))$. The percentage of the increase in wage variation accounted for by this component is: $\beta^2 \frac{\Delta \text{var}(\ln A)}{\Delta \text{var}(\ln W)}$.

To obtain some more intuition on the other terms, consider the situation where the coefficients do not change over time (i.e. $\beta_t = \beta$ and $\alpha_t = \alpha$). In this case:

$$\Delta(\text{var}(w_t)) = \beta^2 \Delta(\text{var}(a_t)) + \alpha^2 \Delta(\text{var}(h_t)) + 2 \alpha \beta \Delta \text{cov}(h_t, a_t) \quad (C5)$$

The variance of wages could increase because the variance of productivity has increased (the first term, $\beta^2 \Delta(\text{var}(a_t))$), or because the variance of the human capital has increased (the second term, $\alpha^2 \Delta(\text{var}(h_t))$) or because the covariance of human capital and firm productivity has become more positive (the third term, $2\alpha \beta \Delta \text{cov}(h_t, a_t)$). The final explanation is equivalence to an increased sorting of “good firms” and “good workers” (Kremer and Maskin, 1996).

Returning to the full decomposition in equation (C4) consider the model where $\alpha_t = 1 - \beta_t$. Simplifying terms we can express this as:

$$\begin{aligned} \Delta(\text{var}(w_t)) = & \beta_t^2 \Delta(\text{var}(a_t)) + (1 - \beta_t)^2 \Delta(\text{var}(h_t)) + \\ & + 2(1 - \beta_t)\beta_t \Delta \text{cov}(h_t, a_t) + 2\Delta\beta_t [\beta_t (\text{var}(a_t)) + \\ & - (1 - \beta_t) \text{var}(h_t) + (1 - 2\beta_t) \text{cov}(h_t, a_t)] \end{aligned} \quad (\text{C6})$$

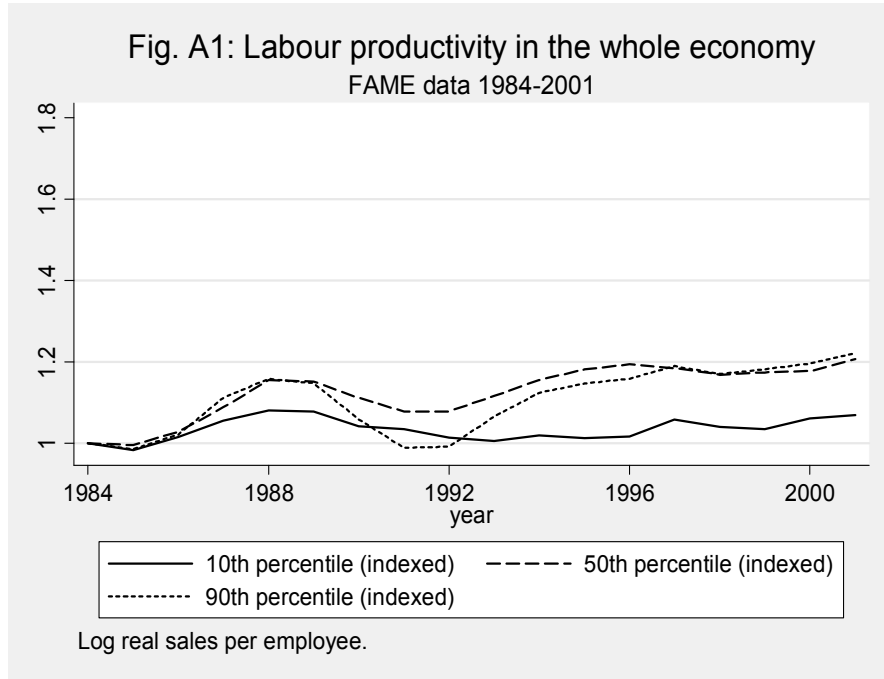
In the paper we show evidence that β_t appears to have risen over time, suggesting the productivity distribution is becoming more important. However, we cannot say for certain whether this also contributes to increased inequality as it depends on the sign of the second line. Since most estimates put $\beta_t < 0.5$ and assume $\text{cov}(h_t, a_t) > 0$ the final term is positive.

Unfortunately, the $\text{var}(h)$ is essentially unobservable in our data so we cannot rule out the possibility that:

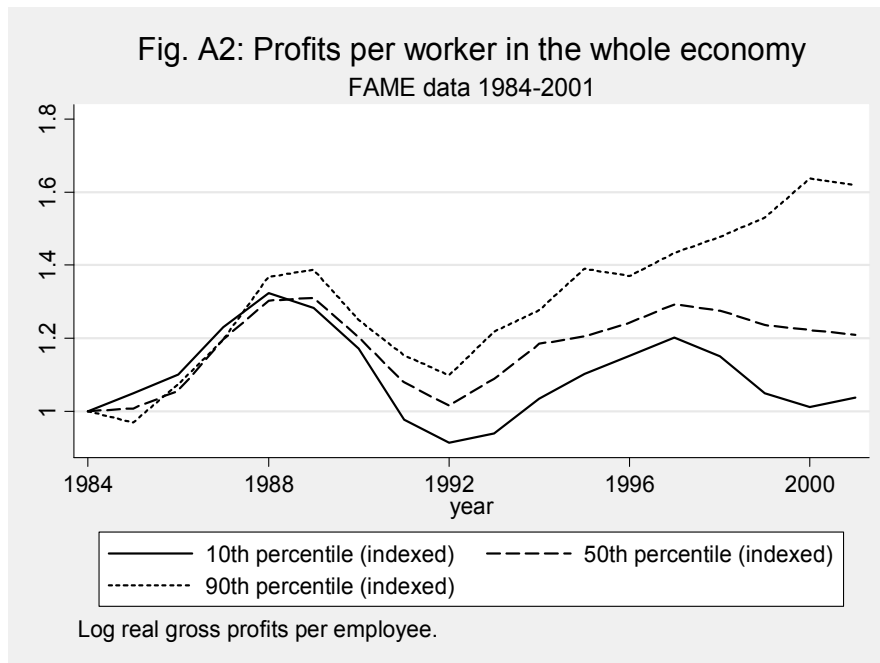
$\beta_t (\text{var}(a_t)) - (1 - \beta_t) \text{var}(h_t) + (1 - 2\beta_t) \text{cov}(h_t, a_t) < 0$ in which case the increase in the impact of productivity on wages would contribute to a fall in inequality.

Using $\beta = 0.3$ and the empirical average variances in our data $\text{var}(w) = .23$, $\text{var}(a) = .55$. Using (C1) and calculating the cross sectional variance residual $\text{var}(h) = 0.37 - 0.21 * \text{cov}(h, a)$. To calculate the final line of (C6):

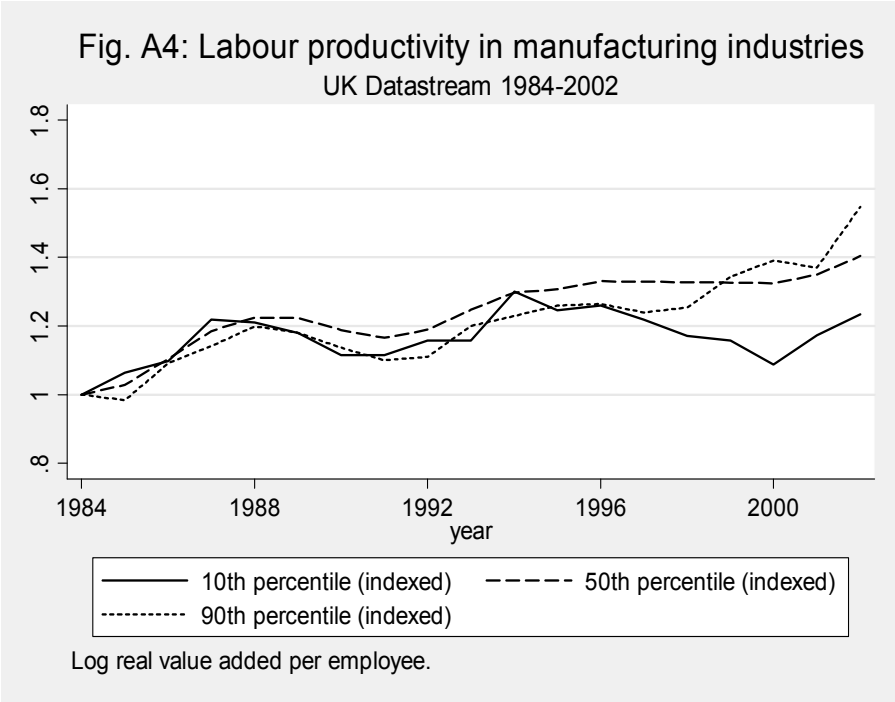
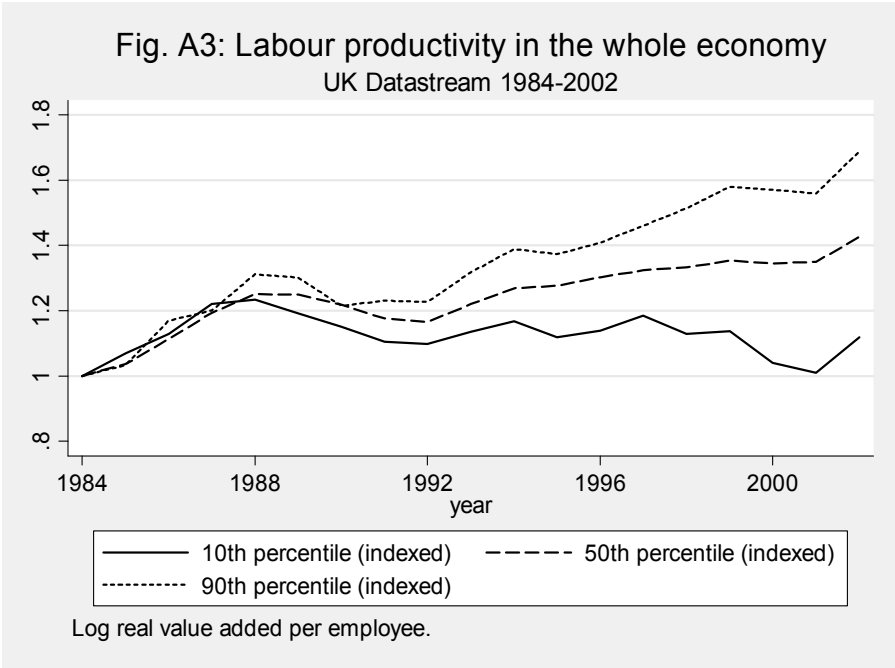
$\beta_t (\text{var}(a_t)) - (1 - \beta_t) \text{var}(h_t) = 0.3 * 0.55 - 0.7 * (0.37 - 0.21 * \text{cov}(h, a)) = -0.094 + 0.147 * \text{cov}(h, a)$. So in order for an increase in the β to have a positive impact on wage inequality we need $\text{cov}(h, a) > 0.64$, a high degree of the level of positive sorting between firms and workers.



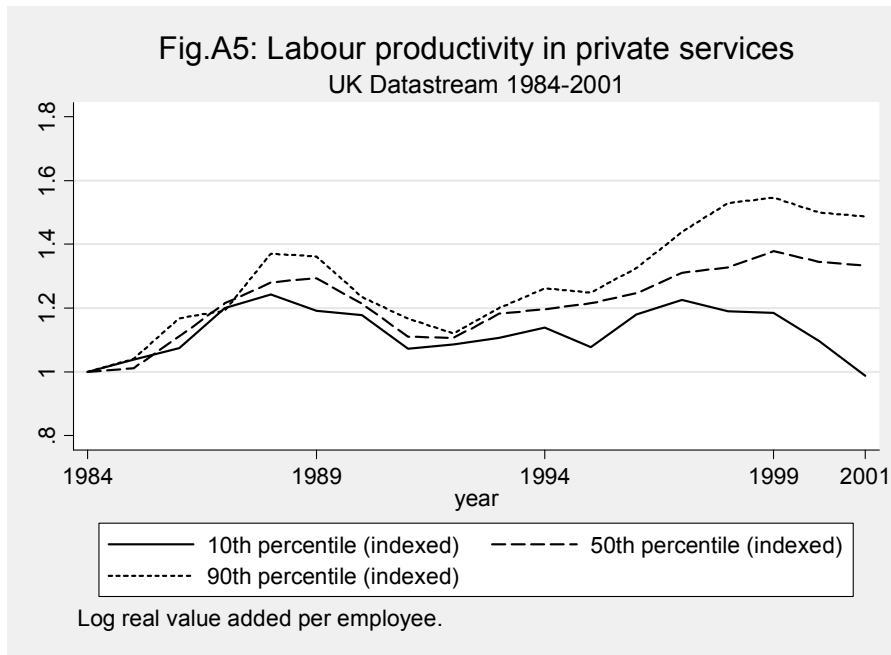
Notes: “Productivity” is measured here by $\ln(\text{sales per worker})$ instead of the more standard value added per worker used elsewhere in the paper.



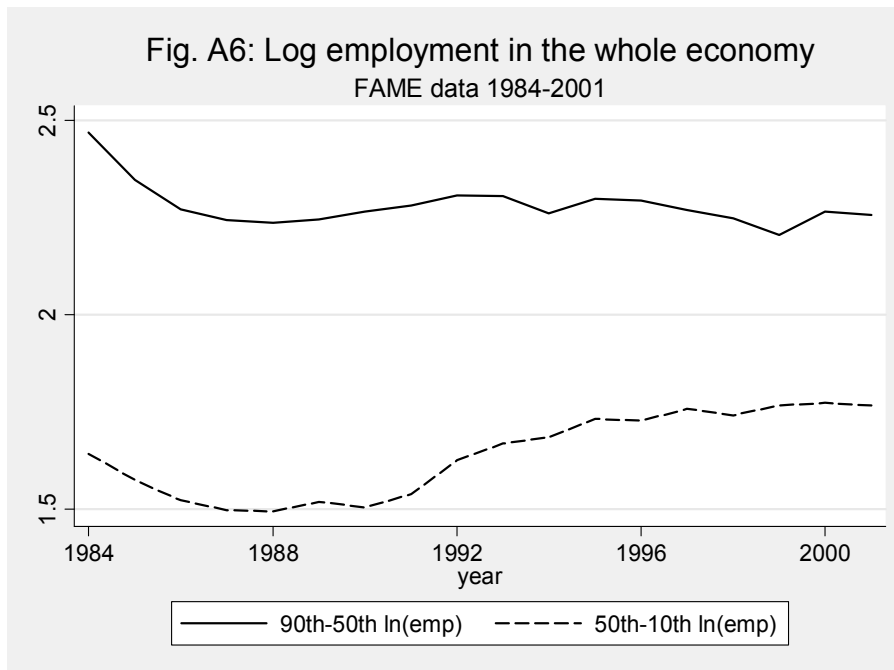
Notes: Gross profits before all deductions (tax, interest, dividends and depreciation) per worker.



Notes: Data is from Datastream On-line company accounts database. This is a strict sub-sample of FAME as it only includes listed firms.



Notes: Data is from Datastream On-line company accounts database. This is a strict sub-sample of FAME as it only includes listed firms.



Notes: 90-50 is the difference of the $\ln(\text{employees})$ at the 90th percentile minus the 50th percentile. 50-10 is the difference of the $\ln(\text{employees})$ at the 50th percentile minus the 10th percentile. FAME sample.

Table A1: Dispersion of firm average wage and labor productivity over time

Panel A: all sectors							
	90th percentile	50th percentile	10th percentile	90th - 10th differential	Mean	Variance	No. of obs.
<i>Labor productivity (log real value added per employee)</i>							
Early (1984-1989)	3.81	2.98	2.36	1.44	3.06	0.54	8803
Middle (1990-1995)	3.96	3.11	2.42	1.55	3.16	0.60	10909
Late (1996-2002)	4.21	3.27	2.50	1.71	3.33	0.69	10841
<i>Log real average wage</i>							
Early (1984-1989)	3.17	2.70	2.21	0.95	2.69	0.19	8803
Middle (1990-1995)	3.45	2.89	2.34	1.11	2.89	0.26	10909
Late (1996-2001)	3.70	3.07	2.45	1.25	3.07	0.33	10841
Panel B: manufacturing and private services							
	90th percentile	50th percentile	10th percentile	90th - 10th differential	Mean	Variance	No. of obs.
<i>Labor productivity (log real value added per employee)</i>							
Early (1984-1989)	3.77	2.99	2.39	1.38	3.06	0.49	7316
Middle (1990-1995)	3.88	3.10	2.43	1.45	3.14	0.53	9468
Late (1996-2002)	4.12	3.25	2.51	1.61	3.30	0.62	9554
<i>Log real average wage</i>							
Early (1984-1989)	3.14	2.69	2.22	0.92	2.68	0.17	7316
Middle (1990-1995)	3.41	2.88	2.35	1.06	2.87	0.23	9468
Late (1996-2001)	3.65	3.06	2.45	1.20	3.05	0.29	9554

Notes: In Panel A “All sectors” keeps all firms in FAME database with at least 10 employees 1984 to 2001 and non-missing data on wages and value added. In Panel B we drop the agriculture, mining, utilities, financial services, health and education sectors.

Table A2: List of industries in the Bank of England Industry Dataset (BEID)

<i>List of industries and their definitions</i>			
Number	Name	SIC92	Industries used in Table 5
1	Agriculture	01,02,05	√
2	Oil and gas	11,12	√
3	Coal & other mining	10,13,14	√
4	Manufactured fuel	23	√
5	Chemicals & pharmaceuticals	24	√
6	Non-metallic mineral products	26	√
7	Basic metals & metal goods	27,28	√
8	Mechanical engineering	29	√
9	Electrical engineering & electronics	30,31,32,33	√
10	Vehicles	34,35	√
11	Food, drink and tobacco	15,16	√
12	Textiles, clothing & leather	17,18,19	√
13	Paper, printing & publishing	21,22	√
14	Other manufacturing	20,25,36,37	√
15	Electricity supply	40.1	√
16	Gas supply	40.2,40.3	√
17	Water supply	41	√
18	Construction	45	√
19	Wholesale, vehicle sales & repairs	50,51	√
20	Retailing	52	√
21	Hotels & catering	55	√
22	Rail transport	60.1	√
23	Road transport	60.2,60.3	√
24	Water transport	61	√
25	Air transport	62	√
26	Other transport services	63	√
27	Communications	64	√
28	Finance	65,66	√
29	Business services	67,70,71,72,73,74	√
30	Public administration & defence	75	X
31	Education	80	√
32	Health & social work	85	√
33	Water treatment	90	√
34	Miscellaneous services	91-99	√

Source: Oulton and Srinivasan (2005)

Table A.3: Descriptive Statistics of the data used in the industry regressions

<i>Series</i>	<i>1984-88 average</i>	<i>1996-00 average</i>	<i>$\Delta(1984-88$ $1996-00)$</i>
90 th -10 th differentials in log(labor productivity)	1.36	1.63	0.266
90 th -10 th differentials in log(average firm wage)	0.801	1.05	0.260
Real ICT capital services /total real capital services	0.034	0.151	0.117
Total real capital services/total hours of work	0.009	0.014	0.005
Proportion of workers with higher degree	0.082	0.145	0.063
Union density share	0.498	0.331	-0.167
Proportion of individuals employed part-time	0.126	0.143	0.017
Proportion of workers who are females	0.315	0.338	0.022
Coefficient of variation in basic hours of work (NES)	0.063	0.08	0.017
Coefficient of variation in total actual hours of work (LFS)	0.126	0.123	-0.003

Note: These are taken from the sample of 33 two digit industries used in the Bank of England Industry Dataset (BEID).

Table A.4: Summary Statistics, FAME Dataset, 1984-2001

<i>Year</i>	<i>No. of firms</i>	<i>Number of employees of firms in the sample</i>
1984	5,244	9,234,232
1985	7,082	10,441,836
1986	7,859	10,714,181
1987	8,849	11,077,291
1988	10,279	11,828,257
1989	10,887	12,384,826
1990	11,176	12,654,988
1991	10,852	12,456,892
1992	10,485	11,817,806
1993	11,205	12,320,312
1994	11,125	11,356,830
1995	10,564	11,488,408
1996	10,839	11,540,081
1997	10,958	11,804,507
1998	11,153	12,107,974
1999	11,293	12,753,770
2000	11,173	13,144,882
2001	11,166	12,987,585

Source: FAME Dataset



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