Firms' Heterogeneity in Capital/Labor Ratios and Wage Inequality

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Abstract

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 using Compustat data. I also show that the increase in the variance of capital/labor ratios across firms is related to the increasing variance of wages. To explain these empirical regularities I adopt a search model where firms differ in their optimal composition of capital between equipment and structure. As the relative price of equipment falls over time the distribution of capital/labor ratios becomes more dispersed across firms. In a frictional labor market this force generates wage dispersion among identical workers. In the model the increase in wage inequality is due only to job changers as they are randomly matched to an increasingly wide variety of jobs (capital/labor ratio). This feature of the model is consistent with recent evidence that indicates that the bulk of the increase in wage inequality took place between plants rather than within plants. Simple estimation of the model indicates that the dispersion of capital/labor ratios can explain up to one half of the total increase in residual wage inequality.

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1 Introduction

Changes in wage inequality re‡ect 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 di¤erential can be accounted by changes in the residuals' distribution.

Most previous theories of residual wage inequality are based on ex-ante di¤erences in unobservable abilities. In this paper I propose a theory based on identical workers matching to an icreasingly dispersed distribution of …rms' capital intensity. In the empirical part of this paper I document the increasing variance of capital intensities in the US economy and the link between the dispersion of wages and the dispersion of capital intensity. In the theory part I build a search model with identical workers matched to di¤erent types of jobs (capital intensities) in equilibrium.

The mainstream view in the literature is that within group wage inequality is the result of the increase in the price of unobserved ability. Many models rely on ex ante di¤erences in ability across individuals. Acemoglu (1999) builds a model where identical …rms search for workers with di¤erent abilities. Skill biased technical change induces …rms to switch from a pooling equilibrium where one job …ts for all, to a separating equilibrium where di¤erent jobs for di¤erent abilities are created. Caselli (1999) suggests that a technological revolution occurs with the introduction of a new type of machine. Operating the new machine requires a new type of skill. Workers have di¤erent costs of learning the new skill and those with lower learning costs can get a higher wage premium. Galor and Moav (2000) claim that ability helps 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 di¤erent skills are increasingly segregated across plants. Segregation occurs because of the complemetarity of task and the exogenous force that sets the mechanism in motion is the increasingly dispersed distribution of skills across workers.

Models based on …xed ex-ante di¤erences in ability are subject to an important criticism. Unobserved ability is a permanent characteristic of the individual therefore all models based on di¤erences in innate ability imply that the rise in residual wage inequality should be accounted by the rise in the variance of the persistent component of individual earnings. Gottschalk and Mo¢ tt (1994, 1995) 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.

My model, like Acemoglu (1999) and Caselli (1999), implies an increasingly dispersed distribution of capital intensity. Unlike those models, my theory is not based on ex-ante differences in ability.

Another possible explanation of the increase in within group wage inequality is an increasingly dispersed distribution of skills across the population. In a single index model there is only one type of skill which is correlated with education. The idea is that within group wage inequality may arise from increased dispersion of unobserved skills in the new cohorts of labor market entrants due for example to increased differences in school quality or in social conditions. Increased dispersion of unobserved ability could affect the returns to education as education and unobserved ability are thought to be positively correlated. If the distribution of skills were more dispersed in the younger cohorts, then we would observe a different college premium for different cohorts. Card and Lamieux (2001) find statistically different returns to education for different cohorts.

The single index model runs into two criticisms. Juhn, Murphy and Pierce (1993) compare the changes in wage inequality and residual wage inequality in the 70s for the cohort aged 25-29 in 1970 with changes in the wage inequality in the 80s for the cohort aged 25-29 in 1980. They find that changes in wage inequality within cohorts are very similar to the general pattern of increasing wage inequality. This suggests that the rise in wage inequality is due to changes in the true returns to observed and unobserved characteristics rather than to the different dispersion of unobserved skills within different cohorts. The single index model of residual wage inequality runs into another difficulty as it predicts that the unobservable skill premium and the college premium always move togheter and therefore this model cannot account for the contemporaneous rise in residual wage inequality and decline in returns to college during the 70s [1].

Unlike the single index model, my model is not based on the increasing dispersion in the supply of skills across workers, but on the increasing dispersion of the demand of skills (capital intensities) across firms.

Another model of residual wage inequality which is neither based on unobserved fixed ability nor on an increasing dispersion of skills in the population is the vintage model proposed by Violante (2002). In each period a new vintage technology embodied in new machines diffuses in the economy.

[1] A model that better explains the differential behaviour of residual wage inequality and the returns to college during the 70s is a two index model of residual wage inequality as proposed in Acemoglu (1998). However Acemoglu (1998) is also based on ex-ante differences in ability.

Workers are ex-ante identical and have vintage speci…c skills. The degree of transferability of these skills between di¤erent vintages is proportional to the productivity di¤erence between the machines. An acceleration in technical change increases the productivity di¤erences across successive vintages and decreases the degree of transferability of skills. As a result wage inequality across identical workers matched to di¤erent vintages of machines rises.

Like Violante (2002), my model is neither based on ex ante di¤erences in abilities nor on increased dispersion of skills. In Violante (2002), a technological acceleration rises wage inequality reducing the degree of transferability of skills. In my model, a decrease in the relative price of equipment capital rises wage inequality increasing the dispersion of capital intensities across …rms.

This paper also connects the existing literature on residual wage inequality to the literature that studies the increasing dispersion of wages across plants (Davis and Haltiwanger 1991). In particular recent work by Dunne et al. (2002) shows that wage dispersion is mainly a between-plant phenomenon. Using establishment-level data from 1975 to 1992 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 can be accounted by between-plant dispersion within the same industries. They also show that a signi…cant fraction of the rising between-plant dispersion can be explained by changes in the distribution of computer investment across plants.

The models by Kremer and Maskin (2000) and Caselli (1999) imply increasing segregation of skills across plants and are therefore consistent with the evidence about between-plant dispersion. However they are based on ex ante di¤erences in ability and therefore are subject to the criticism that residual wage inequality appears to re‡ect also an increase in the transitory part of earnings. Furthermore, as to date, there is no convincing direct evidence of increasing segregation of skills across plants.

This paper bases wage inequality on the increasingly dispersed distribution of jobs. This theory is therefore consistent with rising wage inequality between plants and yet it is not based on ex ante di¤erences in workers' ability.

Finally, an increasingly dispersed distribution of equipment/labor ratios can have an e¤ect on wage di¤erentials across identical workers as long as the market is not competitive and …rm e¤ects are important in determining the wage. This paper is therefore related to the literature on inter-industry wage di¤erentials. There is a controversy on the importance of unobserved person or …rm e¤ects in explaining inter-industry wage di¤erentials. Krueger and Summers (1988) and Gibbons and Katz (1992) claim that the di¤erentials cannot be explained by person e¤ects. Murphy and Topel claim that person e¤ects are the primary explanation. Abowd, Kramarz and Margolis using employer-employee matched dataset estimate that person and …rms e¤ects can account each for approximately 50% of the inter-industry wage di¤erentials.

1.1 New Data

The …rst contribution of this paper is an empirical analysis of the variance of capital/labor ratios across …rms over time. No paper so far has looked at the e¤ect of increased heterogeneity of capital/labor ratios on wage di¤erentials across observationally equivalent workers.

In this paper I use Compustat data to show that the cross sectional variance across …rms of equipment/labor ratios has increased over time. The log standard deviation of equipment/labor ratios increased by about 12% from 1970 nd 1992. The rise occurred both between and within industry.

Subsequently using March CPS data and four waves of the Displaced Workers Survey (DWS) I study the e¤ect of average industry capital intensity on individual wages. I match Compustat and CPS at the industry-year level and I show that a 1% increase in the average industry capital intensity is associated to a 0.11% increase in the average weekly wage in the CPS, to a 0.08% increase in the DWS.

Even more importantly, within industry dispersion of capital/labor ratios is also related to within industry dispersion of wages. The correlation of within industry dispersion of capital intensity and wages is across time and not across industry. The industries where wages are more dispersed are not the same where capital intensity is more dispersed. However, within industry, there is a positive relationship between the growth in the dispersion of wages and the growth in the dispersion of capital intensities.

The reason to study displaced workers is twofold. First in the DWS there is a panel dimension that allows to control for unobserved heterogeneity, secondly displaced workers are less likely to select themselves in the best paying industries or …rms. This implies that the capital intensity premium is more likely to re‡ect "true" …rms' e¤ects rather than sorting.

1.2 Introduction to the Model

In the theory part I build a model that tries to explain the rise in the variance of wages in view of the evidence on the increasing variance across …rms of the equipment/labor ratios.

The model is related to the literature that explains wage dispersion among equivalent workers with di¤erences in …rms' technology. Some of those models as Mortensen and Pissarides [1994], Montgomery [1991], Acemoglu [2000] and Pissarides [1994] consider di¤erent technologies across industries and derive wage dispersion as a consequence of technology dispersion. My model is close to Acemoglu (2000). He also considers a search model with di¤erent in technologies across …rms but he focuses on the effect of more generous unemployment insurance and minimum wages on the composition of jobs.

The intuitive idea is simple. Identical workers are matched randomly to two types of …rms. "Good" …rms invest little in structure and a lot in equipment, "bad" …rms do the reverse. Firms have to do their irreversible capital choices before meeting workers and then there is random matching. As the price of equipment capital falls, …rms with a high ratio invest more and become more productive. Wages for identical workers are more dispersed as a consequence of a higher dispersion of capital intensities.

This mechanism works only through job changers. Only job changers face the chance of being matched to jobs with a higher variance of capital choices. Job stayers are protected in their older jobs and they work with the capital sunk before the match. This is Freeman's [1975] hypothesis that new entrants and displaced workers are more exposed to changes in supply and demand for skills, while job stayers are protected by internal labor markets. This feature of the model that focuses on the role of job changers in explaining the increase of wage inequality is consistent with recent evidence that indicates that the bulk of the increase in wage inequality took place between plants rather than within plants.

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 concludes.

2 Firms Equipment/Labor Ratios

In this section I present some results on the distribution across …rms 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

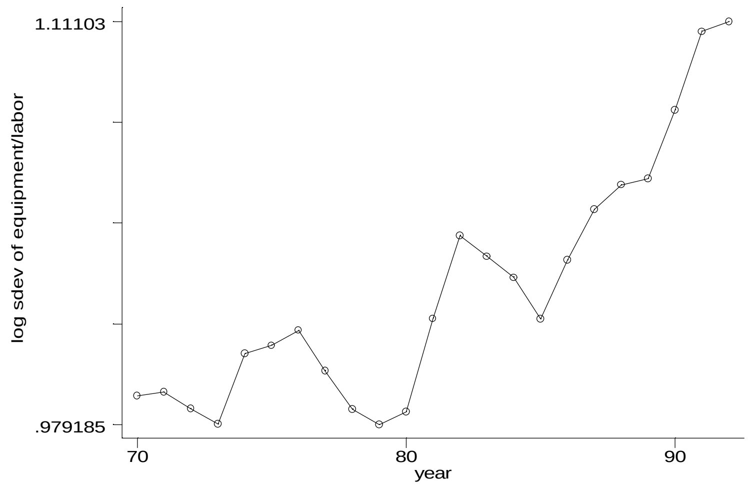

Figure 1: Compustat Industrial Data. Employment weighted log standard deviation of equipment/labor ratios. Equipment capital is de‡ated using 1-digit industry speci…c de‡ators from Bureau of Economic Analysis. Real value at 1992.

total employment.

Figure 1 plots the employment weighted standard deviation of log equipment/labor across …rms in each year. To build the employment/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 de‡ated using the 1-digit industry speci…c de‡ators form the Bureau of Economic Analysis.

Figure 1 shows an increase in the employment weighted standard deviation of log equipment/labor ratios across …rms 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 deviation of equipment/labor ratios is employment-weighted. The dispersion of equipment/labor ratios is interpreted as a sign of a diversi…cation of …rms in the economy.

[2] The results don't change if I exclude from the sample the new …rms that get in the sample after 1974.

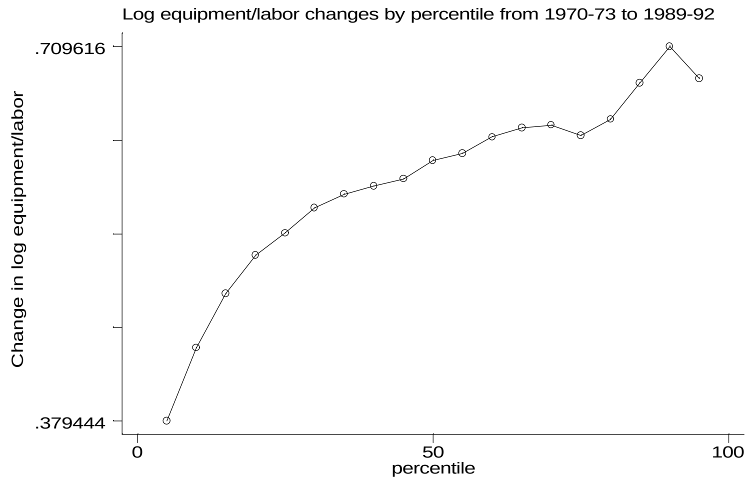

Figure 2: Log real value employment/labor ratio changes by percentile. Employment weights used to calculate percentile distribution. In figure $[p_{89-92}(\log \frac{e}{l}) - p_{70-73}(\log \frac{e}{l})]$ where p is the percentile of the employment weighted log distribution in years 89-92 and years 70-73.

Figure 2 shows that the divergence in equipment/labor ratios is pervasive and not limited to part of the distribution. Figure 2 gives the percentage change in equipment/labor ratios from 1970-73 to 1989-92. The change in real employment/labor ratios at the bottom 10% of the distribution is 55%, at the top 90% of the distribution 103%. The picture exibits a concave shape with inequality rising more at the bottom 50% of the distribution.

The four panels in figure 3 decompose the rise in equipment/labor dispersion in four periods. I look at changes between periods of five years each. The first panel 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. Employment weights are used.

The four panels 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 increase in dispersion of equipment/labor ratios across firms took place in the early and in the late eighties, as the top right and bottom right panel in figure 3 show.

The increase in dispersion is concentrated at the bottom of the distribution in the early eighties (top right panel) with the bottom percentiles left

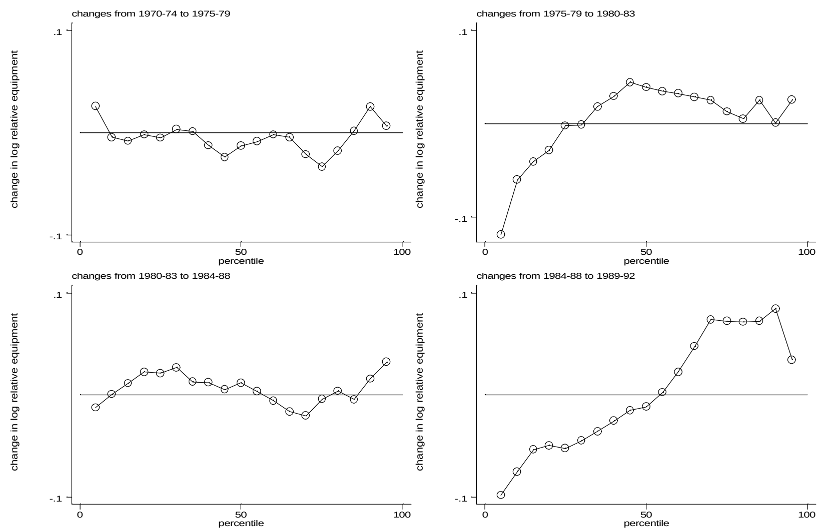

Figure 3: Changes in relative real employment/labor $\frac{e}{l}$ ratio. Four periods t. In figure $[p_t(\log\frac{e}{l}) - p_{t-1}(\log\frac{e}{l})] - [E_t(\log\frac{e}{l}) - E_{t-1}(\log\frac{e}{l})]$ where p is the percentile of the employment weighted log distribution in period t. E is the employment weighted average.

much behind relative to the mean. The increase in dispersion paused somewhat in the mid eighties (bottom left panel) but continued from the mid eighties to the nineties (bottom right panel). In the late eighties (bottom right panel) 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 di¤erentials across industry and across size class. Mean log equipment/labor di¤erentials by industry and size group (…rst column Table 1 and 2) are de…ned as the di¤erence 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.

The sectors with the higher average equipment/labor ratios are agriculture and mining, transportation and utilities, and …nance. These three sectors have much higher equipment/labor ratios than the overall mean. The lower capital intensive industries are wholesale and retail and business and professional services.

The heterogeneity of log equipment/labor ratios across …rms of the same industry is also higher within agriculture and mining, transportation and utilities, and …nance. These results point to a much greater heterogeneity in technology within these sectors.

Equipment/labor ratios are higher at small companies with less than 100 workers and at very large companies with more than 4000 workers. The differences across size groups are less impressive than the di¤erences across industry groups. Di¤erences are larger between small …rms and medium-sized …rms. Firms of small size are more heterogeneous in their equipment/labor ratios than …rms of large size. The heterogeneity of equipment/labor ratios within size classes is decreasing with size.

Looking at the time series changes in table 2, the average equipment/labor ratio within agriculture, transportation, retail, …nance and business and professional services increased less than the overall average between 1970 and 1992. Manufacturing and construction gained ground relative to the mean.

Between …rm equipment/labor dispersion rose in all sectors except for transportation and personal and business services. The highest increases occurred in manufacturing, retail trade, …nance.

The di¤erentials in equipment/labor ratios across size classes increased dramatically over time. The difference between firms of less than 100 workers and firms of more than 4000 workers increased by 50% between 1970 and 1992. Between firm dispersion in equipment/labor ratios increased within all size classes except for companies below 100 workers. Small firms below 100 workers became relatively less capital intensive over time and much more homogenous.

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

Table 1: Time series averages

Industry	Mean log equipment/labor differential	Between firm standard deviation	Frequency
Agriculture/mining	0.79	1.29	1.81
Construction	-0.10	1.02	1.45
Manufacturing	0.05	0.99	59.48
Transportation/utilities	0.66	1.35	7.96
Wholesale/retail	-0.54	0.86	13.36
Finance	0.08	1.82	3.58
Other services	-0.44	1.04	13.06
Size class			
1-100 employees	0.11	1.30	14.3
100-500	-0.03	1.12	23.3
500-1000	-0.01	1.09	13.1
1000-4000	-0.07	1.07	24.9
4000+	0.04	1.03	24.2

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

Table 2: Time series changes 1970-1992

Industry	Mean log equipment/labor differential	Between firm standard deviation	Frequency
Agriculture/mining	-0.09	0.08	0.00
Construction	0.19	0.01	-0.00
Manufacturing	0.14	0.19	-0.12
Transportation/utilities	-0.17	-0.03	0.05
Wholesale/retail	-0.21	0.22	-0.02
Finance	-0.05	0.19	0.00
Other services	-0.03	-0.07	0.09
Size class			
1-100 employees	-0.49	-0.22	0.14
100-500	-0.08	0.09	0.09
500-1000	0.04	0.22	-0.02
1000-4000	0.05	0.29	-0.11
4000+	0.01	0.25	-0.09

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.

2.2 The Juhn Murphy and Pierce Decomposition

To give a characterization of 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. The observable characteristics I consider are industry and size.

Consider the regression:

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

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

Think of the residual u_{it} of equation 1 as reflecting the firm's percentile in the residuals' distribution. θ_{it} is the percentile in the distribution function of the residuals in year t: $\theta_{it} = F_t(u_{it})$. Therefore u_{it} can be written: $u_{it} = F_t^{-1}(\theta_{it})$.

To isolate the contribution of changes in industry and size composition consider:

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

where $\bar{\beta}$ is the average equipment/labor differential calculated over the whole period. $\overline{F^{-1}}(\cdot)$ is the average cumulative distribution of residuals. The time path of the distribution over 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 inter-industry and size specific equipment/labor differentials consider:

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

Calculating the distributions k_{it}, k_{it}^1, and k_{it}^2 for each year in the sample, we can attribute the changes in k_{it}^1 to changes in industry and size composition, the changes in $k_{it}^2 - k_{it}^1$ to changes in inter-industry and size specific

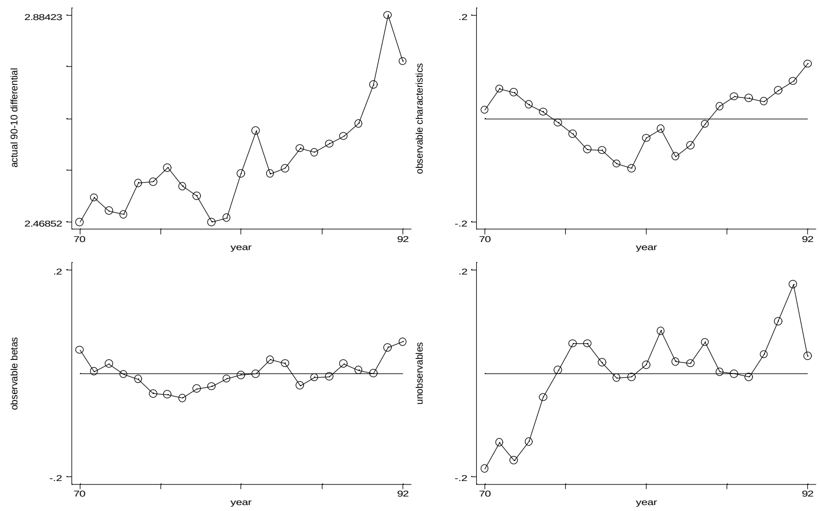

Figure 4: Juhn Murphy and Pierce decomposition. Employment weighted ninetieth-tenth percentile log equipment/labor di¤erentials and components. 1970-1992. Equipment is at real value 1992.

equipment/labor di¤erentials and the changes in k_{it} ¡ k^2_{it} to changes in the distribution of residuals.

The top left panel of …gure 4 plots the time series of the di¤erential between the 90th and the 10th percentile of the employment-weighted log distribution of equipment/labor ratios. The 90-10 di¤erential rose from 2,46 in 1970 to 2,78 in 1992. The other three panels of …gure 4 break down the growth in the 90-10 di¤erential into the three components of the JMP decomposition. Each component is measured as a deviation from its own overall mean.

Over the sample period, the 90-10 log equipment/labor di¤erential rose by 32 log points or 13% (0.32/2.46). The top right panel gives the e¤ect of the changes in the distribution of the observables. The results from the top right panel in …gure 4 reported in table 3 indicate that changes in industrial and size composition over twenty years (holding …xed the equipment/labor di¤erential associated with industry and size) contributed to 28% (0.09/0.32) of the total increase in the 90-10 log di¤erential. As it's clear from the picture (top right panel) changes in observable characteristics started to contribute positively to the increase in equipment/labor dispersion in the

1980s. During the 70s the industrial and size composition of …rms worked towards a reduction of the overall inequality in equipment/labor ratios.

The bottom left panel of …gure 4 looks at the e¤ect of the changing industry and size di¤erentials, keeping the composition of the sample constant. Changes in the industry and size di¤erentials alone (holding …xed the industry and size composition) contributed to 6% (0.02/0.32) of the total increase the 90-10 log di¤erential. Changes in composition and di¤erentials togheter account for 34% of the total increase in the 90-10 di¤erential. The remaining 66% of the total increase in the 90-10 di¤erential is explained by unobservables, i.e. by the rise in within industry-size groups dispersion. The bottom right panel of picture 4 indicates that the e¤ect of unobservables is particularly concentrated in the 1970s rather than in the 80s.

Table 3: Observable and unobservable components of changes in dispersion of log equipment/labor ratios, 1970-1992.

Inequality measure	Total change	Observable quantities	Observable betas	Unobservables
Standard deviation	0.12	0.08	0.00	0.04
90-10 differential	0.32	0.09	0.02	0.21
90-50 differential	0.18	-0.01	-0.01	0.20
50-10 differential	0.13	0.09	0.02	0.02

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

The JMP decomposition can be used to quantify the e¤ects of changes in the observables and the unobservables on all parts of the distribution. Table 3 reports the decomposition of time series changes in the 90-50 and 50-10 log equipment/labor di¤erentials.

Two important results stand out from the table. First, most of the increase in equipment/labor dispersion occurred in the top half of the distribution.

Secondly, the contribution of observables to the increase in equipment/labor ratios across …rms varies according to the inequality measure reported. The increase in between size and industry group inequality accounts for approximately three quarters of the total increase in the standard deviation of equipment/labor ratios. The increase in between group inequality accounts for 84% of the increase in the 50-10 ratio but doesn't explain at all the increase in the 90-50 ratio.

Apparently the capital intesity gap between the 50th percentile of the distribution and the 10th percentile is much more understandable in terms of changes in industrial and size composition and di¤erentials 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 …rms' equipment/labor ratios and wages from 1970 to 1992. First I study the correlation between wages and average industry capital intensity, secondly 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 noticed by Katz and Summers (1989) in the context of inter-industry wage di¤erentials. The correlation between within industry dispersion of wages and within industry dispersion of capital intensities is a novel point.

Di¤erently from previous work I study the relationship between individual wages and the average industry's 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 analisys to displaced workers. Displaced workers have been extensively used in the literature about inter-industry wage di¤erentials [3]. The idea is that an exogenous displacement reduces the problem of sorting of better workers into better paying industries and gives a better measure of the pure industry e¤ect. 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 …rms.

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. I now investigate the relationship formally.

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 industry-year level.

[3] Krueger and Summers (1988), Gibbons and Katz (1992) and Neal (1995) have used the Displaced Workers Survey to study interindustry wage di¤erentials.

Figure 5: Log standard deviation of real weekly wages from March CPS. Employment-weighted log standard deviation of equipment/labor ratios from Compustat. CPI prices and 1-digit industry specific capital deflators at 1992 values

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 [4].

The regression is of the form:

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

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: manufacturing, transport and utilities, wholesale and retail, finance, and other services. Agriculture, mining and construction are dropped because of the low sample size of the year cells

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

in Compustat. Workers in public administration are dropped as Compustat data on capital intensity cover only the private sector.

Wages are de‡ated by the CPI, equipment is de‡ated using 1digit industry speci…c de‡ators from the Bureau of Economic Analysis.

The results show a positive relationship between average industry's capital intensity and weekly wages. The …rst column 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 following four columns report the results of four separate regressions in four di¤erent time periods. They include year dummies but no industry e¤ects. The relationship between wages and capital intensity controlling for year e¤ects is always positive and signi…cant. More capital intensive industries tend to pay higher wages.

Table 5 shows the results of OLS estimation of equation 2 separately for each industry. The results show that the relationship between capital intensity and wages is negative or not signi…cant across time within industries.

3.2 Displaced Workers Survey

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

The use of the DWS has two advantages: First the DWS has a panel dimension that allows to control for unobserved heterogeneity; secondly displaced workers are less likely to select themselves in the most capital intensive industry and within industry in the most capital intensive …rms. As a result the coe¢cient on industry capital intensity are more likely to re‡ect true …rms' e¤ect rather than sorting.

The thought experiment that motivates this analisys is the following: imagine a group of workers is exogenously displaced and then randomly assigned to a new …rm, either within the same industry or in a di¤erent industry. Given the big increase in the dispersion of capital/labor ratios across …rms, 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 predisplacement and 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. The reasons for displacement can be various, 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 6. Controlling for both industry and year effects (first column) capital intensity and wages are not significantly associated. Each following column of table 6 corresponds to a separate regression in each survey year. Inter-industry wage differentials seem to be moderately increasing over time, at least for the part of the inter-industry differential that is captured by capital intensity. In year 1984 an increase of 1% in the industry capital intensity is associated with an increase of 0.08% in the average weekly wage. In 1990 with an increase of 0.14%.

The same pattern is true when the regressions are run using fixed effect estimates. In this case both the information on wages pre and post displacement is used and the average industry capital intensity in the pre-displacement job is matched according to the relevant year and industry. Table 7 reports the results of the fixed effect estimation. A 1% increase in the change in capital intensity is associated to a 0.08% increase in the weekly wage change. The same coefficient is 0.06 in 1984 and 0.12 in 1990. All the regressions in the fixed effect table include years since displacement dummies and years of tenure predisplacement. The regressions also control for the change of industry pre and post displacement.

Table 8 reports the results obtained with OLS and fixed effect on DWS data separately for each industry. As in the case of the CPS, for most industry, there is no significant association between capital intensity and wages in levels (first column). In changes (second column) there is always a positive and significative association between average industry wages and capital intensities.

3.3 Within Industry Dispersion of Wages and Capital Intensities

Equation 2 looks at the effect of average industry capital intensity on average wages but doesn't 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:

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

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

Table 9 shows the results of estimation of equation 3 on March CPS. The results in table 9 show that the positive association between dispersion in capital intensities and dispersion in wages happens within industries. The industries with the higher dispersion of wages are not the same as those with the higher dispersion of capital intensity. Within industry the growth of dispersion in capital intensity is associated with the growth of wage dispersion.

Table 10 shows that this results is driven by the strong association between the growth of dispersion of wages and capital intensity within manufacturing, wholesale and retail and …nance.

The same pattern is present in DWS data. In table 11 the results of estimation of equation 3 on the four DWS waves con…rm the results obtained on CPS data. The correlation between within industry dispersion of capital intensity and within industry dispersion of wages is over time within industry and not across industry.

4 A Theoretical Interpretation

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

In this section I present a model of residual wage inequality based on the increasing variance of …rms' capital intensities. Contrary to most previous models of residual wage inequality, this model is not based on the rising price of ex-ante di¤erences in unobservable abilities.

I suggest that the variance of the distribution of the demand of skills has increased over time. By the variance of the demand of skills I mean the variance of equipment capital investment across …rms. Conversely the distribution of the supply of skills (i.e. unobserved ability across workerss) has not become more disperse over time. In the next section I will review some of the existing evidence that supports both those hypotesis.

I build a search and matching model with identical workers and two types of …rms. Firms di¤er in their optimal composition of equipment and structure. 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 …rms 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 di¤erentials and in particular to the more recent theoretical developments that explain wage dispersion among equivalent workers with di¤erences in …rms' technology. In many of those models …rms are assumed to have di¤erences in technology and wage dispersion is a consequence of technology dispersion. In Mortensen and Pissarides [1994] the di¤erences in productivity across …rms are due to …rm or match speci…c shocks. In Acemoglu [2000] …rms have di¤erent creation (capital) costs. My model is close to Acemoglu [2000]. His model focuses on the e¤ect of unemployment insurance and minimum wages on the composition of jobs . As in that model I assume that …rms can have heterogeneous technologies but I focus on changes in their capital choices over time and the e¤ect on wage inequality.

This paper is also linked to a 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 …rms' investment decisions. When there are few skilled workers and the productivity gap between the skilled and unskilled is limited, …rms 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, …rms are induced to di¤erentiate the types of jobs they o¤er. Some …rms invest in more capital than others and target skilled workers only.

That model, like mine, implies an increasing variance of equipment/labor ratios across …rms. 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 and to ex-ante tecnological di¤erences across …rms.

4.1 Changes in the Distribution of Demand and Supply of Skills

The increase over time in the average demand of skills has been advocated in numerous papers. The most popular reasons are skill biased technical change and trade with developing countries. However skill-biased technical change or organizative changes at the …rm's level may have also increased the variance of the demand of skills.

The clearest exposition of this thesis is in Acemoglu [1999]. In the same paper Acemoglu o¤ers some evidence of the increased variance in the composition of jobs. Such evidence comes from di¤erent sources.

Changing recruitment practices of …rms[5]. Evidence of more selective practices and more accurate screening at recruitment level are interpreted as signs of a changing composition of jobs.

Better matching of …rms and workers. Evidence from the PSID shows that more workers have the exact amount of education required for their job[6]. There is less overeducation or undereducation and this is interpreted as evidence of better matching due to an increased variety of jobs o¤ered.

Changes in the distribution of jobs. Constructing industry-occupation cells and ranking them according to their average wage, there is a shift of employment towards the lower and the higher ranking cells. This is interpreted as changing composition of jobs.

The distribution of on the job training has become more unequal [7]. As on the job training is correlated with high wages and capital investment in the job, this evidence is interpreted as a more unequal distribution of capital investment.

Changes in capital/labor ratios. Caselli [1999] reports a sharp increase in the capital-labor ratio di¤erence between the 90th and 10th most capital intensive industries. This evidence of more unequal distribution of capital-labor ratios across industries is interpreted as changing composition of jobs.

4.2 The Model

In this model there are identical workers and two types of …rms. Firms di¤er in the composition equipment/structure investment. Structure capital is reversible, i.e. when the relationship ends, …rms continue to use the same capital in the next relationship. Equipment capital is irreversible. Equipment capital is optimized but structure capital is …xed. 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.

The driving force of the increasing dispersion of equipment/labor ratios across …rms is the decline in the price of equipment capital. As the cost of equipment capital decreases, "good" …rms that use a lot of equipment capital increase their optimal capital choice. This causes an increase in within wage

[5] Murnane and Levy [1996] and Cappelli and Wilk [1997].

[6] Sicherman [1991].

[7] Constantine and Neumark [1994].

inequality as workers are identical and the non competitive labor marked implies that they receive a wage proportional to the equipment capital they are working with.

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

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

where Y_b and Y_g are intermediate inputs. Since 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 differ in the mix of equipment capital and structure capital. Good firms have a lot of equipment capital, bad firms have a lot of structure capital. Both types of firms can be inactive, vacant or filled. 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 do their irreversible capital choices k_g and k_b. The cost of installation are 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:

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

In a search enviroment the 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. Vacant firms meet unemployed workers at the rate $q(\theta)$, unemployed workers meet vacant firms at the exogenous rate $\theta q(\theta)$ where $\theta = \frac{v}{u}$ is market thightness. 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 but it's a good approximation of the empirical evidence that shows a stable number of job changers over time.

In a competitive labor market "good" jobs and "bad" jobs cannot coexist as workers are identical. In a search model since capital costs are sunk before workers are met, they remain idle until a match is formed. Good jobs will have to recover the bigger costs incurred at creation with higher ‡ow pro…ts.

I solve the model in steady state only and I present the relevant Bellman equations. The discounted value of being unemployed is :

$$rU = µq(µ)[ÁE(k_g) + (1 ¡ Á)E(k_b) ¡ U] \quad (5)$$

An unemployed worker meets a good …rm with probability µq(µ)Á where µq(µ) is the ‡ow probability of meeting a vacant …rm and Á is the proportion of good …rms among the vacancies. When the match takes place and both the worker and the …rm accept the job, the worker gains $E(k_g)$ or $E(k_b)$ and he loses U. For simplicity I assume there are no unemployment bene…ts.

The value of being employed in a good …rm $E(k_g)$ is:

$$rE(k_g) = w(k_g) ¡ ¸(E(k_g) ¡ U) \quad (6)$$

The value of being employed in a bad …rm is:

$$rE(k_b) = w(k_b) ¡ ¸(E(k_b) ¡ U) \quad (7)$$

where $w(k_j)$ is the wage rate for a worker in …rm $j = g; b$ and ¸ is the exogenous rate of quits.

The value of a vacant …rm $V(k_j)$ for $j = g; b$ is:

$$rV(k_j) = q(µ)[J(k_j) ¡ Ck_j ¡ V(k_j)] \quad (8)$$

where q(µ) is the ‡ow probability of meeting an unemployed worker. When the match occurs and both the …rm and the worker don't turn it down, the …rm gains the value of a …lled …rm $J(k_j)$;incurs in the cost of capital Ck_j and it loses $V(k_j)$.

The value of a …rm $j = g; b$ matched with a worker is:

$$rJ(k_j) = p_j k_j^{1 ¡ ®} ¡ w(k_j) ¡ ¸[J(k_j) ¡ V(k_j)] \quad (9)$$

when jobs are destroyed at the exogenous rate ¸ …rms exit the market. The zero pro…t condition for a …rm $j = g; b$ 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 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 favours good firms which have a high ratio equipment/structure and induces them to increase their capital choice k_g.

As soon as there are search frictions, there will be rents in the labour 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 doesn't 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, unemployment rate u, proportion of good firms ϕ in the vacancy pool, market tightness ϑ and wages $w(k_g)$ and $w(k_b)$ 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

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 $Y_g = (1 - u)(1 - \phi)k_g^{1-\alpha}$. And prices are given by:

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

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

Wages are set from 11, substituting 6,9:

$$w(k_j) = \beta(p_j k_j^{1-\alpha} - rc_j) + (1 - \beta)\, rU \tag{14}$$

and from 11,9 and10

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

We have two locuses where labor demand $L_j^d$and labor supply L_j^s of good and bad firms meet. The solution to the system of two equations $L_g^d = L_g^s$ and $L_b^d = L_b^s$ gives the equilibrium values of θ and ϕ.

The two equilibrium loci are:

$$(1 - \beta)(p_g k_g^{1-\alpha} - rU) = [\frac{r(r + q(\theta) + \lambda)}{q(\theta)} - \beta r]c_j + (r + \lambda)Ck_j$$

for $j = b; g$.

Within wage inequality in this model is given by:

$$w(k_g) - w(k_b) = \frac{(r + \lambda)r(c_g - c_b)}{q(\theta)} + (r + \lambda)C(k_g - k_b) \tag{15}$$

Where the optimal capacity k_j comes from $V'(k_j) = 0$.

Wage differences are related to the differences in capital investment but also to the job changing rate λ and to the average duration of a vacancy $q(\theta)$.

4.4 Estimation of Model

To have an idea of the importance of capital/labor ratios in increasing wage di¤erentials I try to estimate equation 15. Assume some values for the parameters of equation 15 over the period 1970-1992 : interest rate $r = 0{:}06,$ the job changing rate $¸ = 0{:}2{:}$ As an estimate of the matching function $q(\#)$ for the US I take the values suggested in Blanchard and Diamond (1989): $q(\#) = (\frac{u}{v})^{®}$ with $® = 0{:}4{:}$ 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 k_g ¡ k_b I take the 90-10 di¤erential in capital/labor ratios across …rms calculated on Compustat data; this value increased by 12% over the period. Estimation of equation 15 indicates that within wage inequality $w(k_g)$ ¡ $w(k_b)$ (90-10 di¤erential of the residual distribution) has increased by roughly 15% point over the period 1970-1992 due to the increasing dispersion of capital/labor ratios across …rms.

According to Juhn, Murphy and Pierce the 90-10 di¤erential of within group wage inequality increased by 30 percentage points from 1970 to 1992 in the US. This means that the mechanism that acts through the increasing dispersion of …rms' capital/labor ratios can account for 1/2 of the total increase in within group wage inequality.

A caveat about this rough estimation is the fact that the results are very sensitive to the assumptions about reversibility of capital. If capital is assumed to be reversible like in Acemoglu (2000) within wage inequality is given by:

$$w(k_g) \text{ ¡ } w(k_b) = \frac{(r + ¸)r(k_g \text{ ¡ } k_b)}{q(\mu)}$$

where now k_j is total capital i.e. equipment and structure. If I estimate this equation the increase in dispersion of capital/labor ratios can explain only 1/30 of the total increase in wage inequality. The main di¤erence is due to the fact that when capital is irreversible , wages appropriate not only part of the ‡ow cost of capital but part of the full sunk investment.

5 Conclusions

In this paper I document the increasing dispersion of capital/labor ratios across …rms in the US labor market using Compustat data. The increase takes place both between and within industries. I also show that the increase in the variance of capital/labor ratios across …rms is related to the increasing variance of log wages. A 1% percent increase in average industry capital intensity is associated to a 0.11% increase in the average weekly wage in the CPS, to a 0.08% increase in the Displaced Workers Survey. More importantly for the scope of this paper within industry variance in capital/labor ratios is also positively related to within industry variance of wages. The correlation is mainly across time within the same industries rather than across industries.

To explain these empirical regularities I adopt a model where …rms di¤er in their optimal composition of capital between equipment and structure. As the relative price of equipment falls over time the distribution of capital/labor ratios becomes more dispersed across …rms and job changers face an increasingly wide variety of jobs. Residual wage inequality increases as identical workers are randomly matched to an increasingly dispersed distribution of capital/labor ratios.

Simple estimation of the model indicates that the dispersion of capital-labor ratios can explain up to one half of the total increase in within group wage inequality.

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Table 4: March CPS 1970-1992 at various intervals.
OLS estimates of the impact of industry equipment/labor ratio on earnings.

Dependent variable: Log weekly earnings

	All years	1970-1975	1976-1980	1981-1985	1986-1992
log(equipment/labor)	0.11*	0.11*	0.16*	0.16*	0.16*
	(0.03)	(0.00)	(0.01)	(0.01)	(0.00)
Time effects	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	No	No	No	No
R-square	0.41	0.46	0.44	0.41	0.38
Observations	568282	129322	134022	137839	167099

Notes: Standard errors in parenthesis account for clustering at the industry and year level. Each column is from a separate regression of log weekly wages on the employment-weighted average log(equipment/labor) by industry and year. Additional controls include a quartic in age, non-white and sex dummies, years of education, year and industry dummies. Data on wages are drawn from March CPS. The sample includes full-time full-year workers aged 20-60 who earned more than 67$ a week in 1982 dollars. Data on average equipment/labor ratios by industry-year are drawn from Compustat. Industries considered are manufacturing, transport and utilities, wholesale and retail, finance, other services.

Table 5: March CPS 1970-1992 at various intervals. Each industry separately. OLS estimates of the impact of industry equipment/labor ratio on earnings.

Dependent variable: Log weekly earnings
Shown in table: Coefficients on employment-weighted average log(equipment/labor)

	All years	R square	N observations
Manufacturing	-0.06* (0.01)	0.44	175845
Transport and utilities	-0.04* (0.01)	0.26	58057
Wholesale and retail	-0.13* (0.02)	0.35	109323
Finance	0.06 (0.05)	0.42	46085
Other services	-0.00 (0.05)	0.38	178972

Notes: Standard errors in parenthesis account for clustering at the year level. Every coefficient shown refers to the log(equipment/labor) and each coefficient comes from a separate regression. Each column is from a separate regression of individual log weekly wages on the average log equipment/labor ratio by year. Additional controls include year dummies, a quartic in age, non-white and sex dummies, years of education. Data on wages are drawn from March CPS. The sample includes full-time full-year workers aged 20-60 who earned more than 67$ a week in 1982 dollars. Data on average equipment/labor ratios by industry-year are drawn from Compustat.

Table 6: Displaced Workers Surveys 1984, 1986, 1988, 1990.
OLS estimates of the impact of industry equipment/labor ratio on earnings.

Dependent variable: Log weekly earnings in the new job.

	All years	1984	1986	1988	1990
log(equipment/labor)	-0.05	0.08*	0.14*	0.12*	0.14*
	(0.05)	(0.03)	(0.01)	(0.01)	(0.01)
Time effects	Yes				
Industry effects	Yes	No	No	No	No
R-square	0.29	0.22	0.28	0.30	0.24
Observations	9787	2028	2622	2632	2679

Notes: Standard errors in parenthesis account for clustering at the industry and year level in the first column and for clustering at the industry level in the other columns. Each column is from a separate regression of log weekly wages on the new job on the employment-weighted average log(equipment/labor) by industry. Additional controls include year dummies (in the first column only), a quartic in age, non-white and sex dummies, marital status, years of education, years of tenure predisplacement, years since displacement and weeks unemployed postdisplacement. The sample includes workers displaced from full-time jobs and is restricted to persons aged 20-60 who were employed at the time of the survey and worked at least 35 hours per week. Data on wages are drawn from the Displaced Workers Surveys 1984, 1986, 1988, 1990. Data on average equipment/labor ratios by industry-year are drawn from Compustat. Industries considered manufacturing, transport and utilities, wholesale and retail, finance, other services.

Table 7: Displaced Workers Survey 1984, 1986, 1988, 1990, 1992. Fixed effect estimates of the impact of industry equipment/labor ratio on earnings.

Dependent variable: Changes in log weekly earnings.

	All years	1984	1986	1988	1990
Change in log(equipment/labor) ratio	0.08* (0.01)	0.06* (0.01)	0.11* (0.01)	0.08* (0.03)	0.12* (0.01)
R-square	0.03	0.05	0.06	0.02	0.03
Observations	9134	1770	2416	2643	2305

Notes: The average log(equipment/labor) is matched by industry and year in the year of the survey and in the year of displacement. Each column is from a separate regression of the change in log weekly wages on the change in the employment-weighted average log equipment/labor ratio. Additional controls include years of tenure predisplacement, and years since displacement dummies. The sample includes workers displaced from full-time jobs and is restricted to persons aged 20-60 who were employed at the time of the survey and worked at least 35 hours per week. Data on wages are drawn from the Displaced Workers Surveys 1984, 1986, 1988, 1990. Data on average equipment/labor ratios by industry-year are drawn from Compustat. Industries considered are manufacturing, transport and utilities, wholesale and retail, finance, other services.

Table 8: Displaced Workers Surveys 1984, 1986, 1988, 1990.
OLS and fixed effect estimates of the impact of industry equipment/labor ratio on earnings. Each industry indicates a separate regression.

Dependent variable: Log weekly earnings and changes in log weekly earnings.
Shown in table: Coefficients on employment-weighted average log(equipment/labor) in the first column. Coefficients on changes in employment-weighted average log(equipment/labor) in the second column.

	Levels	Fixed effect
Manufacturing	0.05 (0.05)	0.16* (0.03)
Transport and utilities	0.08 (0.12)	0.07* (0.04)
Wholesale and Retail	-0.05* (0.02)	0.08* (0.04)
Finance	0.06 (0.04)	0.06* (0.03)
Other services	0.49* (0.24)	0.07* (0.03)

Notes: Standard errors in parenthesis in the first column account for clustering at the year level. Every industry refers to a separate regression. Coefficients shown in the first column refer to the log(equipment/labor) ratio, in the second column to the change in the log(equipment/labor) ratio. In the first column additional controls include a quartic in age, non-white and sex dummies, marital status, years of education, years of tenure predisplacement, years since displacement and weeks unemployed postdisplacement. In the second column additional controls include years of tenure predisplacement, and years since displacement dummies. The sample includes workers displaced from full-time jobs and is restricted to persons aged 20-60 who were employed at the time of the survey and worked at least 35 hours per week. Data on wages are drawn from Displaced Workers Surveys 1984, 1986, 1988, 1990. The sample includes full-time full-year workers aged 20-60 who earned more than 67$ a week in 1982 dollars. Data on employment-weighted average equipment/labor ratios by industry-year are drawn from Compustat.

Table 9: March CPS 1970-1992 at various intervals.
OLS estimates of the impact of employment-weighted variance of within industry equipment/labor ratio on variance of within industry earnings.

Dependent variable: Variance of within industry log weekly earnings

Variance log(equipment/labor)	-0.00 (0.01)	-0.03* (0.01)	0.15* (0.05)	0.02 (0.02)
Time effects	No	Yes	No	Yes
Industry effects	No	No	Yes	Yes
R-square	0.00	0.40	0.57	0.95
Observations	115	115	115	115

Notes: Regression weighted by the number of observations over which the variance of log(equipment/labor) is calculated in each year*industry cell. Each column is from a separate regression of variance of within industry log weekly wages on the employment-weighted variance of log(equipment/labor) by industry and year. The sample includes full-time full-year workers aged 20-60 who earned more than 67$ a week in 1982 dollars. Data on within industry variance of equipment/labor ratios by industry-year are drawn from Compustat. Industries considered are manufacturing, transport and utilities, wholesale and retail, finance, other services.

Table 10: March CPS 1970-1992 at various intervals. Each industry separately.
OLS estimates of the impact of within industry log variance of equipment/labor ratio on within industry log variance of earnings.

Dependent variable: Within industry variance of log weekly earnings
Shown in table: Coefficients on within industry employment-weighted variance of log(equipment/labor)

	All years
Manufacturing	0.43* (0.22)
Transport and utilities	-0.11* (0.02)
Wholesale and Retail	0.26* (0.04)
Finance	0.09* (0.01)
Other services	0.19 (0.11)

Notes: Regressions weighted by the number of observations over which the variance of log(equipment/labor) is calculated in each year*industry cell. Every coefficient shown refers to the within industry variance of log(equipment/labor). Data on wages are drawn from March CPS. The sample includes full-time full-year workers aged 20-60 who earned more than 67$ a week in 1982 dollars. Data on average equipment/labor ratios by industry-year are drawn from Compustat.

Table 11: Displaced Workers Surveys 1984, 1986, 1988, 1990.
OLS estimates of the impact of within industry employment-weighted log variance of equipment/labor ratio on within industry log variance of earnings.

Dependent variable: Within industry variance of log weekly earnings in the new job.

Variance	0.07*	0.05	0.35*	0.21
log(equipment/labor)	(0.04)	(0.03)	(0.11)	(0.26)
Time effects	No	Yes	No	Yes
Industry effects	No	No	Yes	Yes
R-square	0.13	0.21	0.78	0.82
Observations	20	20	20	20

Notes: Regression weighted by the number of observations over which the variance of log(equipment/labor) is calculated in each year*industry cell. The sample includes workers displaced from full-time jobs and is restricted to persons aged 20-60 who were employed at the time of the survey and worked at least 35 hours per week. Data on wages are drawn from the Displaced Workers Surveys 1984, 1986, 1988, 1990. Data on employment-weighted average equipment/labor ratios by industry-year are drawn from Compustat. Industries considered are manufacturing, transport and utilities, wholesale and retail, finance, other services.