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TECHNOLOGY AND THE CHANGE IN WORKFORCE SKILL: AN EXAMINATION OF UNITED STATES LABOR MARKETS 1950-1990

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A Dissertation APPROVED FOR THE DEPARTMENT OF ECONOMICS

BY

Dedication

To the ones who suffered the most through this project, my wife Hanine and my kids Hala and Talal.

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The author wishes to express his gratitude to Dr. Timothy Dunne who directed this research, for his constant encouragement, help and advice which enabled me to complete this dissertation. I would also like to thank all my committee members for their time and helpful comments. The continuous guidance provided by both Dr. D. Huettner, in his capacity as the Department Chair, and Dr. A. J. Kondonassis, as the graduate liaison, is gratefully acknowledged. Special thanks go to Dr. S. Linn for his teachings and inspiration. I also wish to express my appreciation to Dr. W. Clark for accepting a last minute invitation to replace Dr. E. Cunningham as a member of my advisory committee.

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Abstract

This dissertation examines the effects of technological change on the change in the employment (wage) share of skilled workers. The first part of the analysis decomposes the change in the employment share of skilled workers in the United States into within industry and between industry components. The dissertation uses data from the 1950, 1960, 1970, 1980 and 1990 US decennial Censuses. A large within industry component is often interpreted as being consistent with the skill-biased technical change hypothesis. This hypothesis argues that the observed increase in relative wages of more educated workers is due primarily to changes in labor demand driven by changes in technology. The results of the decomposition analysis are consistent with the findings of other researchers suggesting that an increase in the share of skilled workers is driven by a within industry/within region component. However, two specific points are worth highlighting: (1) The between industry component is significantly larger in the 1950s and 1960s compared with the 1970s and 1980s. (2) The services sector shows a different pattern than all other industrial sectors where the between industry component dominates the within industry component for the early periods. The time series pattern possibly suggests an association between the widespread diffusion of distributed computing and the change in the skill mix.

In the second half of the dissertation I examine the relationship between changes in skill and alternative measures of technology. The findings of the regression analysis indicate that there is generally a positive relationship between changes in sectoral capital stocks and the change in the wage share of skilled workers. Moreover, I find that computer investment has a strong positive effect on changes in workforce skill. In addition, regressions that include measures of advanced manufacturing technology, such as networks, robots and flexible manufacturing systems, show that the intensity of technology usage is positively related to the change in the wage share of skilled workers. The effect of the technology variable is stronger over longer periods of time. Overall, the findings in this dissertation generally support the hypothesis that technical change is an important factor in explaining changes in the employment share, wage share and relative wages of more educated and skilled workers.

Chapter One:

Introduction

The changes in the wage structure in the 1980s have been the subject of many recent studies. Three major changes have been highlighted in the literature: a rise in the relative wages of more educated workers, an increase in the relative wages of more experienced workers, and the narrowing of the female/male wage differential. The panels of figure (1) presents data on the first of these phenomenon. They plot the employment share of skilled workers, the wage share of skilled workers, and the relative wage of skilled to unskilled workers for the US economy over the period 1950 to 1990[1]. As shown in figure (1), the share of skilled workers in total employment has increased by more than three folds, from 15.2% in 1950 to 48.6% in 1990. Over the same period, the share of skilled workers in the wage bill has also increased from 20.05% to 63.44%, and the relative average wage of skilled workers rose from 1.4 in 1950 to 1.84 in 1990. While the facts are well established, the more difficult question regarding the cause of the change in both the employment and wage share of skilled workers remains under debate.

To explain these changes in the labor market, economists have focused on three broad classes of explanations: changes in labor supply, changes in labor demand and changes in labor market institutions. The supply side explanation is investigated in

[1] In figure 1, a skilled worker is defined as a worker with more than a high school education.

Katz and Murphy (1992) among others, and their findings suggest that the increase in the relative wage of skilled workers was accompanied by an increase in the supply of these type of workers, contrary to the predictions of the supply side story. A similar conclusion is reported by other researchers including Berman, Bound and Griliches (1994) and Murphy and Welch (1992). Given that the increase in the supply of skilled workers during the 1980s should result in downward pressure on the relative wage of skilled workers, the fact that relative wages of skilled workers increased suggests that there may have been a relative shift in labor demand towards more educated and more experienced workers. Moreover, the relative demand shift for these types of labor, which creates a pressure to increase the relative wage of skilled workers, dominates (in terms of magnitude) the downward pressure on the relative wage caused by the increase in the supply of skilled workers.

Two major demand-side explanations are present in the literature, shifts in international trade and skill-biased technological change. First, the international trade explanation is twofold: (1) Outsourcing where moving unskilled labor-intensive production facilities to developing countries leads to the decline of both the relative wage and the employment share of unskilled workers, and (2) Competition where import penetration causes a reduction in the number of unskilled jobs in the US and a fall in the relative wage of unskilled workers. Empirical findings provide mixed results for the significance of international trade in explaining the increase in the relative wage of skilled workers. Sachs and Shatz (1994) examine the relationship between international trade and the wage structure in the US. Their findings suggest that trade is a major cause of wage inequality, and that a combination of trade and technological change together explain the rising ratio of skilled workers in total employment and the increase in their relative wages. Murphy and Welch (1992) also examined the significance of trade in explaining wage inequalities using a labor supply and demand framework. Their findings indicate that imports have some effect on relative wages, but not large enough to fully explain the changes in the wage structure. In addition, evidence from between versus within industry decompositions' studies find that most of the change in skill occurs within industries. According to the trade explanation, one would expect most of the wage variation to come from the between industries component since changes in the trade environment are viewed as differentially affecting demand across industries. Evidence shows that the within industries component in the wage variation is more dominant suggesting within industry skill upgrading (see Berman, Bound and Griliches (1994) and Dunne, Haltiwanger and Troske (1996)).

The second demand-side explanation is skill-biased technological change which argues that the adoption of new technology in production has increased the demand for skilled workers. For example, replacing the assembly line process by robots leads to the substitution of low skill workers by workers with higher skills. Skill-biased technical change explanation has been explored through indirect evidence provided by either the decomposition analysis, or by different proxies of technologies used in regression analysis. In decomposition analysis, technological change is assumed to cause a shift in the demand for skilled workers across industries, therefore, one would predict the within industries component in the wage variation to be dominant. As cited above, most researchers find the change in the wage share of skilled workers to be dominated by the within industries component.

Another approach is to examine the validity of the relationship between changes in workforce structure and wages and measures of technological change. Measuring technological change appears to be the most challenging issue in this regard. Many researchers treat technological change as the residual claimant theory (Topel (1994)), with the implication that if it is not trade or supply side effect, then by default it must be technology. There is a growing number of studies, however, that have begun to construct measures of technical change. The different measures include such variables as: R&D intensity, capital/labor ratio, employment share of scientists and engineers and investment in computers as a share in total investment. Most of these measures are based on the assumption that technology is embodied in capital, therefore measures of capital deepening or capital intensity will be a good proxy of technology intensity. The strengths and weaknesses of these measures are discussed in chapter two. The findings of Berman, Bound and Griliches (1994), Bound and Johnson (1992), Dunne, Haltiwanger and Troske (1996), among others, suggest a positive relation between measures of technology and the change in the wage share of skilled workers.

In general, the findings of researchers that have examined both the increasing wage differentials in the US and the shift toward more skilled workers in certain sectors, have argued that technological change has been a major driving force behind the increase in the demand for skilled workers. The goal of this dissertation is to further examine the relationship between changes in workforce structure and technical change. The first part of the analysis extends the decomposition literature by constructing new decompositions that include both industry and region dimensions. This is important because if the skill-biased technical change hypothesis is correct then skill upgrading should be present both within industry and within region. Second, this dissertation extends the literature that models changes in workforce structure as a function of changes in technology. The dissertation constructs new measures of technological change including measures of advanced manufacturing technology and plant entry and exit.

In addition, this dissertation provides a detailed examination of the non-manufacturing sector which is often overlooked in the literature. Most of the research cited above has been limited to the manufacturing sector[2]. This raises a question about the generality of their conclusions as it pertains to the non-manufacturing. This is especially important since non-manufacturing accounts for around 80% of total US employment.

The first part of the analysis decomposes the aggregate change in the workforce skill into within and between industry components at both the aggregate and sectoral levels (similar to Berman, Bound and Griliches (1994)). The main findings of the decomposition analysis is that the within component is large relative to

[2] See for example Berman, Bound and Griliches (1994), Bound and Johnson (1992), Davis and Haltiwanger (1991), Dunne and Schmitz (1995), Sachs and Shatz (1994), Van Reenen (1993).

the between component. This is consistent with previous research. However, the findings of this research show that the services sector follows a different pattern than manufacturing, where the between industries component in the variation of the employment share of skilled workers is almost as large as the within component. Moreover, the time trend shows that sectoral contribution of the between and within components is significantly different in the 1950s and 1960s as compared to the 1970s and 1980s. Thus, the basic decomposition patterns are not uniform across sectors or across time.

With respect to regional issues[3], agglomeration economies and the clustering of certain industries in certain locations (i.e. high tech centers in the Silicon Valley in California and Route 128 in Massachusetts) suggest unequal regional skill distribution in the US. For example, Topel (1994) argues that there has been some difference in the regional distribution of wage inequality, and the greater increase in inequality has been in the west region of the country because of the increased immigration of low skill workers, mainly Hispanics and Asians. In this dissertation, both decomposition and regression analysis are used to examine whether there are significant differences in changes in the skill structure of the workforce between different regions in the United States. The results of the decomposition suggest that most of the variation in the change in the wage share of skilled workers is due to the within region component.

The next set of analysis model the relationship between measures of technological change and the change in the wage (employment) share of skilled

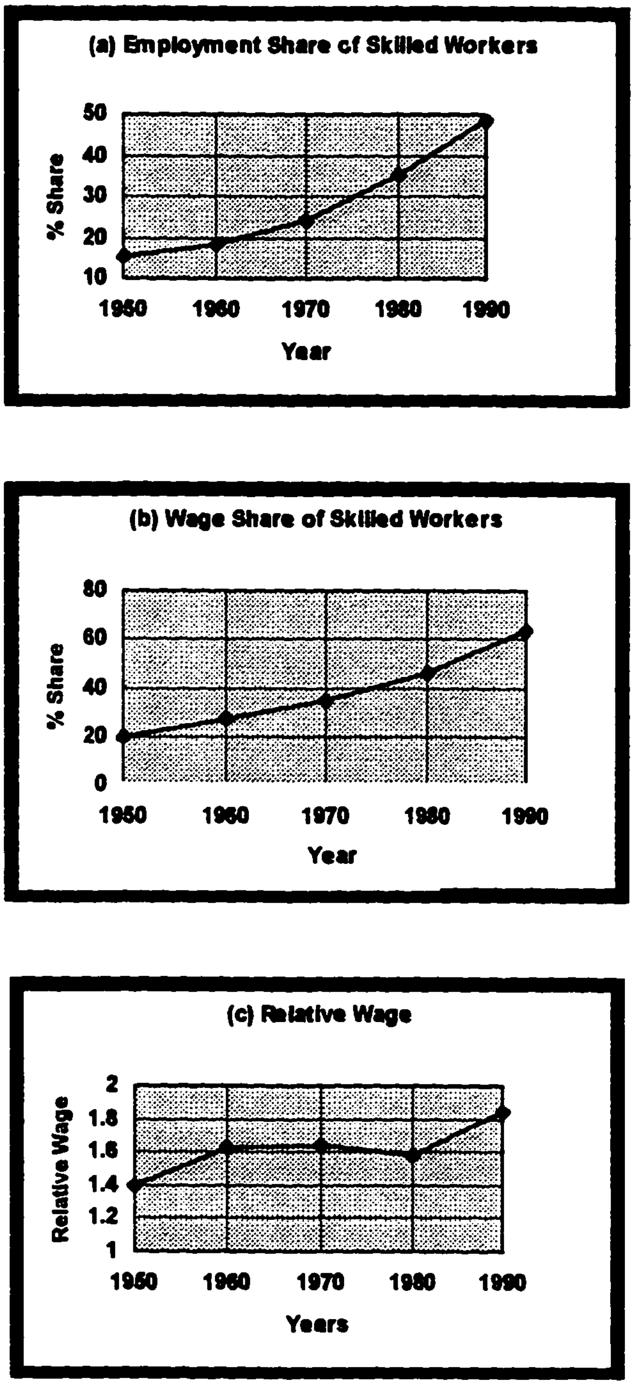
[3] Regions are defined according to the Bureau of the Census as presented in Table 2.

workers. A number of different measures of technology are used to examine the relationship between technology and changes in workforce skills. The capital/output ratio and the share of computer stock in total capital stock are used to examine the effect of both capital deepening and changes in the quality of capital (computer investment) on the change in the wage share of skilled workers. The empirical results show that both capital deepening and investment in computers are positively correlated to the change in the wage share of skilled workers. Moreover, comparing the magnitude of the two capital investment variables indicate that the computer variable has a stronger effect on the change in the wage share of skilled workers than non-computing capital investment.

In addition to examining the relationship between computer investment and changes in workforce structure, I also examine the relationship between advanced manufacturing technology and workforce skill. The effect of advanced manufacturing technology on the change in the skill mix is examined using a technology intensity variable from the Census Bureau's recent Survey of Manufacturing Technology. The variable measures the use of such technologies as flexible manufacturing systems, robots, networks and computer numerically controlled machines. The regression results suggest a positive correlation between the technology variable and the change in the wage share of skilled workers, the effect of technology is stronger over time.

The dissertation is structured as follows: Chapter II reviews the literature including a discussion of the methodologies used in the literature and main issues and empirical findings. Chapter III is divided into three parts related to the decomposition methodology: the first part explains the structure and intuition behind the decomposition model, the second part describes the data set used in this chapter, and the last part investigates the sectoral, regional and metropolitan differences in the distribution of skills. Chapter IV describes the data and methodology used in the regression analysis, along with the empirical results. Chapter V provides closing remarks.

Figure (1)



Source: IPUMS files 1950/1990

Chapter Two:

Literature Review

2.1. Overview:

The rise in the relative wage of skilled workers was pronounced in the 1980s and has attracted many researchers to study its potential explanations. As shown in figure (1), both the employment and the wage share of workers with more than a high school education have increased by more than three fold between 1950 and 1990. Moreover, the relative wage of skilled workers has increased from 1.4 in 1950 to 1.84 in 1990. The rise in the relative wage of skilled workers is a result of both an increase in the price of skill and a sharp decline in the absolute real wages paid to less skilled workers (Gottschalk (1997)). Although the rise in both the wage inequality and the employment share of skilled workers is a widely reported and established fact, controversy still remains over the explanation of these patterns.

There are several alternative explanations as to the increase in both the wage inequality and skill upgrade in the US workforce over the last 40 years. These explanations include: The supply side explanation, the institutional explanation and the demand side explanation. In a simple supply and demand model, the wage gap between different groups of workers (skilled and unskilled) can increase either because of an increase in the demand for skilled workers relative to unskilled workers, or because of a decrease in their relative supply. The effect of changes in the relative supply of skilled workers on the wage gap is straightforward. If the stock of skilled workers grows proportionally faster than does the stock of unskilled workers, then the relative wage of skilled workers will fall, ceteris paribus.

On the demand side, the main competing explanations for the increase in wage inequality are the skill-biased technological change and international trade. The first explanation argues that changes in production practices, mainly the widespread use of computers and related technologies, have increased the demand for more skilled workers, and consequently, their relative wage. The trade story argues that both outsourcing and import penetration have shifted the demand away from unskilled workers. The cheap unskilled labor in developing countries has attracted many US firms to move their unskilled intensive production facilities to other developing countries to benefit from the lower cost of less skilled workers. Moreover, import penetration reduce the demand for low skill intensive goods produced locally because of the cheaper imported goods. As a result, demand for unskilled workers will decrease also, and the competition between unskilled workers for the remaining local jobs reduces their relative wage.

The institutional explanation comes in many shapes and colors, however, only two will be highlighted: Minimum wage and the decline in unions' power. The minimum wage sets a floor to the lower tail of the wage distribution, as a result, it tends to reduce the level of wage inequality. The magnitude of the effect of minimum wage depends on its level relative to other wages and on the number of workers affected by minimum wage. The real value of the minimum wage decreased by more than 30% during the 1980s, leading to increased wage inequality (Fortin and Lemieux (1997)). The other institutional factor that affected wage inequality is the decline in unions' power. Union members usually earn higher wages than non-union members, therefore the increase in collective bargaining coverage should reduce wage inequality. The rate of unionization has declined precipitously during the 1980s, suggesting the possibility that this decline played a role in increasing the wage gap between different groups of workers.

Researchers used two main statistical models to examine the factors causing the change in the wage share of skilled workers: the decomposition and the regression models. The first model decomposes the change in the wage (employment) share of different types of workers in order to determine whether the change is due to within industry or between industry variations. The between industry variation is interpreted in the literature to endure both the trade and the institutional explanations, alternatively, the within industry variations in the change of the wage share of skilled workers is interpreted to support the skill-biased technological change explanation.

The second statistical model used in the literature attempts to test the validity of the different explanations of the change in the wage share of skilled workers using regression analysis. The wage share of skilled workers in the total wage bill is modeled as a function of imports, unionism, size, supply factors, and a proxy of technological change in order to test the significance of each of these variables on changing the wage share of skilled workers. The main problem in applying this method for the current purpose is the lack of measures for technical change. To overcome this problem, researchers use different proxies for technical change raising a question about the quality of these proxies.

In the following sections of this chapter, I will review the literature dealing with the increase in wage inequality, with emphasis on the empirical findings, the way skill has been defined and the proxies used for technical change. The review of the literature will group the findings of empirical research according to the different explanations of the change in the wage share of skilled workers.

2.2. Review of the Findings of Empirical Research:

(a) The Supply Side Explanation:

In a supply and demand framework, assuming a stable labor demand, a decrease in the supply of a certain type of labor will increase their relative wage. Therefore, the supply side theory explains the increase in relative wage of skilled workers by the scarcity of their supply. This explanation is not supported by the fact that the supply of the types of workers whose relative wages increased during the 1980s, has in fact increased in the US.

Katz and Murphy (1992) tested the hypothesis that wage premiums are caused by a shift in the supply of labor using a simple supply and demand framework. The supply side explanation predicts that changes in factors positively affecting supply of skilled workers will vary negatively with changes in their wages, i.e. assume that the supply of skilled workers is positively related to factor X, then X will be negatively related to the changes in skilled workers' wages. Their findings suggest that changes in relative supply has the same sign as changes in wages, implying that the relative supply of skilled workers and their relative wage have both increased in the 1980s.

Bound and Johnson (1992) regressed the change in the relative wage of different types of workers (grouped by their sex/education/age) on variables representing technical efficiency, labor supply, product demand and institutional factors. Their findings suggest a negative relation between the increased of the relative wage of more skilled workers and their relative supply. The same conclusion was reached by: Berman, Bound and Griliches (1994), Channells and Van Reenen (1994), Murphy and Welch (1992).

Topel (1994 and 1997) examined the regional effects of the supply of different types of labor and technical change on regional wage inequality using data from the March Current Population Survey covering the period from 1972 to 1990. His findings suggest that technological change favors skilled workers, creating an upward pressure on wage inequality, while the increase in labor force schooling creates a downward pressure on the wage gap. On the national level, the technical change effect is greater than the supply effect causing overall wage inequality to rise. However, across regions, the supply of different types of workers varies because of immigration, affecting the magnitude of wage inequality between different regions.

Topel concludes that the large inflow of low skill immigrants in the west region creates the largest wage inequality among all US regions.

In general, there is no evidence in the literature to support the supply side explanation, and it has been considered a weak explanation of the changes in the wage share of skilled workers in the 1980s.

(b) The Institutional Explanation:

Only two institutional explanations will be highlighted in this section: Minimum wage laws and the decline in unions' power. The minimum wage sets a floor on the lower tail of the wage distribution, as a result, it tends to reduce the level of wage inequality. The other institutional factor that affects wage inequality is the decline in unions' power. Union members usually earn higher wages than non-union members, therefore an increase in collective bargaining coverage should reduce wage inequality.

The institutional explanation predicts that the decline of the union power in the 1980s caused the wages of unskilled workers to decline. Bound and Johnson (1992) tested the validity of this explanation by including a variable to represent the union effect in their labor demand equation. Their findings suggest that the unions, in general, have a weak effect on wages, therefore, the increasing wage inequality can not be explained by the fall of unionism.

Davis and Haltiwanger (1991) decomposed the variance of the hourly wage differentials. Their findings cast doubt on the significance of unions, they concluded that deunionization has little role in explaining the increase in the wage dispersion over the period 1975-86. This conclusion was further supported by the findings of Channells and Van Reenen (1994) using data from the UK.

Another institutional explanation claims that a decline in real minimum wages will increase wage inequality. According to this explanation, any real increase in the minimum wage will result in decreasing unskilled employment because firms will choose to substitute unskilled workers by more skilled labor. Therefore, the minimum wage increase in the 1980s has caused the shift in the skill mix. There are two main weaknesses associated with this explanation. First, minimum wage workers have a low share in total employment in both the US and UK, and in fact minimum wages did not increase significantly in real terms through the 1980s[4]. Second, even if there was an increase in minimum wages that caused the change in the employment share of skilled workers, it should be accompanied by narrowing the wage gap between skilled and unskilled workers. In fact the employment share of skilled workers and the wage gap have both increased, implying that this explanation is inconsistent with actual observation.

Howel (1995) provides an alternative story along the same lines. He argues that US companies have been competing mainly through reducing domestic wages and by shifting production facilities to low wage countries. As a result, the drop in unskilled workers wage explains the change in wage structure. Moreover, Howel

[4] See Channells and Van Reenen (1994) and Fortin and Lemieux (1997) for a discussion of the minimum wage and union power trends in both the US and UK.

argues that given the low wages, unskilled workers have less incentives to work and may prefer to depend on the social welfare system, leading to a drop in their share in total employment. In general, empirical findings do not support the institutional explanation for the change in the employment share of skilled workers.

(c) Demand Side Explanations:

None of the explanations cited so far has received significant empirical support, which leaves us with the demand side explanations. In fact most of the on-going debate in the literature centers on two major demand side explanations for the change in the wage share of skilled workers: international trade and skill-biased technological change.

(1) International Trade:

According to the international trade explanation, the major economic event in the US since the late 1970s is the expansion of trade with the rest of the world. At the same time other countries, especially developing countries, opened their markets to foreign investment. Severe competition with developing countries, who are low-wage (and low skill) labor intensive economies, makes the US concentrate on skill and capital intensive products. Hence, unskilled labor wages and share in total employment are decreasing due to the competitive advantage of imported products, which is low-wage labor intensive. Moreover, US firms have been moving their production facilities of low-skill labor-intensive products to the developing countries to take advantage of the cheap labor cost, adding more pressure on the wages and employment of unskilled workers.

Sachs and Shatz (1994) examine the relation between trade and the wage structure for the US. Their findings reveal that trade with low-wage countries is more disruptive in terms of the net change in wage differentials and employment shares favoring higher levels of skill. Moreover, low-skill industries have the largest proportionate drop in employment arising from increased import penetration. Sachs and Shatz's evidence points more towards shifts in trade and market prices than towards shifts in productivity as a relevant factor in widening wage inequalities. They conclude that trade is a major cause of inequality in wages, and that the combination of trade and technological changes together explain the rising ratio of skilled workers in total employment and the increase in their relative wages.

Murphy and Welch (1992) attempted to explain the change in wage structure using a supply and demand framework. They examined three possible scenarios for the shift in labor demand: as a normal trend, as a trend caused by the expansion in trade, and as a normal trend accelerated by the expansion in trade. Their findings suggest that imports have some effect on relative wages, but not large enough to fully explain changes in wage structure [5] .

Following the same track and using similar data set, Katz and Murphy (1992) used both a supply/demand framework and decomposition analysis to examine the

[5] Similar findings were reported by Murphy and Welch (1993).

correlation between trade competition and the change in wage inequality. Their results suggest that demand shifts arising from trade competition are in the right direction but too small to explain the change in relative wages. Moreover, the majority of the change in the relative wage of skilled workers is caused by within industry variations. Since the majority of the change in the relative wage of skilled workers is caused by within industry variations, Katz and Murphy conclude that technological changes might be the reason behind the increase in wage inequality, though its effect is hard to measure.

Borjas and Ramey (1994) apply time series analysis (cointegration technique) to evaluate the most common explanations for the increase in wage inequality, using annual data from the Current Population Survey for the period from 1963 to 1991. Their findings suggest that the only variable that consistently shares the same long run trend with wage inequality is the durable goods trade deficit as a percentage of GDP, not only for the 1980s but since 1949.

In the same direction, Bernard and Jensen (1997) examine the effects of exports on wage inequality, using plant level data for the manufacturing sector covering the period 1976-1987. They decomposed the share of skilled workers into within plants and between plants. Afterwards, the within/between components are regressed on variables representing technology and exports, their findings indicate that the increase in plant technology determines the within plant skill upgrading but not of the aggregate wage gap rise. Moreover, the increase in employment at exporting plants contributes heavily to the observed increase in relative demand for skilled workers in manufacturing. Exporters also account for almost all of the increase in the wage gap between skilled and unskilled workers.

In general, empirical evidence suggests that international trade plays a role in explaining the change in the employment (wage) share of skilled workers, though it is not the main factor affecting wage inequality.

(2) Skilled-Biased Technological Change:

The shift in labor demand towards skilled workers, according to the last explanation, is caused by the adoption of new technology that increased the demand for skilled workers at the expense of unskilled workers. It is argued that the widespread adoption of computers and related technology throughout the economy has increased the productivity (and consequently the demand) of skilled workers. As a result of this type of skill-biased technological change, both relative wages and share in total employment of skilled workers have increased (Johnson (1997)).

In his review to the Bureau of Labor Statistics (BLS) research regarding the effect of technological change on employment in the US, Mark (1987) argues that new technology is helping to change the structure of occupations by increasing the demand for higher skill workers at the expense of low skill workers.

Allen (1991) examines how non-neutral technological changes in production are related to changes in the wage structure using cross-section regression analysis. He regresses three dependent variables as proxies of skill (rate of return on schooling, log wage gap of schooling, wage gap for experience) on four different proxies of technology: R&D intensity which is proxied by employment share of scientists and engineers, capital recentness, growth in capital/labor ratio, and total factor productivity growth. Out of the four proxies for technology, only R&D intensity had a significant effect on the demand for skill. Allen's findings indicate a strong correlation between R&D intensity and both return to schooling and experience, implying a strong association between these measures of technological changes and the change in wage structure.

Davis and Haltiwanger (1991) examine different explanations for the rise in wage inequality in the US using a decomposition model on plant level data. Their findings indicate that unions and trade have little role in explaining wage dispersion, and that the most likely cause of the increase in wage inequality is skill-biased technological change. Moreover, plant size is found to be an important factor affecting wage dispersion. In the same context, Reilly (1995) examines the firm size-wage effect and its relation to innovation. His results indicate that human capital investment and technical innovation are complements. Moreover, the size-wage effect can be explained by the fact that larger firms usually adopt new technological improvements before small firms.

Dunne and Schmitz (1995) use a direct measure of technology intensity to test the relationship between the use of advanced technology and employer size-wage premia. Their findings suggest that differences in technology usage is related to significant wage differences. Moreover, when information about technology is included in the wage regressions, the size-wage premia is significantly reduced.

Bound and Johnson (1992) examine a range of alternative hypotheses to explain the change in the wage structure. They regressed the change in wages for different types of workers on variables representing: technical efficiency, supply of labor, product demand, and institutional factors. Their results indicate that the main reason for the change in the wage structure is a combination of skill-biased technological change and changes in unmeasured labor quality. Berman, Bound and Griliches (1994) conduct a similar test using both decomposition and cross sectional analysis. Their results suggest that most of the change in both wage and employment structure is due to skill upgrading within industry, implying that skill-biased technology is an important factor explaining the change in the wage and employment structure [6]. To further investigate this issue, Berman, Bound and Machin (1994) study the change in employment structure in nine developed countries using a similar methodology to the one used by Berman, Bound and Griliches (1994). Their evidence shows that skill-biased technological change is a major cause of the change in wage inequality. Moreover, skill upgrading occurred within the same industries in most of the countries in the sample. Industries with large contribution to skill upgrading are machinery, computers, electrical machinery, and printing and publishing.

[6] The same conclusion was reached by Mark (1987), Allen (1991), Davis and Haltiwanger (1991), Reilly (1995) and Dunne and Schmitz (1995).

Finally, Autor, Katz, and Krueger (1997) believed that more insight on the skill-biased technological change analysis can be gained by: using a supply and demand framework, examining a longer time period than 1980s and 1990s, and comparing manufacturing and non-manufacturing sectors. Their findings indicate that skill-biased technological change started in the 1970s, "but its effects on wage differentials did not show up till the deceleration of the growth of supply of college graduates in the 1980s". Moreover, decomposition analysis shows a different pattern between manufacturing and non-manufacturing sectors. The within-sector college wage bill share growth is much higher in the 1980s than the 1970s for manufacturing, the opposite is true for non-manufacturing. Occupations with higher average pay and higher educational levels have a tendency to expand in sectors that adopted computers at a faster rate.

In conclusion, there is a growing body of evidence in the literature favoring the demand side explanations, where both skill-biased technical change and international trade have a significant role in explaining the change in the wage share of skilled workers. However, through a process of elimination many researchers argue that skill-biased technological change is the main force behind rising wage inequality in the 1980s.

2.3. Empirical Findings regarding the Regional differences in the Skill Mix:

Many researchers attempted to investigate income inequality across different US regions or according to rural/urban status. Topel (1994) tested whether regional differences affect wage inequality among workers of different skills. He used a model of factor demand with data from the March CPS covering the period from 1973 to 1991. Topel found that technological change is skill-biased raising overall inequality. Alternatively, the increase in the supply of skilled workers reduces inequality, until now, the technology effect has dominated the supply effect. Additionally, on the regional level, Topel found no evidence that different regional evolution of wages are demand driven, the whole story, he believes, is on the supply side. Moreover, since the change in labor supply varies across regions, changes in inequality vary also, and the lower the quality of labor supplied, the greater the increase in wage inequality. Therefore, the greatest increase in inequality has been in the west region of the country because of the increased immigration of low skill workers, mainly Hispanics and Asians.

Little and Triest (1996) examine the geographic dimension of technology diffusion in the US manufacturing sector. They use data from the Survey of Manufacturing Technology (SMT hereafter) and run a negative binomial regression analysis. Their findings indicate that geography does make a difference in the speed of adoption of advanced technology, and human capital appears to be an important factor causing the above mentioned difference, i.e. access to skilled workers, defined as workers with high school education or more, is associated with faster rate of technology adoption.

Nissan and Carter (1993) used the 1991 Bureau of Economic Analysis data to examine income inequality across regions over the period from 1929-90. Their findings show a substantial income inequality among regions in the early portion of the period under study, inequality then declined until the late 1970s with differences continuing afterwards.

Regarding the rural/urban (metropolitan) status effect, Renkow (1996) studied the magnitude and causes of the rural/urban earnings differentials using county-level data for North Carolina. His findings show that returns to schooling are significantly lower in rural areas, earnings in rural areas are more sensitive to local labor market conditions, and the divergence in per capita earnings between rural and urban areas is largely attributable to local differences in human capital stock. Chakravorty (1996) analyzed the variation in the distribution of urban income for three different samples: blacks, whites, and both. His findings indicate that local employment conditions and other social factors are important for wage inequality. Moreover, the cause of wage inequality has changed over time from income, racial and industry factors to education, social and demographic factors.

2.4. Measures of Skill and Technical Change:

(a) Skill:

Researchers have mainly used one of two proxies for skill differences: The level of education attainment where a higher level of education implies higher level of skill, and the occupation type, i.e. production workers versus non production workers where production workers are assumed to be less skilled than non production workers.

The problem with the production/non-production definition for skill is that many groups in the non-production type are not skilled workers, i.e. office secretaries and cleaning personnel. As a result, the assumption that production workers are more skilled than non production workers is not always accurate and can lead to confusing results (for more details see Channells and Van Reenen (1994) and Howel (1995)).

The most widely used proxy for skill differences in the literature is education attainment. Bartel and Lichtenberg (1987) argue that highly educated workers have a comparative advantage with respect to learning and adapting to different technologies. The main weakness of this proxy is that it does not take into consideration the substitution effect between different majors in education. For example, in the construction industry, bidding for projects was a job for experienced civil engineers. Recently, construction management (which does not require any engineering background) has been created as a new major to prepare and supervise the bidding process.

(b) Technological change:

Measuring technological changes appears to be the most challenging issue in the attempt to study the forces behind the change in wage share of skilled workers. Because of the measurement difficulty, many researchers treated technological change as the residual of the regression. Johnson (1997) explains this process in the following way: "Admittedly, the preliminary conclusion that technological change caused the relative demand shifts was somewhat tautological: (a) it must be x_1, x_2 or x_3; (b) it was not x_2 or x_3; (c) ergo, it was x_1". Since the residual picks up the effect of all variables excluded from the regression equation, it is a noisy indicator of the effect of technology on the change in the wage share of skilled workers. Other researchers used different proxies such as:

(1) R&D intensity: This measure picks up the effort taken by the firm to improve its product or the production process. In fact, most of the R&D expenditures are oriented towards improving their products as opposed to R&D aimed at improving their production process (Scherer (1984)). The problem with the R&D measure is that it does not tell whether the company's research efforts are fruitful, and whether the firm who originates the innovation has actually used it. This measure was used by Berman, Bound and Griliches (1994), Berman, Bound and Machin (1994) and Sachs and Shatz (1994).

(2) The growth in the capital-labor ratio: Including this variable in the wage equation picks up the effect of capital intensity on the wage structure. This measure includes both types of capital investment: replacing old equipment and acquiring new methods of production. Since the growth in the capital-labor ratio does not separate the two types, it is a noisy proxy for technological change. However, using net capital investment provide a better proxy of technological change under the assumption that technology is embodied in capital. The same argument applies to the use of capital age

as a proxy for technological change. This measure was used by Allen (1991) and Autor, Katz and Krueger (1997).

(3) Employment share of scientists and engineers: This variable is included in the wage equation to pick up the effect of the innovative activity of the firm on the wage structure. Though this is not a direct measure of technology, it is a good proxy for technology because this group of workers usually use advanced technology to carry out their job duties. This measure was used by Allen (1991).

(4) Investment in computers as a share of total investment: Including this variable in the share equation picks up the effect of computer investment on the structure of employment. Though this measure is more related to technological change than the others, it has some weaknesses. First, this measure does not tell who is actually using the computers, therefore, it is difficult to test what level of skill is required to use these machines. Second, there is no information regarding the type of computer, i.e. whether it is used as a scanning machine to help a cashier or as a drawing machine to help an engineer. This measure was used in the literature by Berman, Bound and Griliches (1994), Berman, Bound and Machin (1994) and Autor, Katz and Krueger (1997).

Van Reenen (1993) used a survey containing information about innovation count in the UK manufacturing firms as a measure of technological change. The problem with this measure is that it pinpoints the firm which first developed technologically significant and commercially successful new products and processes, regardless whether that firm used the innovation or not. If the firm does not use the technology, it is unlikely to have any effect on the change in employment structure.

Dunne and Schmitz (1995) used a direct measure of the level of technology intensity used by plants in US manufacturing to study the wage-size premium. The technology variable provides a useful insight to the relation between technology intensity and the change in the wage share of skilled workers. However, since the data is limited to a number of industries in the manufacturing sector, the value of the conclusions drawn from this dataset can not be generalized to the whole economy.

2.5. Summary:

In summary, there is a growing body of evidence in the literature favoring demand side explanations for the change in the wage (employment) share of skilled workers. This trend is based on the increasing evidence supporting this notion from empirical results. However, through a process of elimination, most researchers argue that skill-biased technological change is the most plausible candidate to explain the growth of wage inequality, though they realize the difficulty of measuring and verifying this hypothesis empirically, because of the dependence on indirect measures for technology. Although international trade explanation remains an important factor affecting wage inequality, this study will focus on the effect of technological change on the change of the skill mix. Moreover, recent research is indicating different distribution of the skill mix among different regions, and between rural/urban areas, though little attempt has been made to study the combined effect of industry and region in the distribution of skill.

Chapter Three:

Decomposition Analysis: Theoretical Background and Empirical Results

3.1. Introduction:

This chapter of the dissertation will first discuss the "accounting" procedure used to decompose the change in the employment (wage) share of skilled workers according to the industrial sector, region and rural/urban dimensions. Moreover, the combined effect of industry/region on the change in the skill mix will also be decomposed. The second part of the chapter presents the empirical results for the various decompositions that are conducted in this study.

Decomposition analysis separates the sources of the change in the employment share of skilled workers into within/between industry variations. The between industry variations has been interpreted in the literature to be caused by either trade or institutional factors since these factors will result in the changes in the employment share of skilled workers between industries. However, if within industry variations are the cause of the change in the employment share of skilled workers, this is (i.e. skill upgrading) interpreted by researchers as a result of skill-biased technological change.

3.2. Theoretical Model:

Berman, Bound and Griliches (1994), BBG hereafter, used the following standard decomposition for the change in the share of the workers with skill level **n** :

$$\Delta p_n = \sum_i \Delta s_i \bullet \overline{p_{ni}} + \sum_i \Delta p_{ni} \bullet \overline{s_i} \qquad (1)$$

where,

p_n = the share of skill level **n** in total employment (skill mix).

p_{ni} = skill level **n** employment in industry **i** / total employment in industry **i**.

s_i = employment in industry **i** / total employment .

According to the above formula, the change in the proportion of workers of skill **n**, also referred to as skill mix, is decomposed to between industries (the first part in the right side) and within industries (the second part). Fixing the share of type **n** workers in industry **i** (i.e. holding skill constant), allows only the variations of the employment share of each industry to change. Summing the individual industry variation over all industries yields the between industries component in the change of the employment (wage) share of skilled workers. As a result, the between industries component represents the variation in the skill mix that is caused by the shift in industry employment shares in the economy.

The link between this component of the decomposition analysis and the trade explanation comes from the decline in the demand for unskilled workers caused by outsourcing and import penetration. The low wages of unskilled workers in developing countries, like Mexico, attracts US companies producing unskilled intensive goods to move their plants outside the US to benefit from the cheaper labor cost. This process leads to a fall in the employment share of unskilled labor intensive industries due to changes in the employment shares of industries. Furthermore, competition between unskilled intensive goods produced in the US and cheap imports leads to the loss of local market share to foreign companies. This process decreases the demand for these products, and therefore, reduces their demand for unskilled workers. As a result, the employment share of these industries will decrease, causing a between industries reduction in the employment share of unskilled workers. Both factors (outsourcing and import penetration) cause a reduction in the employment share of different industries, and a between industry variation in the change in the skill mix. Because of this link between the trade explanation and the between industry variations, many researchers interpreted the between industry component of the change in the employment share of skilled workers as support for the trade explanation.

The within industry component is the second part of equation (1) and is calculated by fixing the employment share of each industry, allowing only the employment share of skilled workers in each industry to vary over time. Adding the variations caused by the change in the skill level over all industries, yields the within industry component. Therefore, the within industry component represents the portion of the change in the employment share of skilled workers that is caused by the average increase (or decrease) in the skill level within industries. The interpretation in the literature (BBG) is that the within industry component reflects skill upgrading and the likely impetus for the upgrading is technical change. For example, the adoption of computer technology by firms increases the demand for workers with computing skills. In general, if the new technology is skill-biased, then the industry level use of this technology will increase the demand for skilled workers in that industry. In the literature, researchers use this link between technological change and within industry variations to interpret the latter as an indicator for skilled-biased technological change explanation.

Many researchers who use the decomposition analysis, including BBG, find that most of the change in the wage share of skilled workers is due to within industry variations, suggesting that technological change has caused a shift in the wage and employment structures of skilled workers. For my purposes, this model will be used to decompose the overall change in the share of skilled workers along three different dimensions. First, the industrial sectors dimension where the change in the employment share of skilled workers is decomposed into between/within industries components for each industrial sector. The sectoral decomposition will show whether all sectors follow a pattern similar to manufacturing. Second, the regional dimension in which the change in the employment share is separated into between/within regions components. This decomposition documents whether the change in skill occurs primarily within regions or is due to shifts of employment across regions. Third, the metropolitan decomposition investigates whether the rural/urban (or city center/not city center) changes in skill is due to between or within metropolitan areas.

Equation (1) decomposes the change in the proportion of type **n** workers into between and within industries. If the majority of the change is due to between industries, this will suggest that factors, other than technological changes, have caused the shift in the skill mix of workers. Alternatively, if the change is due to within industries component, which is interpreted in the literature to be due to technological change, then a further decomposition of the within industries component into: within industries/within regions and within industries/between regions (or metropolitan area) will be carried out to investigate the combined effect of industry and region (or metropolitan area) in the distribution of skill. If the shift in employment structure is caused by technological change, we expect the skill upgrade to be within industries/within regions. However, if the change is due to within industries/between regions, then the shift in employment structure is affected by the differences in the regional distribution of the skill mix, i.e. there are significant differences in the supply of skilled workers from one region to another causing the change in the skill mix.

The within industries component in equation (1) can be extended through the decomposition of the proportion of type **n** workers in industry **i**, as follows:

$$\Delta p_{ni} = \sum_{i} \Delta r_{ij} \bullet \overline{p_{nij}} + \sum_{i} \Delta p_{nij} \bullet \overline{r_{ij}} \qquad \textbf{(2)}$$

By substituting the value of $\Delta \mathbf{P_{ni}}$ from equation (2) into equation (1):

$$\Delta p_n = \sum_i \Delta s_i \bullet \overline{p_{ni}} + \sum_i \sum_j \Delta r_{ij} \bullet \overline{p_{nij}} \bullet \overline{s_i} + \sum_i \sum_j \Delta p_{nij} \bullet \overline{r_{ij}} \bullet \overline{s_i} \quad \textbf{(3)}$$

where,

p_n = the share of skill level **n** in total employment .

p_{nij} = skill level **n** employment in industry **i** and region **j** / total employment in industry **i** and region **j.**

s_i = employment in industry **i** / total employment .

r_{ij} = employment in industry **i** and region **j** / employment in industry **i .**

Each of the three terms on the right hand side of equation (3) represents part of the decomposed change in the employment structure, after adding the region dimension. These parts can be interpreted as follows:

(1) The first part is the between industry component of the change in the employment share of skilled workers. This part of the decomposition implies that the change in the employment share of skilled workers is caused by changes in the employment shares of low-skill industries or high skill industries. This is often interpreted by researchers to be consistent with the international trade explanation.

(2) According to the second part of the equation, within industry/ between regions component, skill upgrading occurs across all industries, but at different regional rates. This component represents Topel (1994) story regarding the regional differences in wage inequality. According to Topel, wage inequality is driven by technological change at the national level, however, regional differences in the supply of skilled workers makes the magnitude of wage inequality differ from one region to

the other. For example, assume that the oil industry operates in two states which have different skill distributions: Texas (where the skill level is 4) and Oklahoma (the skill level is 3). If each state has 100 workers in the oil industry in 1980, then the overall industry skill level is 3.5. Assuming that the oil industry decided to take advantage of the high skill labor market in Texas and move part of their operations from Oklahoma to Texas, as a result, the number of workers decreased to 50 in Oklahoma and increased to 150 in Texas. Though the skill level did not change either in Oklahoma or in Texas, the overall industry skill level has increased to 3.75. The increase in the skill level in this case is driven by the regional differences in the supply of different levels of skilled workers.

(3) The third component represents the within industries/within regions component. To calculate this component, both the employment share of industry **i** in total employment and the employment share of industry **i** in region **j** in total employment in industry **i** and region **j** are held constant. Therefore, only the effect of the change in the employment share of skilled workers in region **j** and industry **i** varies over time. As a result, this component captures the variations in the employment share of skilled workers that is caused by the upgrade of skill within industries and regions. Thus, if individual plants were adopting new technologies which leads to changes in the skill level of the workforce, then I would expect a large within industry and within region component.

3.3. Description of The Data:

The Integrated Public Use Microdata Series (IPUMS) is used to perform the decomposition analysis[7]. The IPUMS consists of a series of individual level representative samples from the US decennial census for the years 1850, 1880, and from the period 1900 to 1990. These samples are independent, and they include information on a broad range of population characteristics such as: Wages, labor force participation, occupations, industry, geographic location, fertility, immigration, internal migration, education and other demographic characters. Each IPUMS sample consists of household and individual records. Household records contain information pertaining to an entire household or group quarters residence. Each household record is followed by a series of person records which contains information about each sampled individual in the unit.

This dissertation is using the IPUMS samples for the period from 1950 to 1990. Each of these samples has a 1% density. The total number of personal records in each sample is (in thousands): 1922 for 1950, 1800 for 1960, 2030 for 1970, 2267 for 1980 and 2500 for 1990. In decomposing the change in the share of skilled workers, researchers used one of two definitions for the share of skilled workers: either their share in total employment or their share in total wage bill. In the IPUMS, INCWAGE is the variable that indicates the respondent's total pre-tax wage and salary

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[7] IPUMS, Version 1.0 was created by the Social History Research Laboratory at the University of Minnesota in August 1995. It consists of twenty three samples of American population drawn from eleven censuses, the IPUMS combines them into a single database that assigns uniform codes across years.

income for the previous year. Though this variable allows for a great deal of comparison across years, there are two main problems that limit the use of this variable. First, the IPUMS use the code (999999) when the wage information is not available, therefore, we have to drop all observations with this code before calculating the share in the wage bill. As a result, the sample size drops drastically, especially for the earlier years, i.e. the sample size dropped from 772,640 to 178,746 for the year 1950. Secondly, the wage amounts are expressed in codes that represent midpoints of intervals rather than exact dollar amounts. Each year has a top code representing the midpoint of the next logical interval. Top codes are: 10,050 for 1950, 25,500 for 1960, 50,050 for 1970, 75,005 for 1980, for 1990 all amounts higher than 140,000 are expressed as the state median of all values exceeding 140,000 [8]. For 1950 and 1970, the codes represent the midpoints of hundred-dollar intervals. For 1960, the codes 50 to 9950 represent the midpoints of hundred-dollar intervals and from 10,500 to 24,500 represent the midpoints of thousand-dollar intervals. For 1980, the codes represent the midpoints of ten-dollar intervals. Because of those two problems, the share in the wage bill is not accurate and may under-represent the upper tail of the distribution. As a result, this paper will primarily use the share in total employment measure throughout the decomposition analysis. The share in the total wage bill measure will be used occasionally.

[8] For more details regarding the wage variable see the IPUMS User's Guide Data Dictionary, pages P166-171.

The IPUMS was used to create cells that include information about the number of workers grouped according to their skill type, industry and geographical location. Three different definitions of skill were created, to examine whether the way we define skill makes a difference in the pattern of the distribution of skills:

(1) According to the level of education, skilled workers are defined as the workers with more than 12 years of education, i.e. workers with one or more years of college, this definition will be called the **edu definition** .

(2) The second definition of skill is based on worker's occupation, a form of blue collar/white collar definition which will be denoted as the **occ definition**. According to this definition, a worker is considered skilled if his occupation falls in one of the following categories: Professional and technical, farm owners and farm managers, managers and officials, clerical (except: cashiers, collectors, dispatchers, mail carriers, office machines operators, shipping and receiving clerks, telegraph and telephone operators and kindred jobs), sales workers (except: newsboy), foremen, inspectors, jewelers and watchmakers, locomotive engineers, mechanics, motion picture projectionists, opticians, photoengravers, piano repairmen, stationary engineers, firemen, marshals, policemen and detectives, sheriffs.

(3) The last definition of skill is based also on occupation, but more of a high tech jobs vs. other jobs, we call it the high tech **(HT) definition**. According to this definition, skilled workers are those in the following occupations: Engineers, scientists, computer analysts and researchers, mathematicians, health technologists, science technicians, engineering technicians, other technologists and technicians. This definition may have problems because of the fact that certain occupations (mainly the computer related) were not around in 1950.

It is important to mention that the occupation variable used in the second definition of skill is different than the one used in the third definition. The IPUMS include two variables for occupation (OCC and OCC1950) and two variables for industry (IND and IND1950)[9] . Occupation and industry are among the most problematic census variables in terms of comparability. This is because each census year has coded occupation and industry according to the current Census Bureau classification scheme, which changes considerably over time. The different classification schemes are recorded in the variables IND and OCC in the IPUMS files. To make those variables more comparable, a new variable was created by the Social History Research Laboratory (SHRL) at the University of Minnesota based on the 1950 occupational and industrial coding schemes. The schemes recoded the information contained in the IPUMS variables OCC and IND into the 1950 Census Bureau occupational and industrial classification systems, creating the variables OCC1950 and IND1950. The variable OCC1950 is used in the **occ definition** of skill, while OCC is used in the **HT definition**. Since the classification is different from one census to the other, it was more practical to depend on the IPUMS recoding efforts. On the other hand, we used the OCC variable for the HT definition because it involves a small number of occupations some of which did not exist in 1950 such as computer related jobs.

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[9] See IPUMS User's Guide Data Dictionary, pages P132-137 for industry details, and P118-127 for occupation details.

To enhance the comparability of industry data across all years, we use the IND1950 variable which recodes the information contained in the IPUMS variable IND into the three digit 1950 Census Bureau industrial classification system. The IND1950 variable is also used to classify workers by 1-digit industry sectors as shown in table (1).

For the geographical dimension two variables were used REGION and METCCITY. REGION identifies the household's census region according to the 1990 census regional classification system as shown in table (2), while METCCITY indicates whether households resided within a metropolitan area's central city, or not according to the following coding: (1) Not in SMA, (2) Central city, (3) SMA not central city, (4) SMA central city not known, (5) Area type unknown.

Before proceeding to the empirical results of the decomposition of the employment share of skilled workers, a description to the time trend of the IPUMS data is presented in the four panels of table (3). The employment share of the IPUMS data samples is broken by: industrial sector, occupation, census region and metropolitan status for the period 1950-1990[10] . Panel (a) shows significant shifts in the employment share across industrial sectors over the period 1950-1990. The largest decline was in agriculture (from 14.9% in 1950 to 3.5% in 1990) and manufacturing (from 26.75% in 1950 to 17.6% in 1990), while the largest increase was in services (from 16.2% in 1950 to 32.4% in 1990) and financial services (from

[10] Shares may not add up to 100% due to rounding.

2.9 in 1950 to 6.2% in 1990) and trade (from 18.3% in 1950 to 22.2% in 1990). Panel (b) show the employment share by occupation over the period 1950-1990. Most of the occupations witnessed a drop in their share, the sharpest drop was in: farming jobs, operatives and craftsmen. Alternatively, professional and managerial jobs increased from 14.9% in 1950 to 29.7% in 1990, clerical jobs increased from 11.1% to 18.7% while service workers increased from 9.9% to 14.6% for the same period. Employment share by region show a decline in most regions except: South Atlantic (increased from 14.1% to 18.3%), Pacific (from 9.7% to 14.55%), mountain (from 3.4% to 5.9%) and West South Central (from 9.7% to 11.0%). According to panel (d), employment share dropped from 43.3% to 28.9% for the areas not in SMA, and from 28.9% to 16% for central city areas, over the period 1950-1990. Alternatively, areas in SMA but not city center increased from 20.5% to 26.8%, and areas in SMA with city center unknown increased from 7.2% to 25.1%. The sharp increase in the share of SMA with city center unknown will make it difficult to assess whether the period from 1980 to 1990 has witnessed a new (declining) trend in the share of SMA but not central city areas, or that the decline is due to the sharp increase in the share of SMA with unknown city center.

3.4. Sectoral Differences in The Skill Mix:

Most researchers focused on the manufacturing sector, and it appears that most studies point to technological change as a plausible explanation for the patterns observed in manufacturing [11]. Since manufacturing makes up approximately 17% of the work force (see table 3a), this raises a question whether the pattern observed in manufacturing is found in other industrial sectors. Table (4) shows the trend of the labor share of skilled workers, by industrial sectors, for the three definitions of skill. According to the education and HT definitions, all sectors witnessed a positive increase in the share of skilled workers, but at different rates. For example, based on the education definition (panel a), the share of skilled workers increased by almost seven fold in agriculture, from 4.53% to 28.95%, compared with less than twofold in services, from 31.45% to 61.06%. A similar trend is shown in panel (d) of the same table, where the wage share of skilled workers (based on the education definition) in the total wage bill has increased for all sectors. The occupation definition (panel b) does not show the same consistency across all sectors, though most sectors still show a positive change in the share of skilled workers. However, the employment share of skilled workers (based on the occupation definition) in the agriculture sector decreased from 59.49% to 45.07% from 1950 to 1990, trade declined from 57.64% to 44.48%, and public administration dropped from 58.17% to 51.07% for the same period.

To examine whether there are any differences in the source of the shift in the skill mix between sectors, I apply a decomposition analysis to the change in the share of skilled workers across sectors. The decomposition used is similar to the Berman,

[11] Autor, Katz and Krueger (1997) examined the differences between manufacturing and non-manufacturing, their decomposition analysis show a different pattern between manufacturing and non-manufacturing sectors.

Bound and Griliches (1994) method, the results of the decompositions are presented in tables (5) through (8). Table (5) includes the decomposition results for the employment share of skilled workers for different time intervals based on the education definition, while table (6) presents the results of the same exercise for the change in the wage share of skilled workers in total wage bill. Tables (7) and (8) show the results of the same decomposition based on the occupation and HT definitions of skill for two time intervals: 1050/1990 and 1960/1990[12].

According to the education definition for the period 1950-1990 (table 5), except for services, all sectors and the all industries decompositions of the employment share of skilled workers show that the within industry component is the largest, ranging from 79% for the mining sector to 100% for construction and public administration. Across all industries the within component is 74% of the total change in the employment share of skilled workers over the period 1950-1990[13]. However, the change in the share of skilled workers in the services sector is almost equally divided among the two components. Taking into account the large share of services in the work force (around 32% in 1990), this sector has a significant effect on the economy as a whole. The remaining columns of table (5) include the decomposition results for ten years intervals intended to see whether the short run pattern differs from the long run.

[12] Decomposition analysis for different time intervals were also done for the other skill definitions and the results are not different from what is reported here.

[13] The decomposition of the wage share of skilled workers in total wage bill shows similar results, where the within industries component dominates the change in the wage share of skilled workers.

The panels show two main results: First, the between component is significantly large in the 1950s and 1960s, and starts to decline in the 1970s and 1980s. For example, the results of the decomposition of the change in the employment share of skilled workers show that the between industries component for the services sector 150% in the 1950s, 101% in the 1960s, 23% in the 1970s and 4% in the 1980s. The corresponding figures for other industries are: (1) for mining: 69%, 49%, 2% and 0%, (2) for transportation: 34%, 9%, 8% and 4%, (3) for manufacturing: 27%, 15%, 6% and 8%. The between industries component for all industries for the same time intervals follow the same pattern, the values are: 70%, 53%, 16% and 9%. Table (6) shows a similar pattern when the wage share measure is used: the between industries component across all industries declined from 38% in the 1950s down to 16% in the 1980s. These findings suggest that the change in both the wage and employment shares of skilled workers followed different patterns in the 1950s and 1960s compared with the 1970s and 1980s. Secondly, most industrial sectors, except services, show that the within industries component is consistently larger than the between industries component over all time intervals. On the other hand, the between industries effect was dominant during the 1950s and 1960s for the services sector (150%, 101% according to the employment share measure, and 68%, 62% according to the wage share measure). As a result, and due to the large share of the services sector in total employment in 1950s and 1960s (16% and 21.5% respectively), the between industries component dominates the within component for all industries during those periods. The between effect is 70% of the total change in the employment share of skilled workers in 1950 (53% in 1960 as shown in table 5), and 38% of the change in the wage share in 1950 (40% in 1960, see table 6).

Autor, Katz and Krueger (1997), AKK hereafter, run a similar decomposition for both the wage and employment shares of college graduates (our education definition includes people with more than high school) for different time intervals. Using the employment share, the all industries 1960/1970 decomposition shows that the between industries effect represents 72.5% of the total change (compared with 53% in our case), this is driven by the large between industries component in the non-manufacturing sector, 79.5% (similar to the services sector effect in our analysis)[14].

The occupation definition is close to the blue/white collar definition used by BBG, and I find similar results to their decompositions of the employment share of skilled workers in the manufacturing sector. Though I focus on a longer time interval. BBG find that the within component for the manufacturing sector dominates the between component for all time intervals (similar to what is presented in table 7). The within component accounts for 70% of the total change in the share of skilled workers for the period 1979/1987, compared with 72% in our case for the period 1950/1990. Moreover, BBG focused on manufacturing only, while we include all industrial sectors. Comparing the pattern of the change in the employment share of skilled

[14] The rest of the time intervals provide similar results in general, taking into account the difference in the definition of skill between AKK and this study.

workers across industrial sectors shows a different pattern for the services sector. While the within component is the largest for all other sectors, the between industries component is dominant (accounting for 195% of the total change in the share of skilled workers) for the services sector over the period 1950/1990 as shown in table (7)[15]. The heavy weight of the services sector in the work force affects the all industries decomposition which shows that the between industries component makes 134% of the total change for the period 1950/1990 (63% for 1960/1990).

The mixed trend shown by the occupation definition is possibly due to the vague boundaries of skill according to this definition which makes it difficult to distinguish the white collar worker from the blue collar for many occupation categories. Moreover, the job title, which is the basis of the occupation definition, may require different levels of skill in different industries. For example, a manager of a restaurant or a car shop (who may have high school only) will be considered skilled according to the occupation definition, but unskilled according to the education definition; while a manager of a computer consulting firm will be considered skilled in both definitions. Moreover, the occupation definition assumes that white collar workers are more skilled than blue collar workers, which is not necessarily true for some white collar jobs, i.e. cleaning personnel[16]. As a result, the occupation definition is not always accurate and can lead to confusing results, therefore, from this

[15] We get similar results for the time interval 1960/1990, though the between component drops to 98% of the total change for the services sector (see table 7-b).

[16] For more details see Channells and Van Reenen (1994) and Howel (1995).

point on, this dissertation will focus on presenting and discussing the results of the other two definitions of skill, but will provide the occupation definition based tables in the appendix.

The decomposition results for the high tech (HT) definition show that the within industries component dominates the change in the employment share of skilled workers for all sectors over the periods 1950/1990 and 1960/1990 as presented in table (8). The all industries within component represents 79% and 87% of the total aggregate change in the employment share of skilled workers for the two time intervals, respectively.

In general, the results of the sectoral decomposition of the change in the share of skilled workers show differences in the patterns explaining the change in the skill mix between manufacturing and most of the other sectors in one side, and services in the other side. Moreover, the results also indicate significant differences in the patterns of change between the early years (1950s and 1960s) and the recent years (1970s onwards).

A possible explanation for the difference between early and recent years patterns of change in the share of skilled workers may be found in the discussion of the stages of manufacturing presented in Goldin and Katz (1996). Manufacturing, according to Goldin and Katz, can be envisioned as having two distinct stages: machine maintenance and production. Machine maintenance stage includes machine installation and maintenance required to ensure that the machine is running, while the production stage includes the use of the machine in the production of a certain good. Goldin and Katz argue that capital and skill are always complements in the first stage because a high level of skill will always be required to install machinery and make it run, while the production stage usually requires less skilled workers to create the final product. Whether the adoption of new technology is skill-biased or not depends " on the degree to which the machine maintenance portion's demand for skilled labor is offset by the production process's demand for unskilled labor". This framework is used by Goldin and Katz to explain how certain manufacturing processes can be skill-biased or unskilled-biased [17].

For example, the shift from the artisan shop to the assembly line was unskilled-biased because the number of unskilled workers required in the production stage was much larger than the number of skilled workers required for the machine maintenance stage. Alternatively, the current shift to batch and continuous process methods is skill-biased because it requires more skilled labor in the maintenance stage which leads to a relative increase in the demand of skilled workers. For example, when the automobile industry used the assembly line production method, the number of workers required to work on the production lines (unskilled mainly) were much larger than the number of workers required to install those machines, therefore, using this method increased the demand for unskilled workers, i.e. technology was unskilled-biased. Afterwards, when

[17] Doms, Dunne and Troske (1995) argue that the effect of new technologies on the workforce structure depends on the type of technology adopted, i.e. adoption of factory automation technologies (which is directly used in production) is less correlated with skill upgrading than investment in computers (which is mainly used for managerial and clerical purposes).

the auto industry used automation and robots in production, the new technology replaced many unskilled workers, and increased the demand for skilled workers to operate and maintain the machines, skill-biased technology.

Goldin and Katz framework can be used to provide a possible explanation for the difference between early and recent decomposition patterns during the current computer revolution. During the 1950s and 1960s, mainframe computers were used by the government and some large corporations to carry out few jobs such as: payroll, billings and invoices and other jobs in accounting. During those days, computer services were centralized within companies, and their operations, programming and maintenance jobs were provided by a small number of computer specialists who took care of all computer related services, in other words, computer technology affected the maintenance stage only at that time. However, the introduction of personal computers in the late 1970s, and the diffusion and wide application of personal computers in education and business during the 1980s and 1990s, extended computer usage from the maintenance stage to the production stage. The widespread usage of computers in the production stage increased the demand for skilled workers, causing an overall upgrade of the skill level within industries.

3.5. Regional Differences in The Skill Mix:

This section examines whether the patterns of the change in the skill mix are similar across the regions. There are several reasons why regional patterns may vary:

(1) Agglomeration economies and the concentration of the high tech industries in certain locations, such as: Silicon Valley and Route 128, suggest unequal regional skill distribution in the different US regions. Topel (1994) argues that there has been some differences in the regional distribution of skill and in wage inequality, with the highest increase in wage inequality being in the west region due to the increased immigration of low skilled workers. Little and Triest (1996) suggest that geographical location makes a difference in the speed of adopting new technology which is caused by the differences in the regional distribution of skilled workers. Based on the above, the question is whether there are significant regional differences in the distribution of skill.

(2) It provides a tighter analysis of the technological change hypothesis. If the main driving force behind the increase in the demand for skilled workers is the skill-biased technological change, we expect the share of skilled workers to increase within all regions. Moreover, we expect the within regions to be the largest component in the time region decomposition, and the within region/within industry to be the largest component in the combined region-industry decomposition.

Table (9) shows the labor share of skilled workers by census regions according to the three definitions of skill. Again, with a few exceptions for the occupation definition, the trends indicate a persistent positive change in the share of skilled workers in all regions over the period 1950-1990 (we see the same positive trend when the wage share is used as shown in panel (d)). Moreover, the rate of change in the share of skilled workers has accelerated in the 1970s and 1980s compared with the earlier periods, for all three skill definitions. To examine the factors causing the shift in the skill mix across the regions, we decompose the change in the share of skilled workers into the main regional components: within regions and between regions, as follows:

$$\Delta p_n = \sum_i \Delta R_i \bullet \overline{p_{ni}} + \sum_i \Delta p_{ni} \bullet \overline{R_i} \qquad \textbf{(4)}$$

where,

P$_n$ = the share of skill level **n** in total employment .

P$_{ni}$ = skill level **n** employment in region **i** / total employment in region **i**.

R$_i$ = employment in region **i** / total employment .

The first part of equation (4) represents the between regions component, i.e. how much of the change in the share of skilled workers is due to the unequal change in the employment share of different regions. The second part of the equation represents the within regions component showing the effect of skill upgrade within regions. The results of the time-region decompositions are presented in table (10). All panels show that the within regions component represents more than 90% of the total change in the share of skilled workers for all time intervals, and are consistent for the three definitions of skill. I also examined the change in the wage share of skilled workers in the total wage bill. The results are quite similar, the within regions component dominates the between region component. This results are available upon request.

Industry-Region Decomposition:

The results of the sectoral decomposition of the change in the employment share of skilled workers show that the within industries variation dominates the change in the skill mix, suggesting an upgrade of the skill level within industries. These results raise a question regarding whether the within industry skill upgrade is accompanied with an upgrade of skill within regions or between regions. To investigate the combined regional-industrial effect in the distribution of skilled workers, the within industries component is decomposed further into within industries/within regions and within industries/between regions components[18].

The combined industry-region decomposition is based in equation (3):

$$\Delta p_n = \sum_i \Delta s_i \bullet \overline{p_{ni}} + \sum_i \sum_j \Delta r_{ij} \bullet \overline{p}_{nij} \bullet \overline{s}_i + \sum_i \sum_j \Delta p_{nij} \bullet \overline{r}_{ij} \bullet \overline{s}_i$$

where,

p_n = the share of skill level **n** in total employment .

p_{nij} = skill level **n** employment in industry **i** and region j/total employment in industry **i** and region **j.**

s_i = employment in industry i/total employment .

[18] To do that, we decompose the all industries change in the share of skilled workers, which is the last row of tables (5) through (8), into three main components: between industries, within industries-between regions and within industries-within regions.

r_{ij} = employment in industry i and region j/employment in industry i.

Each of the three terms on the right hand side of the above equation represents part of the decomposed change in the employment structure, after adding the region dimension. These parts can be interpreted as follows:

(1) The first part is the between industry component of the change in the employment share of skilled workers. This implications of this part has been discussed earlier in section 3.3.

(2) According to the second part of the equation, within industry/between regions component, skill upgrading occurs across all industries, but at different regional rates. This component represents Topel (1994) story regarding the regional differences in wage inequality. According to Topel, wage inequality is driven by technological change at the national level, however, regional differences in the supply of skilled workers makes the magnitude of wage inequality differs from one region to the other.

(3) The third component represents the within industries/within regions component, implying that adopting new technology leads to the upgrade of skill level within industries and geographical regions at the same time. If this component is large relative to the other component, then this is consistent with the skill-biased technological change explanation of the change in the skill mix.

Table (11) presents the results of the industry-region decomposition for the three skill definition, over different time intervals. The first three columns show the time interval, the overall change in the share of skilled workers and the between industry component (these results has already been discussed earlier as the last row of tables 5 through 8), while the last two columns for each definition represent the within industry/between regions and the within industry/within regions components, respectively.

The decomposition of the change in the employment share of educated workers for the period 1950-1990 shows that the within industry/within regions component dominates the change in the share of skilled workers (72%). The ten years intervals also show that the within industry-within regions component is significantly larger than the within industry-between regions component. The results of the HT definition follow the same trend. Alternatively, the results for the occupation definition show that the between industries component dominates the change in the skill mix (due to the problems associated with this definition as we pointed out earlier). Moreover, the between industries components is much larger for the early time intervals. However, the combined industry-region decomposition shows that the within industries/within regions effect is larger than the within industries/between regions effect for the occupation definition. This is similar to the results based on other definitions of skill. The results of the decomposition of the change in the wage share of skilled workers, presented in last four columns of table (11), show that the within industry/within regions component dominates the change in the share of skilled workers over the period 1950-1990 (77%), and over all the ten years intervals.

These findings suggest skill upgrading within industries and regions. This is interpreted in the literature as supportive of the technical change explanation for the change in the skill mix.

3.6. Metropolitan Differences in The Skill Mix:

This section investigates whether the distribution of skilled workers differs between the city center and the rural areas. The need for this investigation stems from the argument that there are some differences in the rural/urban distribution of income that are due to local difference in human capital stock (Renkow (1996). Additionally, Chakravorty (1996) studied the determinants of income distribution in US metropolitan areas, and his findings suggest that the cause and structure of inequality has changed in focus and complexity: from income - industry - race mix to education attainment and other social and demographic factors. In order to investigate any possible variation in the skill mix driven by metropolitan status, the METCCITY variable is used to provide a different geographical dimension according to whether the individual lives in: city center, SMA but not the city center, not in the SMA, in the SMA but the city center is unknown. Table (12) shows that the share of skilled workers has increased for almost all the metropolitan areas under the three definitions of skill (also the wage share of skilled workers has increased for all metropolitan areas as shown in panel (d)).

A time-metropolitan area decomposition of the change in the share of skilled workers into a between/within metropolitan areas components is conducted according to equation (4). The between metropolitan areas component shows how much of the change in the share of skilled workers is due to the change in the employment share of metropolitan areas in total employment. On the other hand, the within metropolitan area component shows the part of the change in the skill mix that is caused by the upgrade of skill level within metropolitan areas.

The results of the time metropolitan area decompositions are presented in table (13). The within metropolitan areas is shown to be the dominant component (represents more than 85%) of the total change in the share of skilled workers for the period 1950-1990 and most the ten year intervals between them. These results are consistent for the three definitions of skill (except for the 1960/1970 under the occupation definition). Using the wage share of skilled workers in the total wage bill yields the same dominance of the within metropolitan areas component of the change in the wage share (98% for the period 1950/1990).

3.7. A Combined Industry-Region-Metropolitan Area Decomposition:

To investigate the combined effect of industry-region-metropolitan status on the change of the share of skilled workers, a four level decomposition is conducted:

skill by industry by region by metropolitan status. In essence, the last part of equation (3) will be decomposed into: Within industries/within regions/within metropolitan areas component (WWW hereafter), and within industries/within regions/between metropolitan areas component (WWB hereafter) as follows:

$$\sum_i \sum_j \Delta p_{nij} \bullet \bar{r}_{ij} \bullet \bar{s}_i = \sum_i \sum_j \sum_m \Delta m_{mij} \bullet \bar{r}_{ij} \bullet \bar{s}_i \bullet \bar{p}_{nijm} + \sum_i \sum_j \sum_m \Delta p_{nijm} \bullet \bar{r}_{ij} \bullet \bar{s}_i \bullet \bar{m}_{ijm} \quad (5)$$

where,

p_{nij} = skill level **n** employment in industry **i** and region **j**/total employment in industry **i** and region **j.**

p_{nijm} = skill level **n** employment in industry **i** and region **j** and metropolitan area **m**/total employment in industry **i** and region **j** and metropolitan area **m.**

s_i = employment in industry i/total employment .

m_{ijm} = employment in industry **i** and region **j** and metropolitan area **m**/employment in industry **i** and region **j.**

r_{ij} = employment in industry **i** and region **j**/employment in industry **i.**

The first part of equation (5) represents WWB and the second part represents WWW. According to the technological change hypothesis, we expect that the share of skilled workers to increase across industries, regions, and metropolitan areas (WWW is expected to dominate the change in the share of skilled workers). Alternatively, if WWB is the largest component of the change in the share of skilled workers, this implies that the change in the employment share across metropolitan has a significant role in changing the employment share of skilled workers.

Table (14) presents the results of the decomposition of the employment share according to the three different definitions of skill. The findings show that WWW dominates the change in the share of skilled workers over the whole period (1950/1990) in all cases: 91% and 95% for the education and HT definitions. The WWW component represents 92.3% of the variations in the wage share of educated workers. However, the trend is not consistent for the ten years intervals where WWB is significantly larger in the early periods and declining in the more recent periods. WWB decreases from 22% in the 1950s to -3% in 1980s for the education definition, and from 52.3% to -22% for the HT definition for the same time intervals. The wage share decomposition follows the same pattern, declining from 9.6% in 1950/1960 to -1.9% in 1980/1990.

These findings suggest that the change in both the employment and the wage shares for skilled workers is caused by within industry/within region/within metropolitan areas over the period 1950/1990. These results also suggest that over the last forty years there has been an upgrade in the level of skill within industries, regions and metropolitan areas.

3.8. Summary:

In this chapter, I have investigated the pattern of the change in both the wage and the employment share of skilled workers over the period from 1950 to 1990. The data show that there has been an increase in the share of skilled workers over that period. To investigate the factors causing the change in the skill mix, I decomposed the change in the employment share of skilled workers at the industrial sectors, census regions and metropolitan levels. The decomposition results show that the within industries component dominates the between industries component. Moreover, the within component is also larger for the regional and metropolitan decompositions. These results are consistent with the findings reported by other researchers, suggesting that there is an upgrade of the skill level of workers within industries and regions and metropolitan areas. These results are interpreted in the literature to be consistent with the skill-biased technological change explanation.

The time-industry decomposition results are generally in line with the findings of other researchers showing that the within industries component dominates the between industries component for the change in the skill mix. Moreover, the sectoral decomposition shows a similar pattern for all sectors except services. However, three points are worth highlighting: (1) The between industries component is significantly larger in the early periods (1950s and 1960s) than the most recent periods (1970s and 1980s), implying that the change in both the wage and employment shares of skilled workers follow different patterns between the early time intervals and the more recent ones. (2) The services sector shows a different pattern than all other industrial sectors. The between industries component dominates the change in the skill mix for the early periods for services. Due to the large share of services in total employment, the all industries decomposition for the 1950s and 1960s show a strong between industries effect for the whole economy. This result suggest that the change in the skill mix in the services sector follows a different pattern than all other sectors. (3) Different definitions of skill may yield different results for the decomposition of the change in the skill mix, in our case, data measurement problems (discussed earlier) have caused the occupation definition to have inconsistent results throughout the analysis.

The time pattern of the decomposition results show that the within industries component was stronger in the 1970s and 1980s, causing the vast increase in the employment share of skilled workers and wage inequality. This time pattern is consistent with the technological change story, especially the personal computer revolution starting in the late 1970s. The shift from mainframes and the introduction of personal computers took computers from the maintenance stage to the production stage (Goldin and Katz (1996)), creating a widespread use of personal computers in most industries and regions in the US. The diffusion of the computer technology increased the demand for skilled workers because of the skill-bias of the computer technology and also due to capital-skill complementarity. As a result, both computers and skilled workers witnessed an increase in their demand almost around the same period of time. This match between the widespread of computers and the increase in the employment share of skilled workers is consistent with the skill-biased technical change explanation. However, one must be careful in inferring too much from the decomposition analysis in regards to technical change. Suffice it to say, the results are consistent with a skill-biased technical change story but are certainly inconclusive. In chapter 4, I turn to a more direct analysis of the relationship between changes in skill and changes in technology.

Addendum

Case Study:

A Comparison Between The Skill Mix of Oklahoma And The Surrounding States

In this section, I will examine the distribution of the skill mix in Oklahoma and compare it with the neighboring states, Texas, Louisiana, Kansas and Arkansas. The objective of this comparison is to test whether the pattern of the change in the skill mix in Oklahoma is similar to the surrounding states.

Table (15) presents the relative wage of skilled workers in the five states over the period 1950/1990 according to the three definitions of skill. The national average is also included for comparison purposes. Based on the education definition, four states show a similar trend over time, except for Texas which is a little different. In Texas the relative wage of skilled workers increased in the 1950s, then fell in the 1960s and 1970s (because of the increase in the supply of educated workers) and then increased again in the 1980s. Texas follows the national trend which is slightly different. It shows a positive change in the 1950s and 1960s, a decline in the 1970s and an increase in the 1980s. Panels (b) and (c) show that all five states follow the national trend according to the occupation and HT definitions. Comparing the relative wage of skilled workers in Oklahoma with the national average indicate that

Oklahoma's relative wage was higher than average except in 1990 (education definition), below the national average for the whole period (occupation definition), and above the national average for all years (HT definition).

Moreover, the employment share of skilled workers, in all five states, show a positive trend for the period 1950-1990 under both the education and HT definitions (similar to the national trend), while the occupation definition shows mixed trends, due possibly to the measurement problems discussed earlier. Panel (d) shows that the wage share of skilled workers has increased throughout the period from 1950 to 1990 for all five states and the national average. In general, the historical trend of both the relative wage and the employment share of skilled workers does not show any significant differences in the pattern followed by the five states, which is also consistent with the national averages.

Analysis of Variance:

ANOVA is usually used to compare the means of a continuous dependent variable across certain categories, or groups, of one or more independent variable. These categories divide the observations into mutually exclusive groups. A difference among group means indicates a relationship between the categorical variables defining the groups and the dependent variable. For example, the first row of table (17) represents a one way ANOVA because we have only one independent variable, while the seventh row is a three way ANOVA, the latter can be interpreted as follow:

- The model used to estimate the change in the share of skilled workers (ΔLS), the dependent variable, assumes that it is a function of: state, time and industry mix (the first column of the table includes the dependent variable, while the second includes the independent variables).

- The third column represents the categorical groups that we are testing whether there is a difference among their means, i.e. in this case, we are testing whether there is a significant difference among the mean change in the share of skilled workers between: states, time and industry.

- The F-Value is the ratio produced by dividing the mean square of the estimate by the mean square of error, it tests the null hypothesis that all group means are equal. The (Pr > F) column represents the lowest significance level required to reject the null hypothesis. The last column states the result and conclusion of the ANOVA test to whether there is a significant difference among the means of the corresponding group.

The main findings of the ANOVA test are shown in table (17), and can be summarized as follows:

(1) There is a significant difference in the share of skilled workers between the five states[19] , on the other hand, the state variable appears to make no significant difference in all the other dependent variables, i.e. relative wage, the change in relative wage and the change in the share of skilled workers.

(2) There is a significant difference in all four dependent variables across time, implying that: the share of skilled workers, the relative wage, the change in relative wage and the change in the share of skilled workers vary from one year to another.

(3) Industry mix has no significant effect on the change of relative wage or the change in the share of skilled workers.

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[19] In this regression, the intercept represented Texas, both Louisiana and Arkansas have a negative coefficient, implying that the employment share for these states is significantly less than in Texas. On the other hand, both Oklahoma and Kansas have a positive coefficient, for Oklahoma the coefficient is 0.02.

These finding suggest that there are no significant differences between the five states in the change of relative wage and the change in the share of skilled workers.

Table (1)

Industrial Sectors

Sector	Industries Included
Agriculture, Forestry and Fishing	Agriculture, Forestry and Fisheries.
Mining	Metal, coal and nonmetallic mining. Crude petroleum and natural gas.
Construction	Construction.
Manufacturing	All Durable and non durable goods.
Transportation, Communication and Other Utilities	Railroads, Trucking, Telephone, electricity and all utility and sanitary services.
Wholesale and Retail Trade	All whole sale and retail trade including cars, apparel, petroleum, chemical, food and machinery.
Finance, Insurance and Real Estate	Banking, investment brokerage, insurance and real estate.
Services	Business and repair, entertainment and recreational, personal and professional services.
Public Administration	Postal services, Federal and state and local public offices.

Table (2)

1990 Census Regional and Divisional Classification

Region Name	**States**	**Region Number**
North East Region:		
- New England Division	-Connecticut, Maine, Mass., New Hampshire, Rhode Island, Vermont.	- Region 1.
- Middle Atlantic Div.	- New Jersey, New York, Pennsyl.	- Region 2.
Midwest Region:		
-East North Central Div	- Illinois, Indiana, Michigan, Ohio, Wisconsin.	- Region 3.
- West North Central Div.	- Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota.	- Region 4.
South Region:		
- South Atlantic Div.	- Delaware, D.C., Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia.	- Region 5.
- East South Central Div.	- Alabama, Kentucky, Mississippi, Tennessee.	- Region 6.
- West South Central Div.	- Arkansas, Louisiana, Oklahoma / Indian Territory, Texas.	- Region 7.
West Region:		
- Mountain Div.	- Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming	- Region 8.
- Pacific Div.	- Alaska, California, Hawaii, Oregon, Washington.	- Region 9.

Table (3a)

Employment Share By The Industrial Sector (%)

Sector	1950	1960	1970	1980	1990
Agriculture	14.9	7.2	4.2	3.3	3.5
Mining	1.8	1.0	0.7	1.0	0.8
Construction	6.5	6.0	5.6	6.2	6.5
Manufacturing	26.7	27.1	24.7	21.8	17.6
Transportation	7.7	6.6	6.0	5.8	5.6
Trade	18.3	20.4	21.5	21.6	22.2
Financial Services	2.9	4.4	4.9	5.6	6.2
Services	16.2	22.5	27.1	28.9	32.4
Public Administration	5.0	4.8	5.2	5.8	5.2
Total Sample Employment	687335	860606	1070884	1265752	1461370

Source: Author's tabulation of IPUMS data files.

Table (3b)

Employment Share By The Occupation (%)

Occupation	1950	1960	1970	1980	1990
Professional	7.1	10.5	13.9	15.8	18.2
Farm Owners & Managers	7.9	3.5	1.7	1.3	1.2
Managers	7.8	7.2	6.6	9.2	11.5
Clerical	11.1	17.2	19.2	19.5	18.7
Sales	6.6	8.2	7.7	6.8	6.6
Craftsmen	14.8	12.2	11.9	11.4	10.8
Operatives	21.2	19.3	17.7	15.2	12.4
Service Workers	9.9	13.4	14.5	14.6	14.6
Farm Laborers	6.3	3.1	1.8	1.2	1.0
Laborers	7.2	5.4	5.0	5.0	5.0
Total Sample Employment	689006	854963	1070884	1265752	1478439

Table (3c)

Employment Share By The Region (%)

Region	1950	1960	1970	1980	1990
(1) New England	6.2	6.0	6.0	5.1	5.6
(2) Middle Atlantic	20.0	19.5	18.1	16.3	15.3
(3) East North Central	20.0	19.9	19.2	18.1	16.5
(4) West North Central	9.3	8.8	8.3	7.5	7.1
(5) South Atlantic	14.1	14.0	15.1	16.7	18.3
(6) East South Central	7.6	6.2	6.1	6.2	5.8
(7) West South Central	9.7	9.2	9.6	10.5	11.0
(8) Mountain	3.4	3.7	4.0	5.1	5.9
(9) Pacific	9.7	12.7	13.6	14.5	14.5
Total Sample Employment	461130	579212	744429	917557	1087311

Source: Author's tabulation of IPUMS data files.

Table (3d)

Employment Share By The Metropolitan Status (%)

Metropolitan Status	1950	1960	1970	1980	1990
(1) Not in SMA.	43.3	26.0	25.1	26.4	28.9
(2) Central city of SMA.	28.9	30.5	29.3	25.5	16.0
(3) SMA, not central city.	20.5	25.7	30.4	35.3	26.8
(4) SMA, central city not known.	7.2	2.6	1.9	12.8	25.1
(5) Area type unknown.	0.1	15.2	13.3	0	3.2
Total Sample Employment	461130	579212	744429	942214	1105583

Source: Author's tabulation of IPUMS data files.

Table (4)

The Labor Share of Skilled Workers by Industrial Sectors (1950-1990) (%)

(a) Education Definition

Year	Agri.	Mining	Cons.	Manuf	Transp.	Trade	Fin. Serv.	Services	Public Ad
1950	4.53	8.9	8.79	9.83	9.75	14.3	27.43	31.45	22.46
1960	5.79	13.37	10.17	13.01	12.61	13.83	28.94	33.76	26.99
1970	9.56	18.87	13.57	16.67	18.27	17.73	34.2	39.8	29.6
1980	19.98	28.71	22.83	25.26	30.04	26.94	47.04	50.33	45.08
1990	28.95	38.69	33.38	38.52	45.4	39.33	64.76	61.06	62.24

(b) Occupation Definition

Year	Agri.	Mining	Cons.	Manuf	Transp.	Trade	Fin. Serv.	Services	Public Ad
1950	59.49	21.06	16.87	23.28	25.23	57.64	54.43	46.92	58.17
1960	50.37	27.55	19.31	24.46	26.08	52.74	52.2	43.06	41.23
1970	44.97	31.78	20.21	25.05	26.85	46.64	53.5	45.7	44.11
1980	47.11	35.49	23.26	30.29	30.98	45.37	61.39	50.69	46.74
1990	45.07	39.54	26.65	36.46	32.91	44.48	67.31	53.23	51.07

(c) HT Definition

Year	Agri.	Mining	Cons.	Manuf	Transp.	Trade	Fin. Serv.	Services	Public Ad
1950	0.16	2.39	2.52	2.04	2.25	0.32	0.61	1.86	1.87
1960	0.22	4.15	2.28	3.39	2.62	0.23	0.27	2.23	3.59
1970	0.58	5.79	2.21	4.73	3.22	0.32	0.93	2.82	4.96
1980	2.05	9.52	3.39	6.81	5.93	0.6	2.4	7.17	9.34
1990	2.62	10.85	3.93	8.83	7.7	1.13	4.09	7.99	9.68

The Wage Share of Skilled Workers by Industrial Sectors (1950-1990) (%)

(d) Education Definition

Year	Agri.	Mining	Cons.	Manuf	Transp.	Trade	Fin. Serv.	Services	Public Ad
1950	8.53	11.51	10.95	13.8	12.1	18.63	33	41.47	29
1960	11.91	19.82	13.53	21.25	15.98	22.42	40.59	51.83	32.17
1970	17.78	26.54	17.26	26.65	22.1	27.59	48.68	57.97	37.46
1980	30.11	34.91	28.48	35.88	35	38.91	60.43	66.84	55.4
1990	41.37	49.19	43.34	53.21	54.49	54.95	77.35	78.08	71.61

Table (5)

Time-Sector Decomposition Analysis for The Employment Share of Skilled Workers (Education Def.)

Industry	1950-1990			1950-1960			1960-1970			1970-1980			1980-1990		
	Δp	$\sum_i \Delta s_i \cdot \bar{p}_i$ Between	$\sum_i \Delta p_i \cdot \bar{s}_i$ Within	Δp	$\sum_i \Delta s_i \cdot \bar{p}_i$ Between	$\sum_i \Delta p_i \cdot \bar{s}_i$ Within	Δp	$\sum_i \Delta s_i \cdot \bar{p}_i$ Between	$\sum_i \Delta p_i \cdot \bar{s}_i$ Within	Δp	$\sum_i \Delta s_i \cdot \bar{p}_i$ Between	$\sum_i \Delta p_i \cdot \bar{s}_i$ Within	Δp	$\sum_i \Delta s_i \cdot \bar{p}_i$ Between	$\sum_i \Delta p_i \cdot \bar{s}_i$ Within
Agriculture	0.2442	0.00531	0.23888	0.012597	0.000884	0.011712	0.037632	0.001441	0.03619	0.10422	0.002672	0.10154	0.08975	0.000156	0.08959
%		2%	98%		7%	93%		4%	96%		3%	97%		0%	100%
Mining	0.29784	0.06174	0.23611	0.0447	0.030803	0.013898	0.05494	0.027089	0.02785	0.09845	0.00151	0.09694	0.09975	0.00011	0.09964
%		21%	79%		69%	31%		49%	51%		2%	98%		0%	100%
Construction	0.24589	0	0.24589	0.013784	0	0.013784	0.034039	0	0.03404	0.926	0	0.926	0.10546	0	0.10546
%		0%	100%		0%	100%		0%	100%		0%	100%		0%	100%
Manufacturing	0.28688	0.03469	0.2522	0.031806	0.008683	0.023123	0.036581	0.005586	0.03099	0.08586	0.005578	0.08028	0.13264	0.010152	0.12249
%		12%	88%		27%	73%		15%	85%		6%	94%		8%	92%
Transportation	0.35648	0.03177	0.3247	0.028569	0.009641	0.018928	0.056611	0.005277	0.05133	0.11772	0.009612	0.10811	0.15357	0.006686	0.14689
%		9%	91%		34%	66%		9%	91%		8%	92%		4%	96%
Trade	0.25035	0.00288	0.24747	-0.004663	-0.000661	-0.004001	0.038991	0.001902	0.04089	0.09211	0.005471	0.08664	0.1239	0.002335	0.12157
%		1%	99%		14%	86%		5%	105%		6%	94%		2%	98%
Financial Services	0.37323	0.00177	0.37146	0.015045	0.003288	0.011757	0.05263	0.002568	0.05006	0.12835	-0.004507	0.13285	0.1772	0.004273	0.17293
%		0%	100%		22%	78%		5%	95%		-4%	104%		2%	98%
Services	0.29602	0.12364	0.17237	0.02303	0.034497	-0.011468	0.060366	0.061134	-0.00077	0.1053	0.024588	0.08071	0.10732	0.00466	0.10266
%		42%	58%		150%	-50%		101%	-1%		23%	77%		4%	96%
Public Administration	0.39787	-0.00057	0.39844	0.045308	-0.011043	0.056351	0.026131	0.003154	0.02298	0.15476	0.010092	0.14467	0.17167	-0.001712	0.17338
%		0%	100%		-24%	124%		12%	88%		7%	93%		-1%	101%
All Industries	0.33384	0.087192	0.246652	0.032854	0.0231036	0.009750	0.058630	0.031337	0.02729	0.10896	0.0177088	0.0912549	0.13340	0.012385	0.121011
%		26%	74%		70%	30%		53%	47%		16%	84%		9%	91%

Table (6)

Time-Sector Decomposition Analysis for The Wage Share of Skilled Workers (Education Def.)

Industry	1950-1990			1950-1960			1960-1970			1970-1980			1980-1990		
	Δp	$\sum_i \Delta s_i \cdot \bar{p}_i$ Between	$\sum_i \Delta p_n \cdot \bar{s}$ Within	Δp	$\sum_i \Delta s_i \cdot \bar{p}_n$ Between	$\sum_i \Delta p_n \cdot \bar{s}$ Within	Δp	$\sum_i \Delta s_i \cdot \bar{p}_i$ Between	$\sum_i \Delta p_n \cdot \bar{s}$ Within	Δp	$\sum_i \Delta s_i \cdot \bar{p}_n$ Between	$\sum_i \Delta p_n \cdot \bar{s}$ Within	Δp	$\sum_i \Delta s_i \cdot \bar{p}$ Between	$\sum_i \Delta p_n \cdot \bar{s}$ Within
Agriculture	0.32844	0.01131	0.31713	0.03385	0.005235	0.028612	0.058616	0.003264	0.05535	0.12334	0.004912	0.11841	0.11264	-0.00267	0.11531
%		3%	97%		15%	85%		6%	94%		4%	96%		-2%	102%
Mining	0.37679	0.06061	0.31618	0.08308	0.038336	0.044745	0.067149	0.021111	0.04604	0.08376	-0.006226	0.08998	0.1428	0.002152	0.14065
%		16%	84%		46%	54%		31%	69%		-7%	107%		2%	98%
Construction	0.32398	0	0.32398	0.02582	0	0.025818	0.037353	0	0.03735	0.11219	0	0.11219	0.14862	0	0.14862
%		0%	100%		0%	100%		0%	100%		0%	100%		0%	100%
Manufacturing	0.39409	0.04524	0.34885	0.07448	0.014613	0.059872	0.053988	0.005525	0.04846	0.09233	0.007219	0.08511	0.17329	0.018809	0.15448
%		11%	89%		20%	80%		10%	90%		8%	92%		11%	89%
Transportation	0.42394	0.05041	0.37353	0.03877	0.013274	0.025495	0.06124	0.008931	0.05231	0.12901	0.012485	0.11652	0.19492	0.013011	0.18191
%		12%	88%		34%	66%		15%	85%		10%	90%		7%	93%
Trade	0.36318	0.01529	0.34789	0.03788	0.010104	0.027776	0.051721	-0.003802	0.05552	0.11324	0.007995	0.10524	0.16034	0.006775	0.15357
%		4%	96%		27%	73%		-7%	107%		7%	93%		4%	96%
Financial Services	0.44356	0.00525	0.43831	0.07593	0.005419	0.070508	0.080891	0.004257	0.07663	0.11748	-0.006332	0.12381	0.16926	0.007106	0.16216
%		1%	99%		7%	93%		5%	95%		-5%	105%		4%	96%
Services	0.36609	0.10204	0.26405	0.10352	0.070411	0.033109	0.061437	0.038225	0.02321	0.08865	0.003251	0.0854	0.11248	0.004287	0.10819
%		28%	72%		68%	32%		62%	38%		4%	96%		4%	96%
Public Administration	0.42614	-0.0036	0.42974	0.03174	-0.015581	0.047325	0.052919	0.007057	0.04586	0.17936	0.009148	0.17022	0.16212	-0.00092	0.16304
%		-1%	101%		-49%	149%		13%	87%		5%	95%		-1%	101%
All Industries	0.43396	0.094356	0.339599	0.069439	0.0262176	0.043221	0.075786	0.030230	0.04556	0.11645	0.0146733	0.1017741	0.17228	0.028281	0.144002
%		22%	78%		38%	62%		40%	60%		13%	87%		16%	84%

Table (7)

Time-Sector Decomposition Analysis for The Employment Share of Skilled Workers (Occupation Definition)

Industry	1950/1960			1960/1990		
	Δp_n	$\sum_i \Delta s_i \bullet \bar{p}_{ni}$ Between Ind.	$\sum_i \Delta p_{ni} \bullet \bar{s}_i$ Within Ind.	Δp_n	$\sum_i \Delta s_i \bullet \bar{p}_{ni}$ Between Ind.	$\sum_i \Delta p_{ni} \bullet \bar{s}_i$ Within Ind.
Agriculture	-0.1442	-0.00883	-0.13537	-0.05298	-0.004674	-0.04831
%		6%	94%		9%	91%
Mining	0.18476	0.06617	0.11859	0.11986	0.029471	0.09039
%		36%	64%		25%	75%
Construction	0.09779	0	0.09779	0.07335	0	0.07335
%		0%	100%		0%	100%
Manufacturing	0.13177	0.03731	0.09446	0.12002	0.021713	0.09831
%		28%	72%		18%	82%
Transportation	0.0768	-0.01937	0.09617	0.06828	-0.020047	0.08833
%		-25%	125%		-29%	129%
Trade	-0.13162	-0.01201	-0.11961	-0.08266	-0.018098	-0.06456
%		9%	91%		22%	78%
Financial Services	0.12882	-0.00205	0.13087	0.15109	0.004269	0.14682
%		-2%	102%		3%	97%
Services	0.06317	0.12327	-0.0601	0.10172	0.099337	0.00238
%		195%	-95%		98%	2%
Public Administration	-0.07106	0.00769	-0.07875	0.09839	0.019058	0.07933
%		-11%	111%		19%	81%
All Industries	.045258	0.0606371	-0.015379	.0763529	0.0482952	0.0280577
%		134%	-34%		63%	37%

Table (8)

Time-Sector Decomposition Analysis for The Employment Share of Skilled Workers (High Tech Definition)

Industry	1950/1960			1960/1990		
	Δp_n	$\sum_i \Delta s_i \bullet \bar{p}_n$ Between Ind.	$\sum_i \Delta p_{ni} \bullet \bar{s}_i$ Within Ind.	Δp_n	$\sum_i \Delta s_i \bullet \bar{p}_n$ Between Ind.	$\sum_i \Delta p_{ni} \bullet \bar{s}_i$ Within Ind.
Agriculture	0.024651	0.002818	0.021833	0.024033	0.002359	0.021674
%		11%	89%		10%	90%
Mining	0.084648	0.024907	0.059741	0.067011	0.011584	0.055428
%		29%	71%		17%	83%
Construction	0.014032	0	0.014032	0.016436	0	0.016436
%		0%	100%		0%	100%
Manufacturing	0.067954	0.013462	0.054492	0.054938	0.0068	0.048139
%		20%	80%		12%	88%
Transportation	0.054542	0.009911	0.044631	0.050788	0.001427	0.049361
%		18%	82%		3%	97%
Trade	0.008161	0.000664	0.007498	0.009022	0.000978	0.008044
%		8%	92%		11%	89%
Financial Services	0.034754	-0.000871	0.035625	0.038172	-0.001413	0.039585
%		-3%	103%		-4%	104%
Services	0.061284	0.022658	0.038626	0.057519	0.015727	0.041792
%		37%	63%		27%	73%
Public Administration	0.078033	-0.007032	0.085065	0.060871	0.003689	0.057182
%		-9%	109%		6%	94%
All Industries	0.045198	0.0094508	0.0357467	0.039706	0.0053187	0.0343867
%		21%	79%		13%	87%

Table (9)

The Employment Share of Skilled Workers by Census Regions
(1950-1990) (%)

(a) Education Definition

Year	Region1	Region2	Region3	Region4	Region5	Region6	Region7	Region8	Region9
1950	15.27	14.41	14.82	15.59	13.68	10.25	15.11	20.85	21.4
1960	19.47	18.16	17.37	18.44	16.77	13.59	18.36	22.61	23.92
1970	25.91	23.58	22.6	24.46	22.87	19.5	23.82	29.36	31.59
1980	38.66	35.12	32.08	33.72	33.16	28.73	34.11	40.02	43.45
1990	52.91	47.68	45.97	46.62	47	40.93	46.87	63.95	56.11

(b) Occupation Definition

Year	Region1	Region2	Region3	Region4	Region5	Region6	Region7	Region8	Region9
1950	37.92	37.43	38.54	48.27	40.26	43.16	45.1	45.62	45
1960	36.47	37.28	36.84	43.62	36.71	36.53	38.79	41.05	39.92
1970	38.59	38.52	36.36	41.23	37.91	35.65	38.79	41.04	40.86
1980	44.42	42.85	39.9	43.73	41.69	38.56	42.77	44.4	45.08
1990	49.96	47.05	43.36	45.69	46.81	41.08	45.48	47.1	48.55

(c) HT Definition

Year	Region1	Region2	Region3	Region4	Region5	Region6	Region7	Region8	Region9
1950	1.66	1.77	1.47	1.15	1.17	0.83	1.29	1.37	1.92
1960	2.31	2.22	1.91	1.47	1.6	1.32	1.79	2.25	2.86
1970	3.22	2.83	2.5	2.11	2.61	1.95	2.45	2.97	3.46
1980	6.11	5.05	4.69	4.15	5.02	4.05	5.16	5.8	6.15
1990	7.61	6.15	5.46	4.89	6.49	4.75	5.79	6.47	7.35

The Wage Share of Skilled Workers by Census Regions
(1950 1990) (%)

(d) Education Definition

Year	Region1	Region2	Region3	Region4	Region5	Region6	Region	Region8	Region9
1950	18.92	18.28	18.26	21.02	21.21	16.93	22.88	26.32	25.1
1960	27.27	26.34	24.17	26.94	27.51	22.8	29.07	31.16	32.15
1970	35.91	33.95	30.94	34.56	34.49	29.78	35.68	39.71	42.38
1980	50.16	46.27	41.36	43.97	45.28	39.24	46.17	50.29	54.8
1990	66.8	62.78	59.25	60.38	62.58	55.2	63.4	67.46	70.78

Table (10)

Time-Region Decomposition Analysis for The Share of Skilled Workers
(Nine Census Regions)

Year	Employment Share									Wage Share		
	Education Definition			Occupation Definition			High Tech Definition			Education Definition		
	Δp_n	$\Delta\sum_i r_i \cdot \bar{p}_n$ Between	$\Delta\sum_i p_n \cdot \bar{r}_i$ Within	Δp_n	$\Delta\sum_i r_i \cdot \bar{p}_n$ Between	$\Delta\sum_i p_n \cdot \bar{r}_i$ Within	Δp_n	$\Delta\sum_i r_i \cdot \bar{p}_n$ Between	$\Delta\sum_i p_n \cdot \bar{r}_i$ Within	Δp_n	$\Delta\sum_i r_i \cdot \bar{p}_n$ Between	$\Delta\sum_i p_n \cdot \bar{r}_i$ Within
1990-1950	0.33473	0.006316	0.32842	0.050369	0.0039166	0.046452	0.04713	0.000690	0.04644	0.43449	0.0078757	0.42661
%		2%	98%		8%	92%		1%	99%		2%	98%
1990-1960	0.30203	0.003757	0.29827	0.080411	0.001411	0.079	0.041746	0.000564	0.04118	0.36516	0.0055588	0.3596
%		1%	99%		2%	98%		1%	99%		2%	98%
1990-1980	0.13406	0.001893	0.13216	0.03803	0.0010735	0.036956	0.010553	0.000403	0.01015	0.1725	0.0036853	0.16881
%		1%	99%		3%	97%		4%	96%		2%	98%
1980-1970	0.10662	0.000583	0.10604	0.038915	0.0002287	0.038686	0.024173	0.000116	0.02406	0.11397	0.0012246	0.11275
%		1%	99%		1%	99%		0%	100%		1%	99%
1970-1960	0.06135	0.001643	0.059709	0.003466	0.0002482	0.003218	0.007020	0.000110	0.00691	0.07870	0.0015131	0.077184
%		3%	97%		7%	93%		2%	98%		2%	98%
1960-1950	0.03270	0.001888	0.030814	-0.030042	0.0008867	-0.030929	0.005384	0.000160	0.00522	0.06932	0.0017634	0.067559
%		6%	94%		-3%	103%		3%	97%		3%	97%

Note: W/B means within industries between regions, and W/W means within industries within regions.

Industry-Region Decomposition Analysis for The Share of Skilled Workers
(Nine Census Regions)

Year	Employment Share												Wage Share			
	Education Definition				Occupation Definition				High Tech Definition				Education Definition			
	Δp	$\sum \Delta s \cdot \bar{p}$ Between	$\sum\sum \Delta r \bar{p} \bar{s}$ W/B	$\sum\sum \Delta p \bar{r} \bar{s}$ W/W	Δp	$\sum \Delta s \cdot \bar{p}$ Between	$\sum\sum \Delta r \bar{p} \bar{s}$ W/B	$\sum\sum \Delta p \bar{r} \bar{s}$ W/W	Δp	$\sum \Delta s \cdot \bar{p}$ Between	$\sum\sum \Delta r \bar{p} \bar{s}$ W/B	$\sum\sum \Delta p \bar{r} \bar{s}$ W/W	Δp	$\sum \Delta s \cdot \bar{p}$ Between	$\sum\sum \Delta r \bar{p} \bar{s}$ W/B	$\sum\sum \Delta p \bar{r} \bar{s}$ W/W
1990-1950	0.33304	0.08853	0.00594	0.23865	0.04557	0.06117	0.000968	-0.01654	0.03745	0.00985	-0.000013	0.02858	0.43349	0.09631	0.00634	0.3308359
%		27%	1%	72%		134%	2%	-36%		26%	-1%	76%		22%	1%	77%
1990-1960	0.30085	0.06264	0.00322	0.23484	0.07671	0.04851	0.000875	0.027155	0.03286	0.00504	-0.000291	0.02817	0.36516	0.07156	0.00360	0.2900044
%		21%	1%	78%		63%	1%	35%		15%	-1%	86%		20%	1%	79%
1990-1980	0.13295	0.01251	0.00139	0.11888	0.03449	0.00997	0.000575	0.023768	0.00601	-0.00154	0.000006	0.00758	0.17205	0.02879	0.00199	0.1412699
%		9%	1%	89%		29%	2%	69%		-26%	0%	126%		17%	1%	82%
1980-1970	0.10690	0.01671	0.00076	0.08926	0.03915	0.01577	0.000260	0.023063	0.02138	0.00428	0.000012	0.01708	0.11449	0.0142[illegible]	0.00096	0.0993169
%		16%	1%	84%		40%	1%	59%		20%	0%	80%		12%	1%	87%
1970-1960	0.061	0.03277	0.00130	0.02703	0.00307	0.02163	-0.000087	-0.01843	0.00546	0.00112	-0.000211	0.00458	0.07863	0.03158	0.00104	0.0460031
%		54%	2%	44%		704%	-3%	-600%		20%	-4%	84%		40%	1%	59%
1960-1950	0.03219	0.02330	0.00206	0.00691	-0.0311	0.00520	0.000100	-0.03626	0.00459	0.00243	0.000263	0.00191	0.06832	0.03158	0.00261	0.039323
%		72%	6%	21%		-17%	1%	116%		53%	6%	42%		46%	4%	58%

Note: W/B means within industries between regions, and W/W means within industries within regions.

Table (12)

The Employment Share of Skilled Workers By Metropolitan Status (%)

(a) Education Definition

Year	Not in SMA	C.City	SMA not C.C.	SMA C.C. Unknown
1950	12.46	16.89	18.16	14.71
1960	15.23	19.43	21.92	22.3
1970	20.04	25.59	27.34	26.87
1980	27.04	38.44	38.57	34.34
1990	37.94	51.88	54.64	50.39

(b) Occupation Definition

Year	Not in SMA	C.City	SMA not C.C.	SMA C.C. Unknown
1950	44.44	37.34	42.06	38.28
1960	36.93	35.26	41.23	39.2
1970	35.98	36.28	41.8	39.32
1980	38.47	40.93	45.98	41.36
1990	39.76	44.83	51.47	47.07

(c) HT Definition

Year	Not in SMA	C.City	SMA not C.C.	SMA C.C. Unknown
1950	0.81	1.67	2.4	1.4
1960	1.38	1.9	3.01	1.91
1970	1.84	2.54	3.63	2.6
1980	3.33	5.29	6.2	4.98
1990	3.72	6.32	7.71	6.76

The Wage Share of Skilled Workers By Metropolitan Status (%)

(d) Education Definition

Year	Not in SMA	C.City	SMA not C.C.	SMA C.C. Unknown
1950	17.89	20	23.34	18.63
1960	22.49	26.14	31.28	30.44
1970	28.21	34.64	38.45	37.29
1980	34.86	48.79	50.42	43.59
1990	48.77	67.38	69.25	64.03

Table (13)

Time-Region Decomposition Analysis for The Share of Skilled Workers (Metropolitan Status)

Year	Employment Share									Wage Share		
	Education Definition			Occupation Definition			High Tech Definition			Education Definition		
	Δp_n	$\Delta\sum_i r_i \bullet \bar{p}_n$ Between	$\Delta\sum_i p_n \bullet \bar{r}_i$ Within	Δp_n	$\Delta\sum_i r_i \bullet \bar{p}_n$ Between	$\Delta\sum_i p_n \bullet \bar{r}_i$ Within	Δp_n	$\Delta\sum_i r_i \bullet \bar{p}_n$ Between	$\Delta\sum_i p_n \bullet \bar{r}_i$ Within	Δp_n	$\Delta\sum_i r_i \bullet \bar{p}_n$ Between	$\Delta\sum_i p_n \bullet \bar{r}_i$ Within
1990-1950	0.33474	0.010809	0.32393	0.050064	0.00767	0.042394	0.046955	0.0033	0.04366	0.43459	0.0078683	0.42672
%		3%	97%		15%	85%		7%	93%		2%	98%
1990-1960	0.29708	0.005651	0.29143	0.084052	0.0077778	0.076274	0.040604	0.000918	0.03968	0.36286	0.0056432	0.35721
%		2%	98%		9%	91%		2%	98%		2%	98%
1990-1980	0.13505	-0.007301	0.14235	0.038279	-0.0032977	0.041576	0.010426	-0.001329	0.01176	0.17403	-0.0073366	0.18137
%		-5%	105%		-9%	109%		-13%	113%		-4%	104%
1980-1970	0.10431	0.000934	0.10338	0.039934	0.0026934	0.037241	0.02347	0.000179	0.02329	0.11226	0.0010377	0.11122
%		1%	99%		7%	93%		1%	99%		1%	99%
1970-1960	0.05772	0.002962	0.054756	0.005839	0.0030699	0.002769	0.006709	0.000916	0.00579	0.07657	0.003496	0.07307
%		5%	95%		53%	47%		14%	86%		5%	95%
1960-1950	0.03766	0.005646	0.032013	-0.033988	0.0009484	-0.034936	0.006351	0.001657	0.00469	0.07173	0.0056343	0.0661
%		15%	85%		-3%	103%		26%	74%		8%	92%

Note: W/B means within industries between regions, and W/W means within industries within regions.

Table (14)

Industry-Region-Metropolitan Decomposition of The Share of Skilled Workers* (%)

Year	Employment Share						Wage Share	
	Education Def.		Occupation Def.		HT Def.		Education Def.	
	Between	Within	Between	Within	Between	Within	Between	Within
1950-1990	0.0072899	0.218	0.0073111	-0.027107	0.001088	0.018872	0.012536	0.30523
%	3%	91%	-35%	129%	5%	95%	3.8%	92.3%
1960-1990	0.0036453	0.21841	0.0064008	0.020495	0.000134	0.0212	0.0080616	0.27186
%	1.6%	93%	24%	75%	0.5%	99.5%	2.8%	93.7%
1980-1990	-0.0037367	0.11657	-0.0006873	0.023431	-0.0010071	0.0056757	-0.0027092	0.13958
%	-3%	98%	-3%	98.6%	-22%	122%	-1.9%	98.8%
1970-1980	0.0015206	0.083354	0.0036169	0.018554	0.0002664	0.013848	0.0032908	0.092935
%	2%	93.3%	16%	80.5%	2%	98%	3.3%	93.6%
1960-1970	0.0018664	0.023085	0.0016737	-0.019833	0.0003864	0.00327	0.0041672	0.040083
%	6.8%	85.4%	-9%	107.6%	10.6%	89%	9.1%	87.1%
1950-1960	0.00191	0.00586	0.0005056	-0.039609	0.0004822	0.0004157	0.0037569	0.034434
%	22%	68%	-1.4%	101.2%	52.3%	45.2%	9.6%	87.6%

* This table decomposes the last column of table (11). i.e. the within industry-within region component into a within metropolitan-between metropolitan components. The total of the two components do not always sum up to 100% because after adding the variable METCCITY, we dropped all observations that do not have this variable. this resulted in a smaller number of observations compared with the sample used in table (11).

Table (15)

Comparing The Relative Wage for Oklahoma With The Surrounding States

(a) Education Definition

Year	All States	Arkansas	Kansas	Louisiana	Oklahoma	Texas
1950	1.425	2.046	1.469	1.829	1.611	1.551
1960	1.591	1.97	1.671	1.871	1.751	1.775
1970	1.625	1.786	1.589	1.719	1.712	1.781
1980	1.585	1.615	1.539	1.521	1.669	1.68
1990	1.863	1.665	1.629	1.812	1.785	2.037

(b) Occupation Definition

Year	All States	Arkansas	Kansas	Louisiana	Oklahoma	Texas
1950	1.147	0.877	0.939	1.119	1.072	1.229
1960	1.575	1.507	1.368	1.748	1.532	1.653
1970	1.779	1.699	1.662	1.828	1.784	1.859
1980	1.702	1.583	1.539	1.705	1.692	1.75
1990	2.013	1.761	1.765	2.03	1.933	2.163

(c) HT Definition

Year	All States	Arkansas	Kansas	Louisiana	Oklahoma	Texas
1950	1.996	2.1	1.68	2.49	2.28	2.13
1960	2.321	3.05	2.59	2.83	2.74	2.62
1970	2.151	2.15	2.33	2.45	2.53	2.52
1980	1.847	1.59	1.77	1.81	1.88	1.92
1990	1.883	1.64	1.88	1.89	1.94	2.1

Table (16)

Comparing The Employment Share of Skilled Workers for Oklahoma With The Surrounding States

(%)

(a) Education Definition

Year	All States	Arkansas	Kansas	Louisiana	Oklahoma	Texas
1950	14.03	8.51	18.57	12.48	18.35	16.48
1960	18.54	12.65	21.04	15.81	20.83	19.65
1970	24.10	17.46	27.03	22.27	25.5	24.87
1980	34.33	25.95	36.91	30.72	35.53	35.84
1990	47.04	35.48	49.69	42.32	47.28	49.06

(b) Occupation Definition

Year	All States	Arkansas	Kansas	Louisiana	Oklahoma	Texas
1950	41.75	49.06	50.51	40.54	49.01	44.54
1960	38.06	35.48	45.96	35.3	42.32	39.67
1970	38.54	34.82	42.66	36.95	40.29	39.58
1980	42.27	38.11	45.1	40.69	43.47	43.81
1990	45.49	39.12	46.34	44.11	44.56	46.65

(c) HT Definition

Year	All States	Arkansas	Kansas	Louisiana	Oklahoma	Texas
1950	1.34	0.45	1.24	1.3	1.55	1.41
1960	2.17	0.9	1.89	1.9	1.72	1.94
1970	3.78	1.23	2.01	2.12	2.32	2.78
1980	5.0	3.06	4.7	4.9	4.99	5.56
1990	5.35	3.64	4.89	4.99	4.96	6.36

Comparing The Wage Share of Skilled Workers For Oklahoma With The Surrounding States

(d) Education Definition

Year	All States	Arkansas	Kansas	Louisiana	Oklahoma	Texas
1950	20.05	15.985	25.098	20.689	26.585	23.431
1960	26.99	22.195	30.812	25.999	31.534	30.262
1970	34.57	27.416	37.05	32.994	36.946	37.095
1980	46.22	36.139	47.374	40.275	47.911	48.415
1990	63.44	47.798	61.679	57.067	61.558	66.245

Table (17)

Analysis of The Variance

Dependent Variable	Independent Variables	Comparing Groups	F Value	Pr >F	Significant at α=5%
Labor Share (LS)	State	State	31.6	0.0001	Yes
Relat. Wage(RW)	State	State	0.61	0.6521	No
RW	State, Year.	State	0.57	0.6828	No
		Year	5.1	0.0004	Yes
RW	State*Year	State*Year	4.31	0.0001	Yes
LS	State, Year	State	40.47	0.0001	Yes
		Year	407.86	0.0001	Yes
LS	State*Year	State*Year	75.74	0.0001	Yes
ΔLS	State	State	0.19	0.9432	No
ΔLS	State, Year.	State	0.09	0.9865	No
		Year	499.92	0.0001	Yes
ΔLS	State*Year	State*Year	80.12	0.0001	Yes
ΔLS	State, Year. Industry	State	0.10	0.9818	No
		Year	496.72	0.0001	Yes
		Industry	1.07	0.2586	No
ΔRW	State	State	0.13	0.9733	No
ΔRW	State, Year.	State	0.13	0.972	No
		Year	4.16	0.0157	Yes
ΔRW	State*Year	State*Year	2.01	0.0138	Yes
ΔRW	State, Year, Industry	State	0.18	0.9507	No
		Year	3.58	0.0278	Yes
		Industry	0.45	1.0	No

Chapter Four:

The Role of Capital Intensity and Technology Usage in Skill Upgrading

4.1. Overview:

In the previous chapter, decomposition analysis was used to measure the within/between industry contributions to the change in the employment share of skilled workers. Furthermore, the combined industry/region/metropolitan status decomposition was also conducted to measure how much of the skill upgrade is due to within industry/within region/within metropolitan areas (WWW) and how much is due to an industry employment share changes (WWB). The results of the above decompositions suggest that most of the skill upgrade is due to WWW component, which is consistent with the skill-biased technological change explanation.

It is well known that changes in the production techniques may affect the productivity of workers of different skill levels in each of the jobs in the economy. Biased technological changes are usually classified in terms of which skill level becomes more productive in which jobs as a result of using a particular technology. Johnson (1997) distinguish between four types of biased technology. First, intensive skill-biased technological change where skilled workers become more productive in jobs they already perform. Second, extensive skill-biased technological change where skilled workers become more efficient in jobs that were formerly done by unskilled workers. Third, skill-neutral technological change where the productivity of all groups of workers increase by the same amount. Last, unskilled-biased technological change where the introduction of new technology increase the productivity of unskilled workers in jobs that had previously used higher level of skill.

Out of the four types of biased technology, the extensive skill-biased technological change is more consistent with the observed increase in the relative wage and employment share of skilled workers. For example, the introduction of robotics technology substituted unskilled assembly line workers with workers of higher skills like engineers and computer specialists. The higher demand for engineers will increase their wages, while the lower demand for unskilled workers will decrease their wages. As a result, both the share and the relative wage of skilled workers will increase.

In this chapter, I examine the correlation between the change in the wage (employment) share of skilled workers and different proxies of technological change using the linear regression model. The chapter is organized as follows: the first section includes the theoretical model. Section 2 describes the dataset used to examine the correlation between capital deepening and the change in the wage share of skilled workers, it also presents the empirical findings. The following two sections are structured as section 2, using different datasets. Section 3 uses measures of advanced manufacturing technology, while section 4 includes information regarding the entry-exit of manufacturing plants. The final section summarizes the main findings and conclusions of this chapter.

4.2. Theoretical Model:

To analyze the effect of technology on employment structure, we use a simple labor demand model, similar to the one used by Katsoulacos (1986). The main assumption are:

(1) Production depends on two inputs of labor: skilled and unskilled, denoted **S&U** respectively (ignoring capital for now).

(2) Input prices, $\mathbf{W_u}$ and $\mathbf{W_s}$, are determined exogenously outside the model, which is the case under perfect competition.

(3) The quantity of input **i** (i=S,U) required to produce one unit of output is denoted $\mathbf{a_i}$, and determined by the level of input prices and technology used in production, i.e. $\mathbf{a_i} = f(W_s, W_u, t)$.

(4) (~) denotes proportional rate of change, i.e. $d\ln f(x)$.

(5) Unit cost (c)= $f(W_s, W_u, t) = W_s \bullet a_s + W_u \bullet a_u$

Assuming the production function follows constant returns to scale, then:

$$a_s = \delta c/\delta W_s = S/Y \tag{6}$$

where Y is total output, and similarly,

$$a_u = \delta c/\delta W_u = U/Y \tag{7}$$

Obviously, a_i is homogeneous of degree zero in W_s and W_u implying that if output and factor inputs doubled factor shares (a_i) will stay the same. To derive the relationship between the change in factor input shares and technology, we need to totally differentiate equation (6):

$$da_s = (\delta^2 c/\delta W_s^2)dW_s + (\delta^2 c/\delta W_s \delta W_u)dW_u + (\delta^2 c/\delta W_s \delta t)dt \qquad (8)$$

Since $\mathbf{a}_i$ is homogeneous of degree zero, using Euler's theorem:

$$\delta^2 c/\delta W_s^2 = -(W_u/W_s)\bullet(\delta^2 c/\delta W_s \delta W_u) \qquad (9)$$

Plug equation (9) in equation (8):

$$\tilde{a}_s = -(1/a_s)\bullet(c/c)\bullet(\delta^2 c/\delta W_s \delta W_u)\bullet[(\delta c/\delta W_u)/(\delta c/\delta W_u)]\bullet W_u\bullet[(dW_s/W_s)-$$

$$(dW_u/W_u)]+(1/a_s)\bullet[\delta(\delta c/\delta W_s)/\delta t]\bullet dt \qquad (10)$$

To solve for the above equation, we need three additional definitions:

1- The elasticity of substitution between skilled and unskilled workers (σ_{su}), a measure of the ease with which skilled and unskilled workers can be substituted for one another, in response to changes in factor prices is defined as follows:

$$\sigma_{su} = c(\delta^2 c/\delta W_s \delta W_u)/[(\delta c/\delta W_s).(\delta c/\delta W_u)] \qquad (11)$$

2- The share of skilled and unskilled workers in total cost, are defined separately as

$$\theta_u = (\delta c/\delta W_u)\bullet(W_u/c) = (a_u\bullet W_u)/c \quad (12)$$

$$\theta_s = 1 - \theta_u \quad (13)$$

3- Define $\tilde{b}_s$ as the proportionate reduction in the unit input ($\mathbf{a_i}$) due to technological progress at constant factor prices, and is defined as:

$$\tilde{b}_s = -(1/a_u)\bullet(\delta a_u/\delta t)\bullet dt \quad (14)$$

To arrange equation (10) using the above definitions, we need to plug equations (11), (12) and (14) into equation (10) which reduces to:

$$\tilde{a}_u = \sigma_{su}\bullet\theta_s(\tilde{w}_s - \tilde{w}_u) - \tilde{b}_u \quad (15)$$

The significance of equation (15) is that it decomposes the total change in the unit input demand into: The substitution effect and the technological effect. The interpretation of equation (15) can be summarized as follows:

- The total change in the unit input demand can be separated into the substitution effect between skilled and unskilled workers (represented by the first term in equation (15)), and the effect of the technological process (represented by the last term in the equation).
- The substitution effect is positively related to the elasticity of substitution between skilled and unskilled workers, the share of skilled workers in total employment, and the proportionate change in the relative wage of skilled

workers. Any increase in these three parameters (assuming the level of technology is constant) will lead to an increase in the unskilled labor requirements to produce one unit of output, due to the substitution effect between the two types of labor.

- The second term in equation (15) shows the proportionate reduction in the unit input demand due to technological change, assuming that factor prices are unchanged.

The change in the unit input requirements can be calculated using equations (6) and (7), yielding the following:

$$\tilde{a}_s = \tilde{S} - \tilde{Y} \tag{16}$$

and,

$$\tilde{a}_u = \tilde{U} - \tilde{Y} \tag{17}$$

Combining the above two equations provide the proportionate change in the unit input mix requirements:

$$\tilde{a}_s - \tilde{a}_u = \tilde{S} - \tilde{U}$$

Plug the values of $\tilde{a}_s$ and $\tilde{a}_u$ using equation (15):

$$\tilde{a}_s - \tilde{a}_u = -\sigma_{su}\theta_u(\tilde{w}_s - \tilde{w}_u) - \tilde{b}_s - \sigma_{su}\theta_s(\tilde{w}_s - \tilde{w}_u) + \tilde{b}_u$$

$$= \sigma_{su}(\tilde{w}_u - \tilde{w}_s) + (\tilde{b}_u - \tilde{b}_s)$$

Define β as the effect of technical progress on the firm's desired unskilled/skilled ratio ($\beta = \tilde{b}_u - \tilde{b}_s$) then:

$$\tilde{a}_s - \tilde{a}_u = \tilde{S} - \tilde{U} = \sigma_{su}(\tilde{w}_u - \tilde{w}_s) + \beta \tag{18}$$

In this model, β represents the Hicksian index for the bias of technological change. It measures the proportionate change in the unskilled/skilled ratio attributable to technical change at constant factor prices. Technical change is said to be unskilled labor saving, neutral or skilled labor saving when β is positive, zero or negative, respectively. According to this model, two factors will determine the size of the change in the input mix requirements to produce one unit of output when technology is introduced: the substitution effect between different types of labor and the technology effect.

To trace the factors affecting the share of each input in total employment, we need to proceed with our analysis as follows:

- Denote the average product of skilled labor as **q** = **y/s** (the inverse of $\mathbf{a_s}$), from equation (16) we have:

$$\tilde{Y} = \tilde{S} - \tilde{a}_s$$

- Plug the value of $\tilde{a}_s$ from equation (10), and let $\tilde{T}$[20] $= \theta_u \tilde{b}_u + \theta_s \tilde{b}_s$, and rearrange:

$$\tilde{Y} = \theta_s \tilde{S} + \theta_u \tilde{U} + \tilde{T}$$

Therefore, the change in skilled labor productivity is:

$$\tilde{q} = \theta_u (\tilde{U} - \tilde{S}) + \tilde{T} \qquad (19)$$

In perfect competition, the proportionate change in cost will equal the proportionate change in prices ($\tilde{c} = \tilde{p}$). Totally differentiate the unit cost equation ($c = w_s a_s + w_u a_u$), then divide by c, and using the definitions of input shares (equations 12 & 13) we get:

$$\tilde{c} = \tilde{p} = \tilde{w}_u \theta_u + \tilde{w}_s \theta_s - \tilde{T}$$

As a result,

[20] T is the Hicksian measure of the extent of technological progress, it captures the extent of the reduction in the amount of each input required to produce one unit of output, and the consequent effect on the input shares.

$$\tilde{w}_s - \tilde{p} = \tilde{W}_s = (\tilde{w}_s - \tilde{w}_u)\theta_u + \tilde{T} \qquad (20)$$

The intuition of the last equation is that the proportionate change in the real wage of skilled workers ($\tilde{W}$s) is a function of their relative wages and the technology parameter. The first part of the equation indicates that the proportionate change in the real wage of skilled workers is positively related with both the proportionate change in the relative wage of skilled workers and the share of unskilled workers in total employment (assuming the level of technology is constant). The second part of equation (20) shows that the proportionate change in the real wage of skilled workers depends on the technology effect on the factor input shares. Technological change is said to be skill-biased, neutral or skilled labor saving if the coefficient is positive, zero or negative, respectively.

Wages and productivity of skilled workers will grow at the same rate unless the share of skilled workers changes. In other words, if wages grow more than productivity, the firm will cut the employment of skilled workers to the point where the growth of both wages and productivity reach equality.

Subtracting equation (19) from equation (20) and plugging the value of ($\tilde{U} - \tilde{S}$) from equation (18), we get:

$$\tilde{W}_s - \tilde{q} = \tilde{\Theta}_s = \theta_u[(1 - \sigma).(\tilde{w}_s - \tilde{w}_u) - \beta\,] \qquad (21)$$

Equation (21) implies that the proportionate change in the share of skilled workers in total wage bill (or total employment) can be separated into two effects: (a) The substitution effect represented by the first term in equation (21) shows that the direction of this effect (whether a decrease or an increase) depends on: the proportionate change in the relative wage of skilled workers, and the elasticity of substitution. (b) Technological bias measured by β (since β is a function of technological progress). If technology is unskilled labor saving, i.e. $\beta > 0$, then technological bias will reduce the share of unskilled workers.

In empirical analysis, researchers often estimate a share equation model that is derived from applying Shephard's lemma to a translog cost function. To keep the model simple, we assume that total cost of producing a certain level of output requires a capital stock K, technology level T, and the wages of the two types of labor (skilled and unskilled). Therefore, the cost function can be written as follows:

$$C = f(W_s, W_u, K, T) \qquad (22)$$

The cost function (C) is assumed to be approximated by the translog function. Define a row vector Z={K,L}, as a result, equation (22) can be written as follows:

$$\ln C = \gamma_0 + \gamma_1 \ln W_s + \gamma_2 \ln W_u + 1/2\,[\gamma_{11}(\ln W_s)^2 + \gamma_{12}(\ln W_s)(\ln W_u) + \gamma_{22}(\ln W_u)^2$$

$$+ \textstyle\sum_{j=1} [\gamma_j Z_j + \gamma_{1j}(\ln W_s)(Z_j) + \gamma_{2j}(\ln W_u)(Z_j)] \qquad (23)$$

Shephard's lemma implies the following condition for cost minimization:

$$\delta \ln C / \delta \ln W_i = S_i \tag{24}$$

where S_i is the wage share of the ith labor type in the total wage bill, differentiating equation (23) with respect to $\ln W_s$, taking the first difference yields the following equation for the change in the wage share of skilled workers[21] :

$$\Delta S_{si} = \gamma_o + \gamma_{11} \ln(W_{si}/W_{ui}) + \gamma_{1T} \Delta \ln T_i + \gamma_{1K} \Delta \ln K_i + \varepsilon_{si} \tag{25}$$

where,

ΔS_{si} : the change in the wage (employment) share in total employment of type s workers in industry i, the skill type is defined by either education, experience or occupation cells.

W_{si} : average wage for type s worker in industry i.

W_{ui} : average wage for type u worker in industry i.

T_i : technology intensity in industry i.

K_i : capital stock in industry i.

[21] For more details, see Brendt (1991), chapter 9, and also Bartel and Lichtenberg (1987).

In this specification, γ_{11} will be positive or negative according to whether the elasticity of substitution between type **s** and type **u** workers is below or above 1. γ_{1T} captures the technology intensity effect on the share of type **s** workers in total employment. Technological change will be cost neutral if $\gamma_{1T}= 0$, otherwise, it will be biased towards using (or saving) type **s** workers if $\gamma_{1T} > 0$ ($\gamma_{1T} < 0$). Theory predicts the share of skilled workers to be increasing in $\mathbf{T}_i$, and the share of unskilled workers to be decreasing in that variable. As a result, the signs of γ_{1T} depends on whether **s** belongs to skilled workers or not. Capital-skill complementarity implies that $\gamma_{1K} > 0$.

Equation (25) can be related to the labor demand model through equation (18). According to equation (18), the proportionate change in the relative share of skilled workers is a function of their relative wage and a technology parameter. The share model (equation 25) regresses the same independent variables on the change in the wage (employment)share of skilled workers. Though the two equations use the same measure (the change in the wage share of skilled workers), equation (18) divides that measure by the change in the wage share of unskilled workers, while equation (25) divides the same measure by the total wage bill.

Berman, Bound and Griliches (1994), point out that relative wages in equation (25) can not be treated as exogenous because the dependent variable measures the changes in the skilled workers share in the wage bill and relative wages represent the price of skill. Therefore, BBG believe their estimates will suffer from a version of "division bias". Moreover, they assume that the price of skill does not vary across industries, implying that $\Delta\ln(W_{si}/W_{ui})$ will be constant, therefore they ignored relative wages in their regression since it will only affect the intercept. As a result, BBG's regressions include proxies of technology as the only independent variables[22].

In this study, equation (25) will give the general framework of the regression analysis. Dummy variables representing different time intervals, geographical regions and industrial sectors will be added in order to test whether there are any significant effects driven by regional or sectoral differences. The decomposition part of this dissertation indicates: (1) Significant differences between the manufacturing (and almost all sectors) and the services sector, (2) Different pattern in the between early and recent time intervals, and (3) There are no significant differences in the distribution of skill across regions.

Four different data sets, in addition to the IPUMS, are used to carry on the regression analysis: The Survey of Manufacturer Technology (SMT), The Bureau of Economic Analysis (BEA) wealth dataset, The Bureau of Labor Statistics (BLS) domestic industry output data, and The Census of Manufactures (CM) entry and exit data set. These data sets will be described in the remainder of this section, along with the empirical findings of the regression analysis.

[22] Autor, Katz and Krueger (1997), among many others, followed the same practice and used different proxies of technology as their independent variables.

4.3. Capital-Skill Complementarity and Capital Deepening:

The first set of analysis will focus on examining capital-skill complementarity. Capital-skill complementarity means that skilled workers are more complementary with new capital stock than unskilled workers. As a result, a plant which is more capital intensive is expected to have a higher share of skilled workers. Empirical findings, in general, support the notion of capital-skill complementarity. Bartel and Lichtenberg (1987) find that the age of capital stock (as a proxy of technology), is positively related to the share of educated workers. Berman, Bound and Griliches (1994) also find that skill upgrading is positively correlated with the rate of growth of capital/output ratio.

(1) The BEA Wealth Dataset:

The BEA dataset provides annual estimates from 1947 to 1994 of the gross and net stocks, capital input, depreciation, and discards for fixed nonresidential private capital owned by each two digit establishment based on 1987 SIC industry classification. Two alternative valuation methods are provided: constant cost (millions of 1987 dollars) and current cost values, moreover, capital stock estimates are available by asset's type.

I use the BEA dataset measures for net capital stock at constant 1987 dollars, and detailed industry capital stock and investment in specific categories such as office computing and machinery. These variables are available by the National Income and

Product Account (NIPA) industrial categories (which is based on the 1987 SIC). To reduce measurement error, all capital stock and investment variables are constructed as 5-years centered average[23] .

To match the BEA dataset with the IPUMS, we created an industry concordance between NIPA and IPUMS industrial classifications which is given in table (18). The merged BEA/IPUMS dataset, has 54 industries (based on NIPA industrial categories) for four years covering the period from 1960 to 1990. Moreover, the new dataset provides measures of the share of skilled workers in the wage bill along with detailed capital stock information for the period from 1960 to 1990. However, to make full use of the new dataset, we need additional information regarding industry output.

The real industry output variable is available from the Historical Data Series published by the Bureau of Labor Statistics (BLS) which contains estimates of the domestic industry output (valued in millions of constant 1987 dollars) for three-digit SIC industries. The BLS real output dataset is merged with the BEA/IPUMS according to the industry concordance in table (18). The resulting dataset, BEA hereafter, will provide information about the distribution of skill among all industries, detailed capital stock investment, and real output.

The BEA dataset allow us to examine whether the distribution of skilled workers vary across different industrial sectors. Three variables are constructed from

[23] In constructing the capital stock data, we use procedures similar to Autor, Katz and Krueger (1997).

the BEA dataset: (1) The changes in the log of real net capital stock per unit of output (Δlog k/y), which proxy technology as it measures capital deepening. (2) Changes in the log of real output (Δlog y), which comes from applying Shephard's lemma as shown in the modeling section. The output variable controls for movement across the isoquants. (3) Changes in the log of real net stock of office, computing and accounting machinery capital per unit of real capital stock (Δlog c/k). This variable provides another proxy for technology and measures the change in the composition of capital stock, i.e. the upgrade of capital quality. Trends of the log growth rates of the three proxies of technology are included in table (19). The rate of growth of the capital/output ratio increased slightly from the 1960s to the 1970s, then dropped sharply in the 1980s[24]. On the other hand, the growth rate of both computer stock/output and computer stock/capital show a significant increase over time, implying that computer stock could be associated with the upgrade of skills in the 1980s.

In their regression analysis, Autor, Katz and Krueger (1997) use the log of the lagged computer stock/labor ratio as one of their independent variables (to proxy technology), while the dependent variable is the growth rate of the share of college graduate. They assume that increasing the computer stock/labor ratio at the beginning of the decade will cause a shift in the skill mix during that decade. The lagged effect is the main weakness in AKK analysis. When a company invests in

[24] Autor, Katz and Krueger (1997) noted a similar trend, though they used capital/labor ratio.

computer stock at the beginning of 1997, they will usually hire people to operate and maintain the machines as soon as possible which will affect the share of skilled workers in that company. Assuming that all firms will behave in the same way (otherwise there will be no point in buying the new computers), we expect the growth rate of computer stock to change simultaneously with the growth rate of the share of skilled workers as implied by equations (21) and (25). As a result, we use the growth rate of both: capital stock/output (Δlog k/y), and computer stock/capital (Δlog c/k) as independent variables to be consistent with equations (21) and (25)[25].

The basic regression I run is an extension of equation (25) and given by the following equation:

$$\Delta S_{si} = \gamma_o + \Sigma_R \beta_R D_{1t} + \Sigma_j \beta_j D_{2j} + \gamma_{1K} \Delta \log k/y + \gamma_{1T} \Delta \log c/k + \gamma_{1y} \Delta \log y + \varepsilon_{si} \quad (26)$$

According to the above model, the change in the employment (wage) share of skilled workers is regressed on variables representing:

- Time and industrial sectors dummies to capture any differences in the distribution of skill across different time intervals and industrial sectors.
- The change in the log of capital/output ratio to capture the effect of capital-skill complementarity (capital deepening) on the distribution of the skill mix.

[25] We ran a similar regression to AKK using the log of the lagged computer stock/output (we also did the same using computer stock/capital), the coefficients of both computer stock variables were negative, and we were unable to get the positive sign that AKK report.

• The change in the log of output, this will capture the output size effect on the change in the wage share of skilled workers.

• The change in the log of the share of computer stock in total capital stock, this variable will capture the quality of capital effect on the distribution of skilled workers.

(2) Empirical Findings:

Table (20) presents the results of running three regression models based on equation (26) for the three definitions of skill. Model 1 includes time dummies and Δlog c/k, model 2 adds the change in log output variable to the first model, while the last model adds the (Δlog k/y) variable. The industrial sector dummies show no significant effect on the change of both the wage share and the employment share of skilled workers under all three models and for all three definitions of skill.

According to the occupation definition, only time dummies have a significant effect on the wage (and employment) share of white collar occupations. The estimated coefficients for the time dummies illustrate an increase in the within-industry growth of the wage share of white collar workers in the 1970s and 1980s. All three capital stock variables have an insignificant effect on the skill mix, and introducing these variables to the model does not improve the explanatory power of the model. These results are similar to the findings reported by Doms, Dunne and Troske (1997), using data from the manufacturing sector.

The results of the HT regressions show similar results regarding the significance of the time dummies, additionally, out of the other three variables, the change in the log output is the only variable with significant coefficient. The positive sign for the change in log y suggests that increasing the scale of production is associated with a higher level of wages for skilled workers. Including Δlog y increased R-squared significantly from .045 to .1346 (in panel a), and from .0986 to .1945 (in panel b). Panel (a) illustrates a positive relation between Δlog y and the wage share of HT workers, the value of the coefficient is 0.0429 for the second model (a little less for the last model). To evaluate the magnitude of the change in log y, the predicted value of the dependent variable is calculated using one standard deviation below and one standard deviation above the average value of the Δlog y. One standard deviation below the mean of the Δlog y yields a predicted value of 0.003 for the change in the wage share of HT skilled workers, while the predicted value of the dependent variable reaches 0.0223 when the one standard deviation above the mean is used. The difference between the two predicted values is 0.0196 which is almost equal to the mean value of the dependent variable, indicating that the estimated effect is relatively large in terms of magnitude[26].

The education definition regressions show some differences in the results depending on which dependent variable is used. When the wage share of educated workers is used (see panel a), Δlog c/k is the only variable with a significant coefficient at the 5% level. Model 1 indicate that the time pattern is similar to the

[26] Panel (b) indicates similar results when the change in the employment share of HT workers is used as the dependent variable.

other two definitions of skill, showing an acceleration in the change of the wage share of educated workers in the 1970s and 1980s. The computer investment variable has a positive correlation with the change in the wage share of educated workers, the value of the coefficient is 0.01536. Evaluating the magnitude of the estimate on the mean shows that computer investment causes 12% of the change in the wage share of educated workers between 1960 and 1990[27] . Additionally, evaluating the predicted value using the one standard deviation above and below the mean of Δlog c/k shows a difference of 0.035 in the predicted value of the change in the wage share of educated workers. These results suggest that computer investment has a significant effect in terms of magnitude of the change in skill. The impact of computer investment increases slightly when we add both Δlog y and Δlog k/y (which have no significant effect on the dependent variable). The explanatory power of the model increases from 0.6036 in model 1 to 0.613 in model 2. The positive coefficient of the change in the log capital/ output ratio in model 3 (though insignificant) is consistent with the overall capital-skill complementarity.

Panel (b) presents the results of the regression analysis when the change in the employment share of educated workers is used as the dependent variable. As mentioned earlier, the education definition results are different from panel (a). Model 1 shows that Δlog c/k variable is statistically significant with a parameter value of

[27] To evaluate the parameter at the mean, I multiply the estimated coefficient (0.01536) by the mean of the variable over the period under study (0.76624), then I divide the product by the mean of the dependent variable (0.0985).

0.0125, which also have a significant magnitude. Model 2 indicates that adding the change in log y (which has insignificant parameter) increase the R-squared slightly from 0.6362 to 0.6415. A further addition of the Δlog k/y in model 3 increases R-squared to 0.6711, and shows that all three variables are statistically significant at the 5% level. All three coefficients have positive signs as predicted by the theory. The positive sign in front of Δlog k/y represents the positive correlation between increasing capital deepening (based on capital-skill complementarity) and the change in the skill mix. The positive coefficient for Δlog c/k represents the positive correlation between computer use (high tech capital stock) and the change in the employment share of skilled workers. Evaluating the two proxies of technology at the value of their mean shows that Δlog k/y is responsible for around 6.8% of the change in the skill mix between 1960 and 1990, while Δlog c/k is responsible for 12.7%. These figures imply that Δlog c/k has a stronger effect on the change in the employment share of skilled workers than non computer capital.

The above results are similar to the findings reported by AKK (1997). First, there is a positive relation between all capital stock measures and the change in the wage (employment) share of skilled workers. Second, computer capital in particular has a strong positive relation with the change in the wage share of educated workers. This positive impact is not substantially affected when other capital measures are added to the regression (in fact none of the other measures have a significant coefficient as shown in panel a). Though AKK used the lagged computer capital while I use the growth of computer capital, both results indicate that the magnitude of the computer capital coefficient is much larger than other capital variables. This implies that computer capital has a stronger impact on the changes in workforce skills than the general capital-skill complementarity.

4.4. Advanced Manufacturing Technology:

(1) The SMT:

While computer investment represents one type of technological improvement, there are quite a number of other types of technologies that may be linked to skill upgrading. For example, the introduction of robots, as a different type of advanced technology, has increased the demand for skilled workers. In this section, I examine more closely the relationship between advanced manufacturing technologies and the change in workforce structure.

The 1988 Survey of Manufacture Technology (SMT) is a sample survey of manufacturing establishments with 20 or more employees selected to represent the manufacturing firms classified in Standard Industrial Classification (SIC) major groups 34 - 38. The industries covered in the sample are: Fabricated metal products (SIC 34), non-electrical machinery (SIC 35), electric and electronic equipment (SIC 36), transportation equipment (SIC 37), and instruments and related products (SIC 38). These groups accounted for 43% of employees and value added in US manufacturing as reported by the 1987 Census of Manufacture . The survey includes questions about a plant's usage of seventeen technologies during the year 1987, therefore, the SMT provides information regarding the technology used by manufacturers at the plant level. The seventeen technologies were chosen from the following five technology areas: Design and engineering, fabrication machinery and assembly, automated material handling, automated sensor-based inspection, and communication and control. Table (21) provides information regarding the usage of the seventeen technologies in the major industry groups. Each row represents the percentage of firms in each 2 digit industry that is using each technology. The most heavily used technologies are: Computer aided design, numerically controlled machines, programmable controllers and computers used on the factory floor. Moreover, the SMT also includes information about the regional distribution of the plants, i.e. the nine Census regions[28].

Dunne and Schmitz (1995) use SMT information on technology to construct a measure of technology usage intensity, based on the assumption that the plant that employs more technologies is considered more technologically advanced. Moreover, Dunne and Schmitz constructed a technology scale at the three-digit SIC level for manufacturing industries included in the survey.

In this dissertation, I will use the technology measure constructed by Dunne and Schmitz along with other regional and industrial variables available from the SMT. Dunne and Schmitz (1995) constructed a technology use measure based on the

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[28] For more details see Manufacturing Technology 1988, and Dunne (1991).

assumption that the plant which employ more technologies is more technology intensive than the one who uses less number of technologies. As a result, the number of technologies used in each plant is aggregated in order to construct a technology index at the three-digit SIC industry /nine census regions cells. In the aggregation process, the contribution of each plant was adjusted using both the employment and the SMT weights. As a result, we are able to construct technology use measures representing the following combination: three-digit SIC industry by nine census regions. The first data set used in this analysis, will be called SMT/IPUMS, and is obtained by matching the SMT and the IPUMS by both industry and region cells. Matching the two data sets will provide information about the change in the skill mix, geographical region, industry (though we will be limited to few manufacturing industries), and a direct measure for technology intensity. The significance of having this data set is that it will allow us to add the regional variable to test the significance of technology usage effect on changing the skill mix, and also to test whether there are important differences in the change in skill across regions.

To match the SMT data with the IPUMS, we created an industry concordance between the four-digit SIC industrial categories (used in SMT) and the 1950 Census Bureau Occupational and Industrial Classification system used in the IPUMS. Table (22) includes the concordance between the three-digit SIC codes for manufacturing and IPUMS industrial classification, afterwards, to match the SMT with IPUMS we need to aggregate the three-digit SIC codes to the two-digit industry level.

The SMT/IPUMS dataset provides information on the share of skilled workers in the wage bill by industry and region for the period from 1950 to 1990 matched to the 1988 technology data. For each year, the new dataset has 126 cells according to the combination of the 14 IPUMS industries and the 9 census regions. The number of aggregate cells reduces to 113 after dropping missing values.

The basic regression I am using in this section is an extension of equation (25) as follows:

$$\Delta S_{si} = \gamma_o + \Sigma_R\, \beta_R D_{1t} + \Sigma_j\, \beta_j D_{2j} + \gamma_{1T} T + \varepsilon_{si} \tag{27}$$

According to the above model, the change in the wage share of skilled workers is regressed on variables representing:

- Regional and two-digit SIC industrial dummies to capture any differences in the distribution of skill across different regions and industrial sectors.
- I do not include any time dummies since the SMT is a cross-section dataset available for 1988 only.
- The advanced technology measure.

(2) Empirical Findings:

The combined SMT/IPUMS dataset provides measures on the change of skill mix, technology intensity and regional distribution for SIC manufacturing groups 34-38. These variables allow us to test how technology usage affects the distribution of skill in certain manufacturing industries in different regions. Two measures of skill are used in this regressions: education and high tech (HT) definitions. For each definition, the change in the wage share of skilled workers is regressed on: technology usage in the first model, regional dummies are added to the second model and two-digit SIC industry dummies are included in the last model. The change in the share of skilled workers is measured over three different time intervals: 1960/1990, 1970/1990 and 1980/1990. All variables are weighted by the average (beginning and end of each time interval) of the wage share of skilled workers in region j and industry i in the total wage bill. The mean of our technology usage variable is 6.217.

The two panels of table (23) present the results from estimating equation (27) for the two definitions of skill over three time intervals. All regressions show that technology usage is positively related to the change in the share of skilled workers in the wage bill, and all models also indicate that the technology variable has a stronger effect with longer time intervals, i.e. the technology parameter under the education definition for model 1 is 0.01189 for 1960/1990 period, 0.009 for 1970/1990 and 0.0028 for 1980/1990[29] as shown in panel (a). In addition, there are two points to highlight in the two panels of table (23) regarding the effect of technology use. First, evaluating the technology parameter at the mean for the first model shows that technology usage explains about 29% of the change in the educated workers share in total wage bill between 1960/1990 (24% for 1970/1990 and 12% for 1980/1990 as

[29] The HT definition shows the same trend.

shown in panel (a)). Moreover, evaluating the predicted value of the dependent variable at one standard deviation above and below the mean, yields the following two predicted values: 0.0401 and 0.1077. The difference between the two predicted values is 0.0676, which is around 27% of the change in skill mix. Panel (b) shows similar results for the technology variable for the first model for all time intervals[30].

Second, all regressions indicate that adding both the two-digit and the region dummies increase the explanatory power of the model, consequently, the R-squared for model 3 is higher than model 2 which is, in turn, higher than model 1. This trend is consistent over all time intervals and for the two definitions of skill. Although most of the region and industry dummies have insignificant parameters, the null hypothesis of no industry effect is rejected for both the education and the HT definitions of skill (at 5% level of significance). The F-test values for the education definition are: 4.32 for 1960/1990 period, 6.58 for 1970/1990 and 6.18 for 1980/1990, the corresponding values for the HT definition are: 2.60, 4.66 and 3.51 for the three time intervals.

The hypothesis of no regional effect is rejected only for the education definition of skill at the 5% level of significance. The F-test values for the education definition are: 2.86 for 1960/1990, and 2.10 for 1970/1990 and 3.03 for 1980/1990, and for the HT definition: 1.45, 1.39 and 0.93 for the three time intervals. According to the education definition (panel (a)), all region dummies parameters are significant over the period 1960/1990, almost none for 1970/1990 and two for 1980/1990.

[30] This argument is valid for the other two models and for all time intervals under the HT definition.

These findings suggest that regional differences in the distribution of skill have a larger effect over longer time intervals. Additionally, the 1980/1990 regression indicates that the west north central and the west south central regions have weaker effect (compared with other regions) on the change of educated workers share in the wage bill [31]. Along the same lines, non-electrical machinery has a weaker effect (compared to other industries) on the change in the wage share of educated workers.

In summary, the SMT cross-sectional regressions results are consistent with the findings of other researchers[32], and suggest that the intensity of technology usage is positively related to the change in the wage share of skilled workers. The magnitude of the effect of technology on the skill mix is strong, it accounts for about 29% of the change in the wage share of educated workers. The HT definition of skill shows similar results with a strong magnitude for the technology coefficient. Adding the region and industry dummies increase the explanatory power of the model, though most of the industry and region dummies have insignificant coefficients. However, the F-test results rejects the null hypothesis of no industry effect for both the education and HT definitions. However, region dummies indicate a significant region effect according to the HT definition only. Moreover, the regional difference indicate a weaker effect for the west central states while the industry difference is due to the weaker effect in the non-electrical machinery industry.

[31] The high tech (HT) definition of skill shows no significant differences in the distribution of scientists and engineers and other highly skilled workers across regions for all three different time intervals (see panel b).

[32] Such as BBG (1994), AKK (1997) and Dunne and Schmitz (1995).

4.5. Entry-Exit of Manufacturing Plants:

There are two possible mechanisms to describe the way in which technology is introduced into workplaces: First, the existing plants retool and technology upgrade their technologies, and second, through the entry-exit of plants. According to the first mechanism, when managers realize the economic potential of using updated technology, they introduce them to their plants. If the new technology is skill-biased, then the internal upgrade of technology increases the demand for skilled workers. Alternatively, the second mechanism involves the entry-exit of plants, assuming that new plants (entrants) usually adopt the latest technology, while old plants with outdated technologies are induced to exit (Bernard and Jensen (1997)). If technology is skill-biased, we expect to see a positive correlation between the firm formation and the increase in the wage (and employment) share of skilled workers.

Dunne, Haltiwanger and Troske (1996) measure the contribution of entry and exit of plants through the decomposition of the annual changes of nonproduction labor share over the period 1972-88. Their findings show that the overall contribution of net entry at the annual frequency is small, however, in the longer time intervals, the entry and exit of plants play a substantial role. Two important points should be highlighted in their findings regarding the long run contribution of net entry to the change in the skill mix. First, the nonproduction share of entering plants is (on average) larger than those of exiting plants, implying that the net entry has a positive contribution to the change in the nonproduction labor share. Second, the nonproduction share of entering plants is smaller than those of existing plants, implying that the net entry is not the primary way in which new technology is introduced into the economy.

Based on the above, I will examine the significance and magnitude of the correlation between net entry and the wage (employment) share of skilled workers, using different definitions of skill. Moreover, the dataset provides information regarding the regional and three-digit manufacturing industry distribution of the entry-exit plants. The industrial and regional variables provide an opportunity to examine whether there are any industrial or regional differences affecting the correlation between net entry and the change of the skill mix.

(1) Entry-Exit Dataset:

The entry-exit data set is constructed from Census of Manufactures data that provides coverage of plants responsible for producing all output in four-digit manufacturing industries. In constructing the entry-exit data, Dunne, Roberts and Samuelson (1988) identified the entering and exiting firms in each industry for each census year from 1963 to 1982 (six census years: 1963, 1967, 1972, 1977 and 1982). Afterwards, data for the census years 1987 and 1992 were added to the dataset. As a result, the available data set include the number of entering, exiting and continue plants in each three-digit SIC manufacturing industries for each state[33] .

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[33] For more details about the structure and methodology used see Dunne, Roberts and Samuelson (1988) and (1989).

In order to match the entry-exit data with the IPUMS, we need to make few adjustments. **First**, the five year interval for each census has been extended to ten years through aggregating each two consecutive census years, as a result, we end up with the following intervals: 1963-1972, 1973-1982 and 1983-1992. This step is necessary to match these intervals with the IPUMS intervals: 1960-1970, 1970-1980 and 1980-1990. **Second**, state variable is aggregated to the nine census regions levels. **Third**, two variables are created for each industry/region cell for each time interval: the growth rate of the number of firms between the beginning and end of each interval (growth hereafter), and the firms turnover in each time interval. For each time interval, the average number of firms is calculated using the total number of firms at the beginning and the end of each interval. Consequently, the new variables are calculated as follows:

- Growth = (# of entering firms - # of exiting firms) / average # of firms.
- Turnover = (# of entering firms + # of exiting firms) / average # of firms.

Fourth, the IPUMS industry classification codes are matched with three-digit SIC classification for the manufacturing sector through the concordance in table (22). The resulting dataset from matching the entry-exit data with the IPUMS has 1403 cells representing the combination of 52 manufacturing industries (according to the IPUMS codes), three time intervals and nine census regions.

The basic regression I am using in this section is an extension of equation (25) and is given as follows:

$$\Delta S_{si} = \gamma_o + \Sigma_T \beta_T D_{1t} + \Sigma_R \beta_R D_{1R} + \Sigma_j \beta_j D_{2j} + \gamma_{1G} \text{Growth} + \gamma_{1T} \text{Turnover} + \varepsilon_{si} \tag{28}$$

According to the above model, the change in the wage share of skilled workers is regressed on variables representing:

- Regional and time and two-digit SIC industrial dummies to capture any differences in the distribution of skill across different time intervals, regions and industrial sectors.
- The two entry-exit measures, growth and turnover.

(2) Empirical Findings:

The two panels of table (24) present the results of the four models used in examining the correlation between entry-exit measures and the change in the wage of skilled workers. Two definitions of skill are used: the education and the high tech (HT) definitions. Model 1 includes the time dummies only to examine the time pattern of the change in the wage share of skilled workers. In model 2, I add the two entry-exit variables: growth and turnover, while model 3 adds a two-digit SIC industry dummies and the last model includes a regional dummies. The sample means for the dependent variable, growth and turnover variables are: 0.13128, 0.03537 and 0.7421, respectively.

According to the education definition, model 1 shows the within industries skill upgrading over the different time periods, with the largest effect between the years 1980/1990. The explanatory power of the first model is relatively high (R-squared is 0.7215) suggesting that significant differences in the distribution of skill over time. Model 2 shows that the growth variable is insignificant, and turnover to be negatively related with the change in the wage share of educated workers. Evaluating the magnitude of the estimated parameter of turnover at the value of the mean shows that a 9% decline in the wage share of educated workers is caused by the turnover variable[34]. The explanatory power of model 2 shows a slight increase compared with model 1. The R-squared is 0.726. Different industries have different effects on the wage share of educated workers. A comparison between the estimated coefficients shows that apparel, furniture and rubber products have the largest coefficients, as shown in panel (a) of table (24). Adding the industry dummies to the model increased the negative effect of the variable turnover from -0.0167 in model 2 to -0.0836 in model 3, and increased the R-squared for the third model to 0.7586. Model 4 suggests that the region dummies have no significant effect on the change of the wage share of educated workers.

[34] In fact all the estimated models, under both the education and HT definitions) suggest a negative relation between the change in the skill mix and turnover, moreover, all regressions (except model 4 in panel (b)) show the growth variable is insignificant.

Testing the null hypothesis of no industry effect is rejected at the 5% level for both the education and the HT definitions of skill. The F-test value for the education definition is 8.80 and for the HT definition is equal to 16.10. Alternatively, both the t-test and F-test show that the regional dummies have insignificant effect on the change of the skill mix according to the education definition.

The results of the regressions using the HT definition indicate two main differences from the education definition. First, most of the industry dummies have insignificant coefficients, including apparel, furniture and rubber products. Industries with significant coefficient under the HT definition include petroleum, fabricated steel, electrical equipment and professional equipment. These results indicate that changes in skill differ from one industry to another. For example, apparel, furniture and rubber industries may require a larger share of educated workers, while petroleum, electrical and professional equipment industries require a larger share of engineers.

Second, the region dummies have significant parameters, and including them increased R-squared from 0.4675 in model 3 to 0.4833 in model 4. Moreover, the F-test of the null hypothesis of no regional effect is rejected (the F-test value is 5.10) implying that region dummies affect the distribution of high tech workers. The coefficients of the regional dummies show that the mountain and pacific regions have the largest effect (compared with other regions) on the change in the wage share of high tech workers.

To sum up the results of estimating equation (28) using the Entry dataset, the growth rate of net entry has no significant effect on the wage share of skilled workers, while turnover seems to have a negative effect. A possible explanation for the negative relation between turnover and the change in the skill mix is based on the fact that a higher turnover reflects severe competition in the industry (or market). As a result of the risky business, entrants may reduce their establishment cost in order to reduce their business risk. The lower establishment cost negatively affect the level of technology used by new entrants.

The estimated industry dummies indicate that the change in the skill mix differ from one industry to another, though each definition of skill yield different ranking for the industry effect. These results reflect the fact each industry requires different type of skill. Region dummies show mixed results depending on the definition of skill, under the education definition regional dummies have no significant effect on the change in the wage share of educated workers. Alternatively, the HT definition indicates that the mountain and the pacific regions have had a greater change of the wage share of high tech workers.

4.6. Topel Model:

Topel (1994) uses regional wage differences to study the determinants of relative wages using a model of factor demand in geographic markets. The model used by Topel is based on equation (25), where the demand equation takes the following form:

$$\Delta X_{ijm} - \Delta Z_{jm} = \gamma_{1j} \Delta \log (w_{sm}/w_{nm}) + T_{ij} + e_{ij} \qquad (29)$$

where:

ΔX_{ijm} : is the change in the share of type **i** skill workers in industry **j** and market **m**.

ΔZ_{jm} : the cost share weighted average of the change in the share of the two skill groups in the model, it is calculated as: $\Sigma_i K_{ijm} \bullet \Delta X_{ijm}$.

w_{sm}/w_{nm} : is the relative wage of skilled workers.

T_{ij} : type **i** skill-biased technological change in industry **j**, technical change is assumed to be independent of **m**.

Total regional increase in the demand for type **i** workers will equal the their supply when the market is in equilibrium, implying that: $\Delta X_{im} = \Sigma_j S_{ijm} \bullet \Delta X_{ijm}$, where S_{ijm} is the employment share of skill type **i** in industry **j** and market **m**.

Substituting the above equilibrium condition into equation (29) and solving for the change in the relative wage yields:

$$\Delta \log (W_{sm}/W_{um}) = (\gamma_{1m})^{-1} [(\Delta X_{im} - \textstyle\sum_j S_{ijm} \bullet \Delta Z_{jm}) - (\sum_j S_{ijm} \bullet \Delta T_{ij}) - e_i] \tag{30}$$

The above equation decomposes the change in the log relative wage of skill level **i** in region **m** into two main factors: The change in net supply of type **i** workers in market **m** (which is represented by the first part in the right hand side of the equation), and technical change. $(\gamma_{1m})^{-1}$ is the regional elasticities of complementarities which relates the changes in the regional relative wage to changes in net supply of type **i** workers and technical changes.

To estimate the above model, I use the BEA dataset which was used in section (4.3) because it includes suitable variables to fit equation (30). Workers are divided into two levels of skill according to the education definition, the dataset also includes 45 industries and 9 regions. Two time intervals are used 1960/1990 and 1970/1990, while technical change is proxied by the change in the log of the share of computer stock in total capital stock (Δlog c/k). The first part of the model presents the change in the net supply of factor **i** in market **m**, which is expected to be negatively related to the change in relative wage of skilled workers (i.e. if supply grows faster than demand relative wage will drop for this type of skill). Alternatively, since technical change is assumed to be skill-biased, the second part is expected to have a positive sign. As a result, the final movement of relative wage (whether an increase or a decrease) is determined by the magnitude of each part in equation (30), if net supply of type i workers has a greater effect than technical change, relative wage will drop for that type of workers.

Table (25) includes the estimated parameters for equation (30) for the two time intervals. The estimated coefficient for net supply has a negative sign for both periods, implying that the increase in average school attainment over the last thirty years has a negative effect on the relative wage of educated workers. Technical change (as proxied by $\Delta \log c/k$) has a positive effect on the change in the relative wage of educated workers. Since the relative wage of educated workers have actually increased over both time intervals, this suggest that the magnitude of positive technical change effect is larger than the magnitude of the negative net supply effect. The explanatory power for the 1960/1990 regression shows that adding the region effect increases R^2 from 0.5467 to 0.6568, while R^2 for the 1970/1990 increases by a less amount from 0.8955 to 0.9252. In all cases the 1970/1990 regression has a higher explanatory power than the 1960/1990.

In table (26), the actual and predicted change in log relative wage is recorded by region, along with a decomposition of the model's prediction to the net supply effect and technical change effect for the two time intervals. For the two time intervals and all regions show that the contribution of technical change outweigh the negative effect of net supply, causing relative wage to increase. Actual changes in relative wage show significant regional differences where the west region having the largest increase in relative wage. The increase in the relative wage in the west region is almost two and half times the average in 1960/1990 and around double the average in 1970/1990. To examine where does the large increase come from, I compare the numbers of the west region with the average. For 1960/1990 period, the predicted change in relative wage for the west is 32% higher than the average, however, the net supply component is 6.2% higher in the west while the technical component is 17.5% higher. The 1970/1990 results show a similar pattern, where the predicted relative wage is 42.7% higher in the west than the average, this increase can be related to 4.5% higher net supply and 20% higher technical effect.

4.7. Summary:

In this chapter I have investigated the correlation between the change in the wage share of skilled workers and different proxies of technological change using regression analysis. There are four main findings:

(1) The capital-skill complementarity analysis indicates that there is generally a positive relationship between the various capital stock measures used and the change in the wage share of skilled workers. Additionally, computer capital measure in particular has a strong positive correlation with the change in the skill mix, this positive impact is not significantly affected when other capital measures are added to

the regression. Comparing both the significance and the magnitude of the two capital stock measures (Δlog k/y and Δlog c/k) indicates that the computer capital coefficient has a stronger impact on changes in skills than the general capital-skill complementarity. The intuition behind these results is that computers, in general have a stronger effect on the change of the skill mix. Moreover, not only the quantity of capital stock is important in shaping the change in the workforce structure, it is the quality of capital stock that has the largest impact on the change in the wage share of skilled workers.

(2) The SMT regressions suggest that the intensity of technology use is positively related to the change in the wage share of skilled workers. Moreover, the magnitude of the effect of technology on the skill mix is strong, accounting for about 29% of the change in the change in the wage share of skilled workers.

(3) The entry-exit dataset allow us to examine the significance and magnitude of the correlation between net entry and the wage share of skilled workers, as well as investigating whether there are any industrial or regional differences affecting that correlation. The empirical findings indicate that net entry has no significant effect on the change in the wage share of skilled workers, while the turnover variable has a negative coefficient.

(4) Using Topel (1994) model of factor demand in regional market, I examine the determinants of regional relative wage differences. Empirical results suggest that net supply of skilled workers has a negative effect on the change in relative wages,

however, the negative effect is outweighed by the strong positive effect caused by skill-biased technology.

Table (18)

BEA-IPUMS-SIC Industry Codes Concordance

Industry	IPUMS	SIC	Wealth
Agriculture, Forestry & Fisheries	105, 116, 126	01, 02, 07, 08, 09	1, 2
Metal mining	206	10	3
Coal mining	216	11, 12	4
Crude petroleum and natural gas Extraction	226	13	5
Nonmetallic mining and quarrying, except fuel	236	14	6
Construction	246	15, 16, 17	7
Lumber & Wood products	306, 307, 308	24	8
Furniture and fixtures	309	25	9
Stone, Clay & Glass and glass prod.	316, 317,318 319, 326	32	10
Primary Metal Indust.	336, 337, 338	33	11
Fabricated Metal Products	346, 347, 348	34	12
Industrial Machinery	356, 357, 358	35	13
Electrical mach. equip. and supplies	367	36	14
Motor vehicles and motor vehicle equip	376	371	15
Transportation except Motor Vehicles	377, 378, 379	37, except 371	16
Instrument and related products	386, 387, 388	38	17
Mis. Manufacturing	399	39	18
Food & Kindred Products	406, 407, 408, 409, 416, 417, 418, 419, 426	20	19
Tobacco Manufacturing	429	21	20
Textile Mill Products	436, 437, 438, 439, 446	22	21
Apparel & Other Textile Products	448, 449	23	22
Paper & Allied Products	456, 457, 458	26	23
Printing & Publishing	459	27	24
Chemicals & Allied Products	466, 467, 468, 469	28	25
Petroleum & Coal Prod	476, 477	29	26
Rubber & Mis. Plastic Products	478	30	27
Leather & Leather Products	487, 488, 489	31	28
Railroad Transportation	506	40	29
Local, Interurban Transit	516, 536	41	30
Trucking & Warehousing	526, 527	42	31
Water Transportation	546	44	32
Air Transportation	556	45	33
Pipelines Except Gas	567	46	34
Transportation Serv.	568	47	35
Telephone & Telegram	578, 579	481, 482, 489	36
Radio & TV	856	483, 484	37
Electric & Gas Service	586, 587, 588	491, 492, 493	38, 39
Sanitary Services	596, 597, 598	494, 495, 496, 497	40
Wholesale Trade	606, 607, 608, 609, 616, 617, 618, 619, 626, 627	50, 51	41
Retail Trade	636, 637, 646, 647, 656, 657, 658, 659, 667, 668, 669, 679, 686, 687, 688, 689, 696, 697, 698, 699	52 Through 59	42
Banks & Credit	716	60, 61	44, 45
Security & Commodity Brokers & Other Investment	726,	62, 67	46, 50
Insurance	736	63, 64	47, 48
Real Estate	746, 756	65, 66	49
Hotels & Other Lodging Places	836	70	51
Personal Services	826, 846, 847, 848, 849	72	52
Business Services	806, 808	73	53
Auto Repair & Service & Parking	816	75	54
Mis. Repair Services	817	76	55
Motion Pictures	857	78	56
Amusement & Recreation Services	858, 859	79	57
Health Services	868, 869	80	58
Legal Services	879	81	59
Educational Services	888	82	60
Social Services, Museums, Membership Organizations, Engineering, Management &Other Ser.	896, 897, 898, 899	83, 84, 86, 87, 89	61

Table (19)

Log Changes of Capital and Computer Measures for the BEA Dataset

1960-1990

Variable	1960/70	1970/80	1980/90
Δlog k/y	0.164	0.17	0.047
Δlog c/y	-0.345	1.385	1.613
Δlog c/k	-0.505	1.218	1.566
Δlog y	0.385	0.258	0.23

Notes: The above figures represent the mean values for the 43 industries included in the matched IPUMS/BEA/BLS dataset. Output and capital stock figures are measured in millions of constant 1987 dollars. Each measure is a five years centered average of the respective variable. All capital stock measures are net stock measures.
k/y: real net capital stock per unit of real output.
c/y: real net stock of office, computing and accounting machinery capital per unit of real output.
c/k: real net stock of office, computing and accounting machinery capital per unit of real capital stock.

Table (20)

Computers, Capital Intensity, and Skill Upgrading 1960-1990

(a) Dependent Variable: Change in skilled Workers Share in the Wage Bill.

Variable	Education Definition			Occupation Definition			HT Definition		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept (Capturing interval 1960-1970)	.0528 (.0058)	.0501 (.0093)	.0451 (.0097)	.0095* (.0049)	.0192 (.0079)	.0187 (.0083)	.0123 (.0043)	-.0061* (.0066)	-.0043* (.0069)
1970-1980 Dummy	.0276 (.0108)	.0285 (.0111)	.0283 (.0110)	.0139* (.0092)	.01063* (.0094)	.01061* (.0094)	.0158 (.0079)	.0224 (.0078)	.0225 (.0078)
1980-1990 Dummy	.0671 (.0129)	.0679 (.0131)	.0675 (.0130)	.0423 (.0111)	.0395 (.0111)	.0394 (.0111)	.0104* (.0095)	.0160* (.0092)	.0162* (.0092)
Δ log c/k	.01536 (.0051)	.01542 (.0051)	.0161 (.0051)	.00089* (.0044)	.00068* (.0044)	.00074* (.0044)	-.002* (.0037)	-.0015* (.0036)	-.0018* (.0036)
Δ log y		.00624* (.017)	.01133* (.0171)		.02258* (.0144)	.02211* (.0147)		.0429 (.0121)	.0412 (.0123)
Δ log k/y			.0244* (.0146)			.00225* (.0125)			-.0096* (.0105)
R-squared	.6036	.6040	.6130	.2891	.3031	.3033	.045	.1346	.1405
n	126	126	126	126	126	126	125	125	125

Notes: Standard error in parentheses. All variables are weighted by [(Wit/Wt +Wit+1/Wt+1) /2]. "*" indicates insignificant at the 5% level. The above figures represent the parameters estimate for the matched IPUMS/BEA/BLS dataset regressions. Output and capital stock figures are measured in millions of constant 1987 dollars. All measure is a five years centered average of the respective variable. All capital stock measures are net stock measures.

k/y: real net capital stock per unit of real output.

c/y: real net stock of office, computing and accounting machinery capital per unit of real output.

c/k: real net stock of office, computing and accounting machinery capital per unit of real capital stock.

Table (20)

Computers, Capital Intensity, and Skill Upgrading 1960-1990

(b) Dependent Variable: Change in Skilled Workers Employment Share .

Variable	Education Definition			Occupation Definition			HT Definition		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept (Capturing interval 1960-1970)	.0319 (.0052)	.0232 (.0082)	.0128* (.0085)	-.0218 (.0064)	-.0195* (.0102)	-.0219 (.011)	.0052* (.0030)	-.0084* (.0046)	-.0071* (.0049)
1970-1980 Dummy	.0428 (.0097)	.0455 (.0098)	.047 (.0095)	.044 (.0119)	.0433 (.0122)	.0437 (.0122)	.0161 (.0056)	.0204 (.0054)	.0202 (.0055)
1980-1990 Dummy	.06698 (.0115)	.0691 (.0116)	.0698 (.0112)	.0457 (.0142)	.0451 (.0143)	.0453 (.0144)	.0078* (.0067)	.0112* (.0064)	.0111* (.0064)
Δ log c/k	.0125 (.0044)	.0129 (.0044)	.0136 (.0042)	.0011* (.0054)	.0010* (.0054)	.0012* (.0054)	-.0015* (.0025)	-.001* (.0024)	-.0011* (.0024)
Δ log y		.0210* (.0155)	.0318 (.0153)		-.0057* (.0192)	-.0032* (.0197)		.033 (.0087)	.0317 (.0089)
Δ log k/y			.044 (.0133)			.010* (.0172)			-.0058* (.0078)
R-squared	.6362	.6415	.6711	.2643	.2649	.2669	.0986	.1945	.1982
n	126	126	126	126	126	126	125	125	125

Notes: Standard error in parentheses. All variables are weighted by [(Wit/Wt +Wit+1/Wt+1) /2]. "*" indicates insignificant at the 5% level. The above figures represent the parameters estimate for the matched IPUMS/BEA/BLS dataset regressions. Output and capital stock figures are measured in millions of constant 1987 dollars. All measure is a five years centered average of the respective variable. All capital stock measures are net stock measures.

k/y: real net capital stock per unit of real output.

c/y: real net stock of office, computing and accounting machinery capital per unit of real output.

c/k: real net stock of office, computing and accounting machinery capital per unit of real capital stock.

Table (21)

Percent of Establishments Using Technology by Two-Digit Industry

Technology Group	Two-Digit Industry				
	34	35	36	37	38
Design & Engineering:					
- Computer Aided Design.	26.8	43.2	48.5	39.9	48.9
- CAD Controlled Machines.	13.1	21.6	16.0	16.6	14.6
- Digital CAD.	6.5	11.0	12.8	10.0	12.5
Flexible Machining & Assembly:					
- Flexible Manufacturing Systems.	9.0	11.0	11.9	12.6	10.8
- Numerically Controlled Machines.	32.2	56.7	34.9	37.3	33.6
- Lasers.	2.9	3.6	7.5	6.0	4.3
- Pick Place Robots.	5.7	5.8	13.1	10.4	8.6
- Other Robots.	4.4	5.2	6.9	10.5	4.4
Automated Material Handling:					
- Automatic Storage/Retrieval Systems.	1.0	3.6	4.9	4.7	4.2
- Guided Vehicles Systems.	0.8	1.7	1.8	3.3	1.3
Automated Sensor Based Inspection:					
- Materials Sensors.	6.7	8.5	16.2	12.7	12.2
- Output Sensors.	8.3	9.9	22.2	14.4	15.4
Communication & Control:					
- LAN for Tech Data.	13.4	18.5	24.9	22.0	25.8
- Factory LAN.	11.6	16.3	21.1	18.7	21.3
- Intercompany Computer Network.	14.9	12.4	16.2	21.7	13.8
- Programmable Controllers.	26.8	33.9	38.0	32.0	32.7
- Computers Used on Factory Floor.	21.1	28.1	34.5	27.4	32.3
Number of Establishments	12746	13176	7293	3425	2916

Table (22)

IPUMS / SIC (Manufacturing) Industry Codes Concordance

Industry	IPUMS Code	SIC Code	Industry	IPUMS Code	SIC Code
Logging	306	241			
Sawmills, planing mills, and mill work	307	242, 243			
Misc wood products	308	244, 245, 249	Bakery products	416	205
Furniture and fixtures	309	250	Confectionery and related prod.	417	206
Glass and glass prod.	316	321, 322, 323	Beverage industries	418	208
Cement, concrete, gyps. and plaster products	317	324, 327	Misc & Not specified food prep. and kindred products	419, 426	207, 209
Structural clay products	318	325	Tobacco manuf.	429	210
Pottery and related prd.	319	326	Knitting mills	436	225
Misc nonmetallic mineral &stone products	326	328, 329	Dyeing and finishing textiles,except knit goods	437	226
Blast furnaces, steel works, & rolling mills	336	331	Carpets, rugs, and other floor coverings	438	227
Other primary iron & steel industries	337	332, 339	Yarn, thread, and fabric	439	221,222,223 224, 228
Primary nonferrous industries	338	333, 334	Misc textile mill prod.	446	229
Fabricated steel prod.	346	341, 342,343, 344, 345,346, 347	Apparel and accessories	448	231,232,233 234,235,236 237, 238
Fabricated non-ferrous metal prod.	347	335, 336	Misc fabricated textile products	449	239
Not specified metal industries	348	348, 349	Pulp, paper, and paper-board mills	456	261,262,263 263
Agricultural mach. and tractors	356	352	Paperboard containers and boxes	457	265
Office and store machines	357	357	Misc paper and pulp products	458	264, 267
Misc machinery	358	351, 353, 354 355, 356, 358 359	Printing, publishing, and allied industries	459	270
Electrical mach. equip. and supplies	367	360	Drugs and medicines	467	283
Motor vehicles and motor vehicle equip	376	371	Paints, varnishes, and related products	468	285
Aircraft and parts	377	372	Misc chemicals and allied products & Synthetic fibers	466, 469	281,282,284 286,287,289
Ship and boat building and repair	378	373	Petroleum refining	476	291
Railroad and misc transportation equip	379	374, 375, 376 379	Misc petroleum and coal products	477	295, 299
Professional equip	386	381, 382, 383 384, 385	Rubber products	478	300
Photographic equip and supplies	387	386	Leather: tanned, curried, and finished	487	311
Watches, clocks, and clockwork-operated devices	388	387	Footwear, except rubber	488	313, 314
Misc & Not specified manufacturing industries	399, 499	399	Leather prod. except footwear	489	315, 316, 317,319
Meat products	406	201			
Dairy products	407	202			
Canning and preserving fruits, veg. and seafoods	408	203			
Grain-mill products	409	204			

Table (23)

Technology Usage and Skill Upgrading in SIC Manufacturing Industries 34-38

(a) Dependent Variable: Change in the Wage Share of Educated Workers.

Variable	1960/1990			1970/1990			1980/1990		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept (Capturing Region 9 and Industry 38)	.2206 (.0206)	.2599 (.0243)	.3073 (.0377)	.1881 (.0152)	.1963 (.018)	.2584 (.0285)	.1468 (.0109)	.1533 (.0125)	.138 (.0181)
Region Dummy: Region 1		.0039* (.0293)	.0076* (.0282)		.0186* (.0225)	.0275* (.0208)		.0114* (.01567)	.0073* (.0146)
Region 2		-.0439* (.0236)	-.047 (.0227)		-.027* (.0181)	-.0214* (.0167)		-.0144* (.0128)	-.0181* (.012)
Region 3		-.0530 (.0218)	-.0451 (.0214)		.0123* (.0165)	.0285* (.0155)		.006* (.0112)	.0059* (.0106)
Region 4		-.0689 (.0343)	-.0587* (.0331)		-.0235* (.0257)	-.0066* (.0238)		-.0346 (.0169)	-.0368 (.0158)
Region 5		-.0581* (.0317)	-.0601 (.0299)		-.00077* (.0225)	.0022* (.0205)		.0049* (.0149)	.0012* (.0136)
Region 6		-.1417 (.0434)	-.1355 (.0410)		-.0215* (.0323)	-.0142* (.0293)		-.0171* (.0203)	-.0187* (.0186)
Region 7		-.1135 (.0369)	-.1049 (.0352)		-.0329* (.0256)	-.0209* (.0235)		-.0383 (.0162)	-.0408 (.015)
Region 8		-.0572* (.0505)	-.0482* (.0477)		.015* (.0361)	.0194* (.0329)		.0262* (.0221)	.0222* (.0203)
2-Digit SIC Industry Dummy: Industry 34			-.078 (.0327)			-.0898 (.0259)			-.0031* (.0168)
Industry 35			-.0007* (.0299)			-.0249* (.0232)			.0051* (.0143)
Industry 36			.0099* (.0301)			-.0050* (.0235)			.0371 (.0148)
Industry 37			-.0087* (.0309)			-.001* (.0234)			-.0099* (.0149)
Technology Uage	.01189 (.0028)	.0127 (.0028)	.0074 (.0038)	.009 (.002)	.0082 (.0021)	.001* (.0027)	.0028* (.0015)	.0024* (.0014)	.0040 (.0018)
R-Squared	.1358	.2907	.3952	.1472	.2295	.3901	.0312	.1826	.3447
Mean of the Dependent Variable	.253	.253	.253	.234	.234	.234	.148	.148	.148
n	113	113	113	113	113	113	113	113	113

Note: Standard error in parentheses. All variables are weighted by $[(W_{ijt}/W_t + W_{ijt+1}/W_{t+1})/2]$. "*" indicates insignificance at the 5% level.

Table (23)

Technology Usage and Skill Upgrading in SIC Manufacturing Industries 34-38

(b) **Dependent Variable:** Change in the Wage Share of HT Workers.

Variable	**1960/1990**			**1970/1990**			**1980/1990**		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
Intercept (Capturing Region 9 and Industry 38)	-.0405 (.016)	-.0274* (.0196)	-.0572* (.0302)	-.0295 (.0115)	-.0325 (.014)	.0002* (.0223)	-.0025* (.0079)	.0005* (.0096)	-.0016* (.0144)
Region Dummy: **Region 1**		.0124* (.0239)	.0067* (.0236)		.0051* (.0175)	.0116* (.0165)		-.0057* (.0119)	-.0087* (.0116)
Region 2		-.0123* (.0193)	-.0172* (.019)		.0059* (.0141)	.0105* (.0134)		-.0123* (.0099)	-.0152* (.0096)
Region 3		-.0378 (.0176)	-.0421 (.0178)		.0099* (.0128)	.02* (.0123)		-.015* (.0086)	-.0151* (.0085)
Region 4		-.0224* (.0284)	-.0278* (.028)		.0043* (.0198)	.0147* (.0187)		-.0091* (.0131)	-.0105* (.0127)
Region 5		-.0126* (.0253)	-.0157* (.0245)		.0071* (.0172)	.0093* (.016)		.0015* (.0114)	-.0007* (.011)
Region 6		-.0296* (.0356)	-.0324* (.0345)		.0265* (.0238)	.0308* (.0222)		.0133* (.0156)	.0125* (.0148)
Region 7		-.0504* (.029)	-.0538* (.0282)		.0105* (.0197)	.0185* (.0185)		-.0083* (.0126)	-.0098* (.0121)
Region 8		-.0536 (.0368)	-.0536* (.0357)		-.0465* (.0252)	-.0476 (.0235)		-.001* (.0161)	-.0017* (.0153)
2-Digit SIC Industry Dummy: **Industry 34**			.0124* (.0266)			-.0533 (.020)			-.0061* (.0134)
Industry 35			.0457* (.0242)			-.0017* (.0180)			-.0088* (.0114)
Industry 36			.0473* (.0244)			.0010* (.0183)			.0137* (.0118)
Industry 37			.0128* (.0248)			.0093* (.0181)			-.0151* (.0118)
Technology Usage	.0128 (.002)	.0139 (.0023)	.0148 (.0031)	.0073 (.0015)	.007 (.0016)	.0021* (.0021)	.003 (.0011)	.0036 (.0011)	.0048 (.0014)
R-Squared	.2486	.3266	.3964	.1790	.2339	.3654	.0722	.1359	.2526
Mean of the Dependent Variable	.0282	.0282	.0282	.0171	.0171	.0171	.0182	.0182	.0182
n	103	103	103	103	103	103	103	103	103

Note: Standard error in parentheses. All variables are weighted by $[(W_{ijt}/W_t + W_{ijt+1}/W_{t+1})/2]$. "*" indicates insignificance at the 5% level.

Table (24)

Entry and Exit of Firms in Manufacturing and Skill Upgrading

(a) **Dependent Variable:** Change in the Wage Share of Educated Workers.

Variable	Model 1	Model 2	Model 3	Model 4
Intercept (Capturing interval 1960-1970 and/or Region 9 and/or Industry 39)	.0411 (.0058)	.05192 (.0156)	.0492*	.0173*
Year Dummies:				
1990	.4397 (.0082)	.4399 (.0082)	.4209 (.008)	.4205 (.0082)
1980	.0396 (.0082)	.0392 (.0082)	.0387 (.0077)	.0379 (.0078)
2-Digit SIC Industry Dummies:				
Industry 20			-.0150*	-.0119*
Industry 22			-.0032*	-.0013*
Industry 23			.1254 (.0241)	.124 (.0244)
Industry 24			.03348*	.0343*
Industry 25			.1214 (.029)	.1206 (.0294)
Industry 26			.0039*	.0147*
Industry 27			.1112 (.0199)	.1139 (.0201)
Industry 28			.0431 (.022)	.0473 (.0229)
Industry 29			-.0054*	.0043*
Industry 30			.1136 (.0316)	.1146 (.0317)
Industry 31			.0024*	.0077*
Industry 32			.0467*	.0492*
Industry 33			-.0083*	-.0037*
Industry 34			.0606 (.0212)	.0656 (.022)
Industry 35			.1036 (.0196)	.1055 (.0198)
Industry 36			.0881 (.0195)	.0914 (.0199)
Industry 37			.0413*	.0439 (.0215)
Industry 38			.0385*	.0438*
Region Dummies:				
Region 1				.00549*
Region 2				.00517*
Region 3				.02043*
Region 4				-.00074*
Region 5				.01742*
Region 6				.02000*
Region 7				.00740*
Region 8				-.00835*
Growth		.0286*	-.0404*	-.0538*
Turnover		-.0167*	-.0836 (.0272)	-.0552*
R-squared	.7215	.726	.7586	.7597
n	1361	1348	1348	1348

Note: Standard error in parentheses. All variables are weighted by [(Wijt/Wt +Wijt+1/Wt+1) /2]. "*" indicates insignificant at the 5% level. Standard deviation is not reported for insignificant coefficients due to space limitations.

Table (24)

Entry and Exit of Firms in Manufacturing and Skill Upgrading

(b) Dependent Variable: Change in the Wage Share of HT Workers.

Variable	Model 1	Model 2	Model 3	Model 4
Intercept (Capturing interval 1960-1970 and/or Region 9 and/or Industry 39)	-.025 (.0028)	.0078*	.0029	.0648 (.0170)
Year Dummies:				
1990	.0957 (.0039)	.0971 (.0039)	.0927 (.0038)	.0889 (.0038)
1980	.00548*	.0070*	.0063*	.0063*
2-Digit SIC Industry Dummies:				
Industry 20			-.0112*	-.0332 (.0112)
Industry 22			-.0065*	-.0301 (.0127)
Industry 23			-.0033*	-.0116*
Industry 24			.0042*	-.0132*
Industry 25			-.00163*	-.0121*
Industry 26			-.01344*	-.0418 (.0135)
Industry 27			-.01136*	-.0191 (.0094)
Industry 28			.007438*	-.0107*
Industry 29			-.0426 (.0153)	-.0747 (.0162)
Industry 30			.01*	.0039*
Industry 31			-.0036*	-.0233*
Industry 32			.0029*	-.01105*
Industry 33			-.0042*	-.0207*
Industry 34			.0167*	.0001*
Industry 35			.00096*	-.0066*
Industry 36			.0564 (.0093)	.0478 (.0093)
Industry 37			-.0363 (.001)	-.0466 (.0100)
Industry 38			.033 (.0125)	.0234*
Region Dummies:				
Region 1				-.0224 (.0072)
Region 2				-.027 (.006)
Region 3				-.0251 (.0059)
Region 4				-.0169 (.0074)
Region 5				-.00598*
Region 6				-.0168 (.0079)
Region 7				.00292*
Region 8				.0184*
Growth		.01204*	-.0171*	-.049 (.0175)
Turnover		-.049 (.0104)	-.0429 (.0127)	-.0869 (.015)
R-squared	.3544	.3652	.4675	.4833
n	1373	1358	1358	1358

Note: Standard error in parentheses. All variables are weighted by [(Wijt/Wt +Wijt+1/Wt+1) /2]. "*" indicates insignificant at the 5% level. Standard deviation is not reported for insignificant coefficients due to space limitations.

Table (25)

Estimated Determinants Of the Change in Relative Wage of Skilled Workers

(Elasticities of Complementarity)

Dependent Variable: Change in log of relative wage of educated workers.

Explanatory Variables	1960-1990	1970-1990
- Net Supply	-0.071069	-0.03925
	(0.007460)	(0.002864)
- Technical Change	0.028509	0.011839
	(0.0222568)	(0.0006766)
- Region Effect	Yes	Yes
- R^2 Total	0.6568	0.9252
- R^2 Net of Region Effect	0.5467	0.8955
- R^2 Net of Region and Technical Change Effect.	0.5321	0.8664

Note: All parameters are significant at the 5% level. Standard Deviations in parentheses.

Table (26)

Actual and Predicted Components of the Change in Log Relative Wage of Educated Workers

(a) 1960-1990

Region	Actual Change in Relative Wage	Predicted Change in Relative Wage	Contribution of Net Supply	Contribution of Technical Change
New England	0.13415	0.096	-0.137	0.223
Atlantic	0.14575	0.071	-0.128	0.199
East N. Central	0.11605	0.061	-0.134	0.195
West N. Central	0.04531	0.076	-0.129	0.205
South Atlantic	0.00840	0.076	-0.122	0.198
East S. Central	-0.08714	0.069	-0.112	0.181
West S. Central	0.03829	0.089	-0.120	0.209
Mountain	0.10390	0.104	-0.139	0.243
West (Pacific)	0.20638	0.111	-0.137	0.248
Average	0.07901	0.084	-0.129	0.211

(b) 1970-1990

Region	Actual Change in Relative Wage	Predicted Change in Relative Wage	Contribution of Net Supply	Contribution of Technical Change
New England	0.10182	0.092	-0.141	0.233
Atlantic	0.10999	0.074	-0.134	0.208
East N. Central	0.10793	0.074	-0.132	0.206
West N. Central	0.05694	0.083	-0.133	0.216
South Atlantic	0.07967	0.079	-0.126	0.205
East S. Central	0.00599	0.068	-0.117	0.185
West S. Central	0.09018	0.091	-0.126	0.217
Mountain	0.08785	0.115	-0.137	0.252
West (Pacific)	0.15561	0.127	-0.138	0.265
Average	0.08844	0.089	-0.132	0.221

Note: Predicted components are derived by multiplying the changes in the explanatory variable by the regression coefficients reported in table (25).

Chapter Five:

Summary and Conclusions

Increasing wage inequality between different groups of workers in the US along with the observed shift towards more skilled workers have attracted many researchers to study the sources of these changes. The skill-biased technological change hypothesis is offered by most researchers as a primary explanation for the increase in wage inequality and the increase in the wage and employment shares of skilled workers.

This dissertation examined the skill-biased technological change hypothesis, addressing several important issues. My main findings and my interpretation of these findings are given below.

The decomposition results are consistent with the findings of other researchers showing that the within industries component dominates the change in the skill mix. Moreover, the regional decomposition for the change in the skill mix show that the within regions effect also dominates the between regions effect. The same results are reached when I run a rural/urban decomposition and the combined sectoral/regional decomposition. These findings suggest that there has been an upgrade of skill within industries, regions and metropolitan areas, which is consistent with the skill-biased technological change explanation for the change in workforce skills.

Two more points are worth highlighting: (1) The between industries component is significantly larger in the 1950s and 1960s compared with the 1970s and 1980s. (2) The services sector shows a different pattern than all other industrial sectors where the between industries component dominates the change in the skill mix for the early periods. A possible explanation for the time pattern can be found in the shift from centralized computers to distributed computers by the late 1970s. The widespread diffusion computers into individual workplaces may be the cause of the acceleration in the shift towards more skilled workers.

In addition to the decomposition analysis, I have investigated the relation between different proxies of technology and the change in the wage share of skilled workers. The empirical results indicate that there is a positive relation between all capital investment measures and the change in the wage share of skilled workers. Moreover, computer investment, in particular, has a strong positive relationship with the change in the skill mix. Comparing the magnitude of the two capital stock measures indicates that the computer investment variable has a relatively larger effect. These results imply that the quality of capital stock has a larger effect on the change of skills than just capital deepening. These results are in line with the findings reported by Autor, Katz and Krueger (1997).

In light of the above findings that show a larger effect of computers on the change in the skill mix, I used the SMT dataset to examine whether other advanced manufacturing technologies have the same strong effect on the change in the workforce structure. The results of the regression suggest a strong positive relationship between advanced technologies and the change in the wage share of skilled workers. The advanced technology accounts for around 29% of the change in the skill mix over the period 1960-1990. The effect of the technology variable seems to be stronger over longer periods of time. These results provide more evidence to the hypothesis that the higher the quality of capital stock, the stronger is the effect on the distribution of skills. This is consistent with the view that technical change is often embodied in the capital stock. The proxies for capital quality used in this study, all suggest that "high tech" capital is positively correlated with workforce skill.

The entry-exit dataset allow us to examine the hypothesis that one of the main paths for new technology to be introduced to the economy is through entry and exit of plants. The empirical findings indicate that net entry has no significant effect on the change in the wage share of skilled workers, while the turnover variable has a negative coefficient. These findings are in line with the results reported by Dunne, Haltiwanger and Troske (1996). While at first blush, it may appealing to think of new plants as the primary introducers of new technology, in fact, new plants are often small and labor intensive workplaces. Dunne (1994) reports that there is little difference in advanced technology use by plant age, suggesting older plants workplaces have similar technologies to newer plants. Thus, it is not surprising to see the insignificance of net entry of new plants and a negative effect of the turnover variable on the change of workforce structure.

This dissertation tries to overcome some of the shortcomings of the empirical studies of the sources of the change in workforce structure. The main focus is to investigate the role of technology in changing the skill mix. Within this context, the regional and sectoral effects on the change in the skill mix are also examined.

The results of the decomposition are consistent with the skill-biased technical change story. Moreover, the sectoral decomposition show that the services sector follow a different pattern than manufacturing. As a result, the first contribution of this dissertation is to indicate that the conclusions of previous studies which focused on the manufacturing sector can not be generalized to other industrial sectors. However, it is also important to point to the problem associated with the way the results of the decomposition has been interpreted in the literature. Researchers have interpreted the within industry component as consistent with skill-biased technical change explanation, while the between industry component is consistent with the trade story. The borders between those component are not final, I believe, and there is a gray area in the middle where a within industry component can be caused by international trade[35] .

In evaluating the strengths and weaknesses of this dissertation, I believe the strengths center around the development of new decompositions and the analysis of the relationship between workforce skills and new measures of technology such as

[35] If two companies within the same industry are involved in trade, the first is very efficient and growing while the second is losing to imports. Skilled workers leave the inefficient company and join the successful one, therefore the employment share of the industry in total employment does not change, while the employment share of skilled workers increase in the growing company and declining in the second. This is a within companies movement driven by trade.

SMT variable and the turnover measure. However, it must be recognized that measuring both workforce skill and technology are challenging tasks. In term of the research presented here I believe that there are number of measurement issues that should be highlighted. First, though the education definition of skill is less problematic than the other occupation based definitions, this definition, however, does not take the difference in the quality of education between the 1950s and 1990s into account. Second, the 3-digit industry variable is too broad, and it does not capture significant differences within the 3-digit industries. Third, most technology measures are indirect measures, and there is little information on the composition of capital stock which does not allow testing the effect of different types of technology. The exception is the advanced technology variable which provides a more direct technology measure including the type of technology, however, this variable is limited to a few manufacturing industries.

In conclusion, the findings of this study suggest that technical change is an important factor affecting the change in workforce skill, however, it does not explain all the variations in the change in the skill mix. My research is limited by the scope of this dissertation and data limitation. Further research is still needed to examine the differences between the services and other industrial sectors, and whether changes in the workforce skills are driven by different forces. Moreover, my regression results show that both computer investment an advanced technology have a significant effect on the change in the skill mix. Additional work is still required to examine the effect of different types of technology on the change of skill mix for the whole economy, and whether computer-based technologies have the largest effect on shaping the labor market.

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