Firm Heterogeneity in Capital labor Ratios and Wage Inequality

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1 Introduction

Changes in wage inequality reflect changes in both prices and quantities of individual 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 between 1970 and 1990 can be accounted for by changes in the residuals' distribution. More recently there has been a debate on the extent and the causes of the rise in residual wage inequality during the 1980s and the 1990s. Lemieux (2004) argues that the rise in residual inequality is mostly explained by the decline of the minimum wage in the 1980s and by compositional effects in

the 1990s. Autor, Katz and Kearney (2005a and 2005b, 'AKK' hereafter) claim that residual wage inequality increased even after controlling for labor force composition and its increase in both the 1980s and the 1990s is concentrated in the upper part of the wage distribution. Both Lemieux (2004) and AKK (2005a and 2005b) agree that while the minimum wage explains well the changes in residual wage inequality at the bottom of the distribution, some other explanation is needed to explain the increase at the top.[1] Among the possible explanations, Autor, Levy and Murnane (2003) propose an "asymmetric" version of Skill Biased Technical Change according to which computerization raised the demand for non-routine skills and favored workers at the top (and at the bottom) of the wage distribution relative to those in the middle.[2]

In an attempt to improve our understanding of residual wage inequality, this paper examines its relationship with the dispersion of capital-labor ratios across firms. If technology is embodied in physical capital, then a relationship between wage and capital dispersion can be seen as evidence for a role of technology in the evolution of residual wage inequality. The empirical part of the paper documents the increasing dispersion of capital-labor ratios across firms and provides some empirical evidence of the positive correlation at the two-digit industry level between the dispersion of wages across workers and the dispersion of capital intensity across firms.

The increase in the variance of capital-labor ratios over time is documented using COMPU-STAT data from 1970 to 2002. The results show that the standard deviation of capital-labor ratios across firms increased by about 16 percentage points from the early 1970s to 2002. The upward trend in capital intensity dispersion is common to several different sample cuts and is

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[1] DiNardo, Fortin and Lemieux (1996) and Lee (1999) are also proponents of the minimum wage explanation.

[2] Another possible explanation is based on social norms (Piketty and Saez, 2001 and Saez and Veall, 2005). A simple version of SBTC is difficult to reconcile with many aspects of the increase in wage inequality (Card and DiNardo, 2002).

robust to changes in the composition of the sample.

The correlation between the dispersion of wages and of capital intensity across firms is studied matching COMPUSTAT data from 1970 to 2002 to wage data from the combined May and Outgoing Rotation Group Current Population Survey (May/ORG CPS hereafter) and from the March CPS at the two-digit industry level. Quantile regression results from both the May/ORG and the March samples show that capital-labor ratios dispersion is significantly associated with an increase in the 90-10 log wage differential for males. These estimates suggest that embodied technological change plays some role in explaining the increase in male residual wage inequality both in the 1980s and in the 1990s. The results for females are less clear cut, they consistently indicate an insignificant impact of capital labor dispersion on the female wage distribution in the period 1973-1987, but, depending on the sample and the measure of dispersion of the capital-labor ratio used, they indicate either a significant or insignificant effect in the period 1988-2002.

A second question of interest in the debate on residual wage inequality is that, since most of the increase occurred at the upper tail of the wage distribution, it is plausible that upper and lower tail wage inequality have different technological and institutional causes. The evidence shown in this paper for male workers indicates a significant impact of capital-labor dispersion at the top of the male residual wage distribution (the 90-50 log differential) and an insignificant impact at the bottom of the distribution (the 50-10 log wage differential). These results hold for both periods considered (1973-1987 and 1988-2002) and are robust to the use of different measures of capital-labor dispersion and to several sample cuts. The results for females are mixed and, even in those cases when the impact on the 90-10 differential is significant, do not allow to assess whether the impact of capital-labor dispersion is concentrated at the top or at the bottom of the distribution.

3

The second part of the paper proposes a simple model to explain how residual wage inequality may depend on the increased dispersion of capital intensity across firms. The two main ingredients of the model are non-competitive labor markets and random matching of identical workers to two types of firms. The intuitive idea is simple. There are both "good" and "bad" firms in the economy which differ in the productivity of their capital stocks. The driving force of the model is the exogenous decline of the price of equipment capital. Since the demand for capital of "good" firms is more price elastic, the drop in the relative price of capital equipment will increase the capital stock of "good" firms relative to "bad" firms. As it is typical in a search framework with Nash bargaining, the quasi-rents are shared between workers and firms and wages for identical workers are more dispersed as a consequence of a higher dispersion of capital intensities.

Although this theory is obviously only one possible explanation for the increase in residual wage inequality, 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 (Dunne et al., 2004). Furthermore, the model implies that sectors where the relative price of capital equipment declines more rapidly should also have larger increases in capital dispersion. A simple regression of capital-labor ratios dispersion on relative capital equipment prices supports this hypothesis.

1.1   Related Literature

Work on dispersion of capital-labor ratios is fairly rare. Caselli (1999) uses industry-level data to document the increase in the difference between the 90th and the 10th percentile of the distribution of log capital-labor ratios across four-digit manufacturing industries. Some literature has used establishment-level data to study the dispersion of wages and productivity

across plants. Dunne et al. (2004) decompose the total variance of wages into its between-industry, between-plant and within-plant components and show that most of the increase in wage dispersion is due to between-plant dispersion within industries. 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. Previous work by Doms et al. (1997) finds that an important factor in explaining wage dispersion across plants is the differential adoption of technologies. Unlike for 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 the dispersion of wages and capital intensity.[3] All the papers above use establishment-level data only for the manufacturing sector. In this paper, I use COMPUSTAT data to study the evolution of the distribution of capital intensity over time across firms in all industries.

The increase over time in the demand for skilled workers has been noted 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. Such evidence comes from different sources. For example, Gittleman and Howell (1995) document the changes in the distribution of job quality in the U.S. Acemoglu (1999) ranks industry-occupation cells according to their average wage and shows that there is a shift of employment towards the lower and the higher ranking cells. Goos and Manning (2003) show the same pattern of "polarization of

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[3] Although in the published version, Dunne at al. (2002) focus on the relationship between wage and computer investment across plants, in the NBER Working Paper 7465 version, they also study the relationship between capital intensity and wages. Using manufacturing plant-level data form the Census of Manufacturing (LRD), they report (Table 3) a value of the standard deviation of log capital-labor ratios of 1.05 in 1977, 1.03 in 1982 and 1.08 in 1992. Although the increase is less evident than in COMPUSTAT, the evolution over time (first decreasing and then increasing) seems to be similar. The LRD data covers only the manufacturing sector and the paper reports the results only until 1992. Although the LRD is representative of the manufacturing sector, the capital measure is recorded at cost which is a good measure of the actual value only for the recent capital stock. In COMPUSTAT capital is measured at the capitalized cost minus accumulated depreciation.

work" in the UK. More recently, Autor, Levy and Murnane (2003) suggest that the spread of computerization has raised the demand for cognitive and interpersonal skills used by educated workers; reduced the demand for routine skills common among middle-educated white collar workers and for the routine manual skills of many manufacturing jobs; and had no impact on the demand for non-routine manual skills used in most low-skill service jobs.

In the theoretical part, I propose a model of residual wage inequality based on the increased dispersion of capital-labor ratios across firms. The model is related to Acemoglu (2001) who obtains wage differentials across identical workers in a search equilibrium. While he focuses on the effect of more generous unemployment insurance and minimum wage on the composition of jobs, this version of the model looks at the effect of the price of capital on capital dispersion. The causal force in the model is the decline in the relative price of equipment capital which increases the dispersion of capital-labor ratios across firms, thus raising wage inequality across identical workers.

This paper is also linked to the recent literature that looks directly at the changes in 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 the supply of skilled workers rises (or their relative productivity increases), firms tend to create different jobs for skilled and unskilled workers. That model, like mine, implies an increasing variance in capital-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 capital.

Other models of residual wage inequality like Acemoglu (1999), Caselli (1999), Violante (2002) and Hornstein, Krusell and Violante (2003) are all consistent with an increasingly dispersed distribution of capital intensity. The model presented here builds on the increasing

6

dispersion of capital across firms. Unlike all models above, which interpret unobservable skills as ex-ante differences in ability across individuals, the model of residual wage inequality presented in this paper is based on identical workers who match to different types of firms.

Finally, an increasingly dispersed distribution of capital-labor ratios can have an effect on wage differentials across identical workers as long as the market is not competitive (this model is based on rent-sharing) and firm effects are important in determining the wage. This paper is therefore related to the literature which studies the relative importance of individual and firm effects in explaining inter-industry wage differentials. Abowd, Kramarz and Creecy (2003) use employer-employee matched data to estimate that individual and firm effects can each account for approximately 50% of the inter-industry wage differentials in the US.

The structure of the rest 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 Capital-Labor Ratios

I examine the changes over time in the firm distribution of capital-labor ratios using COM-PUSTAT data from 1970 to 2002.[4] COMPUSTAT is a dataset of all 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. The capital-labor ratio is total capital divided by the number of employees. Capital represents the cost of tangible fixed property, plant and equipment used to generate revenue minus accumulated depreciation, is deflated using the

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[4]Comin and Mulani (2005) and Comin and Philippon (2005) use COMPUSTAT data to document the increase in sales volatility at the firm level.
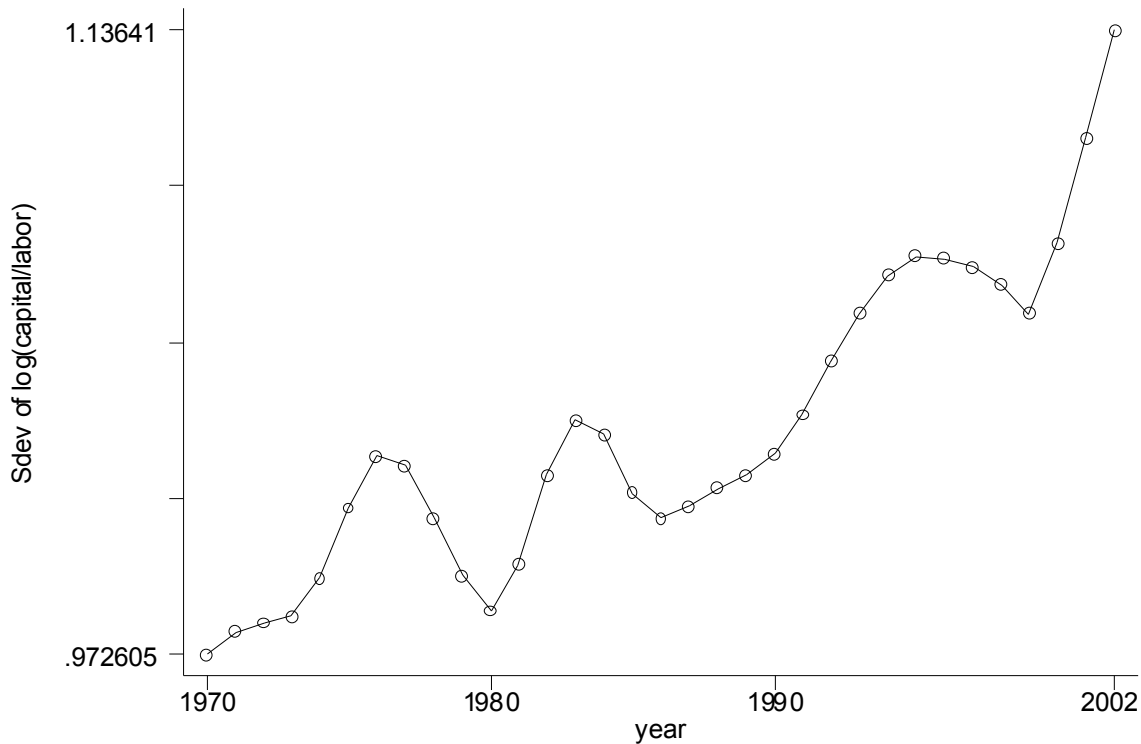
Figure 1: Employment-weighted standard deviation of log capital-labor ratios.

two-digit industry specific deflators from the Bureau of Economic Analysis and is expressed in real 2000 dollars.[5]

The sample is restricted to all companies which have non-zero values of capital and employees in any of the years in the sample period. Firms in the agriculture and construction sector and utilities are dropped due to the small sample size within the industry in most years. Firms in the financial sector do not report information on their capital stock. The sample is further trimmed at the first and ninety ninth percentile of the capital-labor distribution in each year to eliminate outliers. The sample is an unbalanced panel of 16,491 firms and 159,128 observations with between 1 and 33 continuous observations per firm.

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[5]A previous version of this paper used data on equipment capital only. Separate data on the net value of equipment and structure are available only until 1992. Since 1993 equipment capital is available only at current cost which makes the construction of a consistent series impossible. I discuss some of the problems in extending the series of equipment capital in the Appendix. The results on the relationship between dispersion of equipment capital-labor ratios and wage dispersion are similar to those obtained using net total capital and are available upon request.

Figure 1 plots the employment-weighted standard deviation of log capital-labor ratios across firms. The standard deviation of log capital-labor ratios is employment-weighted because this paper is concerned with the increasing dispersion of capital-labor ratios facing workers. The figure shows an increase in the employment-weighted standard deviation of log capital-labor ratios across firms of about 16 percentage points between 1970 and 2002. Alternative measures of dispersion such as the employment-weighted coefficient of variation show a similar evolution, although with ampler cycles, and a similar percentage increase over time. The main results of this paper are robust to using the coefficient of variation instead of the standard deviation of the logs.[6]

Figure 2 shows the divergence in capital-labor ratios at different points of the distribution. Figure 2 plots the 90-10, the 90-50 and the 50-10 percentile difference in log capital-labor ratios. The 90/10 inequality rises steadily since the early 1970s along with the 90/50 inequality. Lower tail inequality stays approximately stable until the early 1980s and then rises. The picture shows that the largest contribution to the overall rise in the 90/10 inequality comes from the top of the distribution (the 90/50) in the earlier period and from the bottom of the distribution (the 50/10) in the later period.

2.1   Controlling for Changes in the Sample Composition

The COMPUSTAT sample ranges from 1970 to 2002. The size of the sample rises over the years as more firms are listed in the stock market raising the possibility that the increase in

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[6]The increase in dispersion in the capital-labor ratio is due to the numerator (net total capital) rather than the denominator (number of employees); there is hardly any increase in the standard deviation of employment over time. Although this paper is about the increasing dispersion of capital-labor ratios across firms, a comparison of the growth in *mean* capital-labor ratios with the data published by the Bureau of Economic Analysis is possible. The overall growth in capital-labor ratios (real net capital divided by full-time equivalent employment) measured in the BEA statistics from 1970 to 1997 (before the BEA changed the industry classification making the comparison difficult) is 37.5% or 41% if we consider only the same 18 two-digit industries of our COMPUSTAT sample. The increase in the employment-weighted average capital-labor ratio over the same period in the COMPUSTAT sample is 53%.
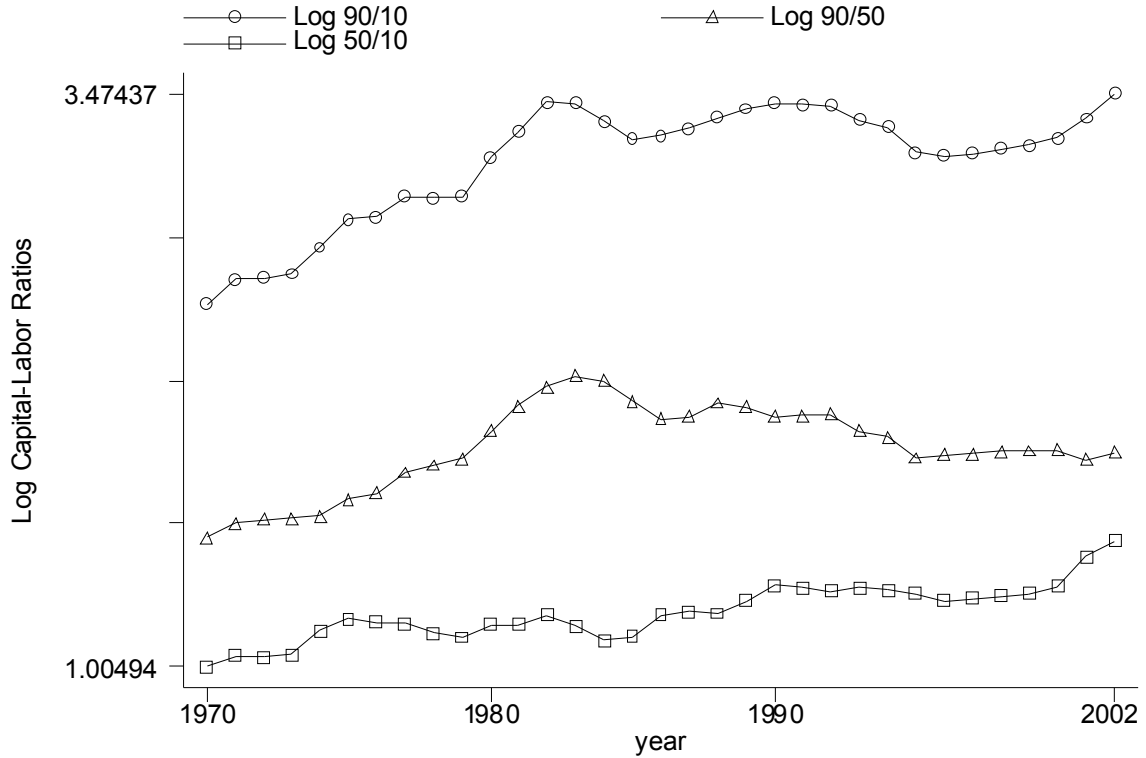
Figure 2: Log 90/10, log 50/10 and log 90/50 capital-labor ratios.

the dispersion of capital-labor ratios is the result of compositional change. Firms which work in emerging industries, younger and smaller firms may have caused the increasing dispersion of capital intensity.[7]

Table 1 reports the descriptive statistics of capital-labor ratios by industry and by size class. In the first column of Table 1, the mean log capital-labor differential by industry and size class is defined as the difference between the average log capital-labor ratio within the group and the overall average log capital-labor ratio. The sectors with the highest average capital-labor ratios are mining, transportation and communication and chemicals and petroleum. The least capital-intensive industries are textiles, wholesale and retail trade. Capital-labor ratios are higher in very large companies with more than 10,000 workers.

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[7]Another reason that could have affected the increasing dispersion is divergence of capital prices at the firm level. However, capital is deflated using industry-specific deflators and this eliminates the possibility that the upward trend in the standard deviation of capital intesity is driven by industry-level price divergence. Although the increase in dispersion may still be driven by divergence in the prices at the firm level within the two-digit industries, I consider this possibility unlikely.

In order to show that the upward trend is not due to the changing sample composition, I focus on the component of the capital-labor ratio which is not due to firm-level characteristics. Formally, I run the following regression:

$$\log(\frac{k}{l})_{it} = \alpha + \beta \log(age)_{it} + \gamma \log(size)_{it} + \eta_i + \varepsilon_{it} \tag{1}$$

where $\log(age)_{it}$ is the log of firm i's age at time t, $\log(size)_{it}$ is the log of its size measured as the number of employees and η_i are industry dummies. Figure 3 plots the standard deviation of the estimated residuals $\widehat{\varepsilon}_{it}$ which increases by approximately 20 percentage points from 1970 to 2002 and has an evolution similar to the standard deviation of the log capital-labor ratios in Figure 1. The upward trend in the 1980s and 1990s persists even after removing the firm-specific component thus rejecting the hypothesis that the pattern of increasing variance is due to a compositional bias.[8]

One further way to test the robustness of the trend to the inclusion of small firms in sample, is to look at the sample of the largest firms in each year, for example the top quintile of the firm-size distribution in each year or all firms with more than 10,000 workers. The upward trend (not shown) in capital-labor dispersion is common to the sample of the largest firms in each year, using both the relative and the absolute measure. Although these samples are selected on size, the robustness of the result shows that the increase in capital-labor dispersion is unlikely to be an artifact of younger and smaller firms entering the sample.

A further concern may be that the increase in capital-labor dispersion is due to measurement error or more in general to issues of firm reorganization. The median year-to-year percentage increase in the capital-labor ratio within firm is 0.2%, however there are cases of

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[8]Other unobservable factors may lead to compositional bias therefore the exercise has been repeated including firm fixed effects (which include industry) with similar results.

4000% increases from one year to the next. For example the increase in dispersion could be due to few cases of large increases in the capital-labor ratios due to mergers and acquisitions (M&A). In an attempt to address this issue, I build a sample of firms which excludes M&A. The top line in Figure 3 shows the standard deviation of log capital-labor ratios in the sample which excludes the mergers. The increase in dispersion is still similar to the increase in Figure 1 suggesting that the increase is not due to an upsurge in mergers.

A related issue concerns the issue of big within-company reorganizations which in principle could also have affected the results. I also considered a sample where the firm-year observations of more than a 100% year-to-year increase in capital-labor ratios have been dropped (this amounts to the top 3.7% of the distribution of year-to year percentage changes in capital-labor ratios at the firm level). Although the increase in dispersion (not shown) is slightly smaller than in the original sample, its evolution is very similar to the one in Figure 1, which makes me more confident that the increase in capital-labor dispersion is not due to few instances of big reorganizations.

In the remainder of the paper, as robustness check, I will show the results on the sample which purges the capital-labor ratios from the effect of the firm age and size and on the sample which excludes M&A. The results obtained for the sample of the top quintile of the largest firms and for the sample which excludes year-to-year increases in capital-labor ratios of more than 100% do not show substantial differences compared with the benchmark sample and are available upon request.

Finally, having verified the robustness of the trend in capital labor ratios dispersion, I investigate whether the upward trend is pervasive or is limited to some industries. To address this question, I calculate the standard deviation of log capital-labor ratios for each industry and regress it on a time trend. The coefficients on time trends (not shown) are positive and
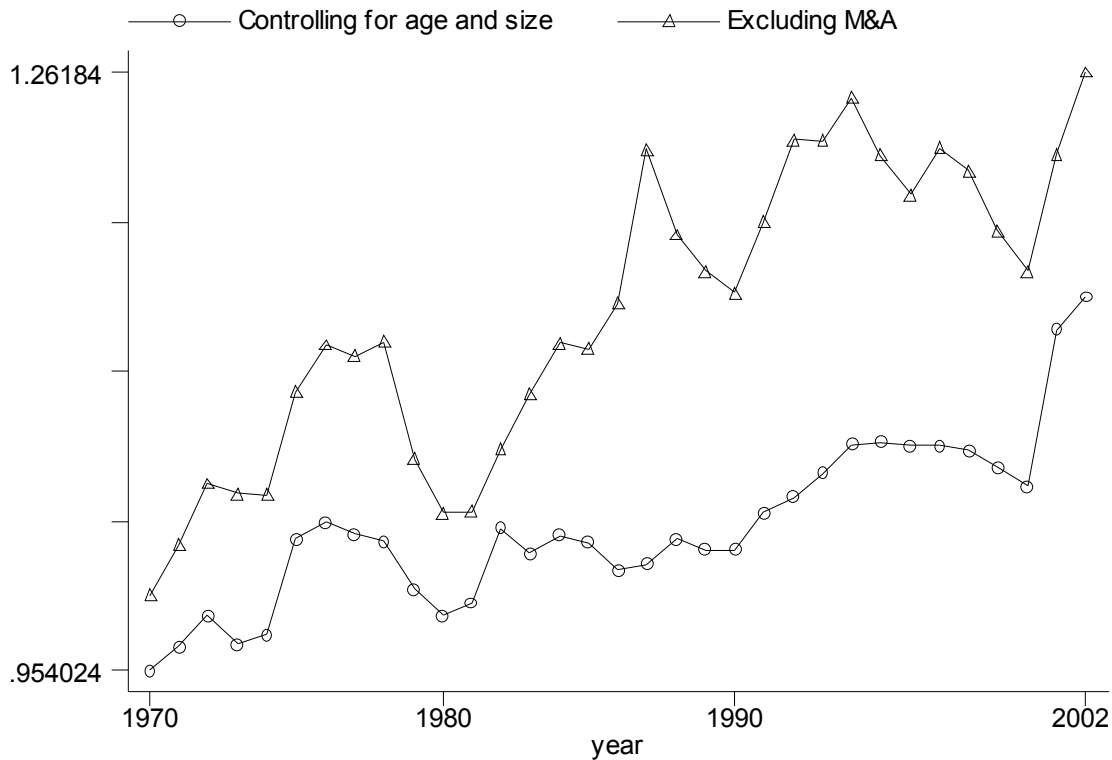
Figure 3: Alternative measures of capital-labor dispersion.

significant in twelve of the eighteen industries, insignificant in one and significantly negative in five industries.

3 Capital-Labor Ratios and Wage Inequality

This section studies the association between residual wage inequality and dispersion of capital-labor ratios. To do so, I match individual wage data from both the combined May and Outgoing Rotation Group CPS (May/ORG) and the March CPS to the industry-specific standard deviation of log capital-labor ratios at the industry-year level.

I use both the May/ORG and the March CPS data because the different results on the evolution of residual wage inequality obtained from the May/ORG and the March CPS have sparked a recent debate. The increase of residual wage inequality in the 1990s is very small

Table 1: Log capital-labor ratios. Average by industry and size class.

Industry	Mean Log Capital-Labor Differential	Between-Firm Standard Dev.	Frequency
Mining	1.09	1.21	5.85
Wood products	-0.22	1.00	1.91
Stone and clay	0.33	0.60	1.22
Primary metals	0.64	0.65	2.28
Fabricated metals	-0.33	0.50	2.31
Machinery	-0.27	0.55	8.38
Electrical machinery	-0.30	0.51	8.98
Transport vehicles	0.01	0.51	3.01
Professional equip.	-0.41	0.69	8.69
Food and tobacco	-0.08	0.58	3.45
Textile and apparel	-0.98	0.71	2.82
Paper and printing	0.32	0.78	3.68
Chemicals and petroleum	0.96	0.98	8.33
Rubber and leather	-0.06	0.63	2.39
Transportation and comm.	1.11	0.93	7.58
Wholesale	-0.36	1.03	5.64
Retail	-0.84	0.55	9.28
Private and business serv.	-0.36	1.08	13.70
Size class			
1-199 employees	-0.07	1.04	29.51
200-999	-0.15	0.91	25.71
1,000-3,999	0.00	0.89	21.77
4,000-9,999	0.08	0.90	9.97
+10,000	0.36	0.84	13.05

Notes: Mean log capital-labor ratios by industry and size groups are relative to the grand mean.

in the May/ORG while it is substantially larger in the March CPS.[9] In this paper I use the May/ORG sample as the main sample and the March sample to check the robustness of the results.

Using the May/ORG CPS, Lemieux (2004) claims that the growth of residual wage inequality in the last decade is due to a spurious composition effect. The composition effect is linked to the increase in the level of experience and education in the workforce, two factors associated with higher within-group wage inequality because of the differential investment in on-the-job training of older and more educated workers. AKK (2005a and 2005b) take a partially different view. While they agree that the growth of residual wage inequality slowed down in the 1990s, they disagree that the growth in residual inequality is due to composition changes. Autor, Katz and Kearney (2005a and 2005b) stress the important observation that the growth of residual wage inequality in both the 1980s and the 1990s is concentrated in the upper tail of the distribution. Their results imply that some technology shock may have played a role in the increase in residual wage inequality at the top of the distribution. This paper explores the correlation between residual wage inequality and a measure of embodied technology such as the stock of capital in view of contributing to the debate on the sources of residual wage inequality.

The May/ORG CPS sample is obtained appending the May CPS 1973 to 1978 to the Outgoing Rotation Group from 1979 to 2002. The sample includes all wage and salary workers age 16 to 64 in current employment with 0 to 39 years of potential experience. The March CPS sample ranges from 1971 to 2003 (earnings years 1970-2002) and is restricted to full-year, full-time workers (those working 35 or more hours per week and at least 40 weeks in the

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[9]The difference is explained by the fact that the March CPS does not measure directly hourly wages of workers paid by the hour and this implies a larger measurement error in March CPS rather than in the May/ORG. There is the possibility that an increase in the number of workers paid by the hour since the 1970s has induced a differential trend in residual wage inequality between the March and the May/ORG CPS (Lemieux, 2004).

previous year) between the age of 16 and 64 and with 0 to 39 years of potential experience. The variable of interest is the log hourly wage in the May/ORG CPS and the log weekly wage in the March CPS.[10]

Figure 4 plots the standard deviation of residual male wage inequality in the May/ORG sample and the employment-weighted standard deviation of log capital-labor ratios from COM-PUSTAT. The residual wage inequality is obtained from a regression of male log hourly wages on year dummies, four education dummies (less than high school, high school, some college, college+), thirteen potential experience categories (0-2, 3-5, 6-8 etc.) and interactions between education and experience categories. The MAY/ORG sample is restricted to the same industries considered in the COMPUSTAT sample. The figure shows that both series grew over time but in a different way. While capital-labor ratio dispersion increased continuously in cycles, residual wage dispersion increased sharply in the early 1980s. This section investigates the possibility that the correlation between residual wage inequality and capital-labor ratios dispersion may not be coincidental at the industry level. In other words I investigate whether industries with larger increases in capital-labor dispersion have also seen larger increases in residual wage inequality.

To document formally the correlation between dispersion of capital-labor ratios and residual wage inequality, I measure the impact of capital-labor dispersion at different quantiles of the residual wage distribution estimating quantile regressions at the 10th, 50th and 90th quantile of the wage distribution.[11] I regress log hourly wages from the May/ORG CPS (and log weekly wages from the March CPS) on the within-industry employment-weighted stan-

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[10] For more details on the CPS sample selection see the data Appendix.

[11] The advantage of using quantile regression instead of an OLS regression of the standard deviation of residual wages on the standard deviation of capital-labor ratios is that we can calculate the impact of capital dispersion at different points of the residual wage distribution. The results obtained regressing the standard deviation of wage residuals as dependend variable are consistent with the quantile regression results and are available upon request.
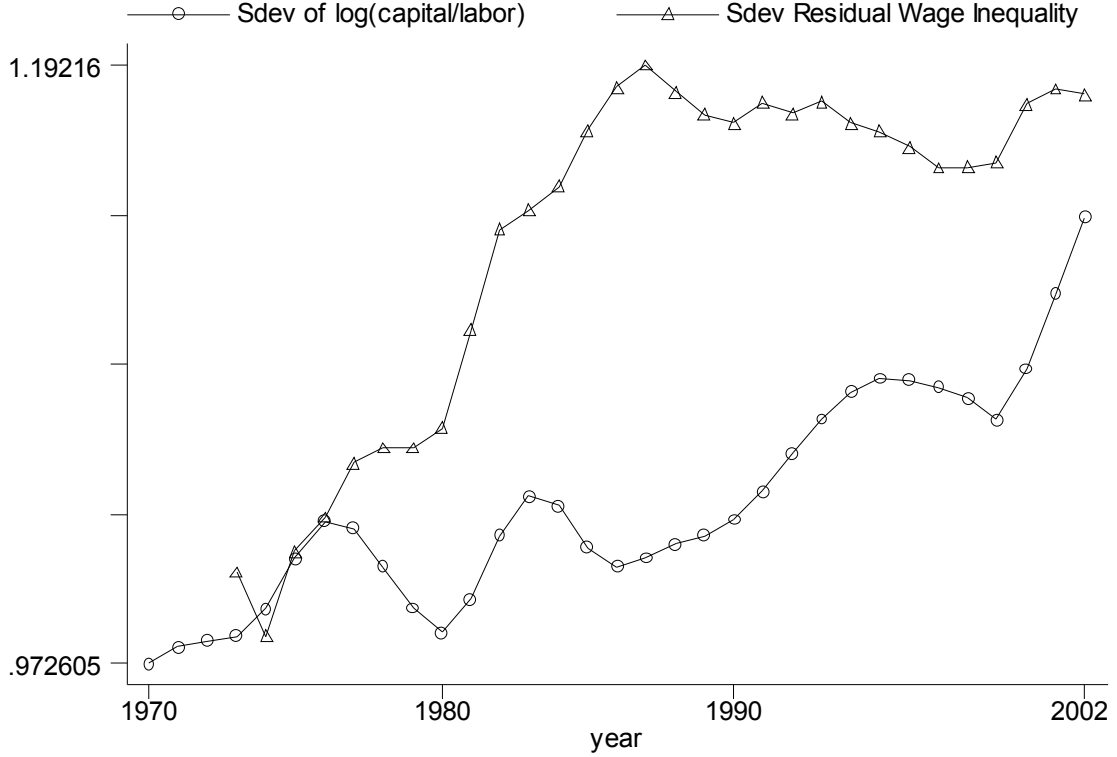
Figure 4: Standard deviation of residual male wage inequality (rescaled: original value*2.6) and employment-weighted standard deviation of log capital-labor ratios.

dard deviation of log capital-labor ratios calculated from COMPUSTAT data. The CPS and COMPUSTAT data are matched at the two-digit industry level.

Let $Q_\theta(\log w_{ijt}|X_{it}, V_{jt})$ for $\theta \in (0,1)$ denote the θth quantile of the distribution of $\log w_{ijt}$, the log wage of individual i at time t in industry j given the covariates. The model of the conditional quantiles is:

$$Q_\theta(\log w_{ijt}|X_{it}, V_{jt}) = \alpha_\theta + X_{it}\gamma_\theta + \beta_\theta V_{jt} \qquad (2)$$

where X_{it} includes four education categories (less than high school, high school, some college, college or more), thirteen potential experience categories (0-2, 3-5, 6-8 etc.) and interactions between education and experience categories. V_{jt} is the employment-weighted standard deviation of the log capital-labor ratio in industry j at time t. α_θ is a vector of year dummies. The

17

parameter of interest is β_θ. Since V_{jt} varies only by industry and year, the standard errors are calculated by bootstrapping methods resampling at the industry-year level, taking all observations within each cluster. The sample drawn during each replication is a bootstrap sample of clusters. The standard errors on β_θ are obtained with 100 replications of samples of size $\frac{N}{10}$.[12] Wages are deflated by the CPI and capital is deflated using the two-digit-industry deflators from the Bureau of Economic Analysis. Both wages and capital are measured in year 2000 dollars.

3.1   Results

The results are organized by gender and time period. The sample is split in two different periods, 1973-1987 (1970-1987 for the March sample) and 1988-2002. The first period is a period of rising residual wage inequality, the second period is a period of stable wage inequality (at least in the May/ORG sample). The second period is the period which raised the debate on the extent and the causes of the growth in residual wage inequality.

Table 2 refers to the results for males and females in the May/ORG CPS sample. It shows the coefficients on the standard deviation of the log capital-labor ratio, β_θ, at the 10th, 50th and 90th quantile of the log hourly wage distribution. Two main results stand out. First, there is evidence of a positive and significant correlation between capital dispersion and the 90th quantile of the wage distribution for both males and females and in both time periods. Second, the coefficients on the standard deviation of the log capital-labor ratio at the 90th quantile of the log wage distribution are always larger than the coefficients at the 10th percentile which are insignificantly different from zero. For example in the sample of men in the period 1973-

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[12]For computational ease the bootstrapping is conducted on a random 10% sample of the CPS. The within industry-year standard errors correction increases the magnitude of the standard errors by a factor of 3 on average with an increase ranging from a factor of 1.9 to a factor of 4.1.

1987, a 1 percent increase in the standard deviation of capital-labor ratios is associated with a 0.170% increase in the wage at the 90th percentile relative to an insignificant increase at the 10th percentile. The size of the effect at the 90th percentile is smaller in the period 1988-2002 (0.072%) but still significant. The coefficient estimates at the 90th percentile of the female wage distribution are 0.140(0.075) in 1973-1987 and 0.208(0.050) in 1988-2002.

The impact of the rising dispersion of capital at different points of the distribution is tested with a t-test of the difference in the coefficients at the different quantiles.[13] The P-values of the t-tests in Table 2 indicate that the difference between the coefficients at the 90th and the 10th quantile is significant at the 5% level or less for males in both periods and for females in the period 1988-2002. It is insignificant for females in the period 1973-1987.

The t-tests of equality of the coefficients at the 90th and 10th quantiles show that there is a significant correlation between capital-labor dispersion and the 90-10 residual wage inequality. However, the work of AKK (2005a and 2005b) highlights the fact that residual wage inequality has not risen in parallel in the upper and lower tail. It is also plausible that upper and lower-tail inequality have different technological and institutional causes. A test of the difference in the coefficients between the 50-10 and 90-50 quantiles would indicate whether capital-labor dispersion is associated with upper or lower-tail wage inequality.

A t-test of the difference in the coefficients between the 50-10 and the 90-50 quantiles gives the following results. The differences between the 90-50 quantiles for males are significant in both periods, the 50-10 differences are insignificant. For females, both the 90-50 and the 50-10 differences are significant in the period 1988-2002. From these results we conclude that at least for males the impact of capital-labor dispersion is significant at the top of the distribution (90-50) and insignificant at the bottom. It is more difficult to establish whether the impact of

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[13] The different quantile coefficients are calculated on the same bootstrapped sample, the t-tests reflect the covariance between the estimates.

capital-labor dispersion was higher at the top or at the bottom of the distribution for females because the results indicate significant differences both at the 90-50 and at the 50-10 in the period 1988-2002 and insignificant differences in the period 1973-1987.

3.1.1 Robustness

Table 3 shows the results for the March CPS sample of log weekly wages. The results for the March weekly wages are qualitatively similar to the May/ORG results for hourly wages for males but indicate an insignificant impact of capital-labor dispersion on the female wage distribution. As in the May/ORG results, the t-tests for both the 90-10 and the 90-50 difference in the coefficients are significant for males in both periods while the 50-10 difference is insignificant. Differently from the May/ORG results, the impact of capital-labor dispersion on female wage inequality is insignificant in the period 1988-2002 as well as in the period 1973-1987.

Finally, in Table 4 I check the robustness of the results using alternative samples and measures of capital-labor dispersion. The Table only reports the P-values of the t-tests of linear restriction of the quantile coefficients. The coefficients are estimated from regressions of the May/ORG log hourly wage on different measures of capital-labor ratio dispersion. As before, all regressions also include year dummies, four education categories (less than high school, high school, some college, college+), thirteen potential experience categories (0-2, 3-5, 6-8 etc.) and interactions between education and experience categories. Capital-labor ratio dispersion (V_{jt} in equation 2) is calculated in the following way. In panel (1) V_{jt} is the coefficient of variation of capital-labor ratios. In panel (2) V_{jt} is the standard deviation of the residuals of the OLS regression of log capital-labor ratio on log age of firm and the log of the number of employees. In panel (3) V_{jt} is the standard deviation of log capital-labor ratios in

the sample which excludes mergers.

The results of the three panels confirm the benchmark results for males: the t-tests of the difference in the 90-50 coefficients are significant in both periods 1973-1987 and 1988-2002 while the tests of the difference in the 50-10 coefficients are mostly insignificant. The results of the three panels also confirm that there is no significant difference between the quantile coefficients for females in the period 1973-1987. The results for females in the period 1988-2002 vary across panel. The results of Panel (1) where V_{jt} is measured as the coefficient of variation of capital-labor ratios and of Panel (3), the sample which excludes mergers, are similar to the results obtained for the March sample i.e. do not reject the hypothesis of equality of the estimated quantile coefficients at the 90th and at the 10th percentile for females in the period 1988-2002. The results based on the sample that controls for age and size of the firms (Panel 2) agree with the results of the benchmark May/ORG sample: capital-labor dispersion is correlated with 90/10 and 90/50 female residual wage inequality in the period 1988-2002.

From the results in Table 2, Table 3 and Table 4, we draw the conclusion that the increase in capital dispersion is related to the increase in the 90-10 residual wage inequality for males in both periods. The impact is significant at the top of the distribution (the difference in the 90-50 coefficients) while is mostly insignificant at the bottom of the distribution (the difference in the 50-10 coefficients). Capital-labor dispersion is not related to female residual wage inequality in the period 1973-1987. It is more difficult to assess whether the impact of capital dispersion affected the wage distribution of females in the period 1988-2002. The May/ORG CPS sample which uses the standard deviation of the log capital-labor ratio as measure of dispersion (or the standard deviation of the log capital-labor ratio purged of age and size effects) indicates a significant impact. The May/ORG sample which uses the coefficient of variation as a measure of capital-labor ratio dispersion and the March sample indicate an insignificant impact. The

May/ORG sample which excludes mergers also indicates an insignificant impact on females in the period 1988-2002.

4   A Theoretical Interpretation

4.1   The Model

On the basis of the evidence presented earlier, this section proposes a model of residual wage inequality based on the increasing dispersion of firms' capital intensities. In this search and matching model there are identical workers matched to two types of firms, we will call them "good" and "bad" firms and we will indicate them respectively with the subscripts g and b. Firms differ in the productivity of their capital stock and in the price elasticity of their demand for capital. The exogenous driving force of the model is the decline of the relative price of equipment capital. As the relative price of equipment decreases over time, "good" firms increase their capital stock relative to "bad" firms thus increasing the dispersion of capital-labor ratios. 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. Nash bargaining is not essential but rent sharing is crucial to the results.

The economy is constituted of a mass 1 of risk neutral workers and a larger mass of risk neutral firms. Workers derive utility from the consumption of a unique final good whose price is normalized to one. The production technology is:

$$Y = (Y_b^\rho + \gamma Y_g^\rho)^{\frac{1}{\rho}} \qquad \text{with } \rho < 1 \qquad (3)$$

where Y_b and Y_g are the intermediate inputs, Y_b is the aggregate production of "bad" firms and Y_g is the aggregate production of "good" firms, γ captures the relative importance of "good"

22

Table 2: May/ORG CPS 1973-2002. Quantile regression coefficients on the standard deviation of log capital-labor ratio

	Males		Females	
Sample Period	1973-1987	1988-2002	1973-1987	1988-2002
Quantile Regression				
10th quantile	0.060	-0.013	0.094	0.065
	(0.066)	(0.057)	(0.061)	(0.048)
50th quantile	0.089	-0.001	0.182**	0.115**
	(0.058)	(0.040)	(0.081)	(0.053)
90th quantile	0.170**	0.072**	0.140*	0.208**
	(0.036)	(0.028)	(0.075)	(0.050)
P-Value from linear restriction				
$H_0 : \widehat{\beta}_{90} - \widehat{\beta}_{10} = 0$	0.0196	0.0463	0.1813	0.0003
$H_0 : \widehat{\beta}_{90} - \widehat{\beta}_{50} = 0$	0.0281	0.0063	0.8857	0.0037
$H_0 : \widehat{\beta}_{50} - \widehat{\beta}_{10} = 0$	0.2051	0.3450	0.0235	0.0409
Obs.	439,384	521,210	246,432	292,934

Notes: All standard errors are clustered at the industry-year level by bootstrapping with 100 replications of size $N/10$. The sample drawn during each replication is a bootstrap sample of clusters. The number of clusters is 270 in the period 1973-1987 and 270 in the period 1988-2002. Results are from regressions of the log hourly wage on the standard deviation (within industry-year cells) of the log capital-labor ratio, year dummies, four education categories (less than high school, high school, some college, college+), thirteen potential experience categories (0-2, 3-5, 6-8 etc.) and interactions between education and experience categories.

Table 3: March CPS 1970-2002. Quantile regression coefficients on the standard deviation of log capital-labor ratio

	Males		Females	
Sample Period	1970-1987	1988-2002	1970-1987	1988-2002
Quantile Regression				
10th quantile	0.027	-0.019	0.090	0.100
	(0.064)	(0.072)	(0.075)	(0.076)
50th quantile	0.064	0.015	0.112**	0.128**
	(0.034)	(0.048)	(0.057)	(0.062)
90th quantile	0.139**	0.067**	0.066	0.123**
	(0.031)	(0.032)	(0.047)	(0.051)
P-Value from linear restriction				
$H_0 : \widehat{\beta}_{90} - \widehat{\beta}_{10} = 0$	0.0208	0.0818	0.6515	0.3567
$H_0 : \widehat{\beta}_{90} - \widehat{\beta}_{50} = 0$	0.0161	0.0923	0.8685	0.5390
$H_0 : \widehat{\beta}_{50} - \widehat{\beta}_{10} = 0$	0.1845	0.1634	0.3132	0.2790
Obs.	212,426	196,508	90,728	103,924

Notes: All standard errors are clustered at the industry-year level by bootstrapping with 100 replications of size $N/10$. The sample drawn during each replication is a bootstrap sample of clusters. The number of clusters is 324 in the period 1970-1987 and 270 in the period 1988-2002. Results are from regressions of the log weekly wage on the standard deviation (within industry-year cells) of the log capital-labor ratio, year dummies, four education categories (less than high school, high school, some college, college+), thirteen potential experience categories (0-2, 3-5, 6-8 etc.) and interactions between education and experience categories.

Table 4: Robustness results: Different measures of within-industry capital-labor dispersion.

Sample Period	Males		Females	
	1973-1987	1988-2002	1973-1987	1988-2002
Panel (1)				
$H_0 : \widehat{\beta}_{90} - \widehat{\beta}_{10} = 0$	0.1022	0.0017	0.6146	0.3496
$H_0 : \widehat{\beta}_{90} - \widehat{\beta}_{50} = 0$	0.0252	0.0000	0.8355	0.2635
$H_0 : \widehat{\beta}_{50} - \widehat{\beta}_{10} = 0$	0.6444	0.8768	0.2916	0.5438
Panel (2)				
$H_0 : \widehat{\beta}_{90} - \widehat{\beta}_{10} = 0$	0.0184	0.0472	0.2061	0.0309
$H_0 : \widehat{\beta}_{90} - \widehat{\beta}_{50} = 0$	0.0065	0.0205	0.8583	0.0086
$H_0 : \widehat{\beta}_{50} - \widehat{\beta}_{10} = 0$	0.3109	0.5040	0.0058	0.3730
Panel (3)				
$H_0 : \widehat{\beta}_{90} - \widehat{\beta}_{10} = 0$	0.0007	0.1180	0.6597	0.6847
$H_0 : \widehat{\beta}_{90} - \widehat{\beta}_{50} = 0$	0.0006	0.0106	0.9531	0.3290
$H_0 : \widehat{\beta}_{50} - \widehat{\beta}_{10} = 0$	0.0819	0.7010	0.6444	0.8565

Notes: P-Values from t-tests of linear restriction of quantile coefficients obtained from quantile regression of May/ORG CPS log hourly wages on different measures of dispersion in capital-labor ratios (within industry-year cells). All regressions also include year dummies, four education categories (less than high school, high school, some college, college+), thirteen potential experience categories (0-2, 3-5, 6-8 etc.), interactions between education and experience categories. Capital-labor ratio dispersion is calculated in the following way. In panel (1) as the coefficient of variation of capital-labor ratios. In panel (2) as the standard deviation of the residuals of the OLS regression of log capital-labor ratio on log age of firm and the log of the number of employees. In panel (3) as the standard deviation of log capital-labor ratios in the sample which excludes M&A.

firms and $\frac{1}{1-\rho}$ is the elasticity of substitution. Intermediate inputs are sold in competitive markets and their prices are:

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

Firms can be inactive, vacant or filled. There is free entry of firms: at every point in time, ϕ inactive firms open a "good" vacancy and $(1-\phi)$ open a "bad" vacancy renting a site at price c. After opening a vacancy and before meeting the workers, firms have to make their irreversible capital choices denoted k_g for "good" firms and k_b for "bad" firms. Firms choose the optimal level of capital maximizing expected profits.[14] Although the investment decision is taken before the match, the cost of installing the capital is incurred only after matching. New and old unfilled vacancies search for workers and only after matching they decide whether to employ the worker and to install the capital. Finally, when workers and firms negotiate the wage, the cost of capital is already sunk.[15]

Production takes place in the form of a match one vacancy-one worker, we call it a "firm". A worker matched with a firm produces:

$$y_j(k,l) = \begin{cases} k_g^{1-\alpha} & \text{with} \qquad prob. = \phi \\ k_b^{1-\delta} & \text{with} \quad prob. = 1-\phi \end{cases} \tag{4}$$

$0 < \alpha < \delta < 1$ i.e. capital is more productive in "good" firms. Matching is random and 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

[14]The endogenous choice of capital k and the constant proportion of "good" jobs ϕ are the main differences from Acemoglu (2001). Since I am not interested in the changing composition of "good" and "bad" jobs but in the changing capital choice given job composition, I keep the parameter ϕ exogenous and make the capital choice endogenous.

[15]This assumption avoids the investment "hold up" problem which arises in models of rent sharing. The cost of installing the capital is assumed to be equal to the relative price of equipment capital to structure capital.

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 and separations into unemployment take place at the exogenous rate λ.

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. When the match takes place, the worker gains $E(k_g)$ or $E(k_b)$ and loses U. For simplicity's sake, I assume there are no unemployment benefits. The value of being employed in a firm $j = g, b$ is:

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

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:

$$rV(k_j) = q(\theta)[J(k_j) - Ck_j - V(k_j)] \tag{7}$$

where $q(\theta)$ is the flow probability of meeting an unemployed worker. When the match occurs the firm gains the value of a filled firm $J(k_j)$, incurs in the cost of installing the capital Ck_j and loses $V(k_j)$. C is the price of installing capital i.e. the price of equipment capital relative to structure capital. The values of a "good" and a "bad" firm matched with a worker are:[16]

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[16]Notice that $J(k_g)$ is different from $J(k_b)$ not only for the value of capital k_j but also because of the different production function, therefore the right notation should be $J_g(k_g)$ and $J_b(k_b)$. For simplicity of notation and since it does not generate confusion, I denote $J_g(k_g)$ as $J(k_g)$ and $J_b(k_b)$ as $J(k_b)$.

$$rJ(k_g) = p_g k_g^{1-\alpha} - w(k_g) - \lambda[J(k_g) - V(k_g)] \tag{8}$$

$$rJ(k_b) = p_b k_b^{1-\delta} - w(k_b) - \lambda[J(k_b) - V(k_b)]. \tag{9}$$

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

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

as the cost of renting a site is c.

As long as there are search frictions, there will be rents in the labor market. Rents will be split with Nash bargaining. Wages $w(k_j)$ will be set such that:

$$(1 - \beta)(E(k_j) - U) = \beta(J(k_j) - V(k_j)) \qquad \text{for } j = g, b. \tag{11}$$

Note that the capital k does not appear in the sharing equation as it is already sunk at the moment of bargaining. Unemployment in steady state will be given by:

$$u = \frac{\lambda}{\lambda + \theta q(\theta)}. \tag{12}$$

4.2 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, 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 $V(k_j) = c$ 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 12.

5) wages are given by equation 11.

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

$$p_g = \left((1 - \phi)^\rho k_b^{(1-\delta)\rho} + \gamma \phi^\rho k_g^{(1-\alpha)\rho}\right)^{\frac{1-\rho}{\rho}} \gamma \phi^{\rho-1} k_g^{(1-\alpha)(\rho-1)} \tag{13}$$

$$p_b = \left((1 - \phi)^\rho k_b^{(1-\delta)\rho} + \gamma \phi^\rho k_g^{(1-\alpha)\rho}\right)^{\frac{1-\rho}{\rho}} (1 - \phi)^{\rho-1} k_b^{(1-\delta)(\rho-1)}. \tag{14}$$

The wage equations in "good" and "bad" jobs $j = b, g$ are set from equation 11, substituting in equations 6 and 8:

$$w(k_g) = \beta(p_g k_g^{1-\alpha} - rc) + (1 - \beta) rU \tag{15}$$

$$w(k_b) = \beta(p_b k_b^{1-\delta} - rc) + (1 - \beta) rU. \tag{16}$$

As in all models of rent sharing, the wage is equal to a weighted average of the surplus and the worker's outside option rU, the weights are given by the bargaining power β. The discounted value of unemployment is obtained from equation 5 combined with equation 11, 7 and 10:

$$rU = \theta q(\theta) \left[\frac{\phi \beta}{(1 - \beta)} \frac{rc}{q(\theta)} + \frac{\phi \beta}{(1 - \beta)} C k_g + \frac{(1 - \phi)\beta}{(1 - \beta)} C k_b \right]. \tag{17}$$

The optimal k_j in equilibrium is obtained maximizing the value of a vacant job: $V'(k_j) = 0$.

The value of a vacant job for a "good" firm $V(k_g) = \frac{q(\theta)}{(r+\lambda)(r+q(\theta))}[p_g k_g^{1-\alpha} - w_g + \lambda c - (r+\lambda)C k_g]$

is obtained using equations 7, 8 and 10. The two equations that determine capital choice when

firms take both prices and wages for given are therefore:

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

and

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

The two equations 18 and 19 determine k_g and k_b given market tightness θ. In these two

equations, the first term indicates the marginal benefit of one more unit of capital whereas

the second term indicates the marginal cost.

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 k_g and makes

them increase their capital choice k_g more than "bad" firms. This result of the model comes

from the two equations above. When the relative price of equipment capital C falls, capital

of "good" firms k_g grows more than k_b: $\frac{\partial(\log k_g - \log k_b)}{\partial \log C} = -\frac{1}{\alpha} + \frac{1}{\delta} < 0$.

Market tightness θ is determined when both the "good" job market and the "bad" job

market are in equilibrium. The equilibrium in each market is given at the crossing of the

"job creation curve" JC_j and the wage equation 15. Since the proportion of good jobs ϕ

is assumed exogenous, the equilibrium in one market will determine the equilibrium on the

other market. Taking the "good" market equilibrium, the job creation curve $\frac{p_g k_g^{1-\alpha} - w_g}{(r+\lambda)} =$

$(\frac{r+q(\theta)}{q(\theta)} - \frac{\lambda}{(r+\lambda)})c + C k_g$ is obtained combining equations 7, 8 and 10 and equalizes the expected

flow profits of a filled job with the expected costs of opening a vacancy. The equilibrium locus that together with equation 18 and 19 (with equations 13, 14 and 17 substituted in) defines the equilibrium θ is:

$$(1 - \beta)(p_g k_g^{1-\alpha} - rU) = [\frac{r(r + q(\theta) + \lambda)}{q(\theta)} - \beta r]c + (r + \lambda)Ck_g. \tag{20}$$

This model provides a formula for the variance of log capital-labor ratios and for residual wage inequality which is consistent with the evidence shown in the empirical part. The variance of log capital-labor ratios depends on the difference between k_g and k_b and the proportion of "good" jobs ϕ. In fact the log capital-labor ratios are distributed according to a binomial distribution with values $\log k_g$ and $\log k_b$ and probability ϕ and $1 - \phi$. The variance of such a distribution is therefore equal to $(\log k_g - \log k_b)^2 \phi(1 - \phi)$ which is increasing in $\log k_g - \log k_b$ for given ϕ. The decline of the relative price of equipment capital C will have an unambiguous effect on the variance of log capital-labor ratios through the increase in $(\log k_g - \log k_b)$, keeping constant the composition of jobs ϕ.[17]

Wage differentials across identical workers (using 15 for $j = b, g$) in this model are given by:

$$\frac{w(k_g)}{w(k_b)} = \frac{\beta(p_g k_g^{1-\alpha} - rc) + (1 - \beta)rU}{\beta(p_b k_b^{1-\delta} - rc) + (1 - \beta)rU}. \tag{21}$$

In this equation the wage differential is expressed in function of the endogenous variables k_g and k_b. The optimal investment k_j is determined in equations 18 and 19. Log wage differentials across identical workers $\log \frac{w(k_g)}{w(k_b)}$ are positively related to log differences in capital stocks $\log \frac{k_g}{k_b}$.

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[17]Figure 2 shows that capital-labor ratio dispersion increased mostly at the top of the distribution (90/50) until the mid 1980s and at the bottom of the distribution (50/10) after the mid 1980s. In this model k_g and k_b are not necessarily associated with the 90th, the 50th or the 10th quantile, here I show the results for the variance of the distribution for generality.

This model suggests a negative correlation between the relative price of equipment capital and capital-labor dispersion and a positive correlation between capital-labor dispersion and wage inequality across observationally identical workers. The correlation between capital-labor dispersion and wage inequality was shown in the previous section, in the next section I test for a the relationship between the relative price of capital and capital dispersion.

4.3 Empirical Implications

To test the model's implication we need to consider equation 3 as representing the production function of a single industry. Then we can exploit differences across industries in the decline of the relative price of capital and in capital and wage dispersion. The exogenous driving force of the model is the declining price of equipment capital relative to structure capital. If the theory is correct, the same industries which saw a larger decline in the relative price of capital equipment should also see a greater rise in dispersion of capital-labor ratios and in residual wage inequality. Table 5 contains the results of OLS regressions of various measures of capital-labor dispersion and of residual wage inequality on the relative price of capital.

Panel A of Table 5 shows the estimates of the following OLS regression:

$$sd(\log \frac{k}{l})_{it} = a + \beta \log C_{it} + \zeta_i + \eta_{it}$$

where $sd(\log \frac{k}{l})_{it}$ is the standard deviation of the capital-labor ratio in industry i at time t and C_{it} is the relative price of equipment capital. Panel B and Panel C of Table 5 show the estimates of the following OLS regression:

$$sd(\widehat{\varepsilon})_{it} = a + \beta \log C_{it} + \zeta_i + \eta_{it}$$

where $\widehat{\varepsilon}$ is the residual of a log wage regression (residuals of log weekly wages for the March CPS and of log hourly wage for the May/ORG CPS) on thirteen experience categories and four education categories, year and sex dummies and interactions between education and experience categories. Both regressions include industry fixed effects ζ_i and are weighted by the inverse of the cell size used to calculate the dependent variable.

The results in Table 5 indicate that capital-labor dispersion is negatively correlated with the relative price of capital within industry over the period 1970-2002. However, the correlation is not significant separately in the 1970-1987 period and in the 1988-2002 period. The correlation between the relative price of capital and residual wage inequality is also negative and significant in both the March CPS and the May/ORG CPS when calculated over the entire period 1973-2002 (1970-2002 for the March CPS). The correlation is significant negative in both subperiods in the March CPS sample and in the period 1973-1987 in the May/ORG sample but is significant positive for the May/ORG in the period 1988-2002. This could be due to the fact that, unlike the March CPS, the ORG CPS shows very little increase (if at all) in residual wage inequality in the period 1988-2002 (see Lemieux, 2004 and AKK, 2005a and 2005b). Overall this evidence supports the view that industries that experienced a larger decline in the relative price of equipment capital were also the same industries which saw a larger increase in the dispersion of capital-labor ratios and residual wages.

5   Conclusions

In the recent debate on the extent and the causes of the rise in wage inequality, Lemieux (2004) has argued that residual wage inequality is explained by institutional changes in the 1980s and by compositional changes in the labor force in the 1990s. AKK (2005a and 2005b) argue

Table 5: Regression of capital-labor ratios dispersion and residual wage inequality on relative price of equipment capital

Panel A: Dep.var: Standard deviation of log (k/l)

	1970-1987	1988-2002	1970-2002
Relative price of equip.	-0.050	-0.060	-0.086**
	(0.044)	(0.039)	(0.025)
Constant	0.738**	0.797**	0.771**
	(0.012)	(0.007)	(0.006)
Observations	324	270	594
Number of industries	18	18	18

Panel B: Dep.var: Standard deviation of residual wage inequality May/ORG CPS

	1973-1987	1988-2002	1973-2002
Relative price of equip.	-0.248**	0.025**	-0.054**
	(0.019)	(0.005)	(0.007)
Constant	0.371**	0.341**	0.361**
	(0.008)	(0.005)	(0.008)
Observations	270	270	540
Number of industries	18	18	18

Panel C: Dep.var: Standard deviation of residual wage inequality March CPS

	1970-1987	1988-2002	1970-2002
Relative price of equip.	-0.154**	-0.146**	-0.211**
	(0.013)	(0.012)	(0.008)
Constant	0.394**	0.461**	0.434**
	(0.008)	(0.013)	(0.010)
Observations	324	270	594
Number of industries	18	18	18

instead that residual wage inequality is a phenomenon concentrated in the upper tail of the wage distribution and has to do with some form of technical change. In particular they suggest that computerization may have had a non-monotonic effect on the wage distribution, favoring workers at the top of the distribution relative to those in the middle and leaving the position of workers at the bottom of the wage distribution relatively unchanged. To contribute to this debate, this paper takes the capital-labor ratio as a direct measure of embodied technology and explores the relationship between residual wage inequality and capital-labor dispersion at different points of the distribution.

This paper documents that the standard deviation of log capital-labor ratios increased by about 16 percentage points from 1970 to 2002 in the US. The correlation between capital-labor dispersion and residual wage inequality is studied matching COMPUSTAT data to CPS data at the industry-year level. I find evidence of a positive correlation between capital-labor dispersion and the 90-10 wage differential for men. The impact of capital-labor dispersion is concentrated at the top of the male residual wage distribution (the 90-50 log differential) and is insignificant at the bottom of the distribution (the 50-10 log differential). This result is robust to different measures of capital-labor dispersion and several sample cuts. This evidence is interpreted in favor of a role of embodied technology in explaining the rise in male residual wage inequality at the top of the wage distribution.

The results for women are less clear cut. Whereas all samples considered indicate an insignificant correlation between capital-labor dispersion and female residual wage inequality in the period 1973-1987, the results are ambiguous in the period 1988-2002. Even in those cases where there is evidence of a correlation between capital-labor dispersion and female residual 90-10 wage differential, it is difficult to assess whether the impact is concentrated at the top of the wage distribution (the 90-50 differential) or at the bottom (the 50-10 differential).

To explain the correlation between capital-labor ratio dispersion and residual wage dispersion, I adopt a search and matching model where identical workers are matched to two types of firms. Firms differ in the productivity of their capital stock and therefore in the price elasticity of their demand for capital. The causal factor in the model is the declining price of equipment capital. 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. An implication of the model is that the industries which see a larger decline in the relative price of equipment capital should also see a larger increase in capital and residual wage dispersion.

A simple test of the model exploits industry variation in the decline of the price of capital and in capital and wage dispersion. OLS regressions of capital-labor dispersion and residual wage dispersion on the relative price of equipment capital at the industry level provide some evidence of a negative relationship between the price of capital and capital and wage dispersion within industry.

It has to be noted that the model presented here is only one of the many possible interpretations of the positive correlation between capital intensity dispersion and wage dispersion. The evidence presented in this paper is in favor of models of residual wage inequality which underline its nature of within-industry across-firms phenomenon. However, this model of residual wage inequality is hard to distinguish empirically for example from a model of perfect sorting of workers of different ex-ante ability into different firms.[18] The model presented in

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[18] Acemoglu (1999), Caselli (1999), Galor and Moav (2000) Kremer and Maskin (1996) propose different theories of residual wage inequality based on ex-ante differences in individual ability. However, the models based on fixed ex-ante differences in ability are at odds with the evidence on the relationship between residual wage inequality and earnings instability (Gottschalk and Moffitt (1994) and the subsequent literature). If unobserved ability is a permanent characteristic of the individual, then the rise in residual wage inequality should be accounted for by the rise in the variance of the permanent component of individual earnings. Gottschalk and Moffitt (1994) and the subsequent literature show that this is not the case and earnings

this paper is based on identical workers and rent sharing and implies an increasing dispersion of rents across firms. A measure of wage rents at the firm level is the share of labor related expenses to the value of sales. A preliminary analysis based on COMPUSTAT data shows that although on average firms pay lower rents to workers over time, the dispersion of wage rents across firms has increased. Assessing the empirical evidence about rent dispersion across firms constitutes an interesting avenue for future research in view of distinguishing between different explanations of residual wage inequality.

Data Appendix

Compustat data.

I used COMPUSTAT annual industrial data on the total number of employees (COMPUSTAT variable name: data29) and on the net capital stock (COMPUSTAT variable name: data8). The net capital stock represents the capitalized cost of property, plant and equipment used to generate revenue minus accumulated depreciation. I consider two-digit industries except for agriculture, construction, utilities and finance. The first three industries are excluded because of their small sample size in various years, the financial industry because financial firms do not report information on capital. The results shown in the paper are based on an unbalanced panel of 16,491 firms and 159,128 observations with between 1 and 33 continuous observations per firm.

Capital is deflated using the two-digit industry specific deflators form the Bureau of Economic Analysis (http://www.bea.doc.gov/bea/dn/home/fixedassets.htm) and is expressed at the real value in year 2000. The use of industry-specific deflators has very little effect on the standard deviation of log capital-labor ratios, namely the standard deviation of log nominal

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instability (the variance of the transitory component of earnings) explains much of the total increase in residual wage inequality.

capital-labor increases from 0.92 in 1970 to 1.13 in 2002. Finally, in the course of the paper I have used the employment-weighted log standard deviation. The use of employment weights compresses the log standard deviation but leaves the pattern over time substantially similar; the unweighted standard deviation of log capital-labor increases from 1.04 in 1970 to 1.35 in 2002.

In the previous version of the paper I used data on equipment capital only. COMPUSTAT provides two different series of capital equipment. The series of capital equipment net of depreciation is available from 1970 until 1992 (officially until 1997 but many firms stopped reporting the net value of equipment capital some years before). From 1984 to 2002 the dataset provides a series of capital equipment evaluated at current cost. There is apparently no way to construct a firm-specific depreciation rate for equipment capital only (total capital depreciation is available) from 1992 to 2002. The only way to build a series for the net value of equipment capital after 1992 is to take the difference in the two series (the current cost minus the net equipment capital) in the overlapping period 1984 to 1992 and build an industry-specific depreciation rate. In the period 1993 to 2002 capital equipment at current cost is depreciated using the average depreciation rate by industry calculated in the overlapping period 1984-1992. Obviously, the resulting series is subject to criticism because it imposes the same depreciation rate across firms of the same industry in the period 1993-2002 and because the depreciation rate is calculated in the previous period 1984-1992. The standard deviation of the log equipment capital-labor ratio of the series constructed in this way (not shown) increases even more than the series of total net capital shown in Figure 1. The quantile regressions of May/ORG CPS log wages on equipment capital-labor ratio dispersion yield qualitative similar results (not shown) to Table 2 in the text produced with total capital i.e. significant impact of equipment capital-labor ratio dispersion at the upper tail of the male wage distribution in

both periods and insignificant results for women in the period 1973-1987. The Figure and the Table for the results on equipment capital are available upon request.

Current Population Survey data.

I use March CPS data for the earnings years from 1970 to 2002. The sample is restricted 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 16 and 64 at the time of the survey and with potential experience between 0 and 39 years. Weekly earnings are calculated as the logarithm of annual earnings divided by weeks worked. Allocated earnings are not excluded. Before 1988 all topcoded values are multiplied by 1.5. After 1989 total wages are the sum of primary and secondary earnings. Topcoded primary earnings are multiplied by 1.5. After 1996 when topcoded primary earnings are assigned the mean of all topcoded earnings, I reassign the topcoded value and then multiply by 1.5. For the secondary earnings the topcode value (99,999 between 1989 and 1995 and 25,000 after 1996) is multiplied by 1.5. Earnings of below $67 per week in 1982 dollars are dropped. Before matching to COMPUSTAT data all earnings observations in agriculture, construction, utilities, finance and real estate and the public sector are dropped.

I use the May CPS for 1973 to 1978 and the CPS ORG for years 1979 to 2003. All samples include wage/salary workers aged 16 to 64 with 0 to 39 years of potential experience in current employment. Hourly wages are the logarithm of hourly earnings for those paid by the hour and the logarithm of usual weekly earnings divided by hours worked last week for non-hourly workers. Topcoded earnings are multiplied by 1.5. Full-time earnings of below $67/week in 1982$ and hourly earnings of below $1.675/hour in 1982$ are dropped as are hourly wages exceeding 1/35th of the topcoded value of weekly earnings. All earnings are deflated by the CPI. Allocated earnings are not excluded.

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