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Firm Heterogeneity in Capital/Labor Ratios and Wage Inequality

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ABSTRACT

Firm Heterogeneity in Capital/Labor Ratios and Wage Inequality*

This paper provides some empirical evidence and a theory of the relationship between residual wage inequality and the increasing dispersion of capital/labor ratios across firms. I document the increasing variance of capital/labor ratios across firms in the US labor market. I also show that the increase in the capital intensity variance across firms is associated with the increasing wage variance across workers. To explain this empirical fact, I adopt a search model where firms differ in their optimal capital investment. The decline in the relative price of equipment capital makes the firm distribution of capital/labor ratios more dispersed. In a frictional labor market, this force generates wage dispersion among identical workers. Simple calibration of the model indicates that the dispersion of capital/labor ratios can account for about one third of the total increase in residual wage inequality.

JEL Classification: J21, J31

Keywords: wage inequality, capital intensity, search models

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1 Introduction

Changes in wage inequality reflect changes in both price and quantities of workers' observable characteristics and changes in residual wage inequality. Juhn, Murphy and Pierce (1993) claim that roughly 60% of the increase in the 90-10 log wage differential can be accounted for by changes in the residuals' distribution, i.e. in unobserved attributes of workers belonging to the same demographic or educational group.

While there are already many studies on increasing wage dispersion, much less research has been devoted to the increasing dispersion of capital intensity across firms. This paper is divided into three parts. The first part is an analysis of dispersion of equipment/labor ratios across firms. The second part provides some empirical evidence of the link between the dispersion of wages across workers and the dispersion of capital intensity across firms. In the third part of the paper, I propose a theory of residual wage inequality based on the increased dispersion of capital intensities across firms.

In the first part of this paper I use panel data on individual firms (Compustat) from 1970 to 1992 to document the increase in the variance of equipment/labor ratios over time. I focus on equipment capital since equipment is complementary to skills and differential stocks of equipment capital across firms may be correlated with the demand for skills. The results show that the log standard deviation across firms of equipment/labor ratios increased by about 12% from 1970 to 1992. The rise in dispersion of equipment/capital occurred both between and within industry and is concentrated in the mid-late eighties.

In the second part of the paper, I study the correlation between the increasing dispersion of wages across workers and the increasing dispersion of capital intensities across firms. The data on wages are from March CPS and five waves of the Displaced Workers Survey (DWS). The reason to study displaced workers is twofold. First, in the DWS there is a panel dimension that allows one to control for unobserved heterogeneity, secondly displaced workers are less likely to select themselves in the best paying industries or firms. This implies that the capital intensity premium is more likely to reflect "true" firms' effects rather than sorting. I match Compustat data on firms' capital intensity to CPS and DWS data on wages at the industry-year level. The results indicate that a 1% increase in the average industry capital intensity is associated with a 0.11% increase in the average weekly wage in the CPS and with a 0.13% increase in the DWS. Consistently with the literature on inter-industry wage differentials, there is no increase in the cross-industry effect of capital intensity on wages over time. More importantly for the purpose of this paper, within-industry dispersion of equipment/labor ratios appears to be related to within-industry dispersion of wages both in the CPS and in the DWS. Both the variance of equipment/labor ratios across firms and the variance of wages across workers have increased over time. The association between the dispersion of equipment/labor ratios across firms and the dispersion of wages across workers holds within industry even after controlling for time dummies.

In the theoretical part I build a model that explains the rise in the variance of wages in view of the evidence on the increasing variance across firms of the equipment/labor ratios. The intuitive idea is simple. The two main ingredients of the model are non-competitive labor market and random matching of identical workers to two types of firms. In a non-competitive labor market, workers' wages are linked to their individual output and therefore to the capital they are matched with. Identical workers are matched randomly to two types of firms that co-exist in equilibrium. "Good" firms have high job creation costs and are more productive, "bad" firms have low job creation costs but are less productive. "Good" firms invest more in equipment capital, "bad" invest less. As the relative price of equipment capital falls, "good" firms with high equipment invest more and increase their productivity relative to "bad" firms. Wages for identical workers are more dispersed as a consequence of a higher dispersion of capital intensities. This feature of the model that explains the increase in wage inequality with increasing dispersion of capital intensities across firms is consistent with recent evidence that indicates that the bulk of the increase in wage inequality took place between plants rather than within plants (Dunne et al., 2002).

1.1 A Brief Overview of the Related Literature

Work on dispersion of capital/labor ratios is fairly rare in the literature. Caselli (1999) uses industry-level data to document the increase in the 90-10 log differential of capital intensities across four-digit manufacturing industries. In this paper, I use data on individual firms to study the increasing dispersion of equipment/labor ratios across firms.

The empirical part of this paper is connected to the literature that uses establishment-level data to study the dispersion of wages and productivity across plants. Davis and Haltiwanger (1991) and Dunne et al. (2002) show that the increase in wage dispersion is mainly a between-plant phenomenon. Using both individual wage data and establishment-level data they decompose the total variance of wages in three components: between-industry, between-plant and within-plant. The results show that most of the increase in wage dispersion is due to between-plant dispersion within the same industries. Related work by Doms et al. (1997) finds that an important factor in explaining wage dispersion across plants is the differential adoption of technologies. Dunne et al. (2002) find that between-plant measures of wage and productivity dispersion have increased over time and are strongly positively correlated. They also find that a significant fraction of the rising dispersion of wages and productivity is associated with changes in the distribution of computer investment across plants.

Unlike the case of wages and computers, however, there has been little analysis of the changes in the distribution of capital intensity over time and of the association between wages and capital intensity.[1] All previously cited papers use establishment-level data limited to manufacturing. In this paper, I use Compustat data to study the evolution of the distribution of capital intensity over time across firms in all industries.

In the theoretical part, I propose a model of residual wage inequality based on the increased dispersion of capital intensities across firms. There are many theories of within-group wage inequality built on the complementarity between unobservable skills and new technologies. Most models, however, interpret unobservable skills as ex-ante differences in ability across individuals. The model of residual wage inequality presented here is not based on ex-ante differences in unobservable ability. In this model, identical workers are matched to different firms.

The mainstream view in the literature is that within-group wage inequality is the result of the increase in the price of unobserved ability. Acemoglu (1999) builds a model where identical firms search for workers with different abilities. Skill-biased technical change induces firms to switch from a pooling equilibrium where one job fits everyone, to a separating equilibrium where different jobs for different abilities are created. Caselli (1999) suggests that a technological revolution occurs when a new type of machine is introduced. Operating the new machine requires a new type of skill. Workers have different costs of learning the new skill and those with lower learning costs can get a higher wage premium. Galor and Maov (2000) claim that ability helps workers to adapt to the new work organization, therefore big organizational changes raise the return to ability. Kremer and Maskin (2000) build a model where production requires many complementary tasks. Wage inequality increases as workers with different skills are increasingly segre-

[1] Although in the published version, Dunne at al. (2002) focus on the relationship between wage and computer investment across plants, in the Working Paper version, they also study the relationship between capital intensity and wages.

gated across plants. Segregation occurs because of the complementarity of tasks and the exogenous force that sets the mechanism in motion is the increasingly dispersed distribution of skills across workers.

Although these models provide explanations through which technology might affect inequality, they are all based on ex-ante differences in ability. Models based on fixed ex-ante differences in ability come under severe criticism. Unobserved ability is a permanent characteristic of the individual, therefore, all models based on differences in innate ability imply that the rise in residual wage inequality should be accounted for by the rise in the variance of the persistent component of individual earnings. Gottschalk and Moffitt (1994) and the subsequent literature show that this is not the case and earnings instability (the variance of the transitory component) explains much of the total increase.

On the basis of this criticism, Violante (2002) and Hornstein, Krusell and Violante (2002) propose a model based on ex-ante identical workers where wage inequality is due to an acceleration of technical change. In each period, a new vintage technology embodied in new machines spreads in the economy. Workers are ex-ante identical and have vintage specific skills. The degree of transferability of these skills between different vintages is proportional to the productivity difference between the machines. An acceleration in technical change increases the productivity differences across successive vintages and decreases the degree of transferability of skills. As a result, wage inequality across identical workers matched to different vintages of machines increases.

The models of Acemoglu (1999), Caselli (1999), Violante (2002) and Hornstein, Krusell and Violante (2002) are all consistent with an increasingly dispersed distribution of capital intensity. My model is built around an increasingly dispersed distribution of capital intensity. Like Violante (2002), my model does not rely on ex-ante differences in abilities. Unlike Violante (2002), my model is not based on a technological acceleration and the reduction in the transferability of skills. In my model, a decline in the relative price of equipment capital increases the dispersion of capital intensities across firms, thus raising wage inequality.

The model presented in this paper is related to the literature that explains wage dispersion among equivalent workers within a search framework. Some of these models such as Montgomery (1991), Acemoglu (2001) and Pissarides (1994) consider firms with different job-creation costs and derive wage dispersion as a consequence of cost dispersion. My model is closest to Acemoglu (2001). He also considers a search model with different job-creation costs across firms but he focuses on the effect of more generous unemployment insurance and minimum wage on the composition of jobs.

Finally, an increasingly dispersed distribution of equipment/labor ratios can have an effect on wage differentials across identical workers as long as the market is not competitive and firm effects are important in determining the wage. This paper is therefore related to the literature on inter-industry wage differentials. There is a controversy on the importance of unobserved person or firm effects in explaining inter-industry wage differentials. Krueger and Summers (1988) and Gibbons and Katz (1992) claim that the differentials cannot be explained by person effects. Murphy and Topel (1990) claim that person effects are the primary explanation. Using employer-employee matched data, Abowd, Kramarz and Creecy (2003) estimate that person and firm effects can each account for approximately 50% of the inter-industry wage differentials in the US.

The structure of the paper is as follows. In the next section I document the increase in the variance of capital/labor ratios between and within industry over time. In section 3, I relate the variance of wages to the variance of capital/labor ratios. In section 4, I present the model that interprets the evidence. Section 5 presents the conclusions.

2 Firm Equipment/Labor Ratios

In this section I examine changes over time in the cross-firm distribution of capital/labor ratios. I use Compustat data from 1970 to 1992. Compustat is a dataset of US companies listed on the stock market. They represent less than 1% of the total number of companies in the US but more than 50% of total employment. Figure 1 plots the employment-weighted standard deviation of log equipment/labor across firms in each year. To build the equipment/labor ratio, I use information on equipment (COMPUSTAT 156) and on the number of employees (COMPUSTAT 129). Equipment represents the capitalized cost of machinery and equipment used to generate revenue minus accumulated depreciation. Equipment is deflated using the 1-digit industry specific deflators form the Bureau of Economic Analysis and is expressed at the real value in 1992.

Figure 1 shows an increase in the employment-weighted standard deviation of log equipment/labor ratios across firms of 12.3% between 1970 and 1992.[2] The increase in dispersion of equipment/labor ratios starts in 1980 and continues through the '80s. This paper is concerned with the increasing dispersion of equipment/labor ratios facing workers, hence the log standard

[2] The results do not change if I exclude from the sample the new firms that are included in the sample after 1974.

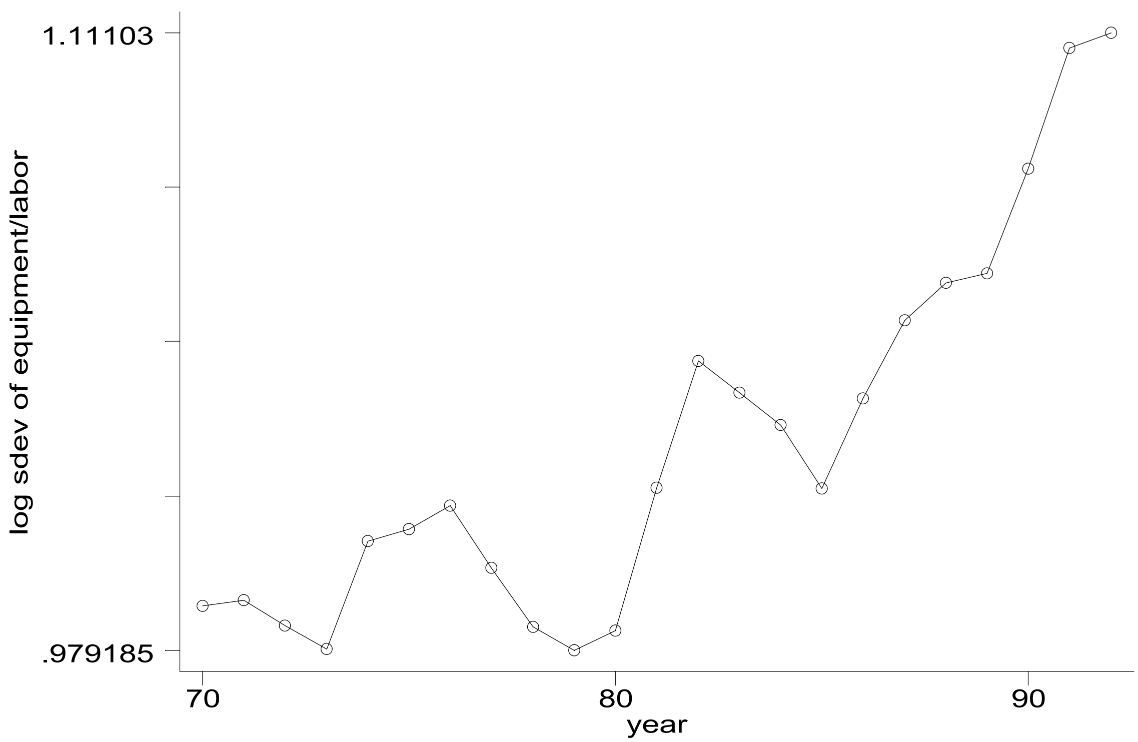

Figure 1: Employment weighted log standard deviation of equipment/labor ratios. Source: Compustat Industrial Data.

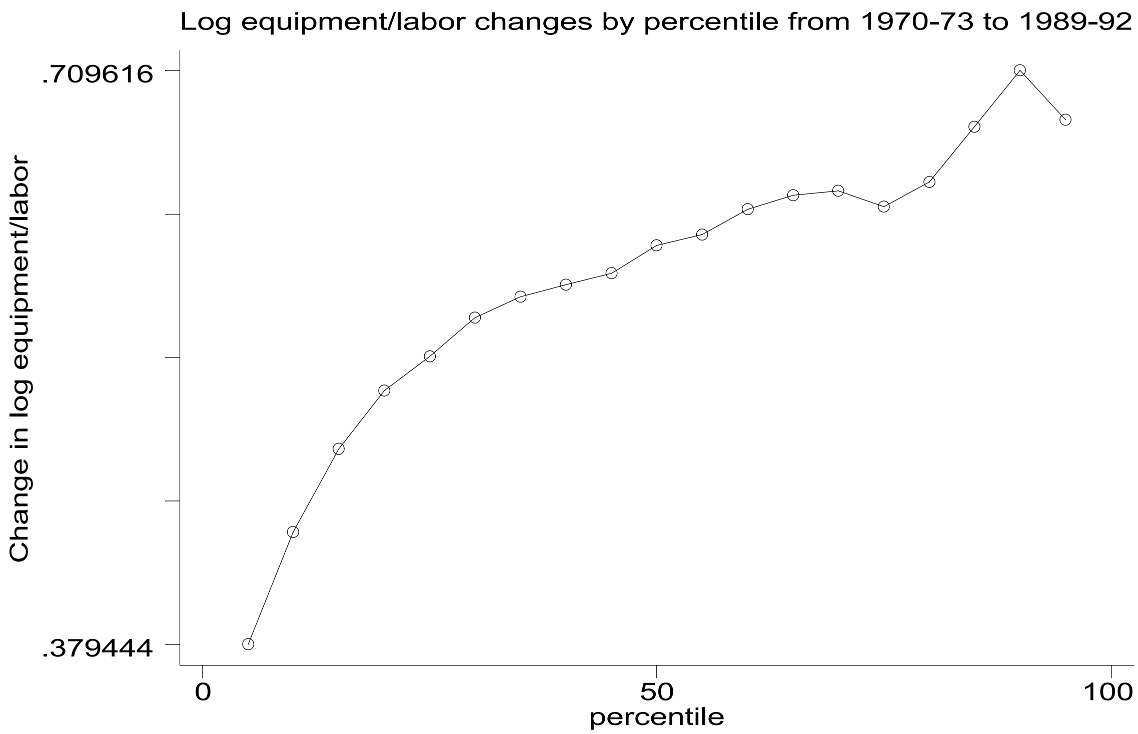

Figure 2: Log equipment/labor ratio changes by percentile between 1970-1973 and 1989-1992.

deviation of equipment/labor ratios is employment-weighted.

Figure 2 shows that the divergence in equipment/labor ratios is pervasive and not limited to part of the distribution. Figure 2 plots the change in log equipment/labor ratios from 1970-73 to 1989-92. The changes are calculated for each fifth percentile of the cross-sectional distribution of firms in 1989-92 and in 1970-73. Each point in figure 2 is calculated as $[p_{89-92}(\log \frac{e}{l}) - p_{70-73}(\log \frac{e}{l})]$ where p is each fifth percentile of the employment-weighted cross-sectional distribution in years 1989-92 and years 1970-73. The change in real equipment/labor ratios at the bottom 10th percentile of the distribution is 55%, at the top 90th percentile of the distribution is 103%. The picture exhibits a concave shape with inequality rising more at the bottom 50% of the distribution.

The four charts in figure 3 decompose the rise in equipment/labor dis-

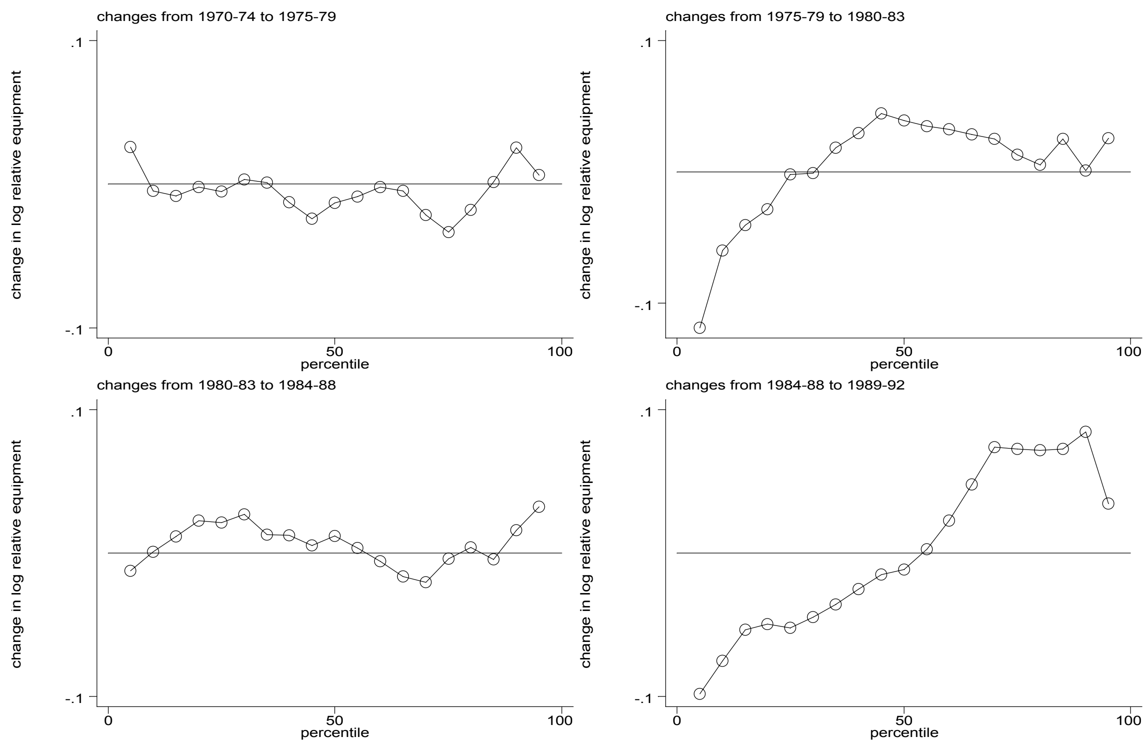

Figure 3: Changes in the log equipment/labor ratio by percentile. Changes relative to the period mean. Four periods.

persion in four periods. I look at changes between each five-year period. The first chart compares log equipment/labor ratios by percentile between the periods 1970-74 and 1975-79. The changes at each percentile are normalized by comparing the change at each percentile with the change in mean log equipment/labor ratios. Each point in figure 3 is calculated as $[p_t(\log \frac{e}{l}) - p_{t-1}(\log \frac{e}{l})] - [E_t(\log \frac{e}{l}) - E_{t-1}(\log \frac{e}{l})]$ where p is each fifth percentile of the employment-weighted log distribution in period t. E is the employment-weighted average. The four charts show that from 1970-74 to 1975-79 and from 1980-83 to 1984-88 equipment/labor ratios at each percentile moved more or less in line with the mean. The top right and bottom right charts in figure 3 show that the increase in dispersion of equipment/labor ratios across firms took place in the early and late eighties. The increase in dispersion is concentrated at the bottom of the distribution in the early eighties (top right chart) with the bottom percentiles left much behind relative to the mean. The increase in dispersion slowed down somewhat in the mid-eighties (bottom left chart) but continued from the mid-eighties to the nineties (bottom right chart). In the late eighties (bottom right chart) the bottom percentiles grew about 10% less than the overall mean, the top percentiles grew about 10% more than the mean.

2.1 Between and Within Industry Dispersion

In this subsection I look at the increase in the dispersion of equipment/labor ratios between and within industry and size groups.

Table 1 and 2 report log equipment/labor differentials across industry and across size class. Table 1 and 2 report the mean capital intensity (column one), the within-group standard deviation (column two) and the frequency in the sample (column three). The mean log equipment/labor differentials by industry and size group (first column Table 1 and 2) are defined as the difference between the average log equipment/labor ratio within the group and the overall average log equipment/labor ratio. Table 1 reports time series averages and table 2 reports time series changes between 1970-73 and 1989-92. I consider four-year groups at the beginning and at the end of the sample to minimize measurement error.

Agriculture and construction are dropped due to their small sample size. The sectors with the highest average equipment/labor ratios (table 1, column one) are mining and transportation and utilities. These two sectors have much higher equipment/labor ratios than the overall mean. The lowest capital-intensive industries are wholesale and retail trade. The heterogeneity of log equipment/labor ratios across firms of the same industry (table

1, column two) is higher within mining, transportation and utilities, and finance. Equipment/labor ratios are higher in small companies with less than 100 workers and in very large companies with more than 4000 workers. The differences across size groups are less impressive than the differences across industry groups. Differences are larger between small and medium-sized firms. Small firms have more heterogeneous equipment/labor ratios than large firms. The heterogeneity of equipment/labor ratios within size classes decreases with size.

Looking at the time series changes in table 2, the average equipment/labor ratio (table 2, column one) in mining, transportation, retail and business and professional services increased less than the overall average between 1970 and 1992. Wholesale and finance gained ground relative to the mean. Between-firm equipment/labor dispersion (table 2, column two) rose in all sectors except for mining, transportation and personal and business services. The highest increases occurred in manufacturing, wholesale trade and finance. The differentials in equipment/labor ratios across size classes increased dramatically over time. The difference between firms with less than 100 workers and firms with more than 4000 workers increased by 50 log points between 1970 and 1992. Between-firm dispersion in equipment/labor ratios increased within all size classes except for companies with less than 100 workers which became relatively less capital intensive over time and much more homogenous.

Finally, the last column of table 2 indicates a sizeable shift from manufacturing to business and professional services and a shift from large firms of more than 1000 workers to smaller firms.

2.2 The Juhn Murphy and Pierce Decomposition

To characterize the contribution of observable and unobservable characteristics to the changes in the equipment/labor distribution over time, I use the distribution accounting methodology of Juhn, Murphy and Pierce (JMP). The observable characteristics I consider are industry and size.

I consider the regression:

$$\log k_{it} = X_{it}\beta_t + u_{it} \tag{1}$$

where $\log k_{it}$ is log equipment/labor ratio in firm i in period t. X_{it} is a vector of observable characteristics which contains 2-digit industries dummies and a quartic in size (number of employees). β_t is the vector of OLS estimated equipment/labor differentials and u_{it} is the residual which reflects price and quantities of unobserved firm characteristics and is independent of X_{it}.

	Mean log equipment/labor differential	Between-firm standard deviation	Frequency
Industry			
Mining	1.07	1.26	1.45
Durable manufacturing	0.00	0.87	40.07
Non durable manufacturing	0.30	0.97	21.82
Transportation/utilities	1.16	1.32	5.12
Wholesale	-0.49	0.97	4.89
Retail	-0.84	0.66	10.79
Finance	-0.26	1.33	3.15
Other Services	-0.13	1.28	12.69
Size Class			
1-100 employees	0.11	1.30	14.31
100-500	-0.03	1.12	23.32
500-1000	-0.01	1.09	13.12
1000-4000	-0.07	1.07	24.93
4000+	0.04	1.03	24.32

Notes: Time series averages. Mean log equipment/labor differentials and between firm dispersion by industry and size groups.

Table 1: Time series averages. Log equipment/labor ratios

	Mean log equipment/labor differential	Between-firm standard deviation	Frequency
Industry			
Mining	-0.28	-0.13	-0.14
Durable manufacturing	0.02	0.08	-6.05
Non durable manufacturing	0.00	0.07	-4.95
Transportation/utilities	-0.27	-0.07	3.45
Wholesale	0.48	0.21	-2.20
Retail	-0.32	0.01	1.30
Finance	0.30	0.40	0.90
Other Services	-0.07	-0.11	9.70
Size Class			
1-100 employees	-0.49	-0.22	15.40
100-500	-0.08	0.09	5.36
500-1000	0.04	0.22	-5.56
1000-4000	0.05	0.29	-10.11
4000+	0.01	0.25	-5.09

Notes: Time series changes between 1970-73 and 1989-92. Changes in log equipment/labor relative to the mean log change and changes in between-firm dispersion by industry and size groups.

Table 2: Time series changes. Log equipment/labor ratio

u_{it} can be written as $u_{it} = F_t^{-1}(\vartheta_{it})$ where ϑ_{it} is the percentile in the distribution function of the residuals in year t. To isolate the contribution of changes in industry and size composition let us consider:

$$\log k_{it}^1 = X_{it}\overline{\beta} + \overline{F^{-1}}(\vartheta_{it})$$

where $\overline{\beta}$ is the average equipment/labor differential calculated over the whole period. $\overline{F^{-1}}(\cdot)$ is the average inverse cumulative distribution of residuals. The time path of the distribution over $\log k_{it}^1$ represents an estimate of the effect of the changes in the distribution of observable characteristics X_{it} on the distribution of equipment/labor ratios. To calculate the marginal contribution of changes in industry- and size-specific equipment/labor differentials let us consider:

$$\log k_{it}^2 = X_{it}\beta_t + \overline{F^{-1}}(\vartheta_{it})$$

Calculating the distributions $\log k_{it}, \log k_{it}^1$, and $\log k_{it}^2$ for each year in the sample, we can attribute the changes in $\log k_{it}^1$ to changes in industry and size composition, the changes in $\log k_{it}^2 - \log k_{it}^1$ to changes in inter-industry and size specific equipment/labor differentials and the changes in $\log k_{it} - \log k_{it}^2$ to changes in the distribution of residuals.

The top left chart of figure 4 plots the time series of the differential between the 90th and the 10th percentile of the employment-weighted log distribution of equipment/labor ratios, $\log k_{it}$. The other three charts of figure 4 break down the growth in the 90-10 differential into the three components of the JMP decomposition. Each component is measured as a deviation from its own overall mean. The top right panel gives the effect of the changes in the distribution of the observables. Changes in observable characteristics started to contribute positively to the increase in equipment/labor dispersion in the 1980s. During the ‘70s, changes in the industrial and size composition of firms contributed to a reduction in the overall inequality in equipment/labor ratios. The bottom left chart of figure 4 looks at the effect of the changing industry and size differentials, keeping the composition of the sample constant. The bottom right chart of figure 4 indicates that the effect of unobservables is particularly concentrated in the 1970s rather than in the 1980s.

The results from figure 4 are reported in table 3. The 90-10 log differential rose from 2.46 in 1970 to 2.78 in 1992 (or 13%). Changes in industrial and size composition over twenty years (holding fixed the equipment/labor differential associated with industry and size) contributed to

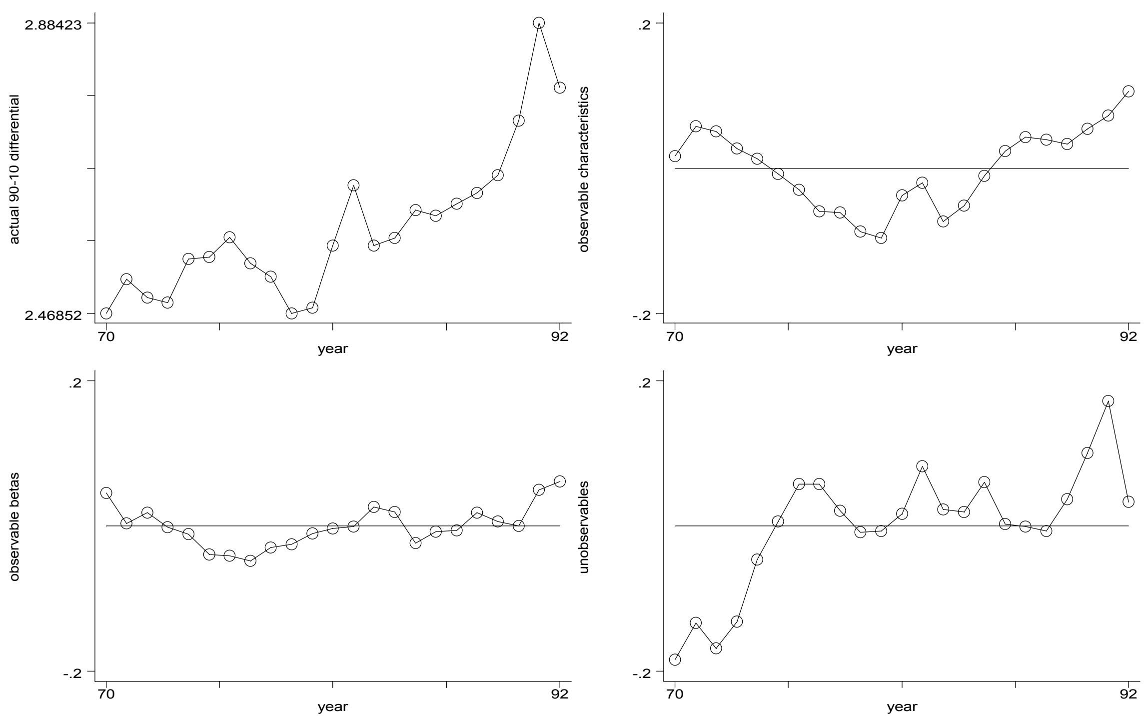

Figure 4: Juhn Murphy and Pierce decomposition 1970-1992.

Inequality measure	Total change	Observable quantities	Observable betas	Unobservable
Standard deviation	0.12	0.08	0.00	0.04
90-10 differential	0.32	0.09	0.02	0.21
90-50 differential	0.13	0.08	0.01	0.04
50-10 differential	0.19	0.09	0.00	0.10

Notes: The regression specification underlying the decomposition contains 2-digit industry effects and a quartic in size.

Table 3: Juhn, Murphy and Pierce decomposition.

28% (0.09/0.32) of the total increase in the 90-10 log differential. Changes in the industry and size differentials alone (holding fixed the industry and size composition) contributed to 6% (0.02/0.32) of the total increase of the 90-10 log differential. Changes in composition and differentials together account for 34% of the total increase of the 90-10 differential. The remaining 66% of the total increase of the 90-10 differential is explained by unobservables, i.e. by the rise in within industry-size groups dispersion. The JMP results indicate that most of equipment/labor ratio dispersion is not due to composition changes. In the next section I am going to focus on the within industry link between capital intensity and wages.

The JMP decomposition can be used to quantify the effects of changes in the observables and unobservables in all parts of the distribution. Table 3 reports the decomposition of time series changes in the 90-50 and 50-10 log equipment/labor differentials. Two important results stand out from the table. First, most of the increase in equipment/labor dispersion occurred in the bottom half of the distribution. Secondly, the contribution of observables to the increase in equipment/labor ratios across firms varies according to the inequality measure reported. The increase in between-size and between-industry inequality (changes in observable quantities and betas) accounts for approximately two thirds of the total increase in the standard deviation of equipment/labor ratios. The increase in between-group inequality accounts for less than half of the increase in the 50-10 ratio and explains more than two thirds of the increase in the 90-50 ratio. Apparently, the capital intensity gap between the 90th percentile of the distribution and the 50th percentile is much more understandable in terms of changes in industrial and size composition and their OLS coefficients than the gap between the 90th and the 50th percentile.

3 The Variance of Capital/Labor Ratios and Wage Inequality

In this section, I document the cross-industry correlation between firms equipment/labor ratios and wages from 1970 to 1992. First, I study the correlation between wages and average industry capital intensity, second, I look at the correlation between within-industry dispersion of wages and within-industry dispersion of capital/labor ratios.

The tendency of capital-intensive industries to pay higher wages has been documented by Katz and Summers (1989) in the context of inter-industry wage differentials. The correlation between within-industry dispersion of wages and within-industry dispersion of capital intensities is a novel point.[3] Unlike previous work, I study the relationship between individual wages and industry capital intensity over time. I match individual wages drawn from March CPS to average capital intensity at the industry-year level drawn from Compustat. I also extend the analysis to displaced workers. Displaced workers have been extensively used in the literature on inter-industry wage differentials.[4] The idea is that an exogenous displacement reduces the problem of sorting better workers into better paying industries and gives a better measure of the pure industry effect. Following the same reasoning, I investigate whether an increasing dispersion of wages for displaced workers is associated with an increasing dispersion of capital intensity across firms.

Figure 5 shows the log standard deviation of weekly wages and the employment-weighted log standard deviation of equipment/labor ratios. Log equipment/labor ratios are drawn from Compustat, log weekly wages are from March CPS. Wage and capital intensity dispersion have three characteristics in common. First the timing of the increase (figure 1). Second the pervasiveness of the increase in dispersion (figure 2). Third the fact that most of the increase is not due to composition changes but to within-group changes (figure 4). In the following section, I formally investigate the relationship between wage and capital intensity dispersion.

[3] The working paper version of Dunne et al.(2002) contains some analysis of the correlation between wages and capital intensities over time in a panel of manufacturing firms.

[4] Krueger and Summers (1988), Gibbons and Katz (1992) and Neal (1995) have used the Displaced Workers Survey to study inter-industry wage differentials.

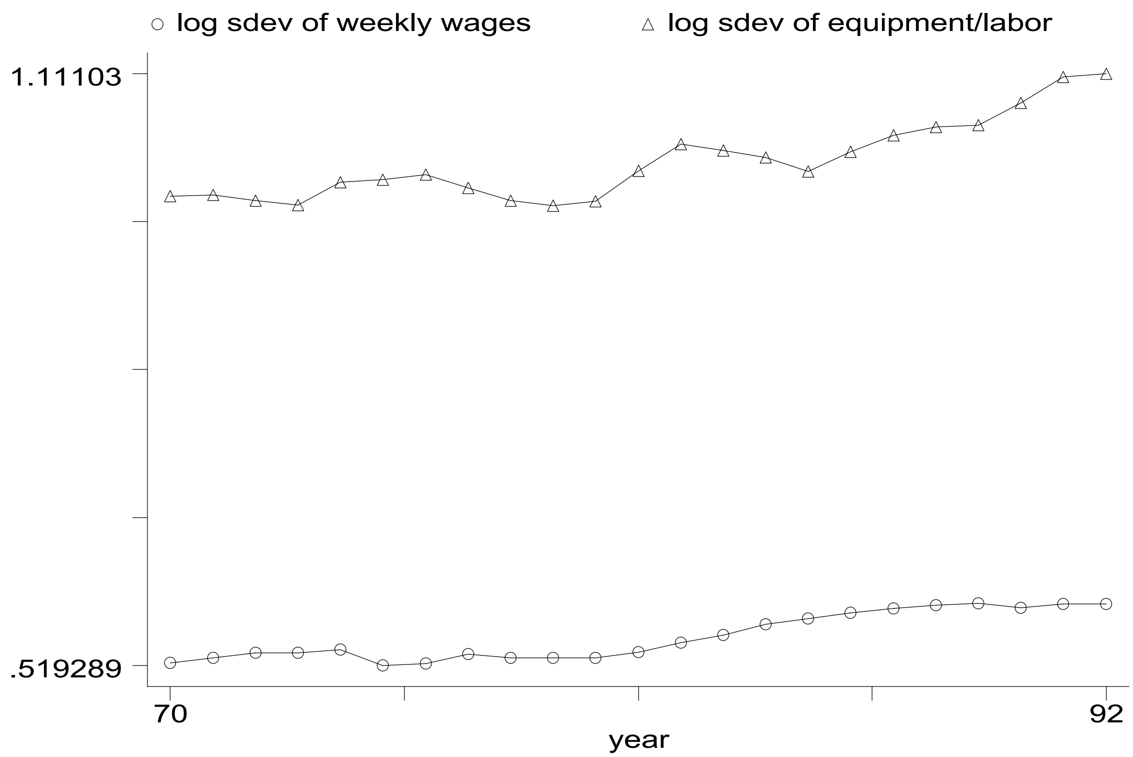

Figure 5: Log standard deviation of real weekly wages from March CPS. Employment-weighted log standard deviation of equipment/labor ratios from Compustat.

3.1 The "Capital Intensity" Premium

I regress log weekly wages from March CPS on industry employment-weighted average log equipment/labor ratios from Compustat. The two datasets are matched at the one-digit industry-year level.

I restrict the March CPS sample to full-year, full-time workers (those working 35 or more hours per week and at least 40 weeks in the previous year) between the age of 20 and 60 at the time of the survey. I use March CPS data from 1971 to 1993 therefore covering earnings from 1970 to 1992. The sample is restricted to workers without allocated earnings, who earned at least $67 per week in 1982 dollars.[5]

The regression is of the form:

$$\log w_{ijt} = \alpha + X_{it}\beta + \gamma \log(\frac{k}{l})_{jt} + \varepsilon_{ijt} \tag{2}$$

where $\log w_{ijt}$ is the wage of individual i at time t in industry j. X_{it} includes year and industry effects, a quadratic in age, years of education, sex, race and marital status dummies. $\log(\frac{k}{l})_{jt}$ is the employment-weighted average equipment/labor ratio in industry j at time t. Standard errors are clustered at the industry-year level. I consider the following industries: mining, durable manufacturing, non-durable manufacturing, transport and utilities, wholesale trade, retail trade, finance, other services. Agriculture and construction are dropped because of the low sample size of the year cells in Compustat. Workers in public administration are dropped as Compustat data on capital intensity cover only the private sector. Wages are deflated by the CPI, equipment is deflated using 1digit industry-specific deflators from the Bureau of Economic Analysis.

Table 4 shows the results of OLS estimation of equation 2 separately for the CPS and the DWS. The results show a positive relationship between industry capital intensity and weekly wages. The first row of table 4 shows that a 1% increase in the industry capital intensity is associated with a 0.11% increase in the average weekly wage. The relationship between wages and capital intensity, controlling for year effects, is always positive and significant. This is the well-known result that more capital-intensive industries tend to pay higher wages. Equipment capital intensity and average wages are slightly negatively correlated within industry (table 4, first and second row and third column), and their correlation is insignificant when I control for both industry and time effects (table 4, fourth column). This result is

[5] This selection of the March CPS is used in Katz and Autor (1999).

consistent with the view that inter-industry wage differentials have not increased over time. The same results are obtained in the second row of table 4 considering the years 1984-1992 of the CPS. This cut of the sample is used to compare the results with the Displaced Workers Survey.

3.2 The Displaced Workers Survey

In this section, I estimate equation 2 by using the Displaced Workers Surveys in years 1984, 1986, 1988, 1990 and 1992. The Displaced Workers Survey is a supplement to the January CPS in years 1984, 1986, 1988, 1990, 1992. The DWS asks whether the workers were displaced in the five years prior to the survey. It contains information about the previous and current wage, industry and occupation and information about a respondent's employment history in the previous 5 years.

There are two advantages to using the DWS: First, the DWS has a panel dimension that allows one to control for unobserved heterogeneity; secondly, displaced workers are less likely to select themselves in the most capital-intensive industries and within industry in the most capital-intensive firms. As a result, the coefficient on industry capital intensity is more likely to reflect the true firm effect rather than sorting. The thought experiment that motivates this analysis is the following: imagine a group of workers is exogenously displaced and then randomly assigned to a new firm, either within the same industry or in a different industry. Given the big increase in the dispersion of capital/labor ratios across firms, we expect to see a positive relationship between the variance of the wages and the variance of capital intensity within and between industry.

I restrict the sample to workers who are employed full time in both the pre-displacement and the current job. This restriction is necessary as the wage information is in terms of weekly wages. The sample is further restricted to workers aged 20-60 at the time of the survey. There can be various reasons for displacement and in the following tables I present the results on the whole sample of displaced workers. The results obtained on the subsample of the displaced because of establishment closings are qualitatively similar.

The results of estimation of equation 2 on DWS data are shown in table 4 row three. The results are similar to those obtained on CPS data. In the pooled sample (row three, first column), a 1% increase in equipment capital intensity implies a 0.13% increase in the average post-displacement wage. Wages and capital intensity are positively associated across industries (row three, second column), but are not associated within industry (row three, third column). Controlling for both industry and year effects, (row three, fourth column), capital intensity and wages are not significantly associated.

The same pattern holds when the regressions are run using fixed effect estimates. In this case, both the information on pre- and post-displacement wages is used and the average industry capital intensity in the pre-displacement job is matched according to the relevant year and industry. Table 4, fourth row, reports the results of the fixed effect estimation. A 1% increase in the change in capital intensity is associated with a 0.06% increase in the weekly wage change (the difference between the post-displacement and the pre-displacement wage). The correlation between capital intensity changes and wage changes disappears when we control for both industry and time effects. All the regressions run with fixed effects include dummies to control for years since displacement (25 dummies: years since displacement go from one to five in each survey wave). The regressions also control for pre- and post-displacement industry change (64 dummies: eight pre-displacement industries combined with eight post-displacement industries).

3.3 Within-Industry Dispersion of Wages and Capital Intensities

Regression 2 looks at the effect of average industry capital intensity on average wages but does not take into account within-industry dispersion in capital/labor ratios. To look at the effect of dispersion of within-industry capital intensity on within-industry wage dispersion I run the following regression:

$$std(\log w)_{jt} = \alpha + \gamma std(\log \frac{k}{l})_{jt} + \varepsilon_{jt} \qquad (3)$$

$std(\log \frac{k}{l})_{jt}$ is the employment-weighted log standard deviation of equipment/labor. This regression is weighted with weights proportional to the number of observations that are used to calculate $std(\log \frac{k}{l})_{jt}$ in each industry-year cell.

Table 5 shows the results of estimation of equation 3 using the March CPS and the DWS. The results that refer to the CPS, table 5 row one and two, show that there is a positive association between capital intensity dispersion and wage dispersion within industries (column three). Wage and capital intensity dispersion are negatively associated across industry (column two). This indicates that the industries with the higher wage dispersion are

Sample	Coefficient on average industry equipment/labor ratio				N obs.
CPS 1970-1992	0.112*	0.154*	-0.052*	0.021	603483
	(0.007)	(0.005)	(0.011)	(0.022)	
CPS 1984-1992	0.168*	0.168*	-0.019	-0.037	226497
	(0.008)	(0.007)	(0.050)	(0.040)	
DWS 1984-1992	0.131*	0.130*	0.090	-0.070	8629
	(0.012)	(0.011)	(0.074)	(0.067)	
DWS 1984-1992 FE	0.060*	0.092*	-0.322*	0.041	8029
	(0.013)	(0.013)	(0.059)	(0.082)	
Time effects	No	Yes	No	Yes	
Industry effects	No	No	Yes	Yes	

Notes: Standard errors clustered. Additional controls include a quartic in age, marital status, non-white and sex dummies, years of education. Industries considered are mining, durable, non-durable manufacturing, transport and utilities, wholesale trade, retail trade, finance, other services.

Table 4: OLS regression of log earnings on average industry equipment/labor ratio

Sample	Coefficient on within-industry standard deviation of equipment/labor ratios				N obs.
CPS 1970-1992	-0.029*	-0.043*	0.113*	0.064*	184
	(0.016)	(0.014)	(0.041)	(0.019)	
CPS 1984-1992	-0.042*	-0.046*	0.098*	0.048*	72
	(0.025)	(0.026)	(0.028)	(0.025)	
DWS 1984-1992	0.196*	0.077*	0.479*	0.209	40
	(0.052)	(0.049)	(0.142)	(0.164)	
Time effects	No	Yes	No	Yes	
Industry effects	No	No	Yes	Yes	

Notes: Weighted regression. Industries considered are mining, durable manufacturing, non-durable manufacturing, transport and utilities, wholesale trade, retail trade, finance, other services.

Table 5: OLS regression of the standard deviation of wages on the standard deviation of equipment/labor ratios

not the same as those with the higher capital intensity dispersion. Column four, however, shows that within industry, the increase in capital intensity dispersion is associated with the increase in wage dispersion.

The same pattern is present in DWS data. The results appear to be stronger but less precise than those obtained on CPS data. Table 5 row three shows the results of estimation of equation 3 on the five DWS waves. The correlation between within-industry capital intensity dispersion and within-industry post-displacement wage dispersion is positive both across industries (column two) and within industries (column three). However, the trend of within-industry wage dispersion is mostly explained by time dummies and is only insignificantly positively associated with the concurrent increase in capital intensity dispersion.

4 A Theoretical Interpretation

This section gives an interpretation of the evidence presented earlier. According to the evidence, the increase in capital intensity dispersion across firms is related to wage dispersion across workers.

In this section, I present a model of residual wage inequality based on the increasing variance of firms' capital intensities. Contrary to most previous models of residual wage inequality, this model is not based on the rising rewards of unobservable abilities. I suggest that the variance in the distribution of the demand for skills has increased over time. By the variance of the demand for skills I mean the variance of equipment capital investment across firms. In the next section, I will review some of the existing evidence that supports this hypothesis.

I build a search and matching model with identical workers and two types of jobs. Firms are ex-ante identical but ex post they differ in their optimal equipment capital investment. Firms sink their capital before searching for workers and the matching is random. As the relative price of equipment decreases over time, the dispersion of capital/labor ratios across firms increases. This force generates wage dispersion across identical workers as job changers and new entrants are matched to an increasing dispersed distribution of jobs.

The model is related to the literature on inter-industry wage differentials and in particular to the more recent theoretical developments that explain wage dispersion among equivalent workers in a search framework. In many of these models, firms are assumed to have differences in job-creation costs and wage dispersion is a consequence of cost dispersion. In both Pissarides (1994) and Acemoglu (2001), firms have different job-creation costs. The focus in Pissarides (1994) is on modelling on-the-job search. My model is close to Acemoglu (2001). His model focuses on the effect of unemployment insurance and minimum wages on the composition of jobs. Like in that model, I assume that firms are ex-ante identical but they set up different types of jobs ex post. Unlike Acemoglu (2001), I focus on the effect of a decreasing price of equipment capital on firms' capital choices and on wage inequality.

This paper is also linked to the recent literature that looks directly at the changes in the variance of the distribution of demand of skills. Acemoglu (1999) builds a model where the increase in the relative supply of skills changes firms' investment decisions. When there are few skilled workers and the productivity gap between the skilled and unskilled is limited, firms create one type of job (one single level of k) and pool across all types of workers. When the supply of skilled workers rises or their relative productivity increases, firms tend to differentiate the types of jobs they offer. Some firms invest in more capital than others and target only skilled workers. That model, like mine, implies an increasing variance in equipment/labor ratios across firms. In that model the increasing dispersion of capital is due to the increase in the relative supply or the relative productivity of skills. In my model, the increasing dispersion of capital is due to the decline in the relative price of equipment.

4.1 Changes in the Distribution of Demand and Supply of Skills

The increase over time in the average demand for skills has been put forth in numerous papers. The most popular reasons are skill-biased technical change and trade with developing countries. However, skill-biased technical change or organizational changes at the firm level may have also increased the variance of the demand for skills. The clearest exposition of this thesis is in Acemoglu (1999). In the same paper Acemoglu provides a summary of some of the evidence on the increased variance in the composition of jobs. Such evidence comes from different sources.

Murnane and Levy (1996) and Cappelli and Wilk (1997) study the changes in firm recruitment practices. Evidence of more selective practices and more accurate screening at recruitment level are interpreted as signs of a changing composition of jobs. Sicherman (1991) provides evidence of better matching of firms and workers. Evidence from the PSID shows that more workers have the exact amount of education required for their job. The higher efficiency of the match could be due to a wider variety of jobs offered. Constructing industry-occupation cells and ranking them according to their average wage, Acemoglu (1999) shows that there is a shift of employment towards the lower and the higher ranking cells. Constantine and Neumark (1994) show that the distribution of on-the-job training has become more unequal. Since on-the-job training is correlated with high wages and capital investment, this evidence can be interpreted as a more unequal distribution of capital investment. Finally, Caselli (1999) shows some direct evidence of more unequal distribution of capital/labor ratios across industries. He reports a sharp increase in the capital/labor ratio difference between the 90th and 10th most capital-intensive industries.

4.2 The Model

In this model, there are identical workers matched to two different types of jobs. Firms are ex-ante identical but ex post they create two different types of jobs. Jobs differ in their job-creation costs (structure capital) and their equipment capital investment. Firms rent a site (structure capital) and immediately after renting a site, before meeting workers, they decide how much equipment capital to install. Equipment capital is irreversible, i.e. when the relationship ends, it becomes obsolete. Equipment capital is optimized but structure capital is fixed. Both types of capital are sunk when the vacancy is opened, expenditure on structure is incurred immediately, expenditure on equipment only when the match takes place. This avoids the "hold up" problem. The driving force behind the increasing dispersion of equipment/labor ratios across firms is the decline in the relative price of equipment capital. As the cost of equipment capital decreases, "good" firms which use a lot of equipment capital increase their optimal capital choice more than "bad" firms. Since labor markets are not competitive and rents are split by Nash bargaining, the increasing dispersion of capital intensities implies an increasing dispersion of wages across identical workers.

The economy is constituted of a mass 1 of risk neutral workers and a larger mass of risk neutral firms. The production technology is:

$$Y = (Y_b^\rho + \gamma Y_g^\rho)^{\frac{1}{\rho}}$$

where Y_b and Y_g are the intermediate inputs. Since the intermediate inputs are sold in competitive markets their prices are:

$$p_b = Y_b^{\rho-1} Y^{1-\rho} \text{ and } p_g = \gamma Y_g^{\rho-1} Y^{1-\rho}$$

Firms can be inactive, vacant or filled. Ex-ante identical firms can choose either one of the two types of intermediate goods (or jobs), the good job g or the bad job b. There is free entry of firms: at every point in time, some inactive firms open a vacancy renting a site at price c_g if it is a "good" firm and c_b if it is a "bad" firm. After opening a vacancy and before meeting the workers, firms have to make their irreversible capital choices k_g and k_b. The cost of installing equipment capital is incurred only at matching. Production takes place in the form of a match one firm-one worker. A worker matched with a firm with capital k_j with $j = g, b$ produces:

$$y_j(k, l) = k_j^{1-\alpha} \tag{4}$$

Matching is random. Workers have the probability ϕ of matching with a "good" firm and $(1-\phi)$ of matching with a bad firm. $\phi = \frac{v_g}{v}$ is the proportion of vacant "good" firms among all vacancies. As in the basic search and matching models, vacant firms meet unemployed workers at the rate $q(\theta)$, unemployed workers meet vacant firms at the rate $\theta q(\theta)$ where $\theta = \frac{v}{u}$ is market tightness. Both firms and workers discount the future at rate r. Quits into unemployment to look for another job take place at rate λ. The rate of quits into unemployment is exogenous.

In a competitive labor market, "good" jobs and "bad" jobs cannot co-exist as workers are identical. In a search model, "good" and "bad" jobs can co-exist. Since capital costs are sunk before workers are met, capital remains idle until a match is formed. In equilibrium, "good" jobs will have to recover the bigger costs incurred at the beginning with higher flow profits. I solve the model in steady state only and I present the relevant Bellman equations. The discounted value of being unemployed is :

$$rU = \theta q(\theta)[\phi E(k_g) + (1-\phi)E(k_b) - U] \tag{5}$$

An unemployed worker meets a good firm with probability $\theta q(\theta)\phi$ where $\theta q(\theta)$ is the flow probability of meeting a vacant firm and ϕ is the proportion of good firms among the vacancies. When the match takes place and both the worker and the firm accept the job, the worker gains $E(k_g)$ or $E(k_b)$ and he loses U. For simplicity's sake, I assume there are no unemployment benefits. The value of being employed in a good firm $E(k_g)$ is:

$$rE(k_g) = w(k_g) - \lambda(E(k_g) - U) \tag{6}$$

The value of being employed in a bad firm is:

$$rE(k_b) = w(k_b) - \lambda(E(k_b) - U) \tag{7}$$

where $w(k_j)$ is the wage rate for a worker in firm $j = g, b$ and λ is the exogenous rate of quits. The value of a vacant firm $V(k_j)$ for $j = g, b$ is:

$$rV(k_j) = q(\theta)[J(k_j) - Ck_j - V(k_j)] \tag{8}$$

where $q(\theta)$ is the flow probability of meeting an unemployed worker. When the match occurs and both the firm and the worker do not turn it down, the firm gains the value of a filled firm $J(k_j)$, incurs in the cost of equipment capital Ck_j and loses $V(k_j)$. The value of a firm $j = g, b$ matched with a worker is:

$$rJ(k_j) = p_j k_j^{1-\alpha} - w(k_j) - \lambda[J(k_j) - V(k_j)] \tag{9}$$

When jobs are destroyed at the exogenous rate λ, firms exit the market. The zero profit condition for a firm $j = g, b$ is:

$$V(k_j) = c_j \tag{10}$$

as the cost of renting a site is c_j. Notice that "good" and "bad" firms face exogenously different rental costs c_j. The crucial ingredient of this model, as described above, is that firms are different in their capital mix. The driving force of this model is the declining relative cost of equipment capital. The declining cost of equipment capital C favors "good" firms which have a high ratio equipment/structure and makes them increase their capital choice k_g. As long as there are search frictions, there will be rents in the labor market. Rents will be split with Nash bargaining. Wages in good firms $w(k_g)$ will be set such that:

$$(1-\beta)(E(k_g) - U) = \beta(J(k_g) - V(k_g)) \tag{11}$$

in bad firms:

$$(1-\beta)(E(k_b) - U) = \beta(J(k_b) - V(k_b)) \tag{12}$$

Equipment capital does not appear in the sharing equation as it is sunk at the moment of bargaining and if the workers leave the relationship, equipment capital has to be scrapped. Unemployment in steady state will be given by:

$$u = \frac{\lambda}{\lambda + \theta q(\theta)} \tag{13}$$

4.3 The Steady State Equilibrium

The equilibrium is given by capital choices k_g and k_b, prices p_g and p_b, unemployment rate u, proportion of good firms ϕ in the vacancy pool, market tightness ϑ and wages $w\left(k_g\right)$ and $w\left(k_b\right)$ such that:

1) for all k_j : $k_j = \arg\max_{k_j'} V(k_j')$ for $j = g, b$.
2) for all k_j, k_j satisfies $V(k_j) = c_j$ for $j = g, b$.
3) all value functions $J(k_j), V(k_j), U, E(k_j)$ are satisfied for $j = g, b$.
4) u satisfies steady state equation 13.
5) wages are given by 11 and 12.

In equilibrium, both "good" and "bad" jobs meet workers at the same rate and workers accept both types of vacancies. Therefore $Y_b = (1-u)\phi k_b^{1-\alpha}$ and $Y_g = (1-u)(1-\phi)k_g^{1-\alpha}$. Prices are given by:

$$p_g = ((1-\phi)^\rho k_b^{(1-\alpha)\rho} + \gamma\phi^\rho k_g^{(1-\alpha)\rho})^{\frac{1-\rho}{\rho}} \gamma\phi^{\rho-1} k_g^{(1-\alpha)(\rho-1)} \tag{14}$$

$$p_b = ((1-\phi)^\rho k_b^{(1-\alpha)\rho} + \gamma\phi^\rho k_g^{(1-\alpha)\rho})^{\frac{1-\rho}{\rho}} (1-\phi)^{\rho-1} k_b^{(1-\alpha)(\rho-1)} \tag{15}$$

Wages are set from 11, substituting 6, 9:

$$w(k_j) = \beta(p_j k_j^{1-\alpha} - rc_j) + (1-\beta)\, rU \tag{16}$$

and from 11, 9 and 10:

$$rU = \theta q(\theta)[\frac{\phi\beta}{(1-\beta)}(\frac{rc_g}{q(\theta)} + Ck_g) + \frac{(1-\phi)\beta}{(1-\beta)}(\frac{rc_b}{q(\theta)} + Ck_b)] \tag{17}$$

The optimal capacity k_j in equilibrium comes from $V'(k_j) = 0$ where $V(k_j)$ is obtained using 8, 9 and 16. The two equations that determine capital choice when firms take both prices and wages for given are therefore:

$$V'(k_g) = \frac{q(\theta)}{(r+\lambda)(r+q(\theta))}[p_g(1-\alpha)k_g^{-\alpha} - C] = 0 \tag{18}$$

and

$$V'(k_b) = \frac{q(\theta)}{(r+\lambda)(r+q(\theta))}[p_b(1-\alpha)k_b^{-\alpha} - C] = 0 \tag{19}$$

In these two equations, the first term indicates the marginal benefit of one more unit of capital while the second term indicates the marginal cost. The crucial result of the model comes from the two equations above. When the relative price of equipment capital C falls, equipment investment of good firms k_g grows more than k_b. Firms with higher creation costs c_j command higher output prices p_j. Since in equilibrium $p_g > p_b$, from equations 19 and 18 we obtain that $k_g > k_b$, and $\frac{\delta(k_g - k_b)}{\delta C} > 0$.

The equilibrium in the "good" job market and in the "bad" job market is given at the crossing of the "job creation curve" JC_j (which is obtained combining equation 8, 9 and 10) and the wage equation 16 in each market. We have two equilibrium loci, one where the "job creation curve" JC_g meets the wage setting curve $w(k_g)$ (equation 16) and the other where JC_b meets $w(k_b)$. The two equilibrium loci that together with 18 and 19 (with 14 and 17 substituted in) define the equilibrium θ and ϕ are:

$$(1-\beta)(p_j k_j^{1-\alpha} - rU) = [\frac{r(r + q(\theta) + \lambda)}{q(\theta)} - \beta r]c_j + (r+\lambda)Ck_j \qquad (20)$$

for $j = b, g$.

This model is particularly appealing as it gives a formula for within-group wage inequality that can be tested with the data used in the empirical part. Within-group wage inequality (using 16 and 20 for $j = b, g$) in this model is given by:

$$w(k_g) - w(k_b) = \frac{(r+\lambda)r(c_g - c_b)}{q(\theta)} + (r+\lambda)C(k_g - k_b) \qquad (21)$$

In this equation, the optimal capacity k_j comes from equations 18 and 19 and $\beta = \frac{1}{2}$. Wage differences across identical workers are related to the differences in structure costs $c_g - c_b$, and capital investment $k_g - k_b$. They are also related to the job changing rate λ and to the average duration of a vacancy $q(\theta)$.

4.4 Back of the Envelope Calculation

To have an idea of the importance of capital/labor ratios in explaining increasing wage differentials, I calibrate equation 21. I assume some values for the parameters of equation 21 over the period 1970-1992 : interest rate $r = 0.06$, the job changing rate $\lambda = 0.2$. As an estimate of the matching function $q(\vartheta)$ for the US, I take the values suggested in Blanchard and Diamond (1989): $q(\vartheta) = (\frac{u}{v})^{\alpha}$ with $\alpha = 0.4$. The unemployment to vacancy ratio $\frac{u}{v}$ is strongly anti-cyclical but on average, during the period 1970-1992, $\frac{u}{v} = 2.5$. For $C(k_g - k_b)$ I take the 90-10 log differential of equipment/labor ratios across firms calculated on Compustat data; this value increased by 0.32 log points over the period. For $(c_g - c_b)$ I take the 90-10 log differential of structure/labor ratios across firms. This value increased by 0.10 log points over the period. Calibration of equation 21 implies that within-group wage inequality, $w(k_g) - w(k_b)$ (90-10 log differential of the residual distribution), has increased by roughly 0.08 log points over the period 1970-1992 due to the increasing dispersion of capital/labor ratios across firms. Calculations from the March CPS show that the actual 90-10 log differential of within-group wage inequality increased by 0.26 log points from 1970 to 1992 in the US. This means that the mechanism that acts through the increasing dispersion of firm capital/labor ratios can account for a little less than one third of the total increase in within-group wage inequality.

A caveat regarding this rough calibration is the fact that the results are very sensitive to the assumptions about capital. If capital is assumed to be a creation cost as in Acemoglu (2001), within-group wage inequality is given by:

$$w(k_g) - w(k_b) = \frac{(r + \lambda) r (k_g - k_b)}{q(\theta)} \tag{22}$$

where now k_j is total capital i.e. equipment plus structure. Calculation on Compustat shows that the 90-10 log differential of total capital/labor ratios increased by 0.28 log points from 1970 to 1992. Calibration of equation 22 shows that the increase in dispersion of capital/labor ratios can explain only about 1/30 of the total increase in wage inequality.

5 Conclusions

In this paper I document the increasing cross-firm dispersion of equipment capital/labor ratios in the US labor market using Compustat data. The increase takes place both between and within industries. I match Compustat data on equipment capital intensity to CPS and DWS data on individual wages at the industry-year level. A 1% percent increase in industry capital intensity is associated with a 0.11% increase in the average weekly wage in the CPS and to a 0.13% increase in the Displaced Workers Survey. More importantly for the purpose of this paper, the increase in the capital intensity variance across firms appears to be positively associated with the increasing wage variance across workers. The correlation holds within industries even after controlling for time effects.

To explain these empirical regularities, I adopt a search and matching model where identical workers are matched to two types of firms. Firms differ in their optimal composition of capital between equipment and structure. In response to the decline in the relative price of equipment capital, the distribution of capital/labor ratios becomes more dispersed across firms. Residual wage inequality increases as identical workers are randomly matched to an increasingly dispersed distribution of capital/labor ratios. Simple calibration of the model indicates that the dispersion of capital/labor ratios can account for up to one third of the total increase in within-group wage inequality.

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