Technology Adoption and Wage Distribution in the U.S. Manufacturing Sector: Quantile Regression Analysis

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This paper examines the effect of technology adoption on the wage dispersion in the U.S. manufacturing sector using the quantile regression method. We obtain two main results. First, during the period of 1970 to 1995, the marginal effect of capital intensity on wage has risen. Second, the marginal effect on high-wage quantiles has risen more than that on low-wage quantiles. These results suggest that (1) high-wage quantile have adopted technologies more actively than others, and (2) high-captial intensity industries have contributed to the widening of wage dispersion over the period.

Keywords: Technology adoption, Wage dispersion, Quantile regression

JEL Classification: C13, E24, J31, O33

I. Introduction

The wage distribution in the U.S. economy has shown a substantial change over the past several decades. In particular, recent studies on wage inequality assert that the wage structure has been changing in favor of high skill, high education, and high

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[**Seoul Journal of Economics** 2006, Vol. 19, No. 2]

ability. According to the theoretical explanations in Kim (2002) and others (Acemoglu 1998, 2001a, 2001b; Aghion and Bolton 1997; Caselli 1999), technological changes are believed to be the main reason. The purpose of this paper is to examine the direction and the bias of the change in wage distribution caused by changes in technology adoption in the U.S. manufacturing sector using the quantile regression method.

In standard estimations, wage is usually assumed to have a (log-) linear relationship with some individual variables such as gender, race, education, experience, marriage, *etc.* or with other industrial and/or macroeconomic variables such as capital intensity, total factor productivity, production and nonproduction worker share, gross domestic product, exports and imports, *etc.* These estimations produce constant coefficients interpreted as elasticities of substitution of the variables in the regression equations. For example, if wage is regressed on capital intensity, the coefficient of capital intensity measures the percent responsiveness of wage to a percent change in capital intensity, and the coefficient has the meaning that the wages of skilled and unskilled workers respond by *the same* rate that the estimated coefficient suggests regardless of the skill level being used in production.

However, this type of standard estimation can hardly contribute to the study on the change in wage distribution, because it provides only one estimate (the conditional mean) and hence it cannot convey information on the change in wage distribution.

To meet this research need, a different method is required and here the quantile regression method is employed. In contrast to the conventional estimation method that estimates only the conditional mean of the dependent variable, the quantile regression method provides different estimates on different quantiles of the dependent variable so that by combining the estimated quantiles we can build up the picture of wage distribution conditional on independent variables. In this paper, the observed wage change is accounted for by the change in capital intensity and the estimation is conducted using the log-linear parametric way.

There are many empirical studies that explore the effect of capital intensity on wages. Allen (1995) reports wage growth is strongly correlated with productivity growth and capital intensity. Goldin and Katz (1998) find a strong positive relationship between capital intensity and the nonproduction worker wage bill. Caselli

(1999) documents a large increase in the interindustry dispersion of capital intensity and relates this change to the skill composition of the labor force. All these studies rely on industrial/macroeconomic data and the standard estimation. On the other hand, Buchinsky (1994) explores the change in the U.S. wage structure using individual data and quantile regression. Pizer (2000) estimates wage premia by quantile regression to examine the effect of trade on wage differentials between union and nonunion workers. Gonzales and Miles (2001) have applied a nonparametric quantile method to analyze the increase in wage inequality in the Uruguayan economy using education and returns on minimum wage.

Most of previous studies included a proxy variable to capture the technology effect on wage or production in lieu of unobserved technology variable (see for example Goldin and Katz (1998)). In this paper, instead, due to proper proxy variables unavailable from the NBER data, alternatively we assume a theoretical relationship between technology and capital intensity, and consider the direction of biased coefficient on capital intensity. Then we attempt to explain the change in the interindustry wage distribution and its implication, using a quantile regression method. In particular, the estimation model has some distinctive features and interpretations regarding the role of technology adoption on the determination of wage that is developed in Kim (2002). According to Kim (2002), technology adoption affects wage both directly and indirectly, and in the latter incident, *via* capital intensity. This study considers the indirect effect using the theoretical exposition between technology and capital intensity in line with Kim (2002).

Through the attempt of this paper, two main results emerge. First, during the period of 1970 to 1995, the marginal effect of capital intensity on wages has risen across all wage quantiles. This implies that the U.S. manufacturing industries have continued to adopt better technologies over time. Second, the marginal effect of capital intensity on high-wage quantiles has risen more than that on low-wage quantiles during the period. This result suggests that industries have adopted different technologies, with high-wage industries adopting new technologies more actively than low-wage industries, and the widening interindustry wage dispersion is a result of technology adoption. This can also be interpreted to provide some evidence for capital-skill complementarity in the U.S. manufacturing sector because it suggests that the increase in capital intensity induced by technology adoption has intensified a biased effect on wage in favor of the industries in high-wage quantiles and therefore it has aggravated the observed wage inequality.

This paper is organized as follows. In section II, we briefly present a framework for modeling. Then we discuss the data description and quantile estimation method in section III. Estimation results are provided in section IV. Section V concludes.

II. Theoretical Framework

This study is an attempt to see how wages are affected by changes in capital intensity, emphasizing the role of adopted technology that affects wage directly and indirectly *via* capital intensity, with help of the developed theory. Hence, the theory needs to be modified to fit the industry data at hand.

The dynamic interaction of technological progress and capital accumulation is originated by Hulten (1975). In his paper, Hulten shows that growth accounting always underestimates the contribution of technological progress to total output because technological progress induces additional capital accumulation and the induced capital accumulation is not counted as contribution of technological progress. In our study Hulten's explanation is modified to account for wage dispersion.

The core assumption in this study is that technology is industry-specific and all workers in one industry share the same technology. This assumption implies that we assume away differences in ability of individual workers and consider the representative worker in each industry. Therefore, we will not consider worker ability as a factor affecting wage determination. Capital, labor, and technology are the production factors for all industries and factor markets for capital and labor are assumed to be competitive. However, we assume that factors take some time to move from one sector to another since first a new technology is adopted and then a change in capital intensity is induced subsequently.[1] Technology is assumed to be neutral and exogenously given.[2]

[1] See Kim (2002) for the theoretical explanation on why and how technology induces capital accumulation.

[2] The question of technology adoption is not discussed explicitly here.

For convenience, the assumption of the linear homogeneity of the production function in capital and labor is maintained. Then the real wage rate in the *ith* industry is given by

$$w_i = w(s_i, k_i), \tag{1}$$

where s_i is the technology adopted and k_i is the capital intensity in the industry. Both s_i and k_i have positive first derivatives on real wage $w_i(\partial w_i / \partial s_i > 0, \ \partial w_i / \partial k_i > 0)$. Since technology is neither observable nor measurable it is impossible to estimate the equation at this stage. One important and useful clue about the link between technology and capital intensity is that both are positively correlated. In the context of this theory, when an industry adopts a new technology, the capital intensity of that industry rises because a higher productivity of capital due to a better technology attracts more capital to the industry. The adoption of a new technology brings its direct effect to the wage and in addition an indirect effect *via* an increase in induced capital due to the new technology. If this induced relationship between technology and capital exhibits one-to-one correspondence, it is possible to formulate technology as a positive function of capital intensity $(\partial s / \partial k_i > 0)$:[3]

$$s_i = s(k_i). \tag{2}$$

To make things simpler we allow a strong assumption of log-linearity to the structure of Eq. (1) and add a log-linear relationship between technology and capital intensity to Eq. (2) in the manner that

$$\ln w_i = \alpha_0 + \alpha_1 \ln s_i + \alpha_2 \ln k_i + v_i . \tag{3}$$

Instead and implicitly, the observed data points are taken as the result of the optimal technology choices by industries given economic alternatives. Since technology is industry-specific, an industry's contemporaneous technology is different from others, which serves the source of wage dispersion and capital intensity across industries.

[3] Contrary to the functional form, the more plausible direction of causation between the two variables may be from technology to capital intensity. The equation only shows that there exists a positive function between the two variables. If one-to-one correspondence holds, however, we can define capital intensity as an inverse function of technology as is shown.

$$\ln s_i = \beta \ln k_i + e_i . \tag{4}$$

When (4) plugged into (3), Eq. (3) becomes

$$\ln w_i = \alpha_0 + (\alpha_1 \beta + \alpha_2) \ln k_i + \varepsilon_i \tag{5}$$

where $\varepsilon_i = \alpha_1 e_i + v_i$, which satisfies the zero conditional mean assumption. Equation (5) will be used in the parametric quantile estimation, which imposes a linear structure on the estimation equation.

One econometric issue concerning Eq. (5) is a possibility of an omitted variable problem due to the omission of the technology variable, s_i. In the actual estimation of Eq. (5), the variable $\ln s_i$ is missing because it is not observable. Without the variable, since s_i is assumed to induce k_i, the estimated coefficient of capital intensity is an inconsistent estimate of the true coefficient, α_2, and therefore it cannot tell the true *direct* effect of capital intensity on real wage.

However, what we are interested in here is not the consistent estimate of capital intensity but the coefficient that can capture the *total* effect of capital intensity on wage. The important feature of Eq. (5) is that when real wage is regressed on capital intensity, what the coefficient actually reflects is both the direct and the indirect effects combined of capital intensity on real wage.

The effect on real wage and capital intensity when an industry adopts a better technology is shown in Figure 1. If an industry has switched technology 1 (s_1) to 2 (s_2), the line shifts up with the slope unchanged. Given the previous level of capital intensity (k_1), this new technology brings a higher wage rate up to B in the short run. But then since this industry's marginal product of capital has risen higher than others due to the new technology, capital flows into this industry until this industry's marginal product of capital is equalized to others', and this additionally *induced* capital pushes the industry's wage further up to C. If we have time-series observations for an industry adopting a new technology, the estimated line would be the segment AC and it would have a steeper slope than the line without technology upgrade (segment AD). This is because we observe the wage indirectly and directly induced by the upgraded technology and the regression line reflects the total effect of a new technology on wage.

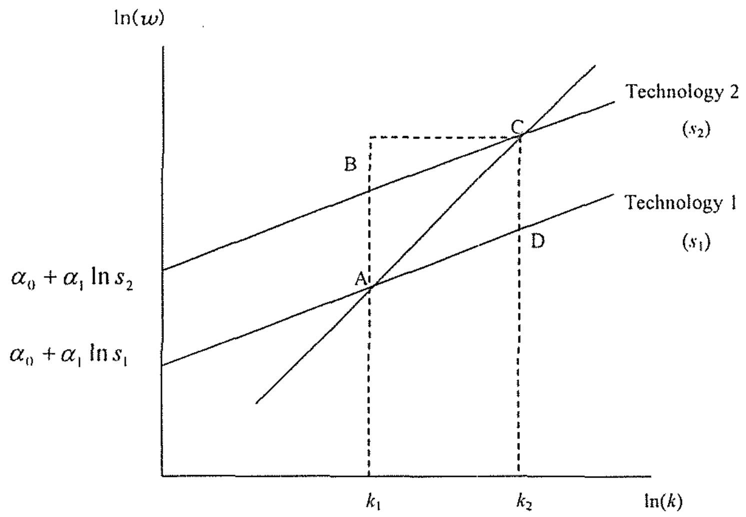


FIGURE 1
TECHNOLOGY ADOPTION AND CAPITAL ACCUMULATION

In contrast, if an *autonomous* rise in capital intensity (k_1 to k_2) takes place without technology upgrade, the change in capital intensity will raise wage only by as much as α_2 in Eq. (3) along the segment AD and the wage will slide up to the point like D which is clearly lower than the point C (the case with technology upgrade). This figure shows that when an industry adopts a better technology over time the slope of the estimated line becomes steeper than otherwise. Hence, by estimating the slopes and tracing their changes over time, we can investigate the trend of technology adoption and the effect of technologies on wage dispersion.

III. Data Description and Estimation Method

A. Data Description

The data used in this study is the disaggregate U.S. manufacturing data provided jointly by the National Bureau of Economic Research (NBER) and the Center for Economic Studies (CES). The database covers all 4-digit manufacturing industries from 1958-96, in the 1987 SIC codes (459 industries). It contains annual industry-

TABLE 1
DESCRIPTIVE STATISTICS

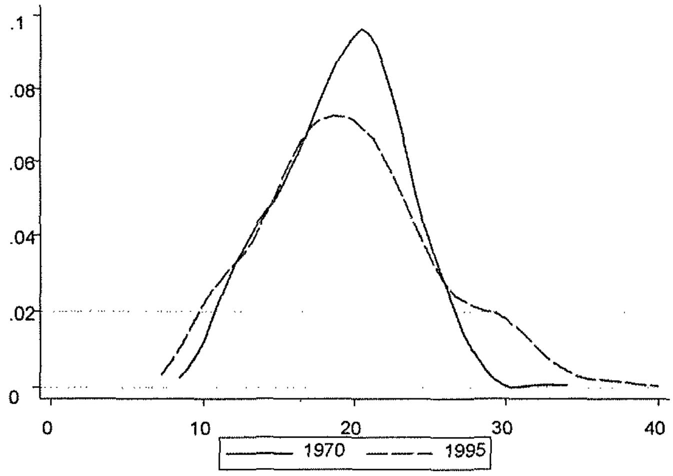
	ln(*w*)		ln(*k*)	
	1970	1995	1970	1995
0.10Q	13.24	12.21	5.22	9.25
0.25Q	16.23	15.76	8.83	20.14
0.50Q	19.40	19.23	14.18	33.89
0.75Q	22.05	22.99	23.31	58.58
0.90Q	24.32	27.51	44.11	112.34
Minimum	9.50	8.66	1.03	2.55
Maximum	32.92	38.57	183.71	537.58
Mean	19.12	19.65	20.38	53.01
Coefficient of Variation	0.212	0.285	1.043	1.161
Skewness	-0.13	0.44	3.26	3.24
Kurtosis	2.59	2.98	18.35	17.44

level data on output, employment, payroll and other input costs, investment, capital stocks, total factor productivity, and various price indexes. It is worth mentioning that the industry data employed here is different from the micro-data usually used in labor economics to examine the characteristics of an individual's wage determination, which often consists of education, experience, gender, and so on. Rather, this study focuses on macroeconomic/industrial features of wage distribution, especially in its relationship with capital intensity, instead of the determinants of individual worker's wage.

The real wage of each industry is obtained by dividing total payroll by total employment that includes production and non-production workers [4] and then by applying the price index. Capital intensity is obtained by dividing real equipment capital by total employment. Table 1 reports the descriptive statistics on real wage and capital intensity.[5] The unconditional wage dispersion measured

[4] Some studies take the share of nonproduction workers in total employment as a proxy to the share of skilled workers, but not here. See for example Dunne, Haltiwanger, and Troske (1997).

[5] See Bartelsman and Gray (1996) for a more detailed description of variables. The data can be obtained at http://www.nber.org/nberces/nbprod96.htm.



Note: Each graph is generated by a kernel density method.

FIGURE 2
UNCONDITIONAL DENSITY OF *PER CAPITA* REAL WAGE

by coefficient of variation indicates that wage dispersion grows more seriously in 1995 than in 1970 (0.212 in 1970 to 0.285 in 1995). Figure 2 generated by a kernel density method also shows that the unconditional density of real wage becomes more disperse in 1995 than in 1970.

B. Estimation Method

Consider the following linear regression model,

$$y_i = x_i\beta + u_i \tag{6}$$

where we assume the independently distributed error term with zero conditional mean. The θth quantile of the conditional distribution of y given x is defined as $Q_\theta(y|x) \equiv \inf\{y|F(y|x) \geq \theta\}$ where $F(y|x)$ is the conditional cumulative density function. Based on Eq. (6), the conditional quantile is given by

$$Q_\theta(y_i|x_i) = x_i\beta + Q_\theta(u_i|x_i)$$

where $x_i\beta$ and $Q_\theta(u_i|x_i)$ are not separately identified. Therefore the quantile regression equation is $y_i=Q_\theta(y_i|x_i)+v_i$, $i=1,\cdots,n$ where $v_i=u_i-Q_\theta(u_i|x_i)$ and thus $Q_\theta(v_i|x_i)=0$.

Following Koenker and Bassett (1978)'s estimation procedure, we can obtain the conditional quantile $Q_\theta(y_i|x_i)$ by minimizing the following objective function:

$$\min_{\beta}\sum_{i=1}^{n}\rho_\theta(y_i-x_i\beta) \tag{7}$$

where $\rho_\theta(z)=\theta\cdot z\cdot I_{[0,\infty)}(z)-(1-\theta)\cdot z\cdot I_{(-\infty,0]}(z)$ and $I(\cdot)$ is an indicator function. By plugging $\rho_\theta(z)$ into Eq. (7), we can rewrite it as

$$\min_{\beta}\left\{\sum_{i\in\{i:y_i\geq x_i\beta\}}^{n}\theta|y_i-x_i\beta|+\sum_{i\in\{i:y_i<x_i\beta\}}^{n}(1-\theta)|y_i-x_i\beta|\right\}. \tag{8}$$

Note that when $\theta=1/2$, (8) yields the Least Absolute Deviation (LAD) estimator which is an important special case for the quantile regression. The estimated conditional quantile is $\hat{Q}_\theta(y_i|x_i)=x_i\hat{\beta}_\theta$ in which the estimated coefficient is a function of the specific quantile value θ. Koenker and Bassett (1978) established the asymptotic normality of $\hat{\beta}_\theta$ such as

$$\sqrt{n}(\hat{\beta}_\theta-\beta_\theta)\xrightarrow{D}N[0,\sigma_\theta^2(Exx')^{-1}]$$

where $\sigma_\theta^2=\theta(1-\theta)/[f_{u(\theta)}^2(0)]$ and $f_{u(\theta)}$ is the density function of u_θ. In this study, considering the non-normality of the error term, we employ bootstrapping standard errors instead of asymptotic standard errors.[6]

IV. Estimation Results

Although the conventional mean regression helps us understand the *on-average* change in the slope parameter, it provides little about the change in wage distribution at different capital intensity levels. Because different wage quantiles could respond differently to

[6] The bootstrap method employed here is the x-y pair method proposed by Koenker (1994). We implemented 100 bootstrap iterations.

TABLE 2
ELASTICITY OF SUBSTITUTION AND TEST STATISTIC

	$\theta=0.1$	$\theta=0.5$	$\theta=0.9$
1970	0.162 (0.015)	0.160 (0.013)	0.098 (0.013)
1995	0.246 (0.010)	0.242 (0.011)	0.258 (0.031)
Test Statistic (H_0: $\beta_\theta^{1970}=\beta_\theta^{1995}$)	−3.581**	−3.827**	−4.439**

Notes: 1) Bootstrap standard errors are in the parentheses.
2) ** indicates the rejection at the 5% significance level.
3) We employ a conservative t-statistic:

$$T_c=(\hat{\beta}_1-\hat{\beta}_2)/\sqrt{2[\mathrm{var}(\hat{\beta}_1)+\mathrm{var}(\hat{\beta}_2)]}\sim t_{df}$$

a change in capital intensity, we employ the parametric quantile regression based on the log-linear functional form in order to examine the effect of technology on conditional wage distribution.

Table 2 reports the estimated slope coefficient (elasticity of substitution) and the bootstrap standard errors for selected three quantiles (0.1, 0.5, and 0.9). The marginal effect of capital intensity measures the increase in the wage which, *ceteris paribus*, would keep an industry in the same quantile when the capital intensity in the industry increases by 1%.

As to the changes in results from 1970 to 1995, Table 2 shows that three wage quantiles in 1995 exhibit greater slopes than their counterparts in 1970. Consistent with the implication provided in Figure 1, the industries in all quantiles have adopted better technologies in 1995. Assuming two dependent samples, the equality test of coefficients between 1970 and 1995 is presented in Table 2.[7] The null hypothesis of equality of marginal effects between the two years is tested by means of t-statistics. Test statistics lead us to reject the equality of two slope coefficients at each quantile. In particular, an apparent increase of elasticity is observed in the high-wage quantile industries (0.098 in 1970 to 0.258 in 1995).

Panels (a) and (b) in Figure 3 depict the result of the quantile estimation for the selected two years (1970 and 1995) and also

[7] Given the time series nature of the samples, we assume the two samples are dependent. Therefore, we construct a *conservative* t-test statistic.

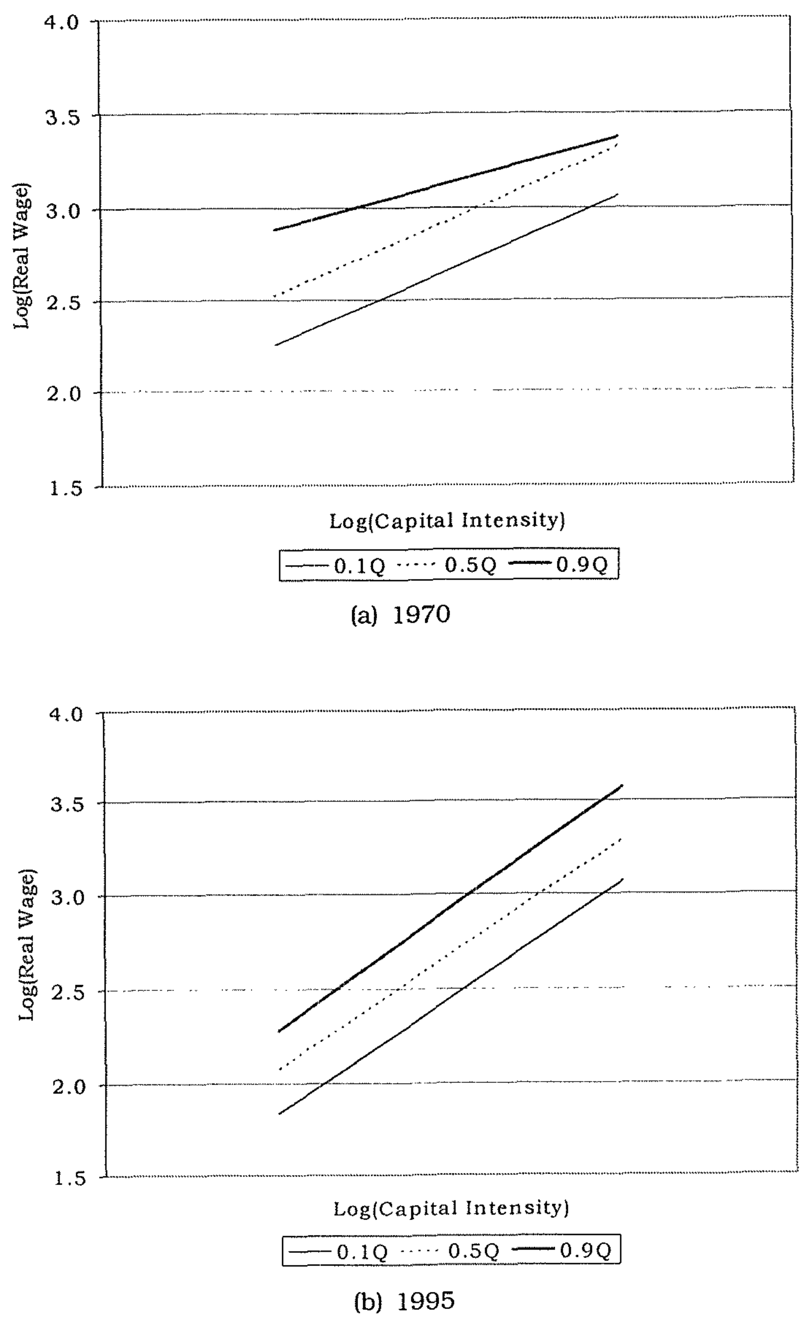


FIGURE 3
QUANTILE REGRESSION LINES: 1970 AND 1995

TABLE 3
WAGE DISPERSION

Year	Low k	Medium k	High k
	Measure (1): Scale Parameter		
1970	0.167	0.122	0.073
1995	0.142	0.128	0.112
	Measure (2): Interquantile Distance		
1970	0.524	0.460	0.387
1995	0.472	0.488	0.503

Note: Low, Medium, and High k denote 0.1, 0.5, and 0.9 quantile values of (K/L), respectively.

provide empirical implications from the within-year comparison. In panel (a), it is shown that a 0.1 wage quantile has a greater slope at a given level of capital intensity than a 0.9 wage quantile.[8] This result implies: First, that the technology gap is bigger in low capital intensity industries; second, that as capital intensity rises wage dispersion tends to fall; third, that low capital intensity industries contribute more to the overall wage dispersion in 1970.

In panel (b), we find different implications from the 1970 case. A 0.9 wage quantile has a slightly greater slope at a given level of capital intensity than a 0.1 wage quantile, though the slope estimates of three wage quantiles are not statistically different. This result implies: First, that high-capital intensities have a *relatively* larger technology gap; second, that compared with the 1970 case, as capital intensity rises wage dispersion *relatively* rises; third, that the overall wage dispersion is affected *relatively* more by high capital intensity industries in 1995.

In Table 3, we present the wage dispersion at given capital intensity. The conditional wage dispersion is measured by the conventional scale parameter consisting of 0.25 and 0.75 quantiles,[9] $(\hat{Q}_{0.75}(y|x)-\hat{Q}_{0.25}(y|x))/(\hat{Q}_{0.75}(y|x)+\hat{Q}_{0.25}(y|x))$, and by the interquantile distance between 0.9 and 0.1 quantiles, $\hat{Q}_{0.9}(y|x)-\hat{Q}_{0.1}(y|x)$.[10] In

[8] We do not report here the t-test statistics for the null hypothesis of equality between the two slope coefficients in adjacent quantiles, but the result tells that the marginal effect at 0.1 wage quantile is greater than that at 0.9 wage quantile.

[9] For references on the statistics and their properties, see Oja (1981) and Ruppert (1987).

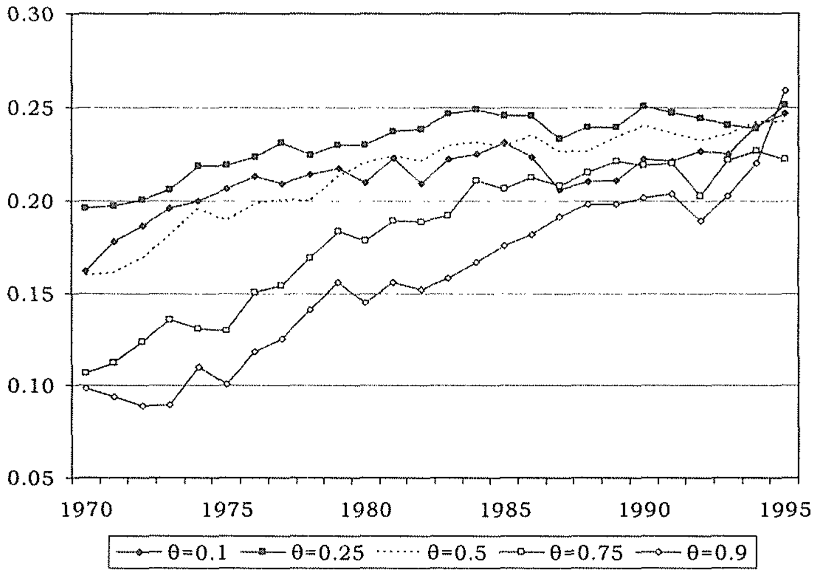


FIGURE 4
CHANGES IN THE MARGINAL EFFECT: 1970-1995

terms of the scale parameter, for the low capital intensity industries the wage dispersion has decreased from 0.167 in 1970 to 0.142 in 1995. On the contrary, for the high capital intensity industries it has increased from 0.073 in 1970 to 0.112 in 1995. In terms of the interquantile distance, a similar trend has also been maintained. For the low capital intensity industries it has fallen from 0.524 in 1970 to 0.472 in 1995, whereas for the high capital intensity industries it has risen from 0.387 in 1970 to 0.503 in 1995. These changes in wage dispersion imply that the high capital intensity industries have contributed *relatively* more to the overall wage inequality than the low capital intensity industries in 1995.

Figure 4 keeps track of the changes in the slope coefficient (elasticity of substitution) of the five different quantiles in the U.S. manufacturing sector for the period of 1970-1995. It confirms the empirical results from the two sample years (1970 and 1995) and

[10] Caselli (1999) and Lemieux (2004) employed the same interpercentile range as a measure of wage dispersion.

shows evidently that low-wage quantiles and high-wage quantiles have responded quite differently to changes in capital-intensity: That is, high-wage quantiles have tended to respond to changes in capital intensity more sensitively than low-wage quantiles over time. The graphical pattern reveals the trend in wage dispersion explained in Table 2 and Table 3: Overall wage inequality has become *relatively* more affected by high capital intensity industries from 1970 to 1995 and this trend has been consistent through the time span.

V. Conclusion

Our paper employs the quantile regression method to analyze the changes in wage distribution resulting from changes in capital-intensity and technologies in the U.S. manufacturing sector. This method, unlike the conventional mean regression, enables us to build and trace the changes in the wage distribution since it estimates several different points of the distribution.

We can obtain two main results through this attempt. First, over the time period of 1970 to 1995, the change in wage distribution is well explained by the change in the response of capital-intensity to technologies. During the time span, all wage quantiles have shown to become more sensitive to the changes in capital intensity. In the framework provided in section II, this result implies that the U.S. manufacturing sector has continued to adopt new technologies. Second, the responsiveness of different wage quantiles to the changes in capital intensity is found different across industries. More specifically, it is observed that high-wage quantiles have become more sensitive than low-wage quantiles over time. This result suggests that industries have adopted different technologies and, more importantly, that high (low)-wage industries have adopted superior (inferior) technologies relative to low (high)-wage industries.

From the two main results combined, we can conclude that the technology gap among industries has induced different marginal effects (elasticity of substitution) of capital intensity on wages, and that the different marginal effects due to technologies have produced the observed wage dispersion in the U.S. manufacturing sector during the period. Also, the overall wage inequality was *relatively* more affected by high capital intensity industries from

1970 to 1995. This interpretation is not only consistent with the capital-technology complementarity documented by many empirical studies on this topic but also provides additional evidence for it in a different way.

(Received 13 October 2005; Revised 6 February 2006)

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