Essays on Knowledge, Technology and Economic Growth

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Abstract

This thesis is motivated by the question, how does computer-related technological change affect the individual's incentive to acquire specialized knowledge? Specifically, will the impact of technological change be homogeneous for all workers regardless of their idiosyncratic characteristics such as educational attainments or occupation? If not, then how do the heterogeneous effects from advances in computer-related technology change the labor market? Based on the related theoretical frameworks from the literature, Chapter 2 focuses on the empirical implementations of heterogeneous impacts of information and communication technology on between-occupation wage differentials and within-group wage differentials, and Chapter 3 examines the impact of computerization on labor productivity and on demand shifts for different types of skilled workers.

Chapter 2 re-investigates the skill-biased technological change puzzle through a different view of technological change. Garicano (2000) and Garicano and Rossi-Hansberg (2006) separate comprehensive skill-biased technological change into information and communication technological changes, which have qualitatively different characteristics. Based on this distinction, I try to show that advances in information and communication technology raise wage differentials between problem solvers and production workers. In contrast, for within-group wage differentials, information technology has homogeneous positive effects on within-group wage differentials for problem solvers and production workers, while communication technology has a heterogeneous impact on the within wage differentials: a positive effect for problem solvers and a negative effect for production workers. Furthermore, empirical analyses based on wage differentials between four occupational layers provide an

important direction for solving the skill-biased technological change puzzle questioned by Card and DiNardo (2002) with different growth rates of information and communication technology.

To explain strong increases in productivity growth across industries in the late 1990s, Chapter 3 suggests that large investments in computer-related capital resulted in the U.S. productivity revival. It also shows that rapid adoption of computer-based assets is a driving force for polarization trends in employment. This is due to heterogeneous demand shifts for different types of skilled workers, accompanied by diverging wage inequality between top-half and bottom-half wage distribution. The implications are based on the theoretical frameworks from Autor, Levy, Murnane (2003) and Autor, Katz, and Kearney (2006) in which (i) price declines in computer-related capital raise relative wages for nonroutine cognitive tasks and nonroutine manual tasks to routine tasks. Thus, middle workers for routine tasks increase their labor supply toward nonroutine cognitive tasks and nonroutine manual tasks through a self-selection process. And (ii) since demand for routine tasks are increased due to cheaper computerization costs, routine tasks, which were performed by middle-skilled workers, are carried out by computer-related capital. Empirical applications in Chapter 3 provide evidence for increasing demand shifts of high-skilled workers and low-skilled workers with the U.S. productivity gains and decreasing demand shifts for middle-skilled workers due to increasing investment for computerization as predicted in the theoretical framework.

Dedication

To my father and mother who have shown me how to communicate with the world.

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Chapter 1

Introduction

Rosen (1983) claimed that Adam Smith's beginning *The Wealth of Nations* with division of labor is not an accident. The rate of returns of specialized knowledge increases with utilization in the specific skills, so that division of labor, specialization in a narrow range of knowledge, and production by the principle of comparative advantage are attributable to the increasing returns of utilization in human capital. Rosen also pointed out that technological advances or new knowledge increase specific knowledge available in the society. The second point implicitly emphasizes that technological change eliminates the constraint of relevant market size for specialized knowledge, which is limited by transaction costs, and thus technological advances increase utilization of specialized human capital.

Associated with the positive impact of technological change on the utilization of specialized knowledge, Chapter 2 explores whether the increased utilization due to technological advances will be homogeneous for all workers, given their different types of knowledge, and if not homogeneous, how technological advances affect rate of returns of specialized knowledge for the heterogeneous workers. Specifically, it focuses on the impact of advances in information and communication technology on incentives for knowledge acquisition among the workers with different types of human capital in the knowledge-based hierarchy. Then, Chapter 2 illustrates how workers' proportionate changes in compensation, which are accompanied by knowledge acquisition changed due to information and communication technological change, affect between-occupational layers wage differentials and within-group wage differentials in the labor market.

As a related work, Garicano (2000) studies how faster and easier ways in communication and knowledge acquisition change workers' incentive to acquire specialized knowledge based on a knowledge hierarchy. To explain the theoretical framework briefly, production requires two inputs, physical capital and knowledge about how to produce. Garicano claims that when there is a matching problem who knows how to solve the problem is unknown, organizing workers based on their knowledge (knowledge-based hierarchy) is the best way to solve the matching problem and use the workers' specialized knowledge optimally. In the knowledge hierarchy, knowledge required for the most common and easiest problem is on the production floor, while knowledge for exceptional and complex problems is located on the top layer. The production worker on the floor can ask workers in the next level of the hierarchy for a solution to a problem he can't solve. Thus, the unsolved problem sets from lower layers will be transferred upward through the hierarchy until they are solved.

Decreasing knowledge acquisition costs and cheaper communication costs due to advances in information and communication technology influence workers' incentive for knowledge acquisition. The lower knowledge acquisition cost resulting from advances in information technology creates an incentive for all workers to acquire more knowledge. For production workers on the production floor, however, cheaper communication costs generate a negative incentive for knowledge acquisition. When production workers confront problems beyond their knowledge, asking for solutions from workers in the higher layer is much easier than before. Thus, advanced methods for communication among workers lead production workers to make less of an effort to acquire knowledge. In contrast, advances in communication technology increase utilization of specialized knowledge, so that increasing rate of returns of specific knowledge for problem solvers lead them to acquire knowledge more.

Based on this theoretical framework, Chapter 2 investigates whether the implications derived from the theory are consistent with the real world. In addition, heterogeneous impacts of information and communication technology on between-group wage differentials provide an important key to solve the skill-biased technological change puzzle that increasing growth rate of overall wage inequality has decreased in the 1990s regardless of continuous advances in computer-based technology.

Chapter 3 begins with stylized facts characterizing the recent U.S. labor market: polarization trends in the employment share and diverging wage evolution between upper-tail and lower-tail wage differentials. Since the late 1990s, there has been a rapid growth rate in the demand shifts for low-skilled workers and high-skilled workers relative to middle-skilled workers. In addition, the U.S. wage structure indicates that with a decreasing growth rate of overall wage differential, wage differential from the top-half wage distribution (wage differential between the 90th and the 50th percentile) has increased continuously, while wage differential from the bottom-half (wage differential between the 50th and the 10th percentile) has decreased. While Chapter 2 investigates the impact of technological change on workers' incentive for knowledge acquisition and on relative rate of returns among different types of skilled workers, Chapter 3 focuses on the relationship between workers' occupational choices by self-selection process and rapid adoptions of computer-related capital. Chapter 3 first presents the theoretical framework for explaining what mechanisms change demand for three skill-types of workers. Then it examines whether these implications are consistent with the stylized facts in the U.S. labor market.

The theoretical framework illustrates that rapid adoption of computerization assets due to the decreasing price of computer-based technology increases relative demand for production inputs of routine tasks such as middle-skilled workers and computer-related capital, and increases relative wages of high-skilled workers for nonroutine cognitive tasks and of low-skilled workers for nonroutine manual tasks. Thus, marginal middle-skilled workers at both ends in the routine tasks reallocate their labor supply toward nonroutine cognitive tasks and nonroutine manual tasks, so that cheaper computerization assets will replace the middle-skilled workers in routine tasks. Consistent with the theoretical framework, Chapter 3 suggests that heterogeneous demand shifts for different types of skilled workers and replacement of middle-skilled workers from routine tasks due to decreasing computerization costs cause the following observations in the U.S. labor market: first, the polarization trend in employment, based on increasing growth rates of employment shares for both high-skilled and low-skilled workers with a decreasing growth rate of employment share for middle-skilled workers, and, second, the polarization pattern of divergent wage trends between increasing upper-tail wage differential and decreasing lower-tail wage differential.

Chapter 2

Skill-Biased Technological Change Puzzles on Wage Differentials Revisited based on Information and Communication Technology

2.1 Introduction

An increase in relative demand for skilled workers across industries has led to an increase in wage differential between skilled workers and unskilled workers in the U.S. labor market since the late 1970s. Considering the decreasing growth rate of the relative supply of college-graduate workers and labor market institutional changes, much research has focused on skill-biased technological change to explain the increasing wage differential. Until the mid-1990s, it was considered an established fact that increasing relative demand for skilled workers, caused by such technological changes as computer development, raises wage differentials between different types of skilled workers. Card and DiNardo (2002), however, argued that, since the evidence in the inequality literature linking skill-biased technological change to increasing wage differentials is weak, skill-biased technological change hypothesis should be re-evaluated to clarify the real factors of increasing wage differentials in U.S. labor market.

Two figure sets associated with overall wage differentials and skill-biased technological changes over 29 industries are used to represent these disagreements between skill-biased technological change hypothesis and Card and DiNardo (2002). Figures 2.1 to 2.5 show trends in overall wage differentials, measured by wage gaps between the 90th and the 10th percentiles, and evolution of skill-biased technological change, based on information and communication technology. Second, Figures 2.22 to 2.26, which can be found in the Appendix, illustrate growth rates of skill-biased technological change and changes in overall wage differentials, the differences in wage gaps between the 90th and the 10th percentiles at two time points. As Card and DiNardo point out, for most of the 29 industries, growth rates of skill-biased technology in the late 1990s were higher than in the early 1990s. At the same time, except for such industries as metal, retail trade, and business services, changes in overall wage differentials decreased in the late 1990s, which is the opposite direction from the prediction of skill-biased technological change hypothesis.

Based on these inconsistent stylized facts, Chapter 2 focuses on the main skill-biased technological change (henceforth, SBTC) puzzle that the growth rate of overall wage inequality has not continued to rise in the late 1990s despite continued advances in computer-related technology. This essay presumes that the disagreement between SBTC hypothesis and Card and DiNardo (2002) might have originated from broad classifications of skill-biased technological changes. That is, various types of computer-related technological changes such as mainframes, data storage devices, computing programs, terminals, tape drives, the Internet, communication devices, and network technology have all been categorized as skill-biased technological change in the literature regardless of the qualitatively different characteristics of these technologies.

Johnson (1997) classifies skill-biased technological changes into intensive skill-biased technological change, extensive skill-biased technological changes, and skill-neutral technological change. The basic assumption for these distinctions is that technological change influences demand for different types of workers heterogeneously, so that relative demand shifts depend on which types of workers will be more productive in what kinds of jobs. Johnson claims that widespread adoptions of computer-related technology such as personal

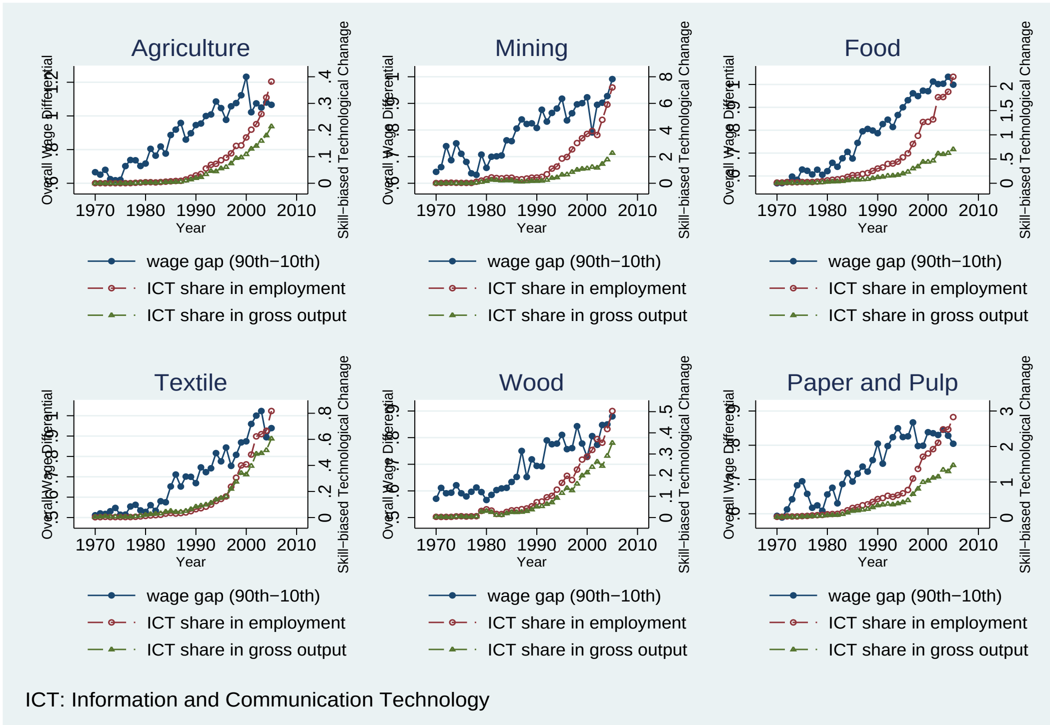

Figure 2.1: Trends in Skill-biased Technological Change and Overall Wage Differentials I

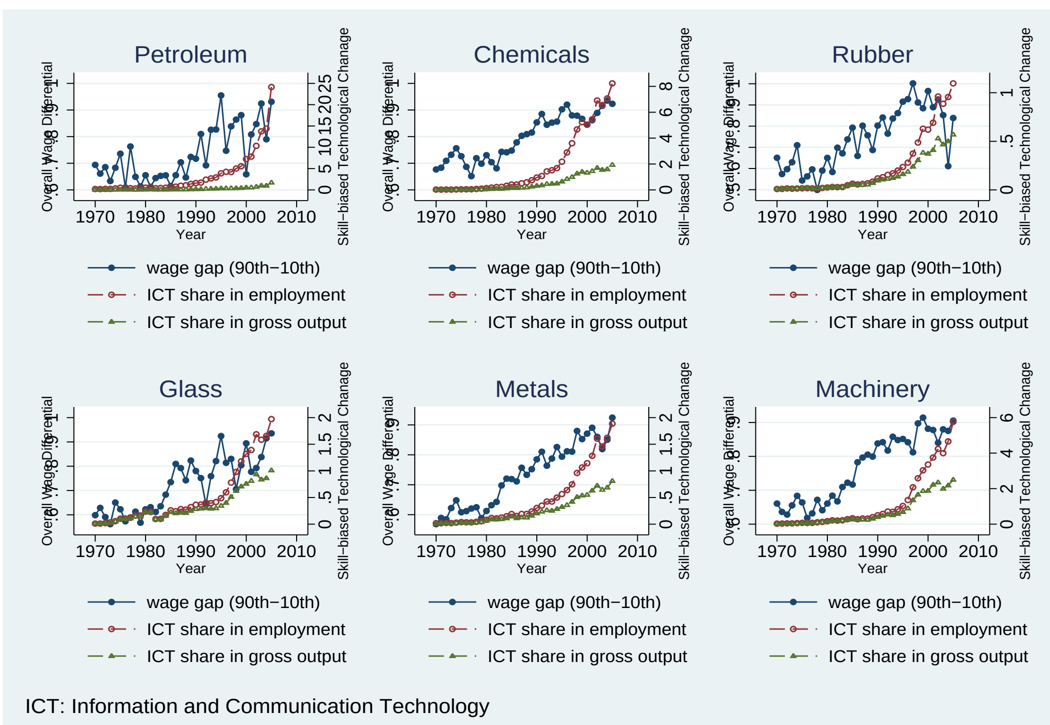

Figure 2.2: Trends in Skill-biased Technological Change and Overall Wage Differentials II

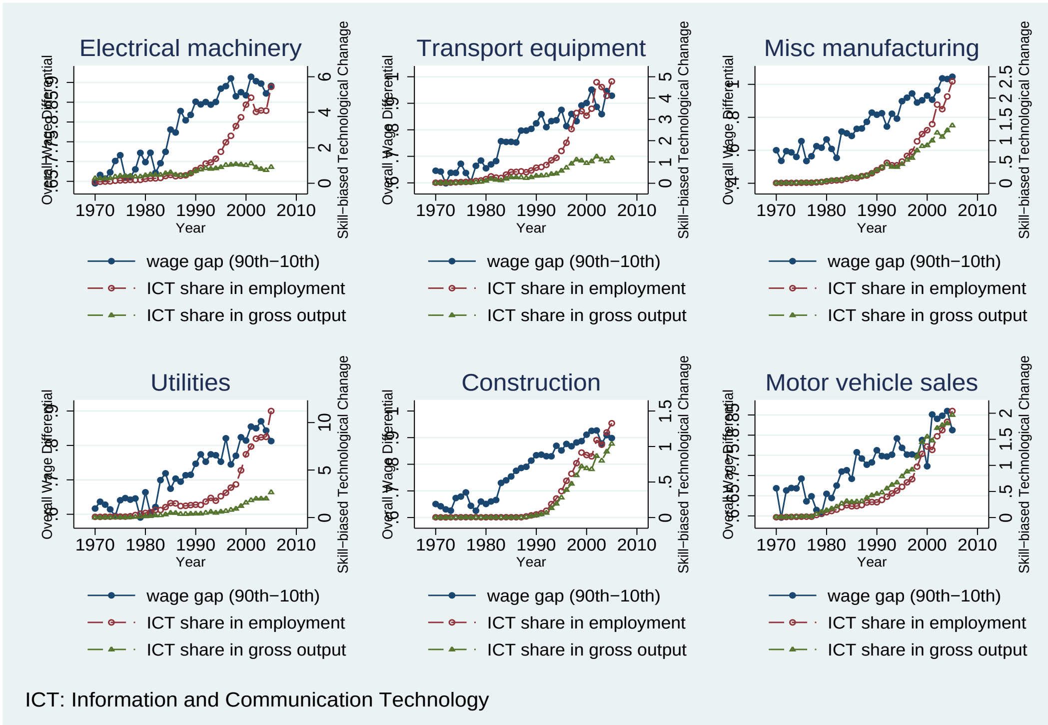

Figure 2.3: Trends in Skill-biased Technological Change and Overall Wage Differentials III

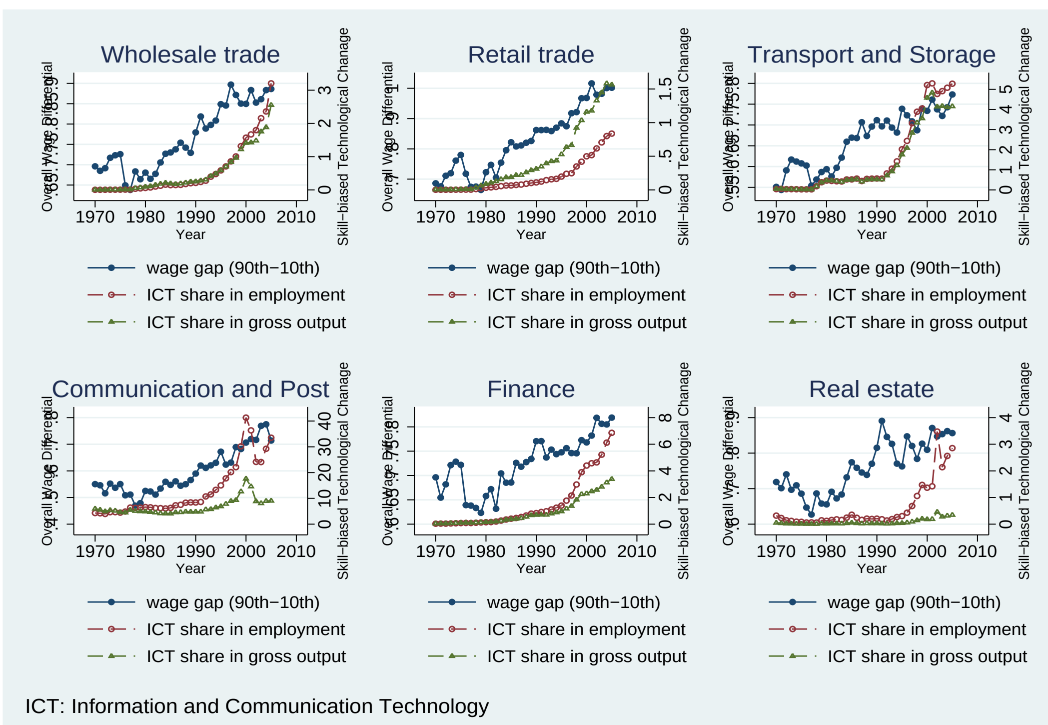

Figure 2.4: Trends in Skill-biased Technological Change and Overall Wage Differentials IV

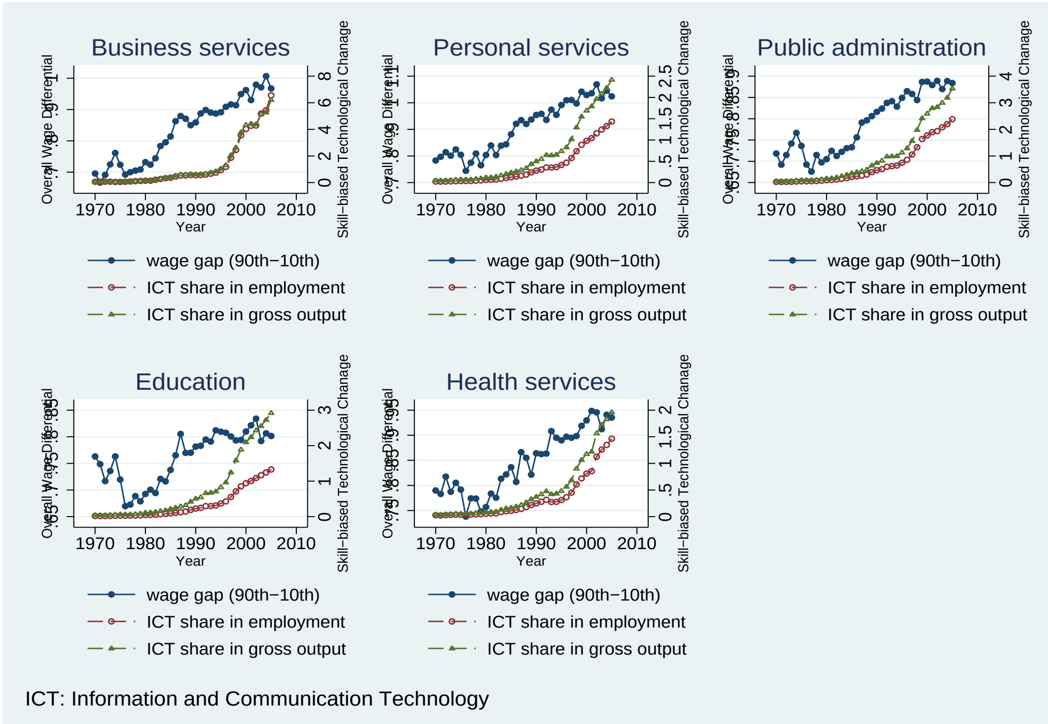

Figure 2.5: Trends in Skill-biased Technological Change and Overall Wage Differentials V

computers definitely increase productivity of workers, especially those whose jobs have a complementary relationship with computer-related technology. Thus, intensive skill-biased technological change increases relative demand for skilled workers, since they will be more productive in their jobs due to advances in technology.

As an example of extensive skill-biased technological change, Johnson (1997) focuses on the use of robotics in the manufacturing industry. The adoption of robots in the manufacturing industry yields two opposite impacts on the demand for workers. A more complicated manufacturing process using robotics increases the demand for skilled workers such as engineers or computer scientists, while the efficiency in the automatic production process caused by newly adopted robotic equipment decreases the demand for unskilled workers. On the other hand, skill-neutral technological changes increase productivity for all workers by the same percentage, so that there are no changes in relative demand for skilled workers to unskilled workers. These classifications suggest that technological advances generate different implications for wage differentials and marginal productivity depending on skill types of the workers. In the SBTC literature, the second classification, extensive skill-biased technological change, has been regarded as the primary skill-biased technological change to explain the increasing relative demand for skilled workers and wage differentials between skilled workers and unskilled workers. However, Johnson's distinctions between intensive and extensive technological changes do not indicate which types of technology should be classified as intensive or extensive technological change.

Garicano and Rossi-Hansberg (2006) separate comprehensive skill-biased technological change into information technology and communication technology. They propose that informational technological change, such as development of computing equipment, reduces the cost of knowledge acquisition and information processing, and communicational technological change decreases communication costs among workers due to advances in network technology such as e-mail and mobile communication devices. In a knowledge hierarchy in which workers are defined by cognitive skill, so the least skilled workers are assigned to the least skilled tasks and the most skilled workers are assigned to the most complex jobs[1], a decrease in communication cost makes communication between skilled and unskilled workers easier and faster.

When unskilled workers confront difficult problems, improved communication methods lead them to ask for answers from skilled workers instead of acquiring the knowledge required to solve the problems themselves. Also, since rate of returns of specialized knowledge is an increasing function of utilization of the knowledge, increasing utilization of skilled workers' knowledge due to advances in communication technology lead problem solvers to acquire knowledge more. Thus, these different incentives for knowledge acquisition due to cheaper communication costs yield the Superstar effect of Rosen (1981) by increasing the concentration of solving complex problems toward skilled workers at top layers of the

[1] Johnson (1997) also assumes that all tasks can be ranked from the most complex (i.e., neurosurgeon) to the least complex (i.e., ditch digger) in his distinction between intensive skill-biased technological change and extensive skill-biased technological change, claiming "if a skilled worker has a comparative advantage in the more complex jobs and an unskilled worker has a comparative advantage in the less complex jobs, then unskilled workers will fill the less complex jobs and skilled workers will fill the rest."

knowledge hierarchy. The wage differential between the most skilled and the least skilled workers increases with advances in communication technology. By contrast, since advances in information technology lead the workers, regardless of their skills, to acquire knowledge more easily than before, knowledge acquisition and decentralization of problem solving increase with decreasing knowledge acquisition costs. However, since problem solvers have a comparative advantage of knowledge acquisition, decreasing knowledge acquisition costs increase wage differentials between workers in the knowledge hierarchy as well.

Rather than using comprehensive skill-biased technological change, separating skill-biased technological change into information technology and communication technology helps better explain the wage structure trend in the U.S. labor market. To explain the differences between the separated skill-biased technological change used here and the comprehensive skill-biased technological change applied in wage inequality literature, this essay uses the simplified SBTC framework from Card and DiNardo (2002), which is primarily used in empirical earning inequality literature such as Bound and Johnson (1992), Berman, Bound and Griliches (1994), Autor, Katz, and Krueger (1998), and Autor, Katz, and Kearney (2005). A constant elasticity of substitution production function for the simplified SBTC framework can be written as

$$\mathrm{Y} = \mathrm{A}[\theta(\eta_s N_s)^{\frac{\sigma-1}{\sigma}} + (1-\theta)(\eta_u N_u)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \tag{2.1}$$

where Y represents the value of output; N_s and N_u the labor supplies of skilled workers and unskilled workers, respectively; η_s and η_u the labor augmenting technological changes for skilled workers and unskilled workers; θ and $(1-\theta)$ the technology parameters for skilled workers and unskilled workers, which could be interpreted as the share of skilled and unskilled workers in the work place, respectively; and σ represents the elasticity of substitution between skilled workers and unskilled workers, which is assumed to be larger than one in this paper. From Equation (2.1), the marginal productivity of skilled workers and of unskilled workers, respectively, can be derived as

$$\mathrm{MP}_s = \mathrm{A}\theta\eta_s(\eta_s N_s)^{\frac{-1}{\sigma}}[\theta(\eta_s N_s)^{\frac{\sigma-1}{\sigma}} + (1-\theta)(\eta_u N_u)^{\frac{\sigma-1}{\sigma}}]^{\frac{1}{\sigma-1}} \quad (2.2)$$

$$\mathrm{MP}_u = \mathrm{A}(1-\theta)\eta_u(\eta_u N_u)^{\frac{-1}{\sigma}}[\theta(\eta_s N_s)^{\frac{\sigma-1}{\sigma}} + (1-\theta)(\eta_u N_u)^{\frac{\sigma-1}{\sigma}}]^{\frac{1}{\sigma-1}} \quad (2.3)$$

By taking the logarithm of the ratio between marginal productivity of skilled workers and of unskilled workers, $\Pi = \left(\frac{\theta}{1-\theta}\right)\left(\frac{\eta_s}{\eta_u}\right)^{1-\frac{1}{\sigma}}\left(\frac{N_s}{N_u}\right)^{\frac{-1}{\sigma}}$, relative wage between skilled workers and unskilled workers can be written as

$$\ln\left(\frac{w_s}{w_u}\right) = \ln\left(\frac{\theta}{1-\theta}\right) + \frac{\sigma-1}{\sigma}\ln\left(\frac{\eta_s}{\eta_u}\right) - \frac{1}{\sigma}\ln\left(\frac{N_s}{N_u}\right) \quad (2.4)$$

where w_s and w_u represent wage for skilled workers and unskilled workers, respectively. Equation (2.4) shows that the relative wage between skilled workers and unskilled workers is a function of technological change and change in the relative labor supply. Thus, without considering the relative labor supply of different types of skilled workers, technological changes become the only way to change the relative wage between skilled workers and unskilled workers.

Card and DiNardo (2002) argue that when the relative labor supply between skilled and unskilled workers is exogenously given, relative wage change will take place only through skill-biased technological change, which involves either an increase in θ or an increase in η_s relative to η_u. As they pointed out, although both types of skill-biased technological change increase the relative wage of skilled workers by increasing relative marginal productivity of skilled workers, each skill-biased technological change - either an increase in θ or an increase in η_s relative to η_u - involves a different mechanism for increasing the relative wage of skilled workers. First, an increase in θ raises the marginal productivity of skilled workers based on Equation (2.2). Since it simultaneously decreases $(1-\theta)$, the increase in θ decreases the marginal productivity of unskilled workers as well. Second, an increase in η_s relative to η_u affects relative marginal productivity between skilled and unskilled workers, Π, through a mechanism whereby a relative increase in η_s raises the marginal productivity of skilled workers without necessarily decreasing the marginal productivity of unskilled workers. Thus, the implications of increasing θ and relatively increasing η_s are consistent with extensive skill-biased technological change and intensive skill-biased technological change from Johnson (1997), respectively.

Based on the SBTC framework, separating skill-biased technological change into information and communication technology involves both an increase in θ and an increase in η_s relative to η_u. Advances in communication technology increase the marginal productivity of skilled workers and decrease the marginal productivity of unskilled workers simultaneously, as explained by the implications of the increase in θ and the extensive skill-biased technological change of Johnson (1997). That is, due to advances in communication technology such as e-mail or mobile devices, communication among all workers is more efficient, so cheaper communication costs compel unskilled workers to ask for a solution from skilled workers when they confront complex problem sets, instead of acquiring the required knowledge themselves. Due to the decreased incentive for knowledge acquisition of less skilled workers, dependency of unskilled workers on skilled workers and a centralization toward top problem solvers in the knowledge hierarchy becomes larger. Thus, the impact of advances in communication technology on between-group wage differentials is similar to the effects of the increase in θ and the decrease in $(1-\theta)$, which cause simultaneously decreasing marginal productivity of unskilled workers and increasing marginal productivity of skilled workers.

In addition, advances in information technology have the same implication from an increase in η_s relative to η_u as in the intensive skill-biased technological change of Johnson (1997). Widespread adoptions of computers in the workplace due to advances in information technology increase marginal productivity of all workers, though these positive effects are biased toward skilled workers in the knowledge hierarchy. Thus, decreasing knowledge acquisition costs increase relative marginal productivity of skilled workers. This is the same result of intensive skill-biased technological change, in that intensive SBTC increases the marginal productivity of skilled workers without necessarily decreasing the marginal productivity of unskilled workers. Therefore, based on the implications described above, this paper posits that separating skill-biased technological change into information and communication technological changes involves both intensive and extensive skill-biased technological change via an increase in η_s relative to η_u and an increase in θ, respectively, which generates homogeneously positive effects and heterogeneous effects on the marginal productivity of skilled workers and unskilled workers.

The organization of Chapter 2 is as follows. Section 2.2 discusses the theoretical model and comparative statics from Garicano (2000) and Garicano and Rossi-Hansberg (2006). Then, Section 2.3 introduces data sources and key facts in the U.S. wage structure from 1968 to 2007 and presents empirical models and estimation results concerning heterogeneous impacts of information and communication technology on wage differentials between occupational layers and within-group wage differentials based on four occupational layers. Section 2.4 concludes with summarizing empirical evidence and findings.

2.2 Theoretical Model

Garicano (2000) studies how advances in information and communication technology affect workers' incentive for specialized knowledge acquisition. Based on Hayek's (1945) optimal uses of available knowledge in society, Garicano claims that knowledge hierarchy is the best way to acquire specialized knowledge when who knows how to solve a problem is unknown. In this knowledge hierarchy, workers on the production floor acquire knowledge about the most common or the least complex problems. When they are confronted with difficult problems, they ask for a solution from the workers in the next layer who deal with more complex problems.

This essay is based primarily on the theoretical frameworks and implications from Garicano (2000) and Garicano and Rossi-Hansberg (2006). In those models, production requires two inputs: physical capital and production knowledge. If communication among workers is available, the efforts to acquire more knowledge for production decrease with production workers acquiring only basic relevant knowledge for their tasks. When workers confront more complex problems, they refer the problems to workers in the higher layer. Since workers have only a narrow range of specialized knowledge and the knowledge involves a tacit characteristic, classifying workers by their specialized knowledge or production know-how is not easy.

Garicano suggests that organizing workers based on the knowledge the worker has solves this matching problem. In the knowledge hierarchy, knowledge for the most common and the easiest problem is found on the production floor while knowledge for exceptional and complex problems is located at the top layer of the knowledge hierarchy. The production worker on the floor asks workers in the next level of the hierarchy for a solution to a problem. Unsolved problem sets are transferred up the hierarchy until they are solved. In this structure, informational technological changes and communicational technological changes, which directly affect knowledge acquisition costs and communication costs, influence workers' incentive to acquire knowledge.

That is, due to advances in information technology, a decrease in knowledge acquisition cost generates an incentive to acquire more knowledge for all workers. Thus, production workers refer unsolved problems to the workers in the higher layers less and the discretion of a worker in the production process will be increased. However, if communication costs decrease by advances in communication technology, production workers choose the easier way, asking someone else, instead of acquiring more complex knowledge themselves. Thus, as production workers' dependency on specialized problem solvers increases, so does the centralization of problem solvers at the top of the knowledge hierarchy.

2.2.1 Knowledge Acquisition for Production

In the knowledge hierarchy, production procedure requires both physical and knowledge inputs. However, unlike the general concept of the production process, this model regards the production procedure as a problem solving process for each worker, so that a production worker should use his knowledge to solve a problem set with his physical capital. Suppose $\Omega \subset R^{+}$ is the set of all possible problems for the workers in the knowledge hierarchy, and $K \subset \Omega$ is defined as the problem set a worker can solve with his knowledge set. Production occurs when problem set $S \in \Omega$ is drawn and solved. Thus, when the problem set $S \in \Omega$, which follows a continuous distribution, satisfies the following condition, $S \in K$, the problem set is solved and production for a worker feasible. Garicano normalizes the density of the problems distribution so that the drawn problems are ordered from the least complex to the least common problems with the density of the problem set assumed to be nonincreasing.

When the time spent for production is defined as t_p, expected output for a worker with constant returns to scale in the production process is written as $E[x] = t_p \int_K dF(S)$. In this model, a worker obtains answers for problem sets when he refers complex problem sets to problem solvers at the higher levels. He assumes that learning cost of an interval S for a problem set is proportional to the problem set's interval, which is the Lebesgue measure of the interval S, $\mu(S)$. Therefore, for a constant unit learning cost α, the learning cost for a problem set $[0, S_j]$ can be written as αS_j, and the expected net output per unit of time for a worker can be defined as

$$E[y] = Pr(S < S_j) - \alpha S_j = \int_0^{S_j} f(\phi) d\phi - \alpha S_j \tag{2.5}$$

The workers choose their optimal knowledge acquisition ranges to maximize their expected net output per unit of time. The first order condition, $f(\phi) = \alpha$, from Equation (2.5) shows that the marginal benefit of knowledge acquisition is equal to the marginal learning cost. As this analysis suggests, a decrease in knowledge acquisition cost due to advances in information technology leads to an increase in incentive for workers to acquire more knowledge.

2.2.2 Communication in the Knowledge Hierarchy

In this structure, workers at different layers acquire different ranges of knowledge, so that utilization rates of acquired knowledge for solving problems increase with communications among the workers. Garicano (2000) introduces two costs into his models: matching a problem set with the worker who knows how to solve it and communicating with workers for the answers. In this model, matching problems to workers who know how to solve them is unknown, and until the problems are completely solved or they are named as puzzles, the unsolved problem set will be transferred to problem solvers in the higher layers. Based on information processing literature, Garicano assumes that, instead of the production workers who are asking for answers from the next higher layer, the receivers who are being asked should pay for the communication costs. That is, communicating or explaining how to solve the problem sets decreases the time available for problem solvers.

The knowledge hierarchy has M layers of size β_j, where $\sum \beta_j = 1$, and each layer can be defined as having the following characteristics: (i) a knowledge set for layer j is $K_j \subset \Omega$, which overlaps layers, (ii) each layer has a list of layers, l_j, whom workers in level j can ask for answers, in which the first layer to be asked by layer j is the layer j itself, and (iii) a time unit, t_c, for a worker in layer j to communicate with workers in lower layers and a time unit, t_p, to engage in production for layer j, where $t_c + t_p \leq 1$. In this model, the time spent in communication, asked by the β_j members in layer j of the β_i workers in layer i, depends on the available knowledge from all layers h, previously asked, with $h \prec_j i$ representing all classes h, which precede class i in layer j's help list. Thus, with the helping cost for problem solvers defined as γ, the time spent by workers in layer i for communicating with other classes can be defined as

$$\beta_i t_h^i = \sum_{j:\, i \in l_j} \beta_j t_h^j \big(1 - F\big(\bigcup_{h \prec_j i} K_h\big)\big)\gamma \tag{2.6}$$

Since output for each class j depends on the (i) probability that β_j members in class j can obtain a solution from at least one layer in class j's help list, (ii) time spent for production by β_j members in class j, and (iii) knowledge acquisition costs for β_j in layer j, the total output for the knowledge hierarchy can be written as

$$y = \sum_{i=0}^{M} \Big(\beta_i t_p^i F\big(\bigcup_{h \in l_i} K_h \big) - \alpha K_i \beta_i \Big) \tag{2.7}$$

To maximize the total output of the knowledge hierarchy using two constraints, the time constraint $t_c + t_p \leq 1$ and the size constraint $\sum \beta_j = 1$, the hierarchy chooses the size of each class, β_i; the knowledge for each class, K_i; a list in each class, l_i; and the time assignment to communication and production. Garicano (2000) shows that any arbitrary initial allocations associated with knowledge of workers and communication among workers can be improved in the knowledge hierarchy, and in the optimum the knowledge hierarchy has four important characteristics:

(1) Specialization: All members in each class specialize either in production or in problem solving. Based on the range of specialization, production workers are characterized by specializing in production, in other words, in drawing problem sets. All other classes concentrate on problem solving and transferring the solution sets to the production workers.

(2) Non-overlapping Knowledge: Since all workers are specialized in each narrow problem set, different classes in the hierarchy have different knowledge sets. When S_{i-1} and S_i are endpoints of the problem sets in class $(i-1)$ and class i, the specialized range for class $(i-1)$ can be defined as $s_{i-1} = S_{i-1} - S_{i-2}$, and the specialized range for class i can be written as $s_i = S_i - S_{i-1}$ where $S_i = \sum_{h=0}^{i} s_h$.

(3) Organization by Frequency: Production workers on the floor acquire knowledge for solving the easiest problems, and problems solvers at the top layers learn knowledge to deal with exceptional matters. Thus, information associated with answers always flows from top to bottom in the knowledge hierarchy, minimizing communication costs.

(4) Pyramidal Organization: The knowledge hierarchy has a pyramidal structure in which the lowest layer is larger in size than each successive layer.

Based on these characteristics, when all members in the knowledge hierarchy are given one unit of time, total output from Equation (2.7) can be written as

$$y = F\Big(\sum_{i=0}^{M} s_i\Big)\beta_0 - \sum_{i=0}^{M} \alpha\beta_i s_i \tag{2.8}$$

where s_i is the specialized range for class i, which can be defined as $S_i - S_{i-1}$, and β_i is the proportion of workers in layer i. Here all members in each class have one unit of time. From Equation (2.6), as a constraint the time spent by workers in class i communicating with workers in lower layers can be written as

$$\beta_i = \beta_0\gamma\Big(1 - F\Big(\sum_{j=0}^{i-1} s_j\Big)\Big) \tag{2.9}$$

Under the assumption that the problem set for production, $S \in \Omega$, follows an exponential distribution, the hierarchy's problem from Equation (2.8) can be defined as

$$\max_{s_i,\beta_i} \lim_{M\to\infty} \Bigg[F\Big(\sum_{i=0}^{M} s_i\Big)\beta_0 - \sum_{i=0}^{M} \alpha\beta_i s_i\Bigg] \tag{2.10}$$

If the cumulative distribution function of exponential distribution, $F(x;\lambda) = 1 - \exp^{-\lambda x}$, where $x \geq 0$, is applied to Equation (2.9), the time constraint can be changed to

$$\beta_i = \beta_0\gamma\Big(\exp\Big(-\lambda\sum_{j=0}^{i-1} s_j\Big)\Big) \tag{2.11}$$

By substituting the time constraint from Equation (2.11) and the size constraint, $\sum_{j=0}^{M}\beta_j = 1$, into Equation (2.10) for β_i and for β_0, respectively, the maximization problem of the knowledge hierarchy for total output can be defined as

$$y = \max_{s_i} \frac{F\big(\sum_{i=0}^{\infty} s_i\big) - \alpha s_0 - \sum_{i=1}^{\infty}\alpha s_i \exp\big(-\lambda\sum_{j=0}^{i-1} s_j\big)\gamma}{1 + \sum_{i=1}^{\infty}\exp\big(-\lambda\sum_{j=0}^{i-1} s_j\big)\gamma} \tag{2.12}$$

where $\beta_0 = \big(1 + \sum_{i=1}^{M}\exp\big(-\lambda\sum_{j=0}^{i-1} s_j\big)\gamma\big)^{-1}$ can be derived from the size constraint,

$\beta_0 = 1 - \sum_{j=1}^{M} \beta_j$.

The first-order condition for the knowledge set for the production worker, s_0, which can be derived from Equation (2.12), can be written as

$$\frac{1}{\sigma} f\Big(\sum_{i=0}^{\infty} s_i\Big) - \frac{\alpha}{\sigma} + \frac{\lambda\alpha\gamma}{\sigma}\sum_{i=1}^{\infty} s_i \exp\Big(-\lambda\sum_{j=0}^{i-1} s_j\Big) + \frac{y}{\sigma}\gamma\lambda\sum_{i=1}^{\infty}\exp\Big(-\lambda\sum_{j=0}^{i-1} s_j\Big) = 0 \quad (2.13)$$

where $\sigma = \big(1+\sum_{i=1}^{\infty}\exp\big(-\lambda\sum_{j=0}^{i-1} s_j\big)\gamma\big)$ from β_0; and from Equation (2.12), the first-order condition for problem solvers in class h to find optimal knowledge set s_h, where $h > 0$ in the knowledge hierarchy, can be written as

$$\begin{aligned}\frac{1}{\sigma} f\Big(\sum_{i=0}^{\infty} s_i\Big) - \frac{\alpha\gamma}{\sigma}\exp\Big(-\lambda\sum_{j=0}^{h-1} s_j\Big) + \frac{\lambda\alpha\gamma}{\sigma}\sum_{i=h}^{\infty} s_{i+1}\exp\Big(-\lambda\sum_{j=0}^{i} s_j\Big) &= \\ -\frac{y\gamma\lambda}{\sigma}\sum_{i=h}^{\infty}\exp\Big(-\lambda\sum_{j=0}^{i} s_j\Big) & \qquad (2.14)\end{aligned}$$

Therefore, the optimal specialized range for a production worker, s_0^*, and the optimal ranges of problem solvers in class j, s_j^*, from Garicano (2000) are derived as

$$s_o^* = \frac{1}{\lambda}\ln\Big(\frac{\gamma\lambda}{\alpha} - \gamma\ln\gamma\Big) \qquad (2.15)$$

$$s_j^* = \frac{1}{\lambda}\ln\Big(\frac{\lambda}{\alpha} - \ln\gamma\Big) \qquad (2.16)$$

Based on the derived optimal specialized ranges for production workers and problem solvers, a decrease in communication cost, γ, increases the optimal solvable range for problem solvers while a decrease in communication cost decreases the specialized problem range for production workers[2]. A decline in knowledge acquisition cost, α, increases the optimal solvable ranges for all production workers and problem solvers[3].

Testable implications about between-group wage differentials can be derived from

[2] $\frac{\partial s_j^*}{\partial\gamma} = \frac{-1}{\lambda\gamma}\frac{1}{\left(\frac{\lambda}{\alpha}-\ln\gamma\right)} < 0$ and $\frac{\partial s_o^*}{\partial\gamma} = \frac{1}{\lambda}\frac{1}{\left(\frac{\gamma\lambda}{\alpha}-\gamma\ln\gamma\right)}\left(\frac{\lambda}{\alpha} - \ln\gamma - 1\right) > 0$

[3] $\frac{\partial s_j^*}{\partial\alpha} = \frac{-1}{\alpha^2}\frac{1}{\left(\frac{\lambda}{\alpha}-\ln\gamma\right)} < 0$ and $\frac{\partial s_o^*}{\partial\alpha} = \frac{-\gamma}{\alpha^2}\frac{1}{\left(\frac{\gamma\lambda}{\alpha}-\gamma\ln\gamma\right)} < 0$

these frameworks. First, the decreased incentive to acquire knowledge about how to solve problems for the production workers leads to an increase in the wage differentials between production workers and problem solvers in different layers. Since the workers choose to ask someone else instead of acquiring more knowledge when they face a difficult problem set, the production workers become increasingly dependent on problem solvers, especially the problem solvers of exceptional problem sets, widening the wage differential between production workers and problem solvers. That is, wage differentials between production workers at the bottom layer of the knowledge hierarchy and problem solvers at the top layers will be raised as a result of advances in communication technology.

Second, decreasing knowledge acquisition costs by advances in information technology lead all workers to acquire knowledge more. Based on the principle of comparative advantage of problem solvers on knowledge acquisition, however, wage differentials between problem solvers and production workers increase due to decreasing knowledge acquisition costs with increasing wage differentials between two occupational layers tending to be larger at the higher layers of the knowledge hierarchy. These implications about between-group wage differentials form the basis for the first part of empirical analysis about whether the derived comparative statics from the theoretical frameworks are consistent with real-world. Meanwhile, an important key to solving SBTC puzzles questioned by Card and DiNardo (2002) will be illustrated.

In addition, based on Garicano and Rossi-Hansberg (2006), workers' different incentive changes for knowledge acquisition caused by cheaper communication costs would be similarly applied to within-problem solvers wage differentials and within-production workers wage differentials. The positive effect of communication technology on incentive to acquire knowledge increases within-group wage differentials for problem solvers, but the negative effect of cheaper communication cost on the incentive decreases within-group wage differentials for production workers. That is, for within-problem solvers wage differential, although increasing utilization and rate of returns for knowledge lead problem solvers to acquire knowledge more, there are still differences of comparative advantages among problem solvers even in the same group. Also, decreasing communication costs for production workers due to easier and faster communication methods make production workers' knowledge in the same group homogeneous. Therefore, implications for within-group wage differentials that within-group wage differentials for problem solvers increase with advances in communication technology, while within-group wage differentials for production workers decreases with cheaper communication costs will be the second basis for the empirical analysis.

2.3 Empirical Application

To see whether the predictions about the impact of information and communication technology on wage differentials from the frameworks are consistent with real patterns in the U.S. labor market, this paper focuses on between-group wage differentials and within-group wage differentials based on four occupational layers: managers, professionals, middle workers, and lower workers. Here the lower workers are assumed to be isolated from advances in information and communication technology measured by rapid adoptions of computing equipment, software and communication devices. Although information and communication technology impacts on wage differentials between lower workers and the other three occupational layers; managers, professionals, and middle workers, respectively, will be primarily based on direct impacts of information and communication technology on each three occupational layers, for comprehensive analysis, lower workers will not be excluded in the between-occupations wage differentials analysis.

For between-occupational layer wage differentials, relative wages between two occupational layers are calculated using data on full-time and full-year workers age 17-65 from the IPUMS CPS. Log real weekly earnings are regressed for each year separately on such variables as years of schooling, experience, experience squared, metro area, gender, white, occupation, and industry. The mean log real weekly wage for each occupational layer used here is the predicted log real weekly wage from these regressions, evaluated at the sample mean only for white and male in a given year. For within-occupational layer wage differen-

Table 2.1: Descriptive Statistics for EU KLEMS Growth and Productivity: 1970-2005

Variables	Observations	Mean	Std. Dev.	Min	Max
Computing Equipment	1044	609.63	2155.38	0.03	26946.68
Communication Equipment	1044	1414.77	4304.16	0.01	54521.07
Software	1044	2798.89	6625.73	1.19	62077.94
Transport Equipment	1044	3898.03	6802.73	95.63	47974.20
Information and Communication†	1044	3902.28	9851.04	0.55	103127.30
Total Capital Asset	1044	47545.98	95128.05	1763.69	789081.50
Number of Employees	1044	4602.26	7298.44	115.00	51069.46
Real Gross Output	1044	428550.70	421881.60	47372.75	3031866.00

† Information and communication technology capital investment such as computing equipment, communication equipment, and software. All capital assets are measured by real gross fixed capital formation in 2005 dollars from EU KLEMS Growth and Productivity Accounts during the periods from 1970 to 2005. (in millions of U.S. dollars) Real Gross outputs are measured in millions of U.S. dollars and total number of employees are measured in thousands units.

tials, the residual wage differential for each group is calculated by wage residuals from the regressions above of log real weekly earnings on education, experience, experience squared, metro area, gender, white, occupation, and industry.

2.3.1 Data and Stylized Facts

Before investigating the impact of information technology and communication technology on wage differentials, this section analyzes the U.S. wage structural changes including data descriptions over the last four decades. For the paper, this information comes from two sources, the IPUMS Current Population Survey and the EU KLEMS Growth and Productivity Accounts. The IPUMS Current Population Survey data for full-time, full-year wage/salary workers age 17-65 with 0 to 58 years of potential labor market experience during the period from 1968 to 2007 (covering earnings years 1967 to 2006 for workers age 16-64 in earnings years) are used to calculate wage differentials between groups and wage differentials within a group. Full-time workers are defined as those who work 35 hours or more per week, and full-year workers worked forty-plus weeks in the previous year. All earnings are deflated by the Personal Consumption Expenditure Price Index (PCEPI). A worker's log real weekly earning is calculated as the logarithm of real annual earnings divided by

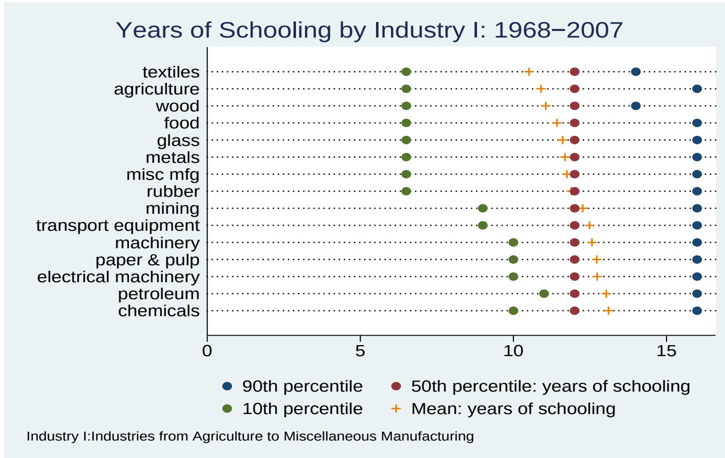

Figure 2.6: Years of Schooling from Agriculture to Misc. Manufacturing: 1968-2007

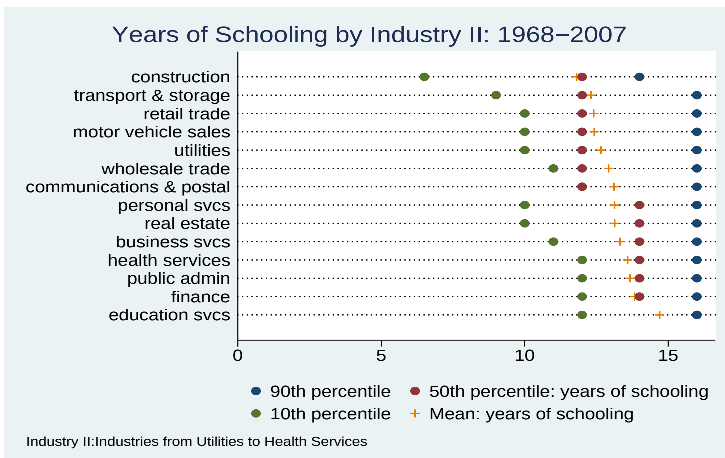

Figure 2.7: Years of Schooling from Utilities to Health Services: 1968-2007

the weeks the worker worked during the prior year. Workers earning less than 67 dollars per week in 1982 dollars (below 112 dollars per week in 2000 dollars or below 125 dollars per week in 2005 dollars) are excluded. All calculations are weighted using CPS sampling weight, person weight. Observations for top-coded earnings are multiplied by 1.5 based on Katz and Murphy (1992) and Autor, Katz, and Kearney (2008).

The 29 broad industry classifications of IPUMS CPS are recategorized to reconcile with industry classifications based on the EU KLEMS Growth and Productivity Dataset. In addition, to measure wage differentials between groups and wage differentials within group,

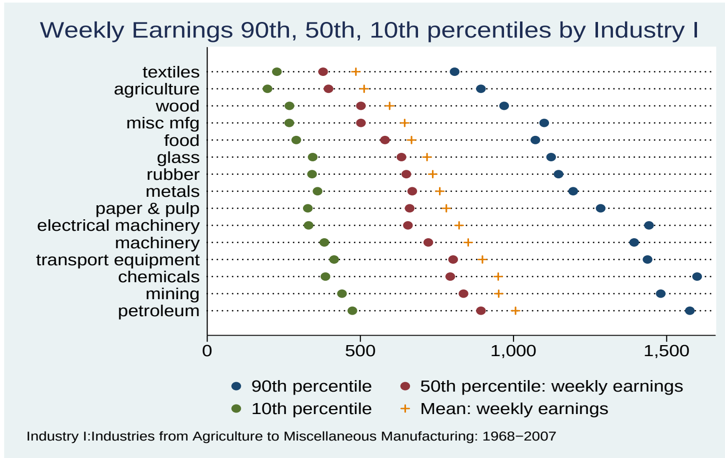

Figure 2.8: Weekly Earnings from Agriculture to Misc. Manufacturing: 1968-2007

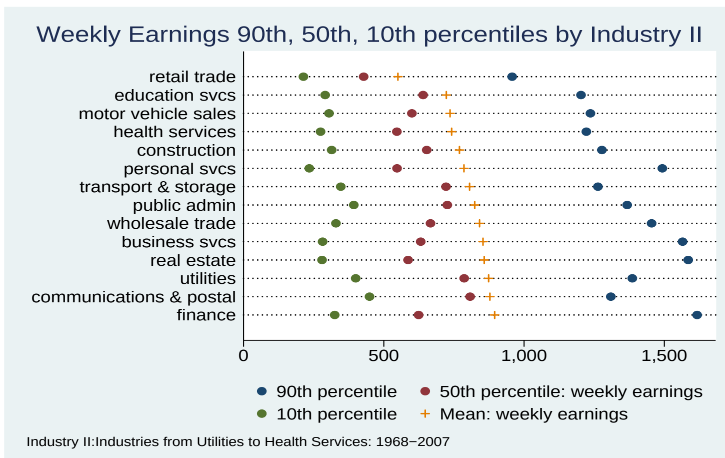

Figure 2.9: Weekly Earnings from Utilities to Health Services: 1968-2007

there are four occupational layers: the higher layer, the middle layer, the lower layer, and one independent layer. Among the 11 occupation classifications of IPUMS Current Population Survey, the manager, officials, and proprietors classifications are considered the higher layer; clerical and kindred, sales workers, craftsmen, farmers, and operatives are regarded as occupations in the middle layer; and service workers and laborers are considered the lower layer. Since the professional and technical (technicians) occupations have independent occupational characteristics, this paper places them in the independent layer located between the higher and the middle layers. Figures 2.6 to 2.11 illustrate the years of schooling and

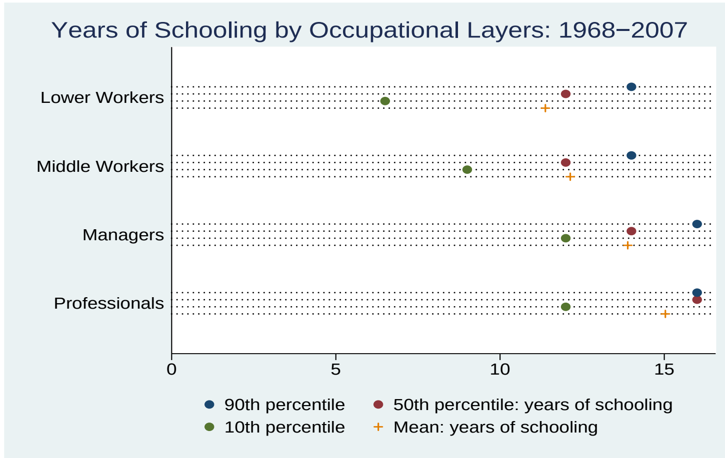

Figure 2.10: Descriptive Statistics for Educational Attainments: 1968-2007

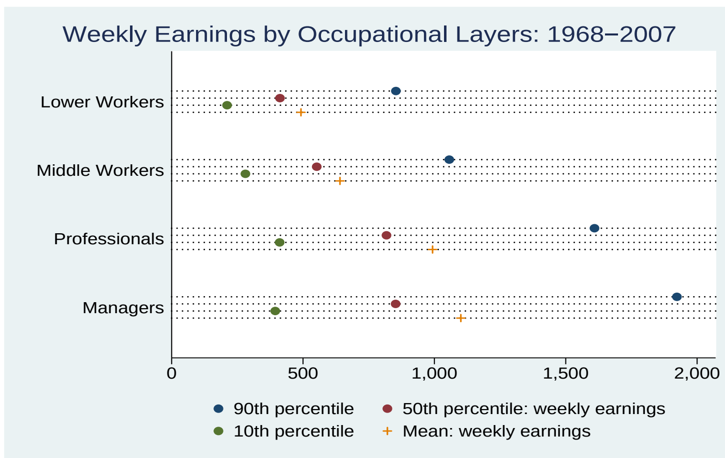

Figure 2.11: Descriptive Statistics for Weekly Earnings of Occupational Layers: 1968-2007

weekly earnings by industry and by occupational layer from the IPUMS Current Population Survey Data. More specific descriptive statistics from the IPUMS CPS Data by industry can be found in the Appendix.

For the measures of information and communication technology, the real gross fixed capital formation data (RGFCF) by industry come from the second data source, the EU KLEMS Growth and Productivity Accounts, for the period from 1970 to 2005 at 2005 dollars. Here, capital investment in computing equipment is used as information technology, and software and communication equipment are used as communication technology.

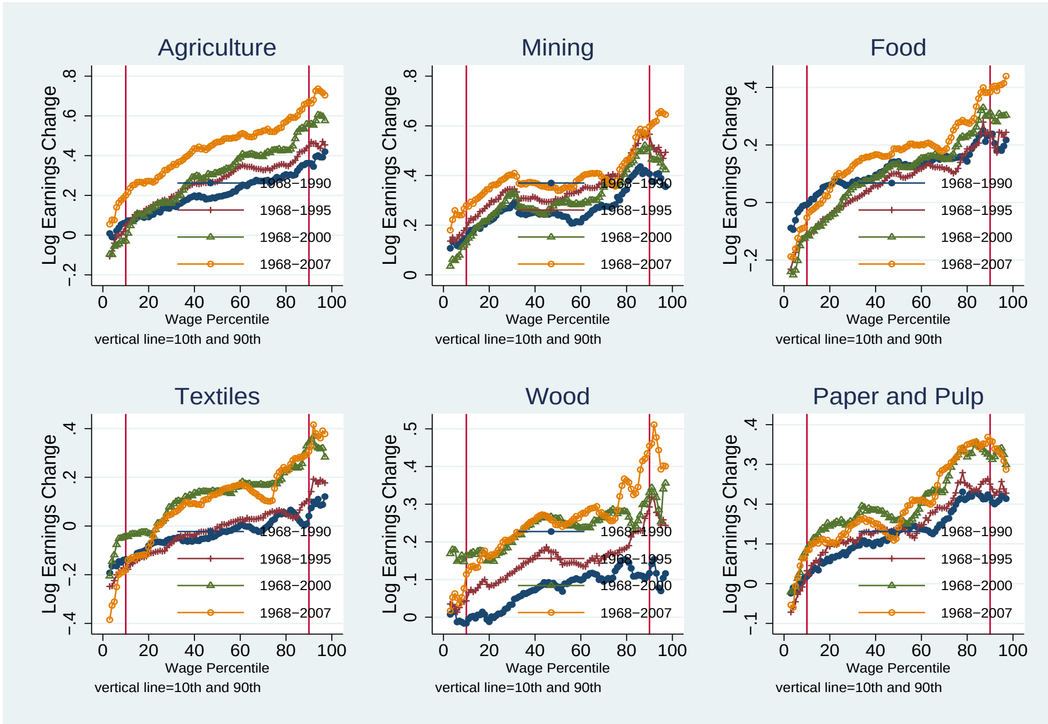

Figure 2.12: Log Real Weekly Earnings Changes over Wage Percentile from 1968 to 2007 I

Since this paper focuses on the impact of computer-related technological changes on wage differentials, only three categories of capital investments - computing equipment, software and communication equipment - are used from the total capital assets, which also includes non-residential structure investments or other machinery and equipment. Furthermore, to eliminate heterogeneity based on industry size, all measurements for information and communication technology are converted into share-type variables divided by total number of employees and real gross output for each industry.

To show the wage structural changes during the last four decades in the U.S. labor market, this section presents two figure sets: (i) the log weekly earnings changes for the period from 1968 to 2007 by wage percentiles from the 3rd to the 97th and (ii) divergent patterns of between-group wage differentials such as increasing wage differentials between managers and middle workers; increasing wage differentials between professionals and middle workers; and decreasing wage differentials between middle and lower workers.

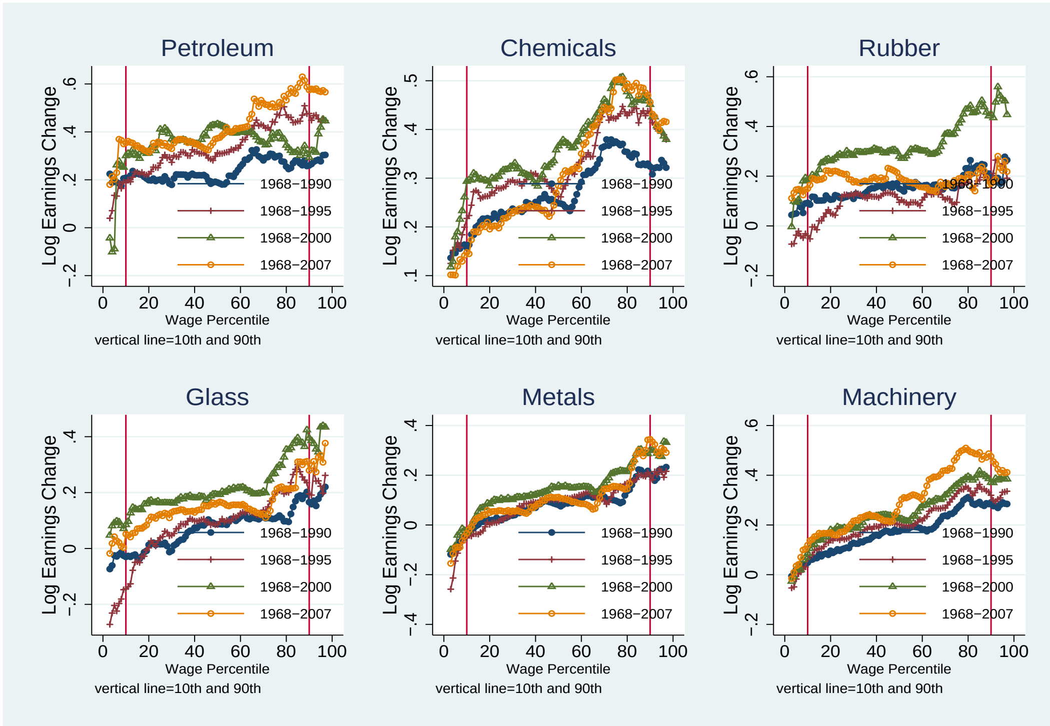

Figure 2.13: Log Real Weekly Earnings Changes over Wage Percentile from 1968 to 2007 II

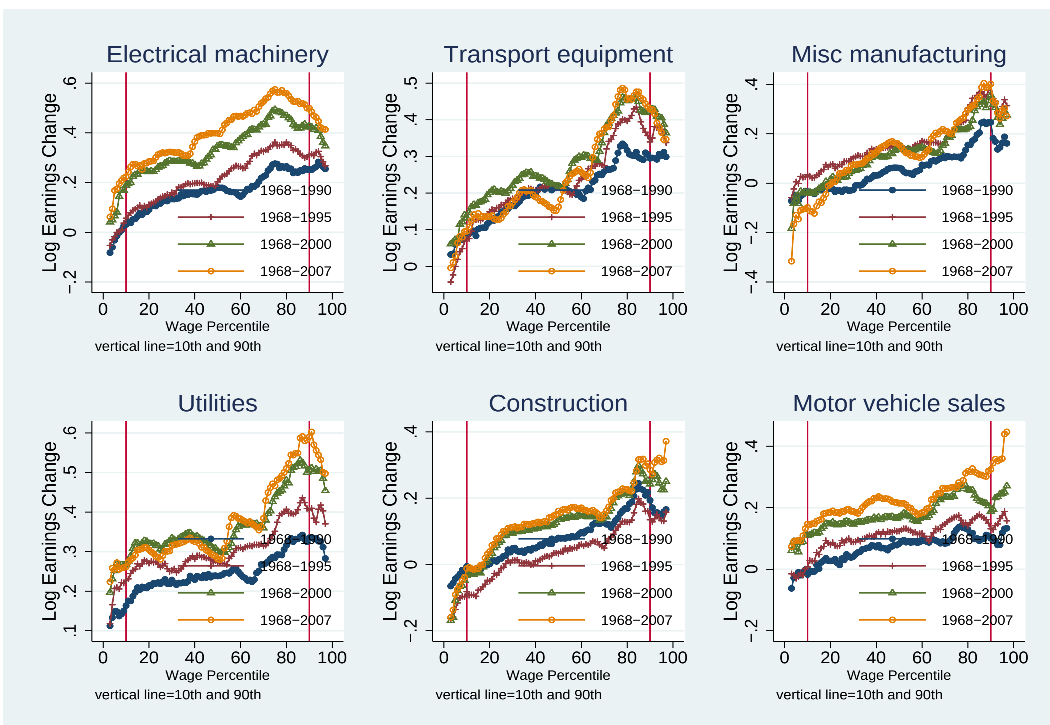

Figure 2.14: Log Real Weekly Earnings Changes over Wage Percentile from 1968 to 2007 III

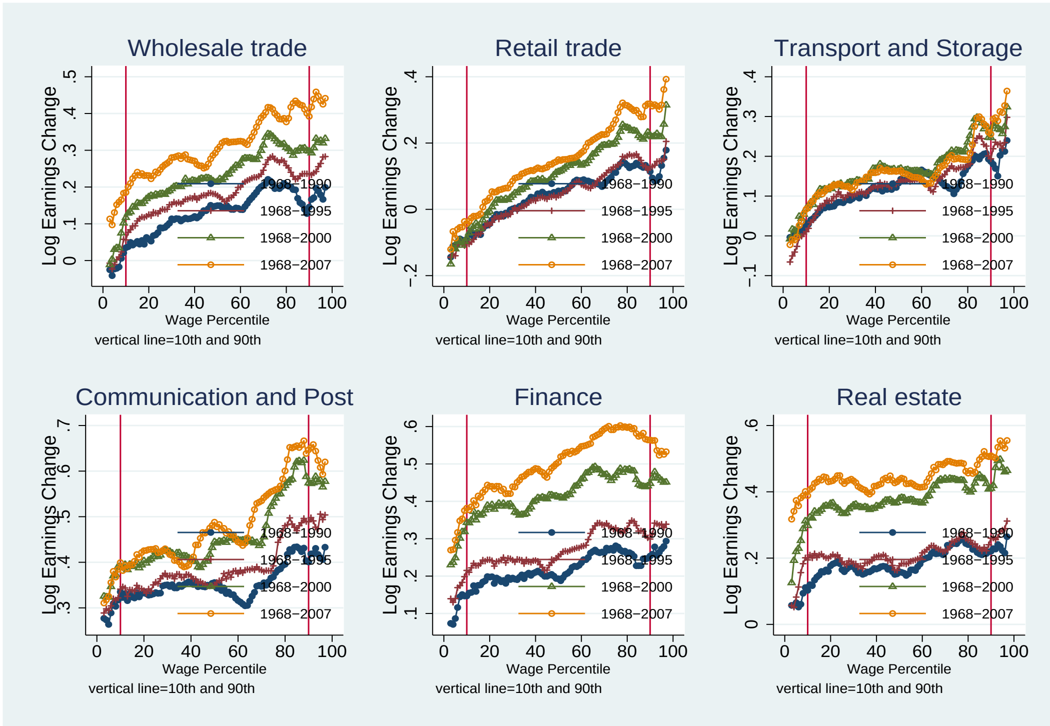

Figure 2.15: Log Real Weekly Earnings Changes over Wage Percentile from 1968 to 2007 IV

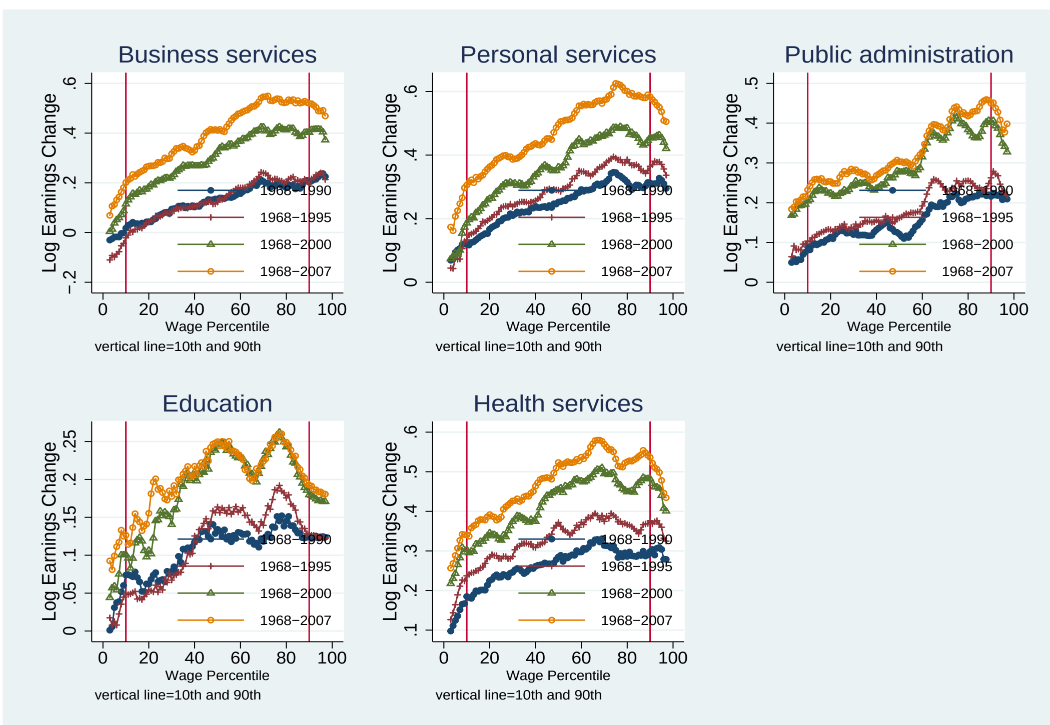

Figure 2.16: Log Real Weekly Earnings Changes over Wage Percentile from 1968 to 2007 V

The first figure set, Figures 2.12 to 2.16, represents changes in log real weekly earnings by industry over wage percentiles from the 3rd to the 97th during the four periods, 1968 to 1990, 1968 to 1995, 1968 to 2000, and 1968 to 2007, using data on full-time and full-year workers age 17 to 65 from the IPUMS Current Population Survey. As these figures showing U.S. wage structural changes by industry indicate, most of the 29 industries exhibit large wage differentials over the last four decades. For example, wage differentials between the 90th and the 10th percentiles have increased by 48.68 log points in textiles, 34.08 log points in wood, 31.86 log points in business activities, and 18.20 log points in finance during the period from 1968 to 2007. Furthermore, log weekly earnings for various lower percentile earners have dropped significantly for the same time period. That is, in 2007 the log weekly earnings below the 18th percentile in food, below the 25th percentile in textiles, below the 10th percentile in metal, below the 10th percentile in the construction, and below the 18th percentile in the retail trade are lower than the log weekly earnings in 1968 for the same percentile and the same industry.

In addition, as Figures 2.12 to 2.16 show, more than two-thirds of the industries indicate homogeneous shocks for all workers in wage distribution from 1995 to 2007 in two patterns, 1968-1995 and 1968-2007, indicating monotone increasing trends over the wage percentiles from the 3rd to the 97th. However, nine industries, including textiles, paper and pulp, chemical, rubber, glass, machinery, miscellaneous manufacturing, utilities, and transport, indicate that log weekly earnings have changed heterogeneously. And overall wage differentials calculated using the wage gaps between the 90th and the 10th percentiles for sub-periods indicate sharply increasing trends of overall wage differentials in the 1980s and decreasing overall wage differential trends since then. Most of the industries as seen in Table 2.10, except for petroleum and communication, recorded the highest wage differentials during the period from 1981 to 1990, but since 1990 overall wage differentials have reported smaller wage differentials than in the previous periods.

The figure sets in Figures 2.17 to 2.21 show three trends in wage differentials between occupational layers: between the managers and the middle layers, between the professionals

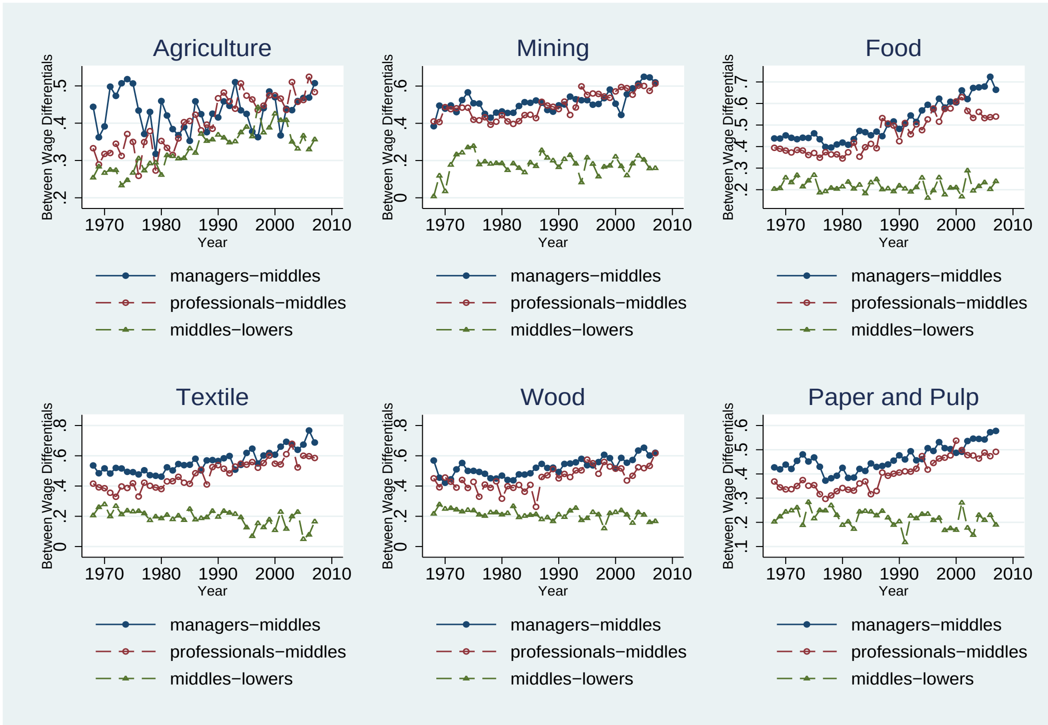

Figure 2.17: Wage Gaps between Managers and Middles and between Middles and Lowers I

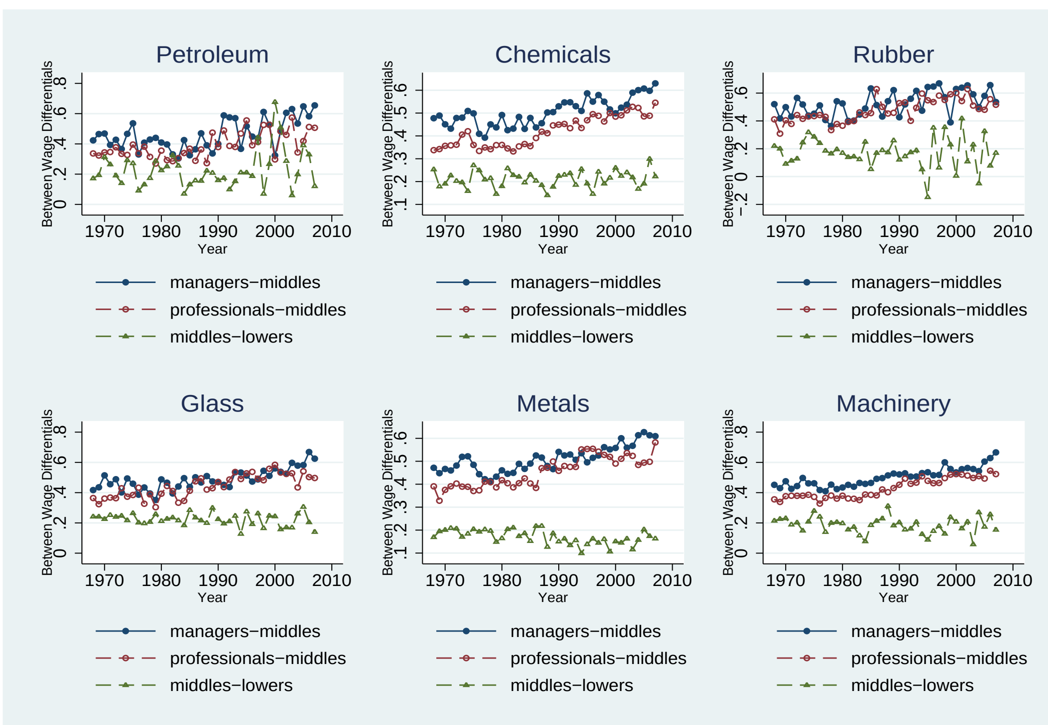

Figure 2.18: Wage Gaps between Managers and Middles and between Middles and Lowers II

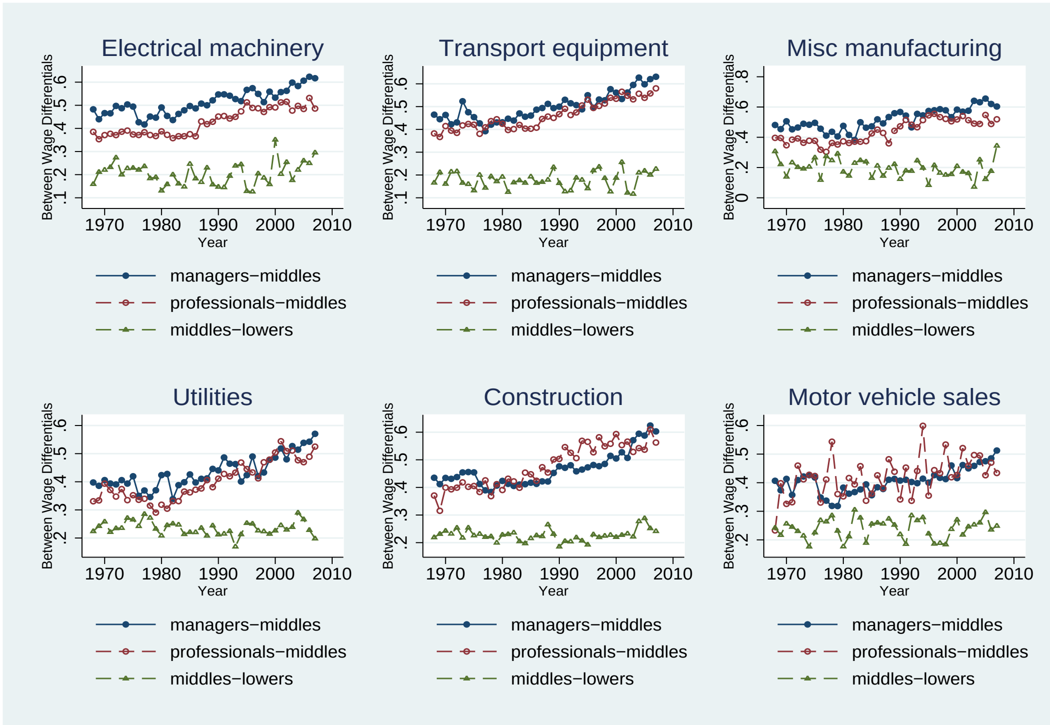

Figure 2.19: Wage Gaps between Managers and Middles and between Middles and Lowers III

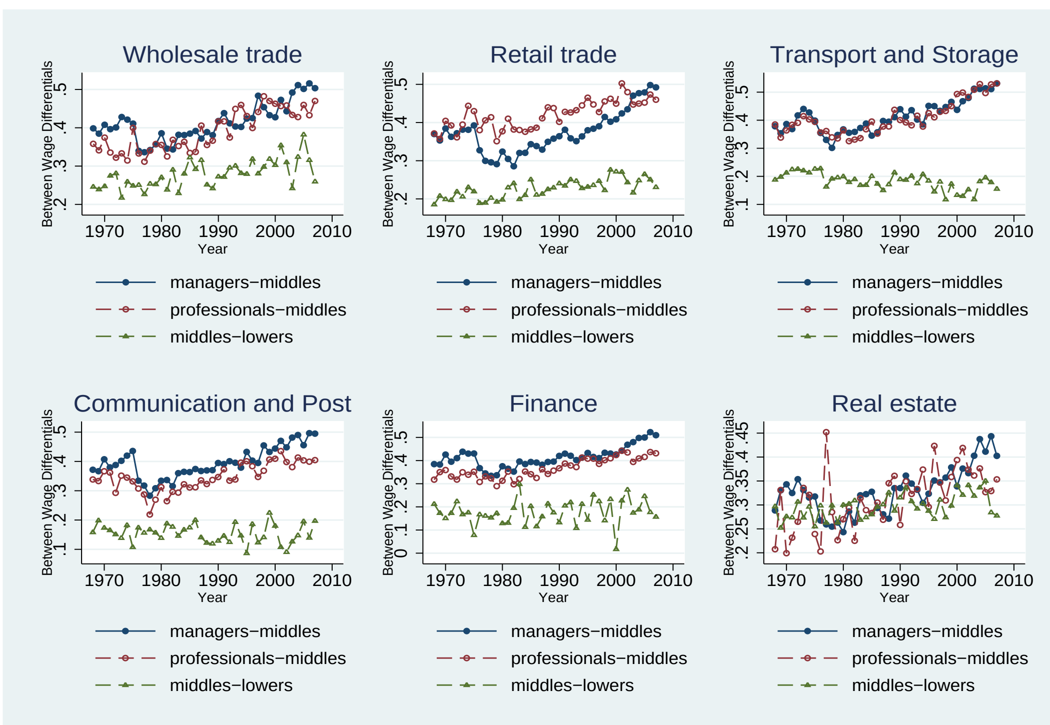

Figure 2.20: Wage Gaps between Managers and Middles and between Middles and Lowers IV

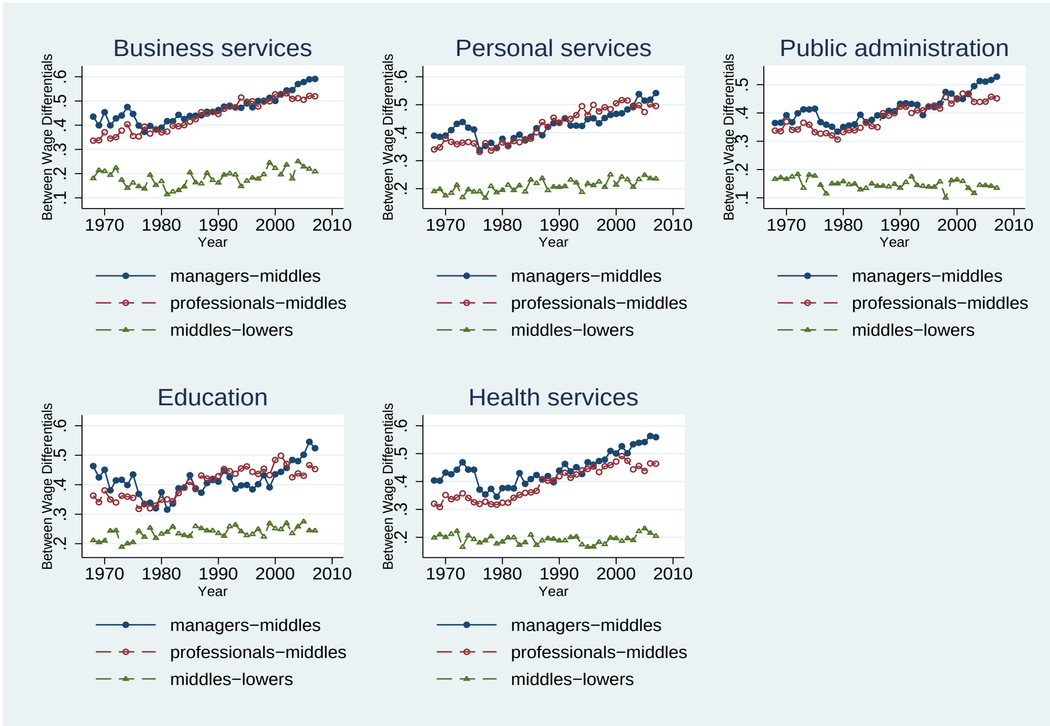

Figure 2.21: Wage Gaps between Managers and Middles and between Middles and Lowers V

and the middle layers, and between the middle layers and the lower layers. All industries, except for the agriculture industry, indicate increasing wage differential patterns between higher layers and middle layers relative to wage differentials between middle workers and lower workers, although higher layers are measured by managers class and professionals class separately. These diverging trends between wage differentials are consistent with the divergence trends between the upper-tail wage inequality measured by the 90th and the 50th percentiles and the lower-tail wage inequality measured by the 50th and the 10th percentiles in Autor, Katz, and Kearney (2008).

2.3.2 Wage Differentials between Occupations

To estimate the effects of information and communication technology on the wage differential between occupational layers, the first empirical model can be written as

$$\ln\left(\frac{\omega_j}{\omega_{j'}}\right)_{it} = \beta_0 + \beta_1 \ln(CompEq)_{it} + \beta_2 \ln(Software)_{it} + \beta_3 \ln(CommEq)_{it} + \beta_4 \ln(RelLabSup)_{st} + \beta_5 LP_{it} + \beta_6 (K/Y)_{it} + \beta_7 (K/N)_{it} + \epsilon_{it} \quad (2.17)$$

where i indicates the 29 industries with indexes of occupations j and j', managers, professionals, middle layer, and lower layer, and ω_{ijt} the wage in the jth occupational layer of industry i at time t. For industry i at time t, $CompEq_{it}$ represents investment in computing equipment, $Software_{it}$ the investment in software, $CommEq_{it}$ the communication equipment investment, $RelLabSup_{st}$ the relative labor supply between occupational layers j and j' in sector s[4], LP_{it} real gross output per worker, $(K/Y)_{it}$ the ratio between total capital assets and real gross output, and $(K/N)_{it}$ the capital-employment intensity measured by total capital assets divided by total number of employees. In literature, computing equipment is defined as computer hardware, including mainframes, personal computers, direct access and other storage devices, printers, terminals, tape drives, and integrated systems. Software is defined as prepackaged, custom, and own-account software (Stiroh, 2002).

Tables 2.2 to 2.5 illustrate the impact of information and communication technology on between wage differentials among the four occupational layers: managers, professionals, middle workers, and lower workers. For the between-occupation wage differentials analysis, this section uses two empirical specifications. First, based on the empirical specification with three types of investments for information and communication technology from Equation (2.17), two-way fixed effect regressions with 29 industry dummies and year dummies from 1970 to 2005 are used. Here, investment for computing equipment is considered information

[4](i) First sector: Agriculture, Mining, Food, Textile, Wood, Paper and Pulp, Petroleum, Chemicals, Rubber, Glass, Metals, Machinery, Electrical Machinery, Transport Equipment, Miscellaneous Manufacturing; (ii) Second sector: Utilities, Construction, Motor Vehicle Sales, Wholesale Trade, Retail Trade, Transport and Storage, and Communication and Post; and (iii) Third sector: Finance, Real Estate, Business Services, Personal Services, Public Administration, Education, Health Service.

technology, and software and communication equipment investment are regarded as communication technology. However, since the estimation results shown in Tables 2.2 and 2.3 indicate the impact of software and communication equipment on between-occupation wage differentials is similar to the finding seen in Tables 2.4 and 2.5, the second empirical specification with a broad measure of communication technology based on investments in software and communication equipment can be defined as

$$\ln\left(\frac{\omega_j}{\omega_{j'}}\right)_{it} = \beta_0 + \beta_1 \ln(CompEq)_{it} + \beta_2 \ln(SoftCommEq)_{it} + \beta_3 \ln(RelLabSup)_{st} + \beta_4 LP_{it} + \beta_5 (K/Y)_{it} + \beta_6 (K/N)_{it} + \epsilon_{it} \quad (2.18)$$

where $SoftCommEq_{it}$ represents the combined investments for software plus communication equipment of industry i at time t. Only computing equipment investment is defined as information technology, while combined investments for software plus communication equipment are considered communication technology. To consider the heterogeneous size of the 29 industries, investments in information and communication technology for both empirical specifications are divided by real gross output and total number of employees in each industry, respectively.

Tables 2.2 and 2.3 show that (i) information technology, which is measured by computing equipment, and two measurements of communication technology - software and communication equipment - have different impacts on between wage differentials depending on the comparison sets, and (ii) for the same comparison set each technological change - informational technological change or communicational technological change - has a heterogeneous impact on between wage differentials. For information technology, decreasing knowledge acquisition costs have a positive effect on four between wage differentials: managers and professionals, managers and middle workers, managers and lower workers, and middle workers and lower workers. As shown in Tables 2.2 and 2.3, regression (1) shows that a one percent increase in information technology measure leads to increased wage differentials between managers and professionals by 0.0215 percent and 0.0209 percent, respectively.

Table 2.2: The Effect of Information and Communication Technology on Wage Differentials among Four Occupations based on Log ICT Capitals-Real Gross Output Intensity I: 1970-2005

Variables	Dependent Variable: Log Wage Gaps Among Four Occupation Layers					
	(1)	(2)	(3)	(4)	(5)	(6)
Log Computing Intensity	0.02145**	0.00434	0.00637	−0.01912***	−0.01588	0.00008
	(0.008)	(0.008)	(0.007)	(0.005)	(0.011)	(0.010)
Log Software Intensity	−0.02267**	−0.00499	0.00083	0.01872***	0.02353*	0.00756
	(0.010)	(0.011)	(0.008)	(0.006)	(0.013)	(0.012)
Log Communication Intensity	−0.00147	0.00081	0.00267**	0.00268**	0.00344	0.00358*
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)
Log Relative Labor Supply	0.04366	0.01192	0.01183	−0.04725	−0.01401	0.10148***
	(0.026)	(0.029)	(0.037)	(0.029)	(0.033)	(0.036)
Output per Worker	0.00423*	0.00488**	0.01503***	0.00226	0.01158***	0.01178***
	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)	(0.003)
Capital-Output Intensity	0.00006	0.00004	−0.00003	−0.00001	−0.00008	−0.00007
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital-Employment Intensity	−0.00002	−0.00002*	−0.00001	−0.000004	0.000002	0.000005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.16020***	0.48479***	0.71785***	0.19637***	0.53440***	0.07281
	(0.036)	(0.078)	(0.053)	(0.053)	(0.058)	(0.087)
Industry Dummies	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes
R-squared	0.3285	0.6988	0.5426	0.7513	0.5776	0.1212
Observations	1044	1044	1044	1044	1044	1044

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Capital investments for information and communication technology are measured by real gross fixed capital formation (flow) in 2005 prices from the EU KLEMS Growth and Productivity Accounts from 1970 to 2005. Capital-output intensity is defined as total capital assets divided by real gross output, and capital-employment intensity is also measured by total capital assets divided by total number of employees. The data associated with wage differentials are from the IPUMS Current Population Survey for full-time and full-year workers age 17-65 from 1968 to 2007. **The first three columns show wage differentials between managers and the three layers of professionals, middle workers, and lower workers, respectively, and the next two columns are based on wage differentials between professionals and the two layers of middle workers and lower workers. Thus, regression (1) is based on wage differential between managers and professionals, regression (2) between managers and middle workers, and regression (3) the wage differential between managers and lower workers. Regression (4) is based on the wage differential between professionals and middle workers and regression (5) the wage differential between professionals and lower workers. The last column, regression (6), is based on the wage differential between middle workers and lower workers.**

Regression (3) shows that a one percent increase in computing equipment increases wage differentials between managers and lower workers by 0.0064 percent and 0.0058 percent, respectively. In the other two comparison sets, between the professionals and the middle workers and between the professionals and the lower workers, advances in information

Table 2.3: The Effect of Information and Communication Technology on Wage Differentials among Four Occupations based on Log ICT Capitals-Total Number of Employees Intensity I: 1970-2005

Variables	Dependent Variable: Log Wage Gaps Among Four Occupation Layers					
	(1)	(2)	(3)	(4)	(5)	(6)
Log Computing Intensity	0.02089^{**}	0.00426	0.00581	-0.01856^{***}	-0.01614	0.00031
	(0.008)	(0.008)	(0.007)	(0.005)	(0.010)	(0.009)
Log Software Intensity	-0.02254^{**}	-0.00510	-0.00202	0.01876^{***}	0.02060	0.00513
	(0.010)	(0.010)	(0.008)	(0.006)	(0.013)	(0.011)
Log Communication Intensity	-0.00161	0.00079	0.00244^{*}	0.00286^{*}	0.00333	0.00365
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)
Log Relative Labor Supply	0.04423	0.01182	0.00752	-0.04887	-0.01454	0.10343^{**}
	(0.026)	(0.028)	(0.036)	(0.031)	(0.033)	(0.038)
Output per Worker	0.00476^{**}	0.00483^{**}	0.01269^{**}	0.00185	0.00894^{**}	0.00924^{**}
	(0.002)	(0.002)	(0.005)	(0.002)	(0.004)	(0.004)
Capital-Output Intensity	0.00005	0.00004	-0.00002	-0.00001	-0.00007	-0.00006
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital-Employment Intensity	-0.00002	-0.00002	-0.00001	-0.000004	0.000004	0.00001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.15392^{***}	0.48344^{***}	0.70161^{***}	0.20039^{***}	0.52259^{***}	0.06495
	(0.038)	(0.078)	(0.051)	(0.048)	(0.057)	(0.087)
Industry Dummies	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes
R-squared	0.3286	0.6988	0.5404	0.7514	0.5755	0.1167
Observations	1044	1044	1044	1044	1044	1044

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Capital investments for information and communication technology are measured by real gross fixed capital formation (flow) in 2005 prices from the EU KLEMS Growth and Productivity Accounts from 1970 to 2005. Capital-output intensity is defined as total capital assets divided by real gross output, and capital-employment intensity is also measured by total capital assets divided by total number of employees. The data associated with wage differentials are from the IPUMS Current Population Survey for full-time and full-year workers age 17-65 from 1968 to 2007. **The first three columns show wage differentials between managers and the three layers of professionals, middle workers, and lower workers, respectively, and the next two columns are based on wage differentials between professionals and the two layers of middle workers and lower workers. Thus, regression (1) is based on wage differential between managers and professionals, regression (2) between managers and middle workers, and regression (3) the wage differential between managers and lower workers. Regression (4) is based on the wage differential between professionals and middle workers and regression (5) the wage differential between professionals and lower workers. The last column, regression (6), is based on the wage differential between middle workers and lower workers.**

technology show a negative impact on the wage differentials. Regression (4) in Tables 2.2 and 2.3 shows that a one percent increase in the information technology measure leads to a decrease in wage differentials between professionals and middle workers by 0.0191 percent and 0.0186 percent, respectively.

For communication technology, the impacts of cheaper communication costs on between wage differentials are not homogeneous. As shown in Tables 2.2 and 2.3, communication technology has a positive effect on three between wage differentials; professionals and middle workers, professionals and lower workers, and middle workers and lower workers; a negative effect on the wage differential between managers and professionals; and mixed effects on wage differentials between managers and middle workers and between managers and lower workers. For example, regression (4) shows that a one percent increase in the communication technology measure raises the wage differential between professionals and middle workers by 0.0187 percent and 0.0188 percent for software and by 0.0027 percent and 0.0029 percent for communication equipment. By contrast, regression (1) indicates that a one percent increase in communication technology leads to a decrease in the wage differential between managers and professionals by 0.0227 percent and 0.0225 percent for software and by 0.0015 percent and 0.0016 percent for communication equipment.

These results allow me to summarize two important implications about impacts of information and communication technology on wage differentials between occupational layers. First, these estimation results support the comparative statics in Garicano (2000) and in Garicano and Rossi-Hansberg (2006), which suggest that advances in both information technology and communication technology increase wage differentials between problem solvers and production workers but through different mechanisms. Through advances in information technology, decreasing knowledge acquisition cost leads to increased marginal productivity for all workers in the knowledge hierarchy, both problem solvers and production workers. However, due to the problem solvers' comparative advantage in knowledge acquisition, wage differentials between problem solvers and production workers should increase with decreasing knowledge acquisition costs. Except for wage differentials between professionals and middle workers and between professionals and lower workers, these results show that decreasing knowledge acquisition costs raise wage differentials between problem solvers at different layers and production workers.

Unlike increasing relative marginal productivity of problem solvers without neces-

Table 2.4: The Effect of Information and Communication Technology on Wage Differentials among Four Occupations based on Log ICT Capitals-Real Gross Output Intensity II: 1970-2005

Variables	Dependent Variable: Log Wage Gaps Among Four Occupation Layers					
	(1)	(2)	(3)	(4)	(5)	(6)
Log Information Intensity†	0.00822**	0.00038	0.00354	−0.00947***	−0.00534	0.00219
	(0.004)	(0.003)	(0.004)	(0.003)	(0.005)	(0.003)
Log Communication Intensity†	−0.00997	0.00013	0.00725*	0.01146***	0.01737**	0.00897
	(0.007)	(0.006)	(0.004)	(0.003)	(0.008)	(0.006)
Log Relative Labor Supply	0.03574	0.01190	0.00024	−0.03471	−0.01446	0.08240**
	(0.024)	(0.028)	(0.035)	(0.028)	(0.033)	(0.030)
Output per Worker	0.00518*	0.00527**	0.01569***	0.00149	0.01114***	0.01146***
	(0.003)	(0.002)	(0.004)	(0.002)	(0.003)	(0.003)
Capital-Output Intensity	0.00007	0.00004	−0.00003	−0.00003	−0.00010	−0.00008
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital-Employment Intensity	−0.00002	−0.00002	−0.00001	−0.000001	0.00001	0.00001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.09791***	0.46110***	0.69166***	0.26005***	0.58025***	0.10483*
	(0.030)	(0.075)	(0.034)	(0.051)	(0.033)	(0.056)
Industry Dummies	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes
R-squared	0.3220	0.6983	0.5427	0.7493	0.5774	0.1188
Observations	1044	1044	1044	1044	1044	1044

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Capital investments for information and communication technology are measured by real gross fixed capital formation (flow) in 2005 prices from the EU KLEMS Growth and Productivity Accounts from 1970 to 2005. Capital-output intensity is defined as total capital assets divided by real gross output and capital-employment intensity is measured by total capital assets divided by total number of employees. †Log information intensity is measured by the log ratio between computing equipment and real gross output, and the log communication intensity is also defined as the log ratio of the software plus commmunication equipments divided by real gross output. The data associated with the wage differentials are from the IPUMS Current Population Survey for full-time and full-year workers age 17-65 during the period from 1968 to 2007. **The first three columns show the wage differentials between managers and the three layers of professionals, middle workers, and lower workers, respectively, and the next two columns are based on the wage differentials between professionals and the other two layers of middle workers and lower workers. Thus, regression (1) is based on the wage differential between managers and professionals, regression (2) between managers and middle workers, and regression (3) between managers and lower workers. Regression (4) shows the wage differential between professionals and middle workers, and regression (5) the wage differential between professionals and lower workers. The last column, regression (6), is based on the wage differential between middle workers and lower workers.**

sarily decreasing marginal productivity of production workers by advances in information technology, advances in communication technology increase problem solvers' marginal productivity, and reduce production workers' marginal productivity. That is, faster and easier communication methods lead production workers to acquire less of the knowledge required

Table 2.5: The Effect of Information and Communication Technology on Wage Differentials among Four Occupations based on Log ICT Capitals-Total Number of Employees Intensity II: 1970-2005

Variables	Dependent Variable: Log Wage Gaps Among Four Occupation Layers					
	(1)	(2)	(3)	(4)	(5)	(6)
Log Information Intensity†	0.00763*	0.00013	0.00142	−0.00896***	−0.00686	0.00072
	(0.004)	(0.003)	(0.004)	(0.003)	(0.005)	(0.003)
Log Communication Intensity†	−0.01051	−0.00008	0.00540	0.01197***	0.01602*	0.00771
	(0.007)	(0.006)	(0.005)	(0.003)	(0.009)	(0.007)
Log Relative Labor Supply	0.03611	0.01175	−0.00258	−0.03579	−0.01492	0.08360**
	(0.024)	(0.027)	(0.035)	(0.029)	(0.034)	(0.030)
Output per Worker	0.00546**	0.00513*	0.01323**	0.00117	0.00845**	0.00898**
	(0.002)	(0.003)	(0.005)	(0.002)	(0.004)	(0.004)
Capital-Output Intensity	0.00007	0.00004	−0.00002	−0.00003	−0.00009	−0.00007
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital-Employment Intensity	−0.00002	−0.00002	−0.00001	−0.000001	0.00001	0.00001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.09035**	0.45795***	0.66741***	0.26483***	0.56392***	0.08697
	(0.033)	(0.073)	(0.030)	(0.046)	(0.035)	(0.058)
Industry Dummies	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes
R-squared	0.3222	0.6983	0.5401	0.7494	0.5753	0.1139
Observations	1044	1044	1044	1044	1044	1044

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Capital investments for information and communication technology are measured by real gross fixed capital formation (flow) in 2005 prices from the EU KLEMS Growth and Productivity Accounts from 1970 to 2005. Capital-output intensity is defined as total capital assets divided by real gross output and capital-employment intensity is also measured by total capital assets divided by total number of employees. †Log information intensity is measured by the log ratio between computing equipment and total number of employees, and the log communication intensity is also defined as the log ratio of the software plus commmunication equipments divided by total number of employees. The data associated with the wage differentials are from the IPUMS Current Population Survey for full-time and full-year workers age 17-65 during the period from 1968 to 2007. **The first three columns show the wage differentials between managers and the three layers of professionals, middle workers, and lower workers, respectively, and the next two columns are based on the wage differentials between professionals and the other two layers of middle workers and lower workers. Thus, regression (1) is based on the wage differential between managers and professionals, regression (2) between managers and middle workers, and regression (3) between managers and lower workers. Regression (4) shows the wage differential between professionals and middle workers, and regression (5) the wage differential between professionals and lower workers. The last column, regression (6), is based on the wage differential between middle workers and lower workers.**

for their tasks and to refer to problem solvers at the higher layer more frequently. Thus, based on these different mechanisms, wage differentials between problem solvers and production workers should increase with cheaper communication costs.

Regression results in Tables 2.2 to 2.5 support the suggestions from the theoretical framework that advances in communication technology raise wage differentials between problem solvers and production workers. Although wage differentials between managers and middle workers and between managers and lower workers show mixed effects, except for the comparison set between managers and professionals, the other comparison sets among the four occupational layers partially support the comparative statics in Garicano (2000) and Garicano and Rossi-Hansberg (2006). In addition, even though lower workers in the hierarchy are assumed to be isolated from advances in information and communication technology, increasing relative marginal productivities of managers, professionals and middle workers to marginal productivity of lower workers should increase wage differentials between managers and lower workers, between professionals and lower workers, and between middle workers and lower workers. Therefore, the increased relative marginal productivities would be indirect evidence supporting the positive impact of cheaper communication costs on between wage differentials.

Second, these estimation results show that, depending on the comparison sets, decreasing knowledge acquisition costs and cheaper communication costs have heterogeneous impacts. In addition, even for the same comparison set, two technological changes generate different effects on wage differentials between occupational layers. For regression (6), both information and communication technology have a positive impact on wage differentials between middle workers and lower workers. However, the regression sets between professionals and middle workers and between professionals and lower workers in regression (4) and regression (5) show a negative impact for information technology and a positive effect for communication technology. By contrast, a regression set between managers and professionals indicates a positive effect for decreasing knowledge acquisition costs, but a negative impact for cheaper communication costs.

The qualitatively different impacts of information and communication technology on wage differentials appear to be significant in solving the skill-biased technological change hypothesis puzzle. In the literature, skill-biased technological change has been regarded as a comprehensive computer-related technological change without distinction between information technological change and communication technological change. The belief that technological changes such as the computer revolution and computer-related technology have caused an increasing relative demand for skilled workers with increasing wage differentials between skilled workers and unskilled workers was supported in earning inequality literature until the mid-1990s. However, based on the observation that overall wage inequality has not continued to increase in the late 1990s in spite of continuous advances in computer-related technology, Card and DiNardo (2002) questioned the inconsistency of previous evidence in favor of skill-biased technological change, requiring re-evaluation of the empirical evidence associated with the SBTC hypothesis and the increasing wage differential. Thus far, these questions have not been fully answered.

Table 2.6 shows the evolutions of the growth rates for each investment in information and communication technology. The average annual growth rate of computing equipment decreased sharply in the early 1990s, and increased in the late 1990s. For communication technology, the annual growth rate of software equipment investment experienced a decrease in the early 1990s but recovered to the previous level of growth rates after 1995. The average annual growth rate of communication equipment showed similar trends in software investment. Three factors - the decrease in the growth rate of computing equipment, the recovered growth rate of software, and the increase in the growth rate of communication equipment in the late 1990s - help provide an answer to the question posed by Card and DiNardo (2002) about the SBTC puzzles with heterogeneous characteristics of information and communication technology.

Focusing on the comparison sets - wage differentials between managers and professionals, between managers and middle workers, and between managers and lower workers - increasing forces from advances in information technology on these wage differentials might be attenuated by decreasing forces of advances in communication technology, especially due to the sharp increase in the growth rates of communication equipment plus software in the late 1990s, on between wage differentials for the three comparison sets. Thus, the explanation for why comprehensive skill-biased technological change decreased overall wage

Table 2.6: Information and Communication Technological Changes over All Industries: 1970-2005

Variables	Annual Growth Rates of Information and Communication Technology				
	1970-1980	1981-1990	1991-1995	1996-2000	2001-2005
Computing Equipment	0.1401	0.1561	0.0527	0.0861	0.0103
Communication Equipment	0.1205	0.0925	0.0422	0.0762	0.0168
Software	0.1521	0.1621	0.1074	0.1501	0.0493
Software and Communication	0.1259	0.1021	0.0601	0.1160	0.0224
ICT Investment†	0.1239	0.1050	0.0508	0.0858	0.0119
Non−ICT Investment‡	0.1134	0.0615	0.0465	0.0491	0.0625
Total Investment	0.1152	0.0628	0.0404	0.0213	0.0355

† ICT in investments include information and communication technology such as computing equipment, software investments, and communication equipment. ‡ Non−ICT in investments include non-information and communication technology such as transport equipment, other machinery and equipments, total non-residential investments, residential structures, and other assets. Capital investments are measured by real gross fixed capital formation (flow) in 2005 prices from the EU KLEMS Growth and Productivity Accounts from 1970 to 2005.

inequality in the late 1990s despite advances in computer-related technology derives from the separation of skill-biased technological change into information technological change and communication technological change, each exhibiting different growth rates of investment patterns over the past decades. If these technological changes and their heterogeneous impacts on wage differentials between occupational layers are regarded as a comprehensive information technological change and a homogeneous impact on the wage differentials continuously, the relationship between increasing computer-related skill-biased technological change and slightly decreasing wage inequality in the late 1990s should remain an unsolved puzzle.

2.3.3 Within Wage Differentials

This section explores the impact of information and communication technology on within wage differentials based on Garicano (2000) and Garicano and Rossi-Hansberg (2006). To calculate within-group wage differentials, standard deviations of wage residuals, residual wage differential between the 90th and the 10th percentiles, residual wage differential between the 90th and the 50th percentiles, and residual wage differential between the

90th and the 75th percentiles are used.[5] Wage residuals are calculated from the regressions of log real weekly earnings on years of schooling, experience, experience squared, metro area, gender, white, occupation, and industry for a given year. In addition, consistent with the theoretical framework, this section focuses primarily on wage differentials within top managers and wage differentials within production workers with supplementary analysis for within professionals wage differential. Since it is assumed that the lower worker class is isolated from information and communication technological change, the fourth group in this section is not considered.

The empirical methodology used here is a two-way fixed effect regression with 29 industry dummies and year dummies from 1970 to 2005. Information and communication technology are measured through three capital investments: computing equipment for information technology and software and communication equipment for communication technology. To consider different characteristics for each industry, technological change measures are converted into share-type variables based on real gross output and total number of employees. The empirical specification for within wage differentials based on four occupational layers can be written as

$$\Gamma_{ijt} = \beta_0 + \beta_1(Comp)_{it} + \beta_2(SofCom)_{it} + \beta_3 LP_{it} + \beta_4(K/Y)_{it} + \beta_5(K/N)_{it} + \epsilon_{it} \quad (2.19)$$

where i indicates 29 industries with indexes of three occupational classes, j and j', managers, professionals, and middle layer,[6] while Γ_{ijt} represents the wage differentials within group j in industry i at time t. For industry i at time t, $(Comp)_{it}$ represents information

[5] For robust measurements of top problem solvers and production workers, general measurements such as standard deviations from wage residuals and residual wage differential between the 90th and the 10th percentiles and specific measurements such as residual wage differential between the 90th and the 50th percentiles and residual wage differential between the 90th and the 75th percentiles are applied for within wage differential analyses.

[6] This section assumes that there are four occupational layers among 11 occupations from the IPUMS Current Population Survey: (1) the higher layer such as managers, (ii) the independent layer including professionals, (iii) the middle layer of clerical, sales workers, craftsmen, operatives and farmers, and (iv) the lower layer including service workers and laborers. Although professionals could be classified in the same layer as managers, due to the independent characteristics of professional occupations, the professional class is a separate occupational layer, which is located between the higher layer and the middle layer.

technology, which is measured by investment in computing equipment; $(SofCom)_{it}$ indicates communication technology measured by investment in software plus communication equipment; $(LP)_{it}$ indicates real gross output per worker; $(K/Y)_{it}$ is the ratio between total capital assets and real gross output; and $(K/N)_{it}$ is the capital-employment intensity measured by total capital assets divided by total number of employees.

Table 2.7 shows that information technology measurements from regression (1) to regression (8) and communication technology measurements from regression (2) to regression (8) have a positive impact on within wage differentials for managers. When top problem solvers are generally defined as managers, the broad measurements of wage differentials within this group, such as standard deviation of wage residuals and residual wage differentials between the 90th and the 10th percentiles within managers, support the implications from the theoretical framework about positive impact of information and communication technology on within wage differentials. Also, the specific measurements for within wage differentials for top problem solvers, such as residual wage differentials between the 90th and the 50th percentiles and between the 90th and the 75th percentiles, support the comparative statics in Garicano (2000) and Garicano and Rossi-Hansberg (2006).

However, unlike this positive impact of information and communication technology on within wage differentials for top managers, advances in information technology and in communication technology have the opposite effect on within wage differentials for production workers. That is, decreasing knowledge acquisition costs increase within-group wage differentials for all occupational layers, while advances in communication technology act as an equalizer for wage distribution among production workers in that cheaper communication costs reduce the incentive to acquire knowledge for production workers. Instead, since production workers ask for solutions from problem solvers when faced with difficult problems, decreasing incentive for knowledge acquisition and increasing dependency of production workers on problem solvers, especially top problem solvers who deal only with exceptional matters and the most complex problems, lead to a decrease within wage differentials for production workers and to an increase between production workers and problem solvers.

Table 2.7: Effects of Information and Communication Technology on Residual Wage Differentials Within Managers: 1970-2005

Variables	Real Gross Output Intensity				Total Number of Employees Intensity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Information Technology Intensity	0.07304***	0.17881***	0.13373***	0.07487***	0.02997***	0.01294	0.01842	0.00947
	(0.018)	(0.044)	(0.037)	(0.023)	(0.011)	(0.052)	(0.037)	(0.022)
Communication Technology Intensity	−0.00294	0.00014	0.00349	0.00376	0.00047	0.00619	0.00277	0.00115
	(0.002)	(0.008)	(0.006)	(0.005)	(0.001)	(0.004)	(0.002)	(0.001)
Output per Worker	0.00187	0.00337	0.00478	0.01507***	−0.00594	−0.01189	−0.00618	0.00943*
	(0.008)	(0.024)	(0.007)	(0.003)	(0.009)	(0.020)	(0.006)	(0.005)
Capital-Output Intensity	−0.00010	0.00011	−0.00015	−0.00008	−0.00010*	0.00014	−0.00010	−0.00005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital-Employment Intensity	−0.00003**	−0.00014***	−0.00006*	−0.00004	−0.00004***	−0.00016***	−0.00007**	−0.00005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.51089***	1.15406***	0.62077***	0.30137***	0.52363***	1.17606***	0.63685***	0.30950***
	(0.019)	(0.048)	(0.022)	(0.016)	(0.019)	(0.039)	(0.018)	(0.016)
Industry Dummies	yes	yes	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.2478	0.1414	0.1045	0.0710	0.2490	0.1338	0.0940	0.0650
Observations	1044	1044	1044	1044	1044	1044	1044	1044

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Capital investments for information and communication technology are measured by the real gross fixed capital formation (flow) in 2005 prices from the EU KLEMS Growth and Productivity Accounts from 1970 to 2005. The capital-output intensity is defined as total capital assets divided by real gross output, and the capital-employment intensity is measured by total capital assets divided by total number of employees. Associated with wage differentials, the IPUMS Current Population Survey data for full-time, full-year wage/salary workers age 17-65 from 1968 to 2007 (covering earnings year 1967 to 2006 for workers age 16-64 in earnings years) are used. **In the first set from regression (1) to regression (4), information technology is calculated as the investment in computing equipment divided by real gross output and communication technology is defined as investments in software plus communication equipment divided by real gross output. In the second set from regression (5) to regression (8), information technology is measured by the investment in computing equipment per worker, and communication technology is measured by investments in software and communication equipments per worker. Within-group wage differentials are determined by four measurements: standard deviations from wage residuals, wage residuals between the 90th and the 10th percentiles, wage residuals between the 90th and the 50th percentiles and wage residuals between the 90th and the 75th percentiles within managers from regression (1) to (4) in the first set and from regression (5) to (8) in the second set, respectively.**

Table 2.8: Effects of Information and Communication Technology on Residual Wage Differentials Within Middle Workers: 1970-2005

Variables	Real Gross Output Intensity				Total Number of Employees Intensity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Information Technology Intensity	0.02809**	0.06658**	0.04130	0.03399*	0.01987***	0.04221***	0.03552***	0.02229**
	(0.013)	(0.026)	(0.026)	(0.019)	(0.005)	(0.010)	(0.010)	(0.009)
Communication Technology Intensity	−0.00431**	−0.00614	−0.00390	−0.00521**	−0.00179***	−0.00264*	−0.00376***	−0.00291***
	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Output per Worker	0.00720	0.02723**	0.00447	−0.00023	0.00564	0.02182*	0.00221	−0.00078
	(0.004)	(0.011)	(0.006)	(0.003)	(0.005)	(0.011)	(0.007)	(0.004)
Capital-Output Intensity	−0.00002	0.00011	−0.00009	−0.00007*	−0.00003	0.00011	−0.00009	−0.00007*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital-Employment Intensity	0.00001	−0.00001	0.00001	−0.000004	0.000005	−0.00001	0.00001	−0.00001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.36360***	0.85475***	0.41072***	0.20219***	0.36608***	0.86372***	0.41464***	0.20269***
	(0.010)	(0.026)	(0.013)	(0.007)	(0.011)	(0.025)	(0.014)	(0.008)
Industry Dummies	yes	yes	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.6682	0.5858	0.6001	0.4294	0.6711	0.5880	0.6073	0.4333
Observations	1044	1044	1044	1044	1044	1044	1044	1044

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Capital investments for information and communication technology are measured by the real gross fixed capital formation (flow) in 2005 prices from the EU KLEMS Growth and Productivity Accounts from 1970 to 2005. The capital-output intensity is defined as total capital assets divided by real gross output, and the capital-employment intensity is measured by total capital assets divided by total number of employees. Associated with wage differentials, the IPUMS Current Population Survey data for full-time, full-year wage/salary workers age 17-65 from 1968 to 2007 (covering earnings year 1967 to 2006 for workers age 16-64 in earnings years) are used. **In the first set from regression (1) to regression (4), information technology is calculated as the investment in computing equipment divided by real gross output and communication technology is defined as investments in software plus communication equipment divided by real gross output. In the second set from regression (5) to regression (8), information technology is measured by the investment in computing equipment per worker, and communication technology is measured by investments in software and communication equipments per worker. Within-group wage differentials are determined by four measurements: standard deviations from wage residuals, wage residuals between the 90th and the 10th percentiles, wage residuals between the 90th and the 50th percentiles and wage residuals between the 90th and the 75th percentiles within middle workers from regression (1) to (4) in the first set and from regression (5) to (8) in the second set, respectively.**

All regression sets in Table 2.8 are consistent with the predication suggested by the theoretical framework. In the first regression set based on real gross output intensity, information technology measurements show positive coefficients for within wage differentials for production workers. For example, there is a 0.0666 in regression (2) and a 0.034 in regression (4). On the other hand, communication technology measurements exhibit a negative impact on within wage differentials. For example, there is a -0.0043 in regression (1) and a -0.0039 in regression (3). In addition, based on total number of employees intensity, the second regression set shows the positive impact of decreasing knowledge acquisition costs and the negative effect of cheaper communication costs on within wage differentials for middle workers. For example, a one unit increase in the information technology measure leads to a 0.0199 unit increase wage differential within-middle workers in regression (5), while a one unit increase in communication technology decreases wage differentials within-middle workers by a 0.0018 unit in regression (5).

Table 2.9 shows the effect of information and communication technology on within wage differentials for professionals. Based on the positive coefficients of information technology measurements from regression (1) to (8) and the negative coefficients from communication technology in regression (1) to regression (8) except for regression (5), one can see that decreasing knowledge acquisition costs raise wage differentials within professionals, but cheaper communication costs act as a wage equalizer among professionals. Therefore, the within wage differentials analysis presented in Tables 2.7 to 2.9 supports the comparative statics in Garicano (2000) and Garicano and Rossi-Hansberg (2006), showing that decreasing knowledge acquisition costs from advances in information technology raise within wage differentials for three occupational layers - managers, middle workers, and professionals - while cheaper communication costs from advances in communication technology raises within wage differentials for managers, but decreases within wage differentials for middle workers and professionals.

Table 2.9: Effects of Information and Communication Technology on Residual Wage Differentials within Professionals: 1970-2005

Variables	Real Gross Output Intensity				Total Number of Employees Intensity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Information Technology Intensity	0.02099	0.03079	0.02873	0.02560	0.00702	0.01888	0.03360**	0.03245**
	(0.013)	(0.033)	(0.023)	(0.017)	(0.008)	(0.015)	(0.015)	(0.013)
Communication Technology Intensity	−0.00052	−0.01383	−0.00392	−0.00913**	0.00090	−0.00192	−0.00347**	−0.00472***
	(0.003)	(0.010)	(0.005)	(0.004)	(0.001)	(0.002)	(0.001)	(0.001)
Output per Worker	−0.00193	0.00829	0.00231	0.00329	−0.00495	0.00813	0.00034	0.00390
	(0.003)	(0.006)	(0.007)	(0.006)	(0.004)	(0.005)	(0.005)	(0.004)
Capital-Output Intensity	−0.00012**	0.00009	0.00007	0.00023***	−0.00012**	0.00005	0.00007	0.00022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital-Employment Intensity	0.000003	−0.00005	0.00001	−0.00002	0.000001	−0.00005	0.00001	−0.00002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.40320***	0.92530***	0.43081***	0.19644***	0.40822***	0.92475***	0.43457***	0.19536***
	(0.013)	(0.039)	(0.031)	(0.025)	(0.014)	(0.038)	(0.030)	(0.024)
Industry Dummies	yes	yes	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.2780	0.2122	0.1219	0.0678	0.2788	0.2114	0.1232	0.0692
Observations	1044	1044	1044	1044	1044	1044	1044	1044

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Capital investments for information and communication technology are measured by the real gross fixed capital formation (flow) in 2005 prices from the EU KLEMS Growth and Productivity Accounts from 1970 to 2005. The capital-output intensity is defined as total capital assets divided by real gross output, and the capital-employment intensity is measured by total capital assets divided by total number of employees. Associated with wage differentials, the IPUMS Current Population Survey data for full-time, full-year wage/salary workers age 17-65 from 1968 to 2007 (covering earnings year 1967 to 2006 for workers age 16-64 in earnings years) are used. **In the first set from regression (1) to regression (4), information technology is calculated as the investment in computing equipment divided by real gross output and communication technology is defined as investments in software plus communication equipment divided by real gross output. In the second set from regression (5) to regression (8), information technology is measured by the investment in computing equipment per worker, and communication technology is measured by investments in software and communication equipments per worker. Within-group wage differentials are determined by four measurements: standard deviations from wage residuals, wage residuals between the 90th and the 10th percentiles, wage residuals between the 90th and the 50th percentiles and wage residuals between the 90th and the 75th percentiles within professionals from regression (1) to (4) in the first set and from regression (5) to (8) in the second set, respectively.**

2.4 Concluding Remarks

Incorporating empirical methods in the theoretical framework from Garicano (2000), this paper looked for consistency between comparative statics from theoretical models and real world data and attempted to solve the SBTC puzzle, posed by Card and DiNardo (2002) regarding skill-biased technological change. For the SBTC puzzle, this paper adopts the practice of separating skill-biased technological changes into information and communication technology and points out the broad classification problem of skill-biased technological change. Since skill-biased technological change is assumed to be a comprehensive computer-based technological change in the literature, advances in comprehensive computer-related technology are predicted to have a positive impact on wage inequality homogeneously. However, as theoretical frameworks suggest, separating skill-biased technological changes into information and communication technology uncovers qualitatively different characteristics, so that advances in information and communication technology will have heterogeneous impacts on workers' marginal products depending on their occupational characteristics.

Based on the estimation results from between-group wage differentials, advances in information technology measured by computing equipment raise wage differentials between managers and professionals, between managers and middle workers, between managers and lower workers, and between middle workers and lower workers. The increasing wage differentials between managers and the other three occupations support the implication from Garicano (2000) and Garicano and Rossi-Hansberg (2006) about the positive effect of decreasing knowledge acquisition costs on wage differentials between problem solvers and production workers. For advances in communication technology, which are measured by software and communication equipment, the positive impacts on between wage differentials support the comparative statics from theoretical framework that cheaper communication costs increase wage differentials between problem solvers and production workers partially. In addition, the negative impact on wage differentials between managers and professionals and the mixed effect between managers and middle workers from cheaper communication costs provide important information for solving the SBTC puzzle. The sharp increase in investments in communication equipment and software in the late 1990s and the corresponding estimation results on between managers and professionals and between managers and middle workers lead me to propose that the negative impact of communication technology on the comparison sets may suppress the positive impact of information technology on these wage differentials. Thus, contracted wage differentials by the cheaper communication costs in the late 1990s would affect decreasing overall wage differential measured by wage gaps between the 90th and the 10th percentiles.

For within-group wage differentials, this paper supports the predictions from Garicano (2000) and Garicano and Rossi-Hansberg (2006) concerning the impact of information and communication technology on within-group wage differentials as well. Advances in information technology raise within-group wage differentials for managers representing top problem solvers and middle workers representing production workers homogeneously. Cheaper communication costs, however, raise within-group wage differentials for managers, while lead to a decrease within-group wage differentials for middle-workers.

In sum, this paper provides empirical evidence supporting the comparative statics in Garicano (2000) and Garicano and Rossi-Hansberg (2006). First, advances in information and communication technology raise wage differentials between problem solvers and production workers. Second, for information technology, decreasing knowledge acquisition costs increase within-group wage differentials for each occupational layer. Finally, for communication technology, available cheaper communication costs act as a wage equalizer among production workers but raise wage differentials within top problem solvers, who deal only with exceptional problems. The first and third implications present a Superstar effect in Rosen (1981) in that production workers acquire only the basic knowledge required for the task, due to cheaper communication costs, and instead of acquiring more knowledge, they ask for solutions from the problem solvers when they face difficult problems. The reduced incentive for knowledge acquisition due to advances in communication technology increases the dependency of production workers on problem solvers, and thus centralization of problem solvers toward the top of the knowledge hierarchy should increase. Therefore, advances in communication technology increases wage differentials between problem solvers and production workers and within-group wage differentials for top problem solvers in the knowledge hierarchy.

Furthermore, since distinguishing between information technological change and communication technological change does not generate the same effects on all comparison sets, previously assumed comprehensive skilled-biased technological change may provide misleading implications about wage differentials. In addition, due to different growth rates of capital investments in computing equipment, software and communication equipment over the last decades as presented in Table 2.6,[7] realized patterns of wage differentials could be different from the predictions of comprehensive skill-biased technological change. These misguided conjectures based on comprehensive skill-biased technological change were not consistent with the phenomenon that although computer-related technological changes have continued in the late 1990s, the increasing growth rate of overall wage differential has slowed down. Thus, this phenomenon, prior to the separation of skill-biased technological change into information and communication technology, was considered a skill-biased technological change puzzle. With the heterogeneous effects of separated information and communication technology, this paper provides a key to solving the SBTC puzzle in that increasing wage differentials between managers and professionals, between managers and middle workers, and between managers and lower workers due to advances in information technology might be attenuated by suppressing forces from advances in communication technology in the late 1990s, which have negative impacts on these between-occupational wage differentials.

[7] In Table 2.6, each capital investment in computing equipment, software, or communication equipment has a different time period recording the highest investment growth rates among sub-periods from 1970 to 2005. Moreover, growth rates for each capital investment over time are different from the growth rates of investment for information and communication technology, which would be a proxy variable for comprehensive skill-biased technological change.

2.5 Appendix

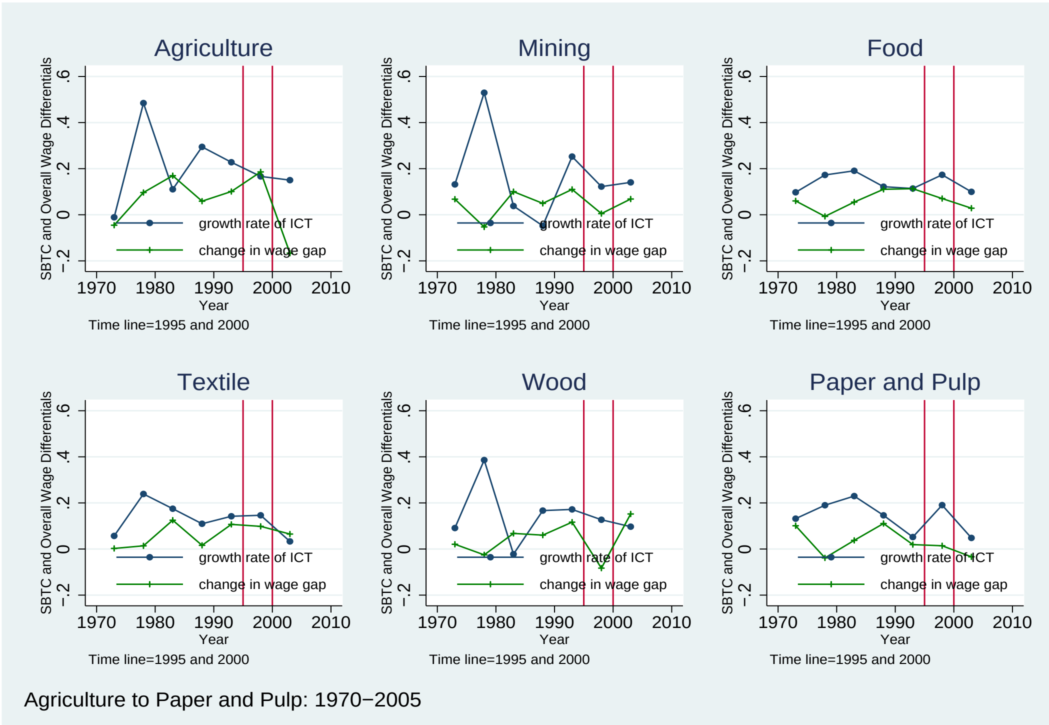

Figure 2.22: Growth rates of Skill-biased Technological Change and Differences in Wage Gaps I

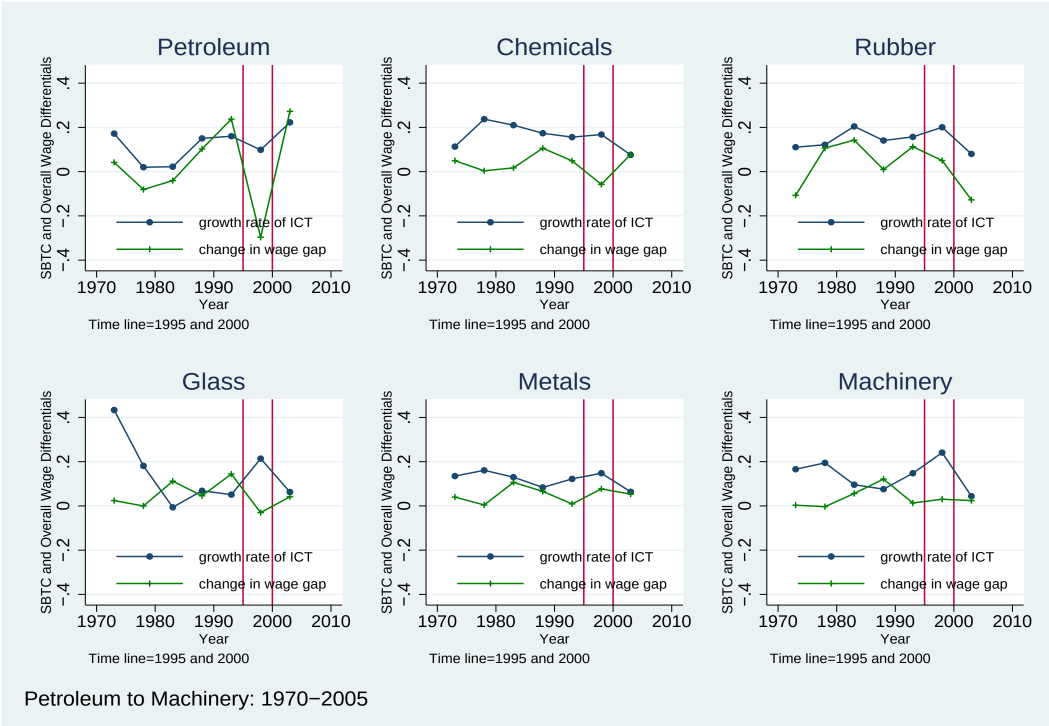

Figure 2.23: Growth rates of Skill-biased Technological Change and Differences in Wage Gaps II

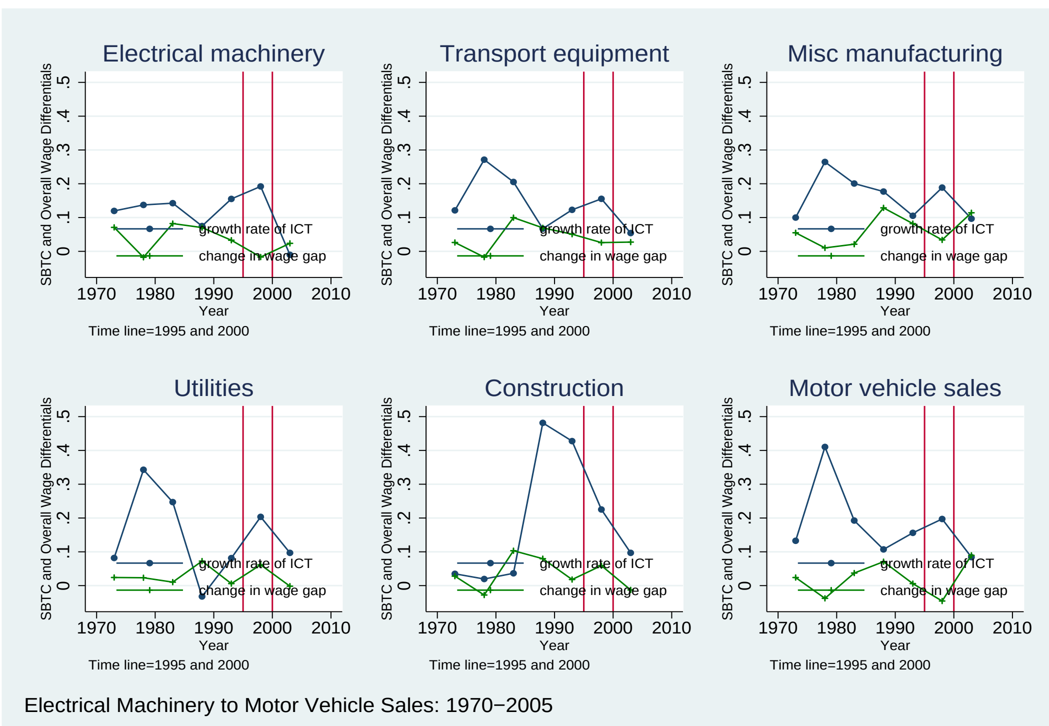

Figure 2.24: Growth rates of Skill-biased Technological Change and Differences in Wage Gaps III

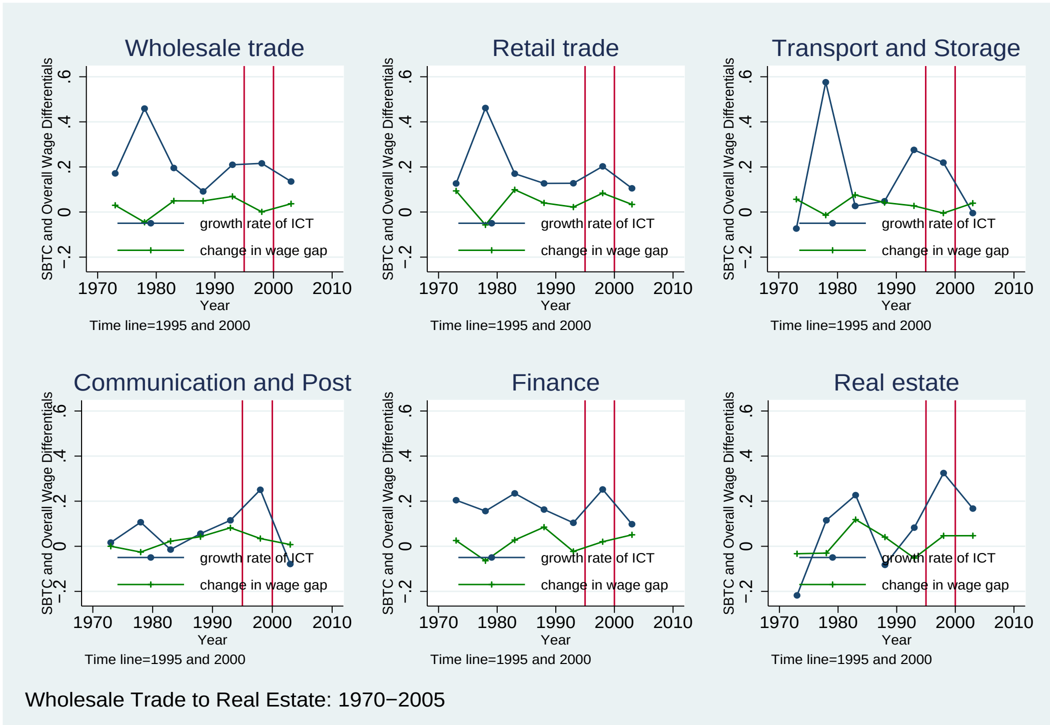

Figure 2.25: Growth rates of Skill-biased Technological Change and Differences in Wage Gaps IV

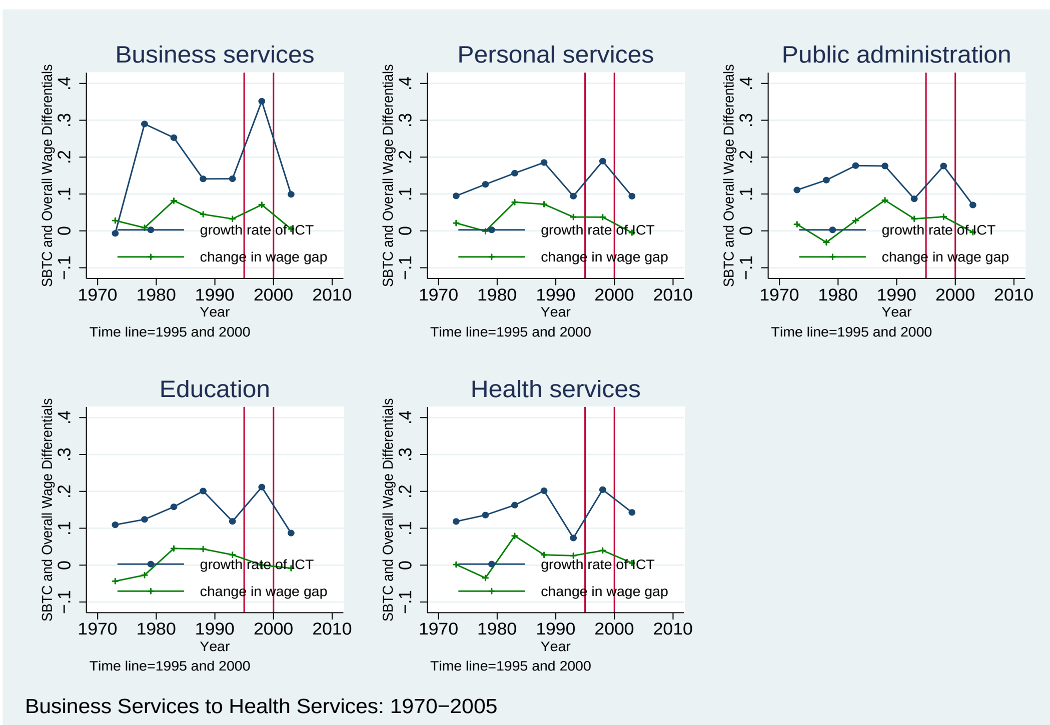

Figure 2.26: Growth rates of Skill-biased Technological Change and Differences in Wage Gaps V

Table 2.10: Overall Wage Differentials by Industry over Five Sub-periods from 1968 to 2007

Industry	Wage Differentials between 90th and 10th Percentile: 1968-2007					
	1968-1980	1980-1990	1990-1995	1995-2000	2000-2007	1968-2007
Agriculture, Hunting, Forestry, and Fishing	0.0704	0.2286	0.1009	0.1859	−0.1142	0.4716
Mining and Quarrying	0.1170	0.1499	0.1101	0.0051	−0.0649	0.3172
Food, Beverages and Tobacco	0.0781	0.1657	0.1132	0.0704	0.0085	0.4357
Textiles, Textile, Leather and Footwear	0.0367	0.1411	0.1070	0.0983	0.1037	0.4868
Wood and of Wood and Cork	0.0047	0.1281	0.1165	−0.0829	0.1744	0.3408
Pulp, Paper, Printing and Publishing	0.0505	0.1483	0.0192	0.0142	0.0437	0.2759
Coke, Refined Petroleum and Nuclear Fuel	−0.0106	0.0620	0.2377	−0.2962	0.2280	0.2209
Chemicals and Chemical Products	0.0433	0.1231	0.0490	−0.0577	0.1507	0.3085
Rubber and Plastics	−0.0499	0.1524	0.1129	0.0504	−0.2458	0.0200
Other Non-Metallic Mineral	0.0384	0.1576	0.1440	−0.0301	−0.0821	0.2277
Basic Metals and Fabricated Metal	0.0716	0.1724	0.0090	0.0769	0.0488	0.3786
Machinery, Nec	0.0650	0.1774	0.0132	0.0301	0.0714	0.3572
Electrical and Optical Equipment	0.0696	0.1527	0.0329	−0.0168	0.0372	0.2758
Transport Equipment	0.0445	0.1694	0.0509	0.0260	0.0424	0.3331
Manufacturing, Nec and Recycling	0.1304	0.1499	0.0821	0.0339	0.1032	0.4995
Electricity, Gas and Water Supply	0.0888	0.0828	0.0059	0.0615	0.0905	0.3296
Construction	0.0161	0.1829	0.0180	0.0592	0.0218	0.2980
Sales and Maintenance of Motor Vehicles and Motorcycles	0.0098	0.1079	0.0060	−0.0456	0.0993	0.1773
Wholesale Trade and Commission Trade†	0.0116	0.0989	0.0693	0.0008	0.0261	0.2067
Retail Trade, except of Motor Vehicles and Motorcycles	0.0650	0.1393	0.0221	0.0839	0.0507	0.3610
Transport and Storage	0.0380	0.1177	0.0274	−0.0049	0.0108	0.1890
Post and Communication	0.0006	0.0650	0.0821	0.0343	0.0653	0.2474
Financial Intermediation	−0.0059	0.1127	−0.0228	0.0203	0.0777	0.1820
Real Estate Activities	−0.0414	0.1593	−0.0523	0.0467	0.0080	0.1204
Renting and Other Business Activities	0.0578	0.1269	0.0325	0.0708	0.0306	0.3186
Community Social and Personal Services	0.0436	0.1503	0.0375	0.0373	0.0093	0.2781
Public Administration, Defense, Compulsory Social Security	0.0151	0.1111	0.0327	0.0384	0.0205	0.2177
Education	−0.0384	0.0890	0.0280	0.0004	−0.0129	0.0661
Health and Social Work	0.0063	0.1072	0.0257	0.0398	0.0170	0.1960
Mean	0.0354	0.1355	0.0555	0.0190	0.0352	0.2806
Standard Deviations	0.0440	0.0371	0.0584	0.0799	0.0890	0.1162

† Wholesale Trade and Commission Trade, excluding Motor Vehicles and Motorcycles. These values are calculated as those in Figures 2.12 to 2.16 based on log real weekly earning changes over wage percentiles during the period from 1968 to 2007.

Table 2.11: Descriptive Statistics by Industry from IPUMS CPS Data I: 1968-2007

Agriculture	Observations	Mean	Std. Dev.	Min	Max
Weekly Earnings	31819	512.23	500.27	125.00	9396.55
Annual Earnings	31819	26095.90	25833.37	5000.00	479224.00
Total Weeks Worked Last Year	31819	50.70	2.96	40.00	52.00
Years of Schooling	31819	10.90	3.89	0.00	16.00
Age	31819	37.42	12.10	17.00	65.00
Experience	31819	19.54	13.13	0.00	58.00
Year	31819	1989.89	11.62	1968.00	2007.00
Mining	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	18725	951.65	614.74	125.18	10661.88
Annual Earnings	18725	48636.68	31921.35	5361.71	554417.50
Total Weeks Worked Last Year	18725	50.94	2.58	40.00	52.00
Years of Schooling	18725	12.26	2.76	0.00	16.00
Age	18725	39.16	11.30	17.00	65.00
Experience	18725	19.90	11.96	0.00	58.00
Year	18725	1987.34	10.96	1968.00	2007.00
Food	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	39916	666.96	479.89	125.02	11300.19
Annual Earnings	39916	34163.30	24894.04	5001.26	587609.81
Total Weeks Worked Last Year	39916	51.03	2.34	40.00	52.00
Years of Schooling	39916	11.42	3.07	0.00	16.00
Age	39916	39.46	11.75	17.00	65.00
Experience	39916	21.04	12.56	0.00	58.00
Year	39916	1986.95	11.82	1968.00	2007.00
Textiles	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	41693	485.38	434.46	125.00	11369.53
Annual Earnings	41693	24654.89	22413.37	5014.59	545737.56
Total Weeks Worked Last Year	41693	50.52	2.78	40.00	52.00
Years of Schooling	41693	10.51	3.17	0.00	16.00
Age	41693	40.38	12.35	17.00	65.00
Experience	41693	22.87	13.31	0.00	58.00
Year	41693	1983.46	10.85	1968.00	2007.00
Wood	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	25262	595.49	449.51	125.00	10003.08
Annual Earnings	25262	30344.13	23179.05	5044.89	490151.00
Total Weeks Worked Last Year	25262	50.81	2.62	40.00	52.00
Years of Schooling	25262	11.06	3.08	0.00	16.00
Age	25262	38.47	11.88	17.00	65.00
Experience	25262	20.42	12.74	0.00	58.00
Year	25262	1987.68	11.66	1968.00	2007.00

Table 2.12: Descriptive Statistics by Industry from IPUMS CPS Data II: 1968-2007

Paper and Pulp	Observations	Mean	Std. Dev.	Min	Max
Weekly Earnings	44577	780.63	593.66	125.02	11439.42
Annual Earnings	44577	40145.23	30818.18	5035.37	594849.63
Total Weeks Worked Last Year	44577	51.28	2.01	40.00	52.00
Years of Schooling	44577	12.72	2.46	0.00	16.00
Age	44577	39.47	11.65	17.00	65.00
Experience	44577	19.75	12.20	0.00	58.00
Year	44577	1987.79	11.30	1968.00	2007.00
Petroleum	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	4670	1006.57	647.07	128.85	8131.73
Annual Earnings	4670	51820.07	33617.78	5797.01	422850.00
Total Weeks Worked Last Year	4670	51.33	1.77	40.00	52.00
Years of Schooling	4670	13.03	2.46	0.00	16.00
Age	4670	41.30	11.36	18.00	65.00
Experience	4670	21.27	11.97	0.00	58.00
Year	4670	1984.51	11.57	1968.00	2007.00
Chemicals	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	30098	950.12	703.92	125.02	9411.24
Annual Earnings	30098	49001.65	36561.78	5850.88	489384.53
Total Weeks Worked Last Year	30098	51.43	1.72	40.00	52.00
Years of Schooling	30098	13.11	2.60	0.00	16.00
Age	30098	40.51	11.06	17.00	65.00
Experience	30098	20.41	11.58	0.00	58.00
Year	30098	1988.18	11.96	1968.00	2007.00
Rubber	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	5697	736.29	494.18	126.98	7984.47
Annual Earnings	5697	37781.48	25709.21	5586.95	415192.25
Total Weeks Worked Last Year	5697	51.15	2.07	40.00	52.00
Years of Schooling	5697	11.89	2.70	0.00	16.00
Age	5697	39.96	11.42	17.00	65.00
Experience	5697	21.07	11.97	0.00	55.00
Year	5697	1985.51	11.51	1968.00	2007.00
Glasses	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	13089	717.68	460.26	125.18	11204.05
Annual Earnings	13089	36659.95	23755.12	5363.97	515386.38
Total Weeks Worked Last Year	13089	50.95	2.38	40.00	52.00
Years of Schooling	13089	11.61	2.85	0.00	16.00
Age	13089	40.00	11.59	17.00	65.00
Experience	13089	21.40	12.32	0.00	57.00
Year	13089	1985.95	11.67	1968.00	2007.00

Table 2.13: Descriptive Statistics by Industry from IPUMS CPS Data III: 1968-2007

Metals	Observations	Mean	Std. Dev.	Min	Max
Weekly Earnings	52403	759.33	499.97	125.02	11439.42
Annual Earnings	52403	38855.40	25893.42	5191.72	594849.63
Total Weeks Worked Last Year	52403	51.04	2.22	40.00	52.00
Years of Schooling	52403	11.68	2.80	0.00	16.00
Age	52403	40.50	11.83	17.00	65.00
Experience	52403	21.82	12.56	0.00	58.00
Year	52403	1984.89	11.77	1968.00	2007.00
Machinery	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	50582	852.04	608.61	125.03	12253.78
Annual Earnings	50582	43732.84	31503.83	5695.85	550010.56
Total Weeks Worked Last Year	50582	51.18	2.10	40.00	52.00
Years of Schooling	50581	12.56	2.55	0.00	16.00
Age	50582	39.58	11.53	17.00	65.00
Experience	50582	20.02	12.11	0.00	57.00
Year	50582	1986.17	11.19	1968.00	2007.00
Electrical Machinery	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	57847	822.32	672.42	125.02	11439.42
Annual Earnings	57847	42261.07	34864.34	5009.99	594849.63
Total Weeks Worked Last Year	57847	51.20	2.08	40.00	52.00
Years of Schooling	57847	12.74	2.62	0.00	16.00
Age	57847	39.77	11.39	17.00	65.00
Experience	57847	20.04	11.92	0.00	57.00
Year	57847	1986.68	11.45	1968.00	2007.00
Transport Equipment	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	50418	898.62	544.97	125.18	9766.81
Annual Earnings	50418	45995.25	28295.54	5579.40	507874.03
Total Weeks Worked Last Year	50418	51.03	2.29	40.00	52.00
Years of Schooling	50418	12.49	2.58	0.00	16.00
Age	50418	40.76	11.24	17.00	65.00
Experience	50418	21.28	11.75	0.00	58.00
Year	50418	1986.98	11.76	1968.00	2007.00
Miscellaneous Manufacturing	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	19531	644.68	574.68	125.02	14085.22
Annual Earnings	19531	33013.21	29519.51	5278.86	563408.75
Total Weeks Worked Last Year	19531	51.00	2.42	40.00	52.00
Years of Schooling	19531	11.75	2.93	0.00	16.00
Age	19531	38.74	11.81	17.00	65.00
Experience	19531	20.00	12.42	0.00	57.00
Year	19531	1987.95	11.09	1968.00	2007.00

Table 2.14: Descriptive Statistics by Industry from IPUMS CPS Data IV: 1968-2007

Utilities	Observations	Mean	Std. Dev.	Min	Max
Weekly Earnings	33200	873.64	549.16	125.89	10601.03
Annual Earnings	33200	45090.30	28396.30	5476.14	485500.91
Total Weeks Worked Last Year	33200	51.54	1.53	40.00	52.00
Years of Schooling	33200	12.66	2.47	0.00	16.00
Age	33200	41.12	11.01	17.00	65.00
Experience	33200	21.47	11.62	0.00	57.00
Year	33200	1988.17	11.52	1968.00	2007.00

Construction	Observations	Mean	Std. Dev.	Min	Max
Weekly Earnings	121917	769.67	585.54	125.00	14859.65
Annual Earnings	121917	38915.86	30059.26	5000.00	713263.00
Total Weeks Worked Last Year	121917	50.43	3.16	40.00	52.00
Years of Schooling	121916	11.81	2.77	0.00	16.00
Age	121917	38.09	11.48	17.00	65.00
Experience	121917	19.29	12.02	0.00	58.00
Year	121917	1990.29	11.99	1968.00	2007.00

Motor Vehicle Sales	Observations	Mean	Std. Dev.	Min	Max
Weekly Earnings	38169	736.13	601.47	125.02	9218.29
Annual Earnings	38169	37827.61	31165.21	5033.08	440255.41
Total Weeks Worked Last Year	38169	51.24	2.11	40.00	52.00
Years of Schooling	38169	12.42	2.21	0.00	16.00
Age	38169	38.04	11.78	17.00	65.00
Experience	38169	18.63	12.14	0.00	55.50
Year	38169	1989.02	11.68	1968.00	2007.00

Wholesale Trade	Observations	Mean	Std. Dev.	Min	Max
Weekly Earnings	76523	841.30	722.80	125.02	11439.42
Annual Earnings	76523	43303.31	37421.19	5033.08	594849.63
Total Weeks Worked Last Year	76523	51.33	1.99	40.00	52.00
Years of Schooling	76523	12.92	2.49	0.00	16.00
Age	76523	39.22	11.44	17.00	65.00
Experience	76523	19.30	11.84	0.00	58.00
Year	76523	1988.98	11.33	1968.00	2007.00

Retail Trade	Observations	Mean	Std. Dev.	Min	Max
Weekly Earnings	217491	550.29	511.39	125.00	12101.52
Annual Earnings	217491	28212.40	26487.53	5000.00	629279.13
Total Weeks Worked Last Year	217491	51.05	2.43	40.00	52.00
Years of Schooling	217491	12.40	2.47	0.00	16.00
Age	217491	36.68	12.38	17.00	65.00
Experience	217491	17.31	12.81	0.00	58.00
Year	217491	1989.87	11.76	1968.00	2007.00

Table 2.15: Descriptive Statistics by Industry from IPUMS CPS Data V: 1968-2007

Transport and Storage	Observations	Mean	Std. Dev.	Min	Max
Weekly Earnings	75241	805.70	551.49	125.02	12253.78
Annual Earnings	75241	41254.26	28426.48	5147.43	587609.81
Total Weeks Worked Last Year	75241	51.09	2.35	40.00	52.00
Years of Schooling	75241	12.31	2.46	0.00	16.00
Age	75241	40.39	11.27	17.00	65.00
Experience	75241	21.09	11.91	0.00	58.00
Year	75241	1988.62	11.73	1968.00	2007.00
Communications and Postal	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	45663	878.20	514.00	125.00	11300.19
Annual Earnings	45663	45301.29	26657.44	5083.50	587609.81
Total Weeks Worked Last Year	45663	51.50	1.57	40.00	52.00
Years of Schooling	45663	13.11	1.83	0.00	16.00
Age	45663	40.59	10.83	17.00	65.00
Experience	45663	20.49	11.15	0.00	53.50
Year	45663	1987.66	11.58	1968.00	2007.00
Finance	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	105130	895.22	950.76	125.02	12253.78
Annual Earnings	105130	46162.45	49222.99	5166.51	594849.63
Total Weeks Worked Last Year	105130	51.43	1.82	40.00	52.00
Years of Schooling	105130	13.83	1.87	0.00	16.00
Age	105130	37.94	11.39	17.00	65.00
Experience	105130	17.13	11.54	0.00	58.00
Year	105130	1990.12	11.38	1968.00	2007.00
Real Estate	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	26269	857.87	953.21	125.00	14859.65
Annual Earnings	26269	44096.40	49247.45	5001.26	713263.00
Total Weeks Worked Last Year	26269	51.26	2.14	40.00	52.00
Years of Schooling	26269	13.14	2.62	0.00	16.00
Age	26269	41.76	11.74	17.00	65.00
Experience	26269	21.62	12.25	0.00	58.00
Year	26269	1991.06	11.11	1968.00	2007.00
Business Services	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	103402	853.61	848.68	125.00	11653.44
Annual Earnings	103402	43861.52	43892.27	5001.26	587609.81
Total Weeks Worked Last Year	103402	51.18	2.37	40.00	52.00
Years of Schooling	103402	13.32	2.52	0.00	16.00
Age	103402	37.47	11.13	17.00	65.00
Experience	103402	17.16	11.44	0.00	58.00
Year	103402	1993.11	10.78	1968.00	2007.00

Table 2.16: Descriptive Statistics by Industry from IPUMS CPS Data VI: 1968-2007

Personal Services	Observations	Mean	Std. Dev.	Min	Max
Weekly Earnings	111208	785.74	874.78	125.00	14389.67
Annual Earnings	111208	40375.70	45213.03	5103.07	748263.00
Total Weeks Worked Last Year	111208	51.15	2.34	40.00	52.00
Years of Schooling	111207	13.13	2.81	0.00	16.00
Age	111208	38.74	11.69	17.00	65.00
Experience	111208	18.62	12.30	0.00	58.00
Year	111208	1991.60	11.40	1968.00	2007.00
Public Administration	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	117604	824.08	466.86	125.00	12253.78
Annual Earnings	117604	42562.81	24209.00	5388.54	594849.63
Total Weeks Worked Last Year	117604	51.57	1.52	40.00	52.00
Years of Schooling	117604	13.67	2.09	0.00	16.00
Age	117604	41.37	10.92	17.00	65.00
Experience	117604	20.70	11.29	0.00	58.00
Year	117604	1989.34	11.56	1968.00	2007.00
Education Services	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	168252	722.79	476.39	125.00	15505.72
Annual Earnings	168252	36661.67	24358.79	5000.00	713263.00
Total Weeks Worked Last Year	168252	50.72	3.05	40.00	52.00
Years of Schooling	168252	14.70	2.17	0.00	16.00
Age	168252	41.72	11.17	17.00	65.00
Experience	168252	20.02	11.60	0.00	58.00
Year	168252	1989.83	11.75	1968.00	2007.00
Health Services	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weekly Earnings	196859	741.86	825.41	125.00	13716.60
Annual Earnings	196859	38201.62	42621.95	5001.26	713263.00
Total Weeks Worked Last Year	196859	51.36	1.99	40.00	52.00
Years of Schooling	196859	13.59	2.34	0.00	16.00
Age	196859	40.25	11.49	17.00	65.00
Experience	196859	19.68	11.94	0.00	58.00
Year	196859	1991.12	11.34	1968.00	2007.00

1. Agriculture :: Agriculture, Hunting, Forestry, and Fishing; 2. Mining :: Mining and Quarrying; 3. Food :: Food, Beverages and Tobacco; 4. Textiles :: Textiles, Textile, Leather and Footwear; 5. Wood :: Wood and of Wood and Cork; 6. Paper & Pulp :: Pulp, Paper, Printing and Publishing; 7. Petroleum :: Coke, Refined Petroleum and Nuclear Fuel; 8. Chemicals :: Chemicals and Chemical Products; 9. Rubber :: Rubber and Plastics; 10. Glass :: Other Non-Metallic Mineral; 11. Metals :: Basic Metals and Fabricated Metal; 12. Machinery :: Machinery, Nec; 13. Electrical Machinery :: Electrical and Optical Equipment; 14. Transport Equipment :: Transport Equipment; 15. Misc. Manufacturing :: Manufacturing, Nec and Recycling; 16. Utilities :: Electricity, Gas and Water Supply; 17. Construction :: Construction; 18. Motor Vehicle Sales :: Sales and Maintenance of Motor Vehicles and Motorcycles; 19. Wholesale Trade :: Wholesale Trade and Commission Trade, except of Motor Vehicles and Motorcycles; 20. Retail Trade :: Retail Trade, except of Motor Vehicles and Motorcycles; 21. Transport & Storage :: Transport and Storage; 22. Communications & Postal :: Post and Communication; 23. Finance :: Financial Intermediation; 24. Real Estate :: Real Estate Activities; 25. Business Services :: Renting and Other Business Activities; 26. Personal Services :: Community Social and Personal Services; 27. Public Administration :: Public Administration, Defense, Compulsory Social Security; 28. Education Services :: Education; and 29. Health Services :: Health and Social Work.

Chapter 3

Computerization, Productivity and Polarization in Skill Demands: How does the smart machine change the U.S. labor market?

3.1 Introduction

What computers do to the workplace - how computers affect a worker's productivity or how computers change the required skills for the tasks and eventually how computerization causes wage differentials among different skill-types of workers - has been the focus of much research. The positive correlation between computer-related technological changes and widening overall wage differential, caused by relatively increasing demand for skilled workers, has been regarded in the literature as evidence of skill-biased technological change (Katz and Murphy, 1992; Autor, Katz and Krueger, 1998; Card and Lemieux, 2001; Acemoglu, 2002). In addition, the sharply increasing growth rate of labor productivity in the U.S. economy in the late 1990s, which was stimulated by increasing investments in computer-related capital and known as the U.S. productivity revival, supports the positive impact of computers on worker's productivity (Stiroh, 2002).

Since the 1990s, however, the U.S. wage structure has shown different wage inequality trends from the previous decade. The growth rate of overall wage differentials, measured by the wage gap between the 90th percentile and the 10th percentile, has decreased in the 1990s. With the decreasing growth rate of the overall wage differential, growth rates of wage gaps between different types of workers - based on their educational attainments or their occupations - have also decreased in the 1990s. Especially, the decreasing growth rate of overall wage inequality in the l990s has occurred through two disparate trends. The wage differential in the upper half of the wage distribution, measured by the wage gap between the 90th percentile and the 50th percentile, has increased continuously. In contrast, the wage differential in the lower half of the wage distribution, measured by the wage gap between the 50th percentile and the 10th percentile, has shown a decreasing pattern (Autor, Levy and Murnane, 2003; Autor, Katz and Kearney, 2006).

The U.S. productivity revival and the divergent wage inequality trends of upper-tail and lower-tail wage distributions with increasing investments in computerization lead us to think about the impact of computer-related technology on labor productivity and on the demands for different types of skilled workers. That is, if computerization requires one specific type of skilled worker more and other types of skilled workers less, then which types of workers will be benefited and which types of workers will be disadvantaged by computer-related investments. Associated with these questions, this paper examines (i) whether computerization adopted by industry contributes to the U.S. productivity revival and heterogeneous demand shifts for different types of skilled workers and (ii) how strong investments in computer-based technology affect the U.S. labor market phenomena in the late 1990s. For the labor market phenomena, I will focus on (1) the polarization pattern in employment, as coined by Goos and Manning (2003), to illustrate the much faster growth rates of employment in tasks for high-skilled workers and for low-skilled workers relative to middle-skilled workers, and (2) the polarization trend in wage structure, implying the divergent trends of upper-half wage inequality and lower-half wage inequality.

Table 3.15 in the Appendix shows different types of descriptive statistics concerning the labor productivity growth from 1970 to 2005. The period 1995-2000 records the highest annual growth rate of any other sub-periods, 2.72 percent, over a total of 29 industries.

Although labor productivity growth rates vary across industries, ranging from -0.86 percent in wood to 15.93 percent in electrical and optical equipment, 26 industries show positive growth rates in labor productivity in this period. Similarly, Table 3.16, which can be found in the Appendix, presents summary statistics concerning computerization from 1970 to 2005, where the largest investments in computerization assets occurred in the period from 1995 to 2000 with highest annual growth rate, 19.85 percent, and a range from 9.87 percent (petroleum and nuclear fuel) to 35.17 percent (renting and other business activities).

For both increases in growth rates of labor productivity and computerization investments in the late 1990s, much research documents the possible link between two defining characteristics in the U.S. economy (Jorgenson and Stiroh, 2000; Oliner and Sichel, 2000; Jorgenson, 2001). These papers show that, based on aggregate growth accounting, strong investments in computer-related assets were a driving force behind U.S. productivity growth in this period. Instead of aggregate growth accounting technique, which would miss the variation in productivity gains across industries, Stiroh (2002) investigates the resurgence of the U.S. productivity growth in the late 1990s by industry level, focusing on the link between computerizations and labor productivity gains. Based on Stiroh's disaggregated analysis, this paper, first, focuses on productivity gains by industry level to find relationships between strong investments in computerization and the rapid growth rate of labor productivity.

Second, associated with trends in the U.S. labor market, Autor, Katz and Kearney (2006) claim that overall wage inequality in the top half of wage distribution has recorded a secular rise, while overall wage inequality in the bottom half of wage distribution has ceased since the late 1980s. Although Autor, Levy, and Murnane (2003) focus on employment shifts and wage changes only between high-skilled workers and middle-skilled workers and Autor, Katz, and Kearney (2006) investigate those relationships only between middle-skilled workers and low-skilled workers, two papers provide similar implications for understanding U.S. labor market patterns. They argue that, due to decreasing computerization costs, wages of high-skilled workers and low-skilled workers increased relative to middle-skilled workers. Thus, middle-skilled workers move from routine tasks toward nonroutine cognitive tasks, usually performed by high-skilled workers, or nonroutine manual tasks, usually carried out by low-skilled workers. In addition, since decreasing computer prices raise demand for routine tasks, computerization assets, which are close substitutes for middle-skilled workers in the routine tasks, will displace the middle-skilled workers in the routine cognitive and routine manual tasks.

Furthermore, due to the complementary relationship between nonroutine cognitive tasks and routine tasks (routine cognitive and routine manual tasks), increasing investments for computerization capital raise wage of high-skilled workers in nonroutine cognitive tasks, so that the wage differential between high-skilled and middle-skilled workers increases. Based on these frameworks, they claim that the divergent trends of wage inequality in the U.S. labor market should be accompanied by employment polarization, which is caused by movements of middle-skilled workers with decreasing the price of computer-related technology. Therefore, based on these implications for the U.S. labor market, this paper also investigates employment polarization trends and divergent wage evolution of the U.S. wage structure between upper-tail wage distribution and lower-tail wage distribution with increasing investments in computerization assets.

For the polarization trends in employment as the first characteristic in the U.S. labor market, Figures 3.1 to 3.5 plot growth rates of employment shares for four periods, 1980-1990, 1990-1995, 1995-2000 and 2000-2005, based on three types of skilled workers' employment shares during the period from 1970 to 2005. In the period from 1980 to 1990, growth rates of the employment share for high-skilled workers are the highest among these three types of workers for 27 industries.[1] Also, growth rates of employment share for low-skilled workers are the lowest among these three skill-types of workers and below zero for all industries in the 1980s.

In the period from 1990 to 1995, the growth rates of the employment share for high-skilled workers show a generally decreasing trend in more than 20 industries. The growth rate of high-skilled worker's share in total employment increased only in the industries of

[1]The wood and glass industries do not follow this trend.

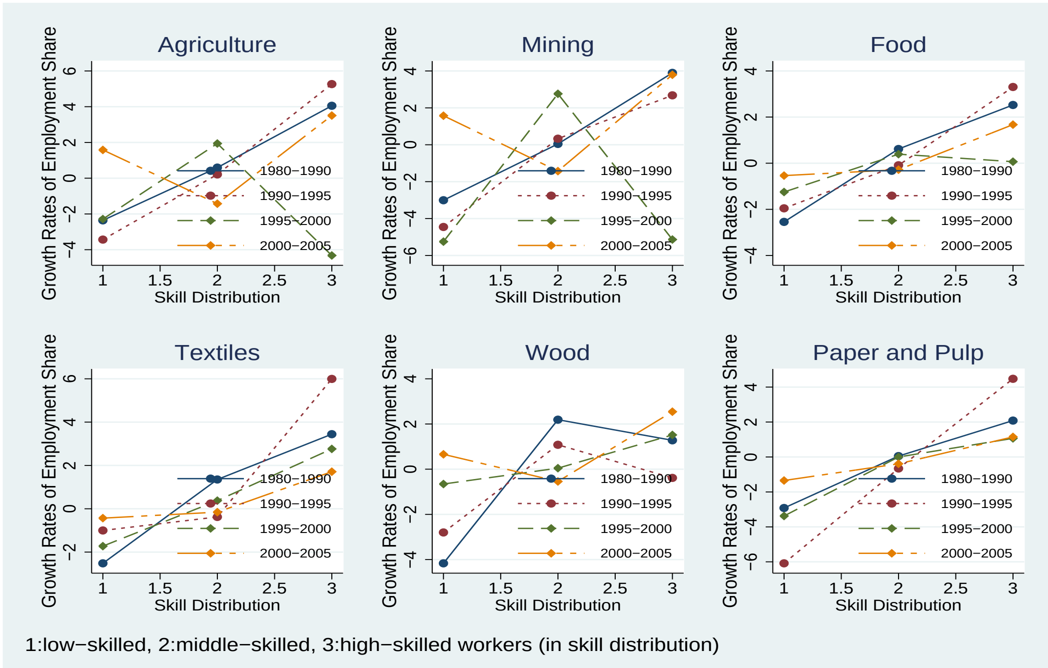

Figure 3.1: Annual Growth Rates of Employment Share among Three Types of Workers I

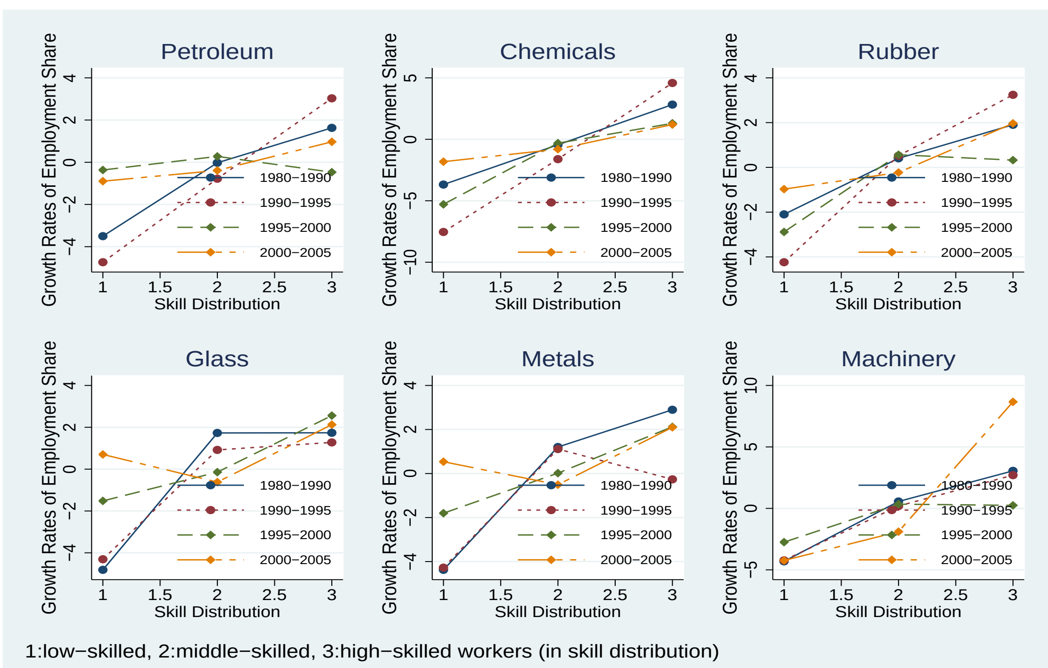

Figure 3.2: Annual Growth Rates of Employment Share among Three Types of Workers II

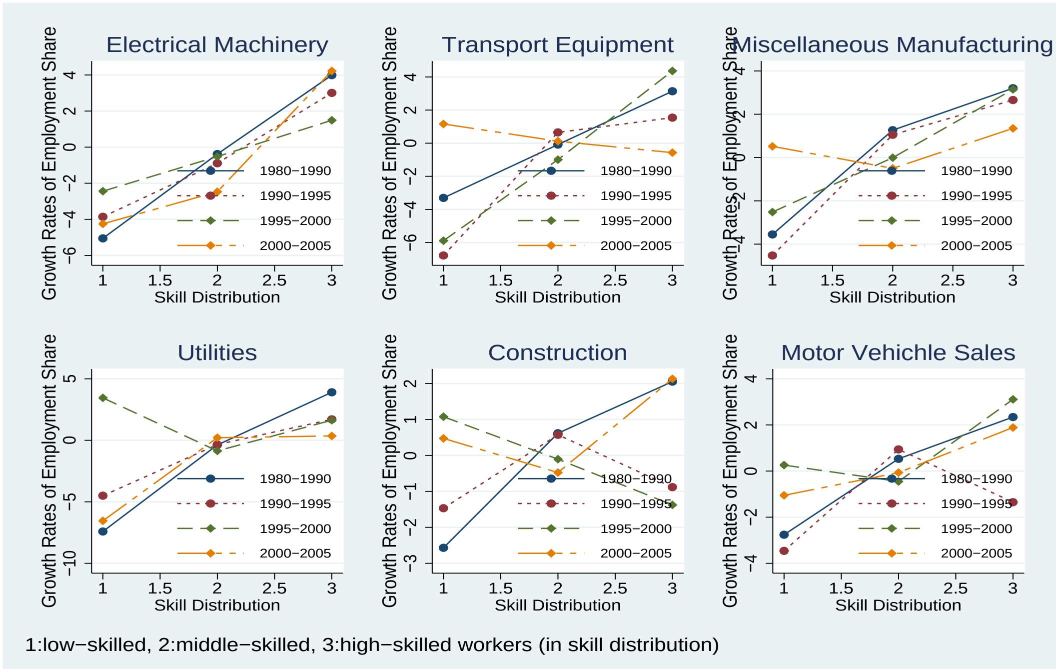

Figure 3.3: Annual Growth Rates of Employment Share among Three Types of Workers III

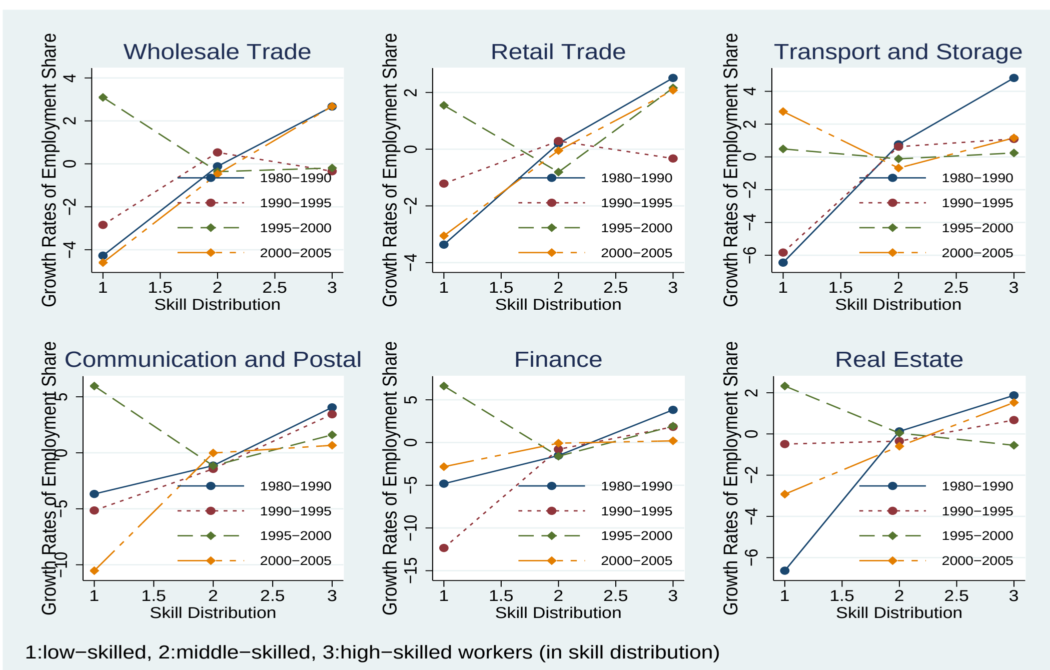

Figure 3.4: Annual Growth Rates of Employment Share among Three Types of Workers IV

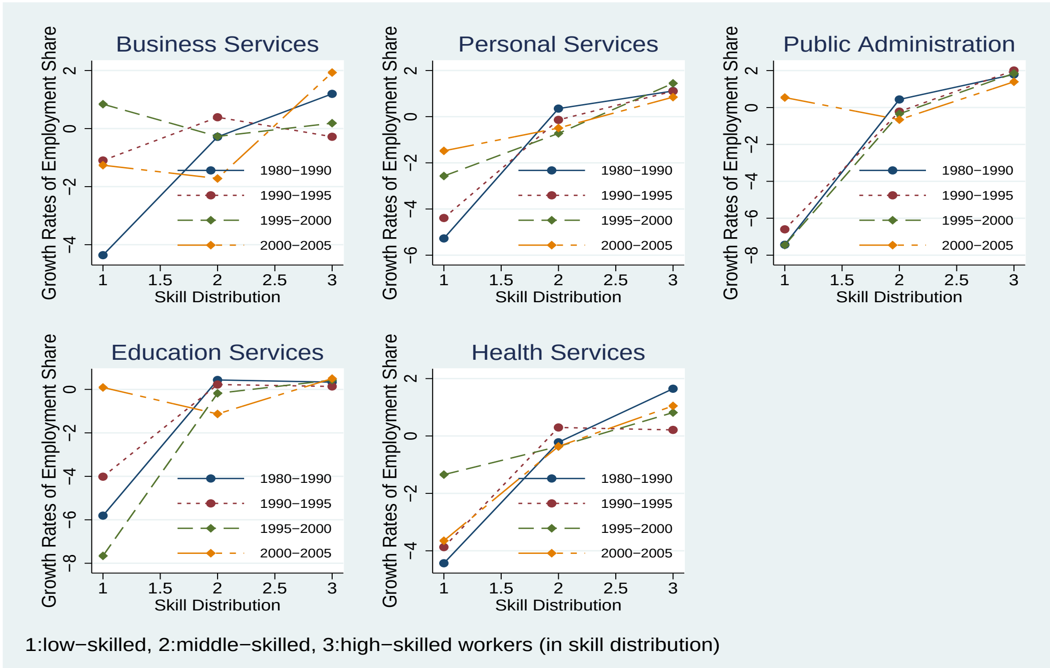

Figure 3.5: Annual Growth Rates of Employment Share among Three Types of Workers V

agriculture, food, textile, paper and pulp, petroleum, chemicals and rubbers. However, except wood, metal, construction, motor vehicle sales, wholesale trade, retail trade, and business services, the growth rates of employment share for high-skilled workers of the other industries were highest among the three skill-types of workers. The trends from these seven industries, which show a reverse v-shape, are mainly caused by decreasing growth rates of employment share of the high-skilled workers, not by increasing demands for middle-skilled workers. In this period, the growth rates of employment share for low-skilled workers are still lower than the previous period, excepting for food, textile, wood, electrical machinery, utilities, wholesale trade, business, and education.

The third period (1995 to 2000) is a transition one. Some industries, such as wood, glass, motor vehicle sales, utilities, wholesale trade, retail trade, communication and post, finance, and business services, show the earlier polarization trends in employment during this period. However, for most industries, the growth rates of the employment share for high-skilled workers did not increase, while growth rates for low-skilled worker employment shares increased significantly relative to the period from 1980 to 1990. Thus, the earlier polarization in employment was caused primarily by sharp increases in the growth rate of employment share for low-skilled workers. Except for the mining industry, the growth rates of employment share for middle-skilled workers either decreased relative to the 1980s or remained similar to the growth rates for the first period.

In the period from 2000 to 2005, the employment polarization trends by industry level are consistent with the polarization trend in the U.S. economy from Autor et al. (2006). It seems that three factors caused polarization patterns in employment across industries: recovered growth rates of the employment share for high-skilled workers, increased growth rates of the employment share for low-skilled workers, and decreased growth rates for middle-skilled workers in employment share. However, some industries showing polarization trends in the late 1990s, such as utilities, wholesale trade, retail trade, communication and post and finance, do not exhibit polarizations in employment continuously in this period, with sharply decreasing growth rates in low skilled workers' employment share. Similarly, Figures 3.17 to 3.21 in the Appendix, all of which are based on the 3 sub-periods 1980-1988, 1988-1996, and 1996-2005, indicate polarization trends in employment share during the period from 1996 to 2005 except for the food, petroleum, rubber, and health services industries. In these industries, rapid growth rates in the employment share of low-skilled workers occurred, but as shown in the earlier polarization trends in Figures 3.1 to 3.5, the growth rates for high-skilled workers' employment share do not exhibit increasing trends.

For diverging wage differential trends as the second labor market phenomenon, an increasing pattern of upper-tail wage distribution and a decreasing pattern of lower-tail wage distribution in the U.S. labor market can be found in the industry analysis. Figures 3.6 to 3.10 present wage inequality between the 90th and the 50th percentiles and wage inequality between the 50th and the 10th percentiles for each industry[2]. Among the 29 industries,

[2]For these figures, log weekly earnings from the 90th, 50th and 10th percentiles were calculated for each industry and for each year using data for full-time, full-year wage/salary workers age 25-55 with 2 to 48 years of potential labor market experiences during the period from 1968 to 2007 (covering earnings year 1967 to 2006 for workers age 24-54 in earnings years) from the IPUMS Current Population Survey data. Here full-time and full-year workers are considered as those who worked more than 35 hours per week and forty-plus weeks in the prior year.

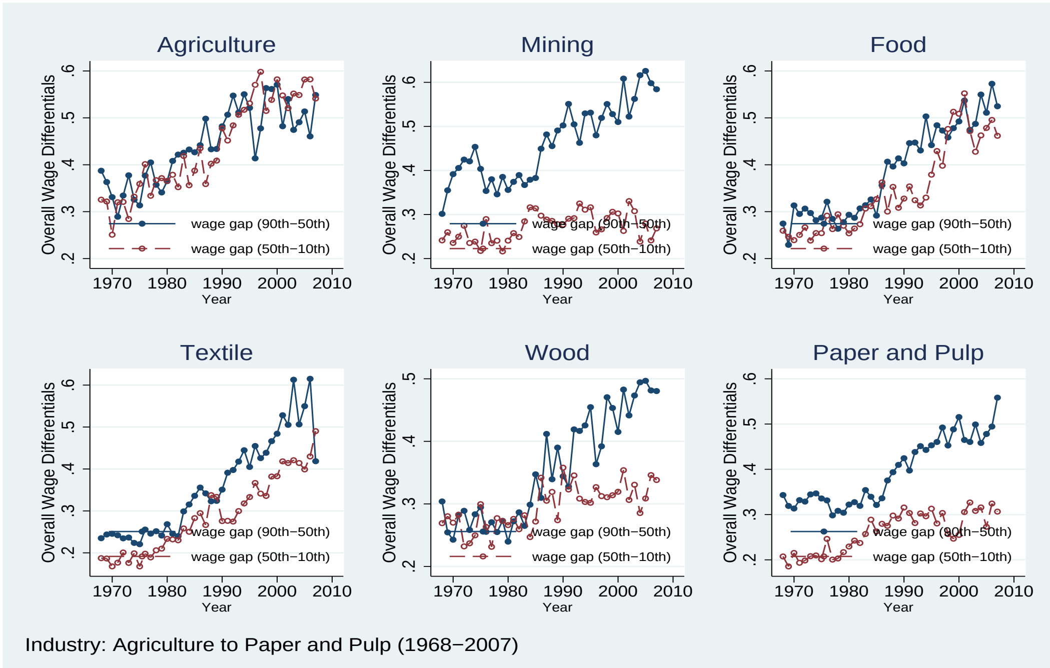

Figure 3.6: Wage Differentials between 90th and 50th and between 50th and 10th percentiles I

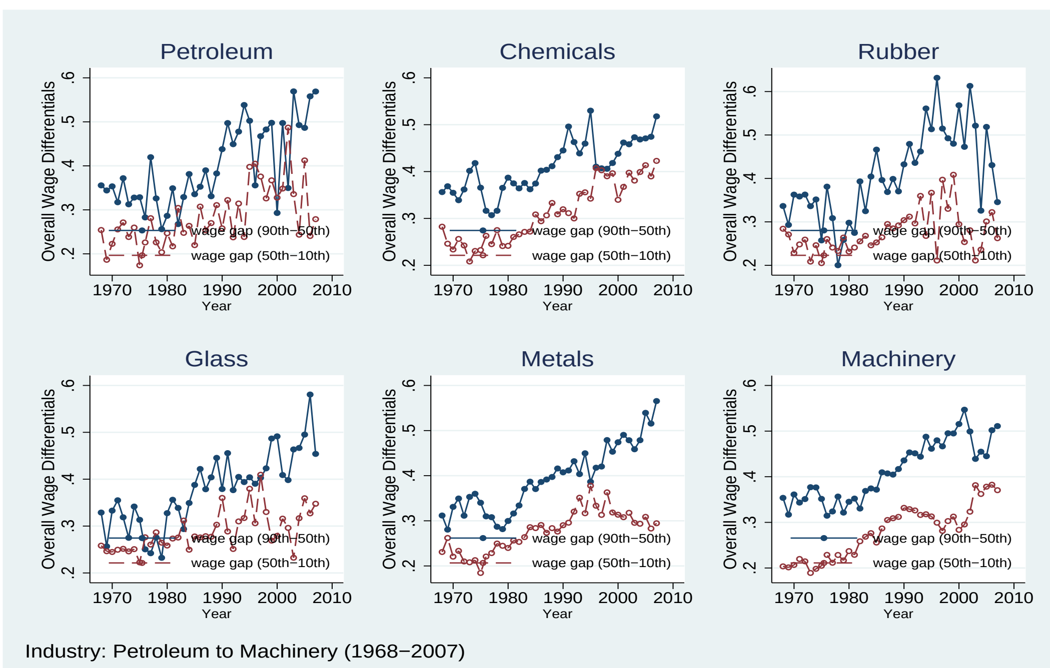

Figure 3.7: Wage Differentials between 90th and 50th and between 50th and 10th percentiles II

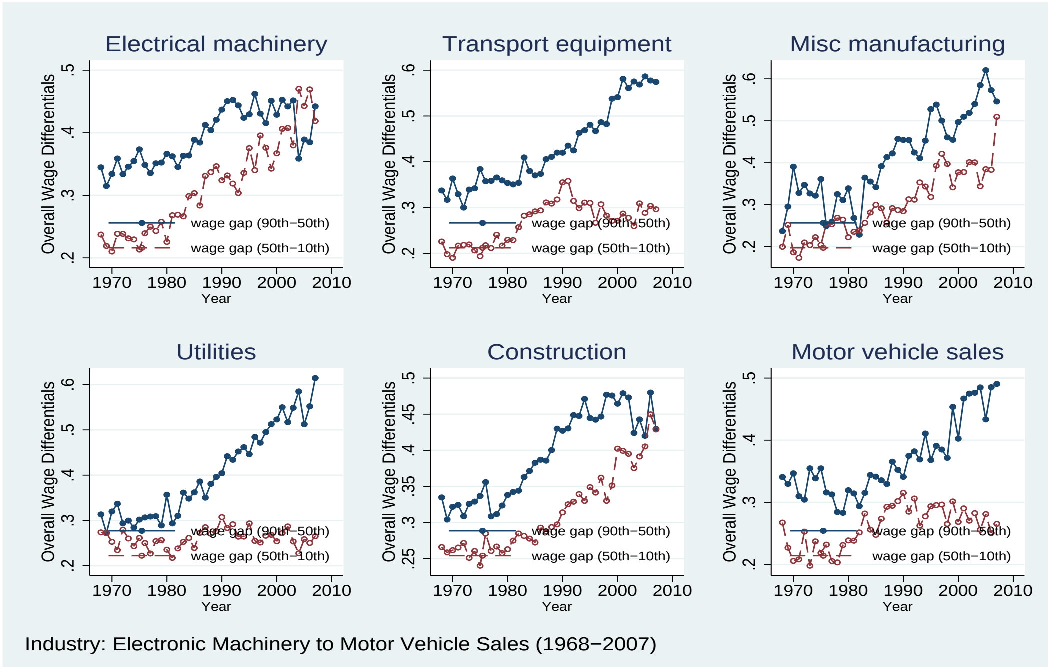

Figure 3.8: Wage Differentials between 90th and 50th and between 50th and 10th percentiles III

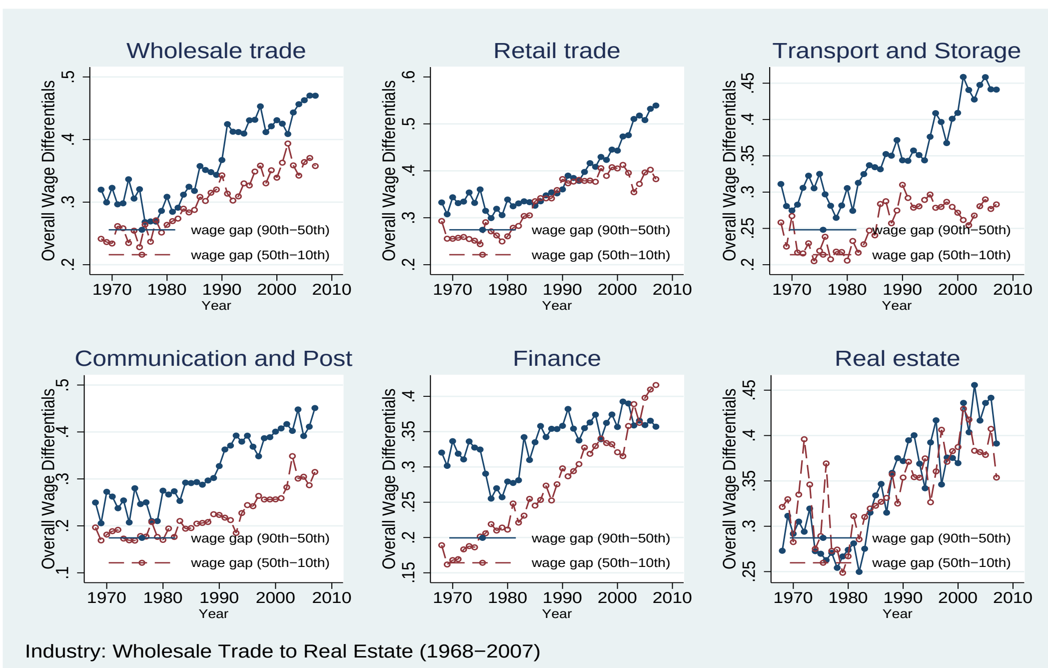

Figure 3.9: Wage Differentials between 90th and 50th and between 50th and 10th percentiles IV

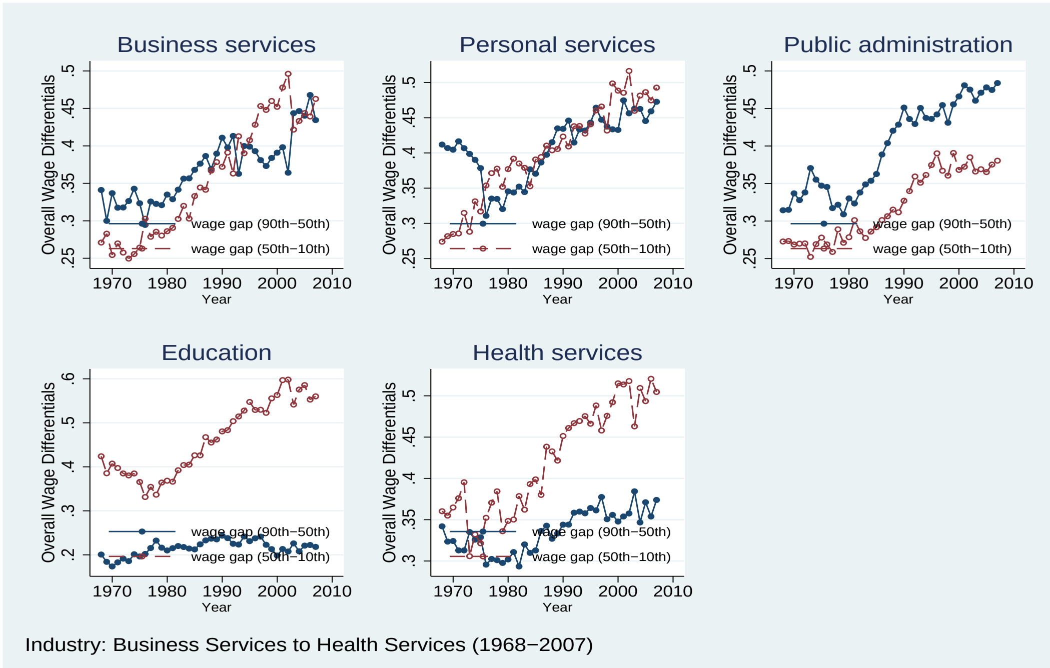

Figure 3.10: Wage Differentials between 90th and 50th and between 50th and 10th percentiles V

17 industries, including mining, paper and pulp, metals, transport equipment, utilities, and transport & storage, exhibit divergent patterns in wage equality between upper-tail and lower-tail wage distribution as shown in Autor, Katz and Kearney (2006), whose work is based on the total economy[3]

This paper is organized as follows. Section 3.2 explains the theoretical framework applied in this chapter. Section 3.3 introduces data sources and presents empirical applications - difference-in-difference approach and share equation estimation methods for the growth rate of labor productivity and demand shifts for three types of skilled workers based on the employment shares and wage bill shares. Section 3.4 concludes with the implications and findings from this paper.

[3]Industries such as food, textile, miscellaneous manufacturing and communication & post show parallel increases in wage inequality between the top half and the bottom half wage distribution, and in industries such as education and health service, increasing trends of wage inequality below the 50th percentile are more sharply defined than the increasing trends above the 50th percentile.

3.2 Theoretical Framework

3.2.1 Skill Demands for Four Tasks

Autor, Levy, and Murnane (2003) and Autor, Katz, and Kearney (2006) assume that there are four categories of workplace tasks: nonroutine cognitive tasks, routine cognitive tasks, routine manual tasks, and nonroutine manual tasks. The routine tasks are those accomplished through explicit programmed rules and as such could be done by machines following these programmed instructions exactly. By contrast, nonroutine tasks can not be sufficiently understood or handled by completely coded instructions or exact formulas for accomplishing the tasks. For example, nonroutine cognitive tasks include problem solving, forming and testing hypotheses, medical diagnosis, or managing multiple analytic tasks. As Polanyi (1966) posited, these types of tasks require tacit knowledge, obtained only by the perceptions or practical skills of individuals, so that workers can accomplish such tasks only when the required knowledge is embedded in the workers.

A worker's occupational choice will be determined by his self-selection process based on comparative advantage as in the Roy model (1951). There are three different types of workers based on education levels: high-skilled workers, middle-skilled workers, and low-skilled workers[4]. Autor, Levy, Murnane (2003) and Autor, Katz, and Kearney (2006) document polarization in skill demands for three types of skilled workers based on four observations: (1) computer capital substitutes for workers in tasks having explicit programmed instructions such as routine cognitive and routine manual tasks; (2) production inputs for routine tasks, which are computerization assets or human labor in efficiency units, complement workers for abstract tasks such as nonroutine cognitive tasks; (3) workers involved in nonroutine manual tasks such as janitors or waiters are isolated from advances in computer-related technology; (4) the occupational choices of workers are partially dependent on their

[4] High-skilled workers, who have 16 years of schooling and more, can choose nonroutine cognitive tasks or routine tasks such as routine cognitive tasks and routine manual tasks through self-selection. Similarly, middle-skilled workers, who have from 12 to 15 years of schooling, can choose all four categories: nonroutine cognitive tasks; routine cognitive tasks; routine manual tasks; and nonroutine manual tasks. Low-skilled workers, who have less than 12 years of education, can choose routine tasks and nonroutine manual tasks based on their comparative advantages.

educational attainments.

However, Autor, Levy, Murnane (2003) focus only on skills demand changes between nonroutine cognitive tasks and routine tasks such as routine cognitive and routine manual tasks without considering the isolated nonroutine manual tasks from computerization. And Autor, Katz, and Kearney (2006) investigate the heterogeneous shifts of skill demands only between routine tasks and nonroutine manual tasks with the limitation that among the three types of skilled workers only high-skilled workers could choose nonroutine cognitive tasks. Thus, this paper removes the limitation of occupational choice for middle-skilled workers from routine tasks to nonroutine cognitive tasks and integrates these theoretical frameworks to present the real patterns of the U.S. labor market based on three types of skilled workers.

Before the empirical analysis of how computerization affects the U.S. labor market, polarization trends in employment and wages, this section illustrates the integrated theoretical model. Four tasks – nonroutine cognitive tasks, N; routine tasks, R, which include routine cognitive and routine manual tasks; and nonroutine manual tasks, M – are used to produce output, Q, which sells at unity, in the form of the Cobb-Douglas function:

$$Q = N^{\alpha} R^{\phi} M^{\sigma} \tag{3.1}$$

where $0 < \alpha, \phi, \sigma < 1$ and $\alpha + \phi + \sigma = 1$; $N, R,$ and M represent nonroutine cognitive tasks, routine tasks for both routine cognitive tasks and routine manual tasks, and nonroutine manual tasks, respectively. Nonroutine cognitive tasks will be performed by high-skilled workers and middle-skilled workers; routine tasks by middle-skilled workers in the efficient units or computer-related assets; and nonroutine manual tasks by middle-skilled workers and low-skilled workers. The production function in Equation 3.1 can also be written, based on production inputs, as

$$Q = L_N^{\alpha} (L_R + K)^{\phi} L_M^{\sigma} \tag{3.2}$$

where $L_N, L_R,$ and L_M are production labor inputs for nonroutine cognitive tasks N, both routine cognitive and routine manual tasks R, and nonroutine manual tasks M, respectively; K represents computer-based assets as a production capital input for routine task R; and the computerization assets will be supplied elastically in the market at price μ.

This model assumes that all skilled workers have different productivity endowments in that a high-skilled worker has n_j efficiency units for nonroutine cognitive tasks and r_j efficiency units for routine tasks; a middle-skilled worker has n_j, r_j, and m_j efficiency units for nonroutine cognitive tasks, routine tasks, and nonroutine manual tasks, respectively; and a low-skilled worker has r_j efficiency units for routine tasks and m_j efficiency units for nonroutine manual tasks, with $0 < n_j, r_j, m_j \leq 1, \forall j$. Thus, a high-skilled worker can choose to supply n_j efficiency units for nonroutine cognitive tasks, r_j efficiency units for routine tasks, or a convex combination $L_j^h = [\lambda_j n_j, (1-\lambda_j) r_j]$, where $0 \leq \lambda_j \leq 1$ for both nonroutine cognitive tasks and routine tasks. A middle-skilled worker can supply either n_j, r_j, or m_j efficiency units for nonroutine cognitive tasks, routine tasks, and nonroutine manual tasks or a convex combination $L_j^m = [\kappa_j n_j,\ \chi_j r_j, (1-\kappa_j-\chi_j) m_j]$, where $0 \leq \kappa_j, \chi_j \leq 1$. And a low-skilled worker also can choose to supply r_j efficiency units for routine cognitive and rountine manual tasks or m_j efficiency units for nonroutine manual tasks with combined labor supply $L_j^l = [\delta_j r_j, (1-\delta_j) m_j]$, where $0 \leq \delta_j \leq 1$ for routine tasks and nonroutine manual tasks.

From Autor, Levy, Murnane (2003), three primary conditions for market equilibrium are that (i) due to perfect substitutability between human labor for routine tasks and computer-related capital, the wage per efficiency unit for routine tasks, which is equal to marginal productivity, should be the same as the price of computer-related capital, μ; (ii) workers' occupational choice through self-selection clears the labor market; and (iii) the economy operates on the demand curve of the aggregate production function. Associated with the labor supply, the relative efficiency unit of individual j for routine tasks to nonroutine manual tasks and the relative efficiency unit of individual j for nonroutine cognitive tasks to routine tasks are defined as $E_j = \frac{r_j}{m_j}$ and $S_j = \frac{n_j}{r_j}$, respectively. Between routine tasks and nonroutine manual tasks, individual j chooses nonroutine manual tasks if $E_j < E^*$ and chooses routine tasks, otherwise. In addition, individual j chooses routine tasks if $S_j < S^*$ and nonroutine cognitive tasks if $S_j > S^*$ for her occupational choice between nonroutine cognitive tasks and routine tasks. Here E^* and S^* are relative efficiency units between routine tasks and nonroutine manual tasks and between nonroutine cognitive tasks and routine tasks at labor market equilibrium, respectively.

Thus, when E^* is equal to $\frac{\omega_M}{\omega_R}$ and S^* to $\frac{\omega_R}{\omega_N}$, marginal workers from each side with relative efficiency units of E^* and S^* will choose their potential tasks indifferently. That is, marginal workers will choose routine tasks and nonroutine manual tasks indifferently if E^* is equal to $\frac{\omega_M}{\omega_R}$. And marginal workers will choose nonroutine cognitive tasks and routine tasks indifferently when S^* is equal to $\frac{\omega_R}{\omega_N}$. Thus, all labor supplied in efficiency units for nonroutine cognitive tasks, routine tasks and nonroutine manual tasks are calculated by $L_N(S^*) = \sum_j n_j \cdot I[S_j > S^*]$, $L_R(S^*, E^*) = \sum_j r_j \cdot I[S_j < S^*] + \sum_j r_j \cdot I[E_j > E^*]$ and $L_M(E^*) = \sum_j m_j \cdot I[E_j < E^*]$ with an indicator function $I[\cdot]$.

Based on the third condition that for market equilibrium the economy operates on the demand curve of the aggregate production function, production efficiency requires for nonroutine cognitive tasks, routine tasks and nonroutine manual tasks

$$\omega_N = \frac{\partial Q}{\partial L_N} = \alpha L_N^{\alpha-1}(L_R + K)^{\phi} L_M^{\sigma} \tag{3.3}$$
$$\omega_R = \frac{\partial Q}{\partial L_R} = \phi L_N^{\alpha}(L_R + K)^{\phi-1} L_M^{\sigma} \tag{3.4}$$
$$\omega_M = \frac{\partial Q}{\partial L_M} = \sigma L_N^{\alpha}(L_R + K)^{\phi} L_M^{\sigma-1} \tag{3.5}$$

and the relative efficiency unit between routine tasks and nonroutine manual tasks, E^*, and the relative efficiency unit for nonroutine cognitive tasks and routine tasks such as routine cognitive and routine manual tasks, S^*, can be written as

$$E^* = \frac{\omega_M}{\omega_R} \quad = \quad \frac{\sigma}{\phi} \frac{L_R(E^*, S^*) + K}{L_M(E^*)} \tag{3.6}$$

$$S^* = \frac{\omega_R}{\omega_N} \quad = \quad \frac{\phi}{\alpha} \frac{L_N(S^*)}{L_R(E^*, S^*) + K} \tag{3.7}$$

The following comparative statics of relative efficiency units for routine tasks, E^*, and for nonroutine cognitive tasks, S^*, with a decreasing price of computer-based capital, μ, show that, first, increasing adoption of computer-related technology raises the relative demand for routine tasks to nonroutine manuals tasks, $\frac{L_R(E^*, S^*)+K}{L_M(E^*)}$. It leads to an increase in the relative wage for nonroutine manual tasks to routine tasks and simultaneously raises the relative efficiency unit between routine tasks and nonroutine manual tasks, represented as $E^* = \frac{\omega_M}{\omega_R}$. Subsequently, the decreasing price of computer-related assets leads to an increase in the relative demand for routine tasks to nonroutine cognitive tasks, $\frac{L_R(E^*,S^*)+K}{L_N(E^*)}$. Thus, it increases in the relative wage of nonroutine cognitive tasks to routine tasks, while it decreases the relative efficiency unit between nonroutine cognitive tasks and routine tasks, $S^* = \frac{\omega_R}{\omega_N}$.

Due to perfect substitutability between computerization assets and middle-skilled workers for routine tasks, the decline in price of computer-related capital leads to a decrease in wage for middle-skilled workers by a one-for-one ratio, $\frac{\partial \ln \omega_R}{\partial \ln \mu} = 1$. Using this one-for-one response, comparative statics results can be written as[5]

$$\frac{\partial \ln(\frac{L_R(E^*, S^*)+K}{L_M(E^*)})}{\partial \ln \mu} = \frac{1}{\phi - 1} < 0 \quad \text{and} \quad \frac{\partial \ln(\frac{\omega_M}{\omega_R})}{\partial \ln \mu} = \frac{1}{\phi - 1} < 0 \tag{3.8}$$

$$\frac{\partial \ln(\frac{L_N(S^*)}{L_R(E^*, S^*)+K})}{\partial \ln \mu} = \frac{1}{1 - \phi} > 0 \quad \text{and} \quad \frac{\partial \ln(\frac{\omega_R}{\omega_N})}{\partial \ln \mu} = \frac{1}{1 - \phi} > 0 \tag{3.9}$$

It implies that, since workers for routine tasks and nonroutine manual tasks make their occupational choices based on the self-selection process, from increasing adoption of computer-

[5]For relative demand and relative efficiency unit between routine tasks and nonroutine manual tasks and, use $\omega_R = \phi\left(\frac{L_N}{L_M}\right)^{\alpha}\left(\frac{L_R(E^*, S^*)+K}{L_M}\right)^{\phi-1}$, and $\omega_R = \phi\left(\frac{L_M}{L_N}\right)^{\sigma}\left(\frac{L_N}{L_R(E^*, S^*)+K}\right)^{1-\phi}$ for relative demand and relative efficiency unit between nonroutine cognitive tasks to routine tasks.

based capital, an increased relative efficiency unit between routine tasks and nonroutine manual tasks, E^*, leads the middle-skilled workers, especially marginal workers below-average for routine tasks, to allocate their labor supply from routine tasks to nonroutine manual tasks. Similarly, a decreased relative efficiency unit between nonroutine cognitive tasks and routine tasks, S^*, moves marginal workers above-average from routine tasks toward nonroutine cognitive tasks.

The increasing demands for the production input of routine tasks and displacement of middle-skilled workers from routine tasks toward nonroutine tasks support increasing use of computer-related capital for routine tasks. Consistent with Autor, Levy and Murnane (2003) and Autor, Katz, and Kearney (2006), (i) the decline in price of computer-related capital raises the wages for nonroutine manual tasks and nonroutine cognitive tasks relative to routine tasks, (ii) marginal workers among middle-skilled workers, those below-average and above-average for routine tasks, increase their labor supply toward nonroutine manual workers and nonroutine cognitive tasks, respectively, (iii) computer-related assets will carry out routine tasks which were previously performed by middle-skilled workers, and it raises the wages for high-skilled workers for nonroutine cognitive tasks due to complementarity. These conclusions could be a rationalization for the empirical analysis explaining the characteristics of the U.S. labor market, i.e., polarization patterns in employment share changes and wage differentials.

3.2.2 Skill Demands at Industry Level

The framework of skill demands for three types of workers with four tasks can be applied to production functions of industry i. From Equation 3.2, the production function for industry i with three production inputs can be written as

$$q_i = n_i^{\alpha_i} r_i^{\phi_i} m_i^{\sigma_i} \tag{3.10}$$

where $0 < \alpha_i, \phi_i, \sigma_i < 1$ and $\alpha_i + \phi_i + \sigma_i = 1$; $\alpha_i, \phi_i,$ and σ_i denote industry-specific factors for each production input; $n_i, r_i,$ and m_i represent production inputs, respectively, for nonroutine cognitive tasks, routine tasks (routine cognitive tasks and routine manual tasks), and nonroutine manual tasks with high-skilled workers for nonroutine cognitive and routine tasks, middle-skilled workers for all four tasks, low-skilled workers for middle-skilled workers and low-skilled workers, and computer-related capital assets, which are perfectly substitutable for labor production inputs for the routine tasks.

Following Autor, Levy and Murnane (2003), consumer preferences, which are presented with a Dixit-Stiglitz utility function, can be defined as

$$U(q_1, q_2, \ldots, q_i, \ldots, q_z) = \Big(\sum_i^z q_i^{1-v} \Big)^{\frac{1}{1-v}} \tag{3.11}$$

where $0 < v < 1$. When the product price for each industry is inversely related to the quantity produced from industry i, represented as $p_i(q_i) = q_i^{-v}$, the profit maximization for industry i can be written as

$$\max_{n_i, r_i, m_i} \Pi = q_i^{1-v} - \omega_N n_i - \omega_R r_i - \omega_M m_i \tag{3.12}$$

and the first-order conditions for production inputs, $n_i, r_i,$ and m_i, for nonroutine cognitive tasks, routine tasks (routine cognitive and routine manual tasks), and nonroutine manual tasks, respectively, can be derived as

$$\omega_N = \alpha_i(1-v)\, n_i^{-\alpha_i v + \alpha_i - 1}\, r_i^{-\phi_i v + \phi_i}\, m_i^{-\sigma_i v + \sigma_i} \tag{3.13}$$

$$\omega_R = \phi_i(1-v)\, n_i^{-\alpha_i v + \alpha_i}\, r_i^{-\phi_i v + \phi_i - 1}\, m_i^{-\sigma_i v + \sigma_i} \tag{3.14}$$

$$\omega_M = \sigma_i(1-v)\, n_i^{-\alpha_i v + \alpha_i}\, r_i^{-\phi_i v + \phi_i}\, m_i^{-\sigma_i v + \sigma_i - 1} \tag{3.15}$$

Thus, based on the first-order conditions, the derived production input demands for nonroutine cognitive tasks, routine tasks, and nonroutine manual tasks in industry i can be written as

$$
\begin{aligned}
n_i^* &= \left(\frac{\omega_R}{\phi_i(1-v)}\right)^{\frac{-1}{v}} \left(\frac{\omega_N}{\omega_R}\frac{\phi_i}{\alpha_i}\right)^{\frac{-\phi_i v+\phi_i-1}{v}} \left(\frac{\omega_N}{\omega_M}\frac{\sigma_i}{\alpha_i}\right)^{\frac{-\sigma_i v+\sigma_i}{v}} && (3.16)\\
m_i^* &= \left(\frac{\omega_N}{\alpha_i(1-v)}\right)^{\frac{-1}{v}} \left(\frac{\omega_M}{\omega_N}\frac{\alpha_i}{\sigma_i}\right)^{\frac{-\alpha_i v+\alpha_i-1}{v}} \left(\frac{\omega_M}{\omega_R}\frac{\phi_i}{\sigma_i}\right)^{\frac{-\phi_i v+\phi_i}{v}} && (3.17)\\
r_i^* &= \left(\frac{\omega_M}{\sigma_i(1-v)}\right)^{\frac{-1}{v}} \left(\frac{\omega_R}{\omega_M}\frac{\sigma_i}{\phi_i}\right)^{\frac{-\sigma_i v+\sigma_i-1}{v}} \left(\frac{\omega_R}{\omega_N}\frac{\alpha_i}{\phi_i}\right)^{\frac{-\alpha_i v+\alpha_i}{v}} && (3.18)
\end{aligned}
$$

The comparative statics from the derived demands for production inputs of nonroutine cognitive tasks, routine tasks (routine cognitive and routine manual tasks), and nonroutine manual tasks consistently presents that decreasing prices in computer-related capital increase the demand for all four types of tasks - nonroutine cognitive tasks, routine cognitive tasks, routine manual tasks, and nonroutine manual tasks - for each industry i. Thus, at the industry level increasing demands for production inputs in routine tasks will be replaced by cheaper computer-related capital in response to middle-skilled workers' movement from routine tasks toward nonroutine cognitive and nonroutine manual tasks.

$$
\begin{aligned}
\frac{\partial \ln n_i}{\partial \ln \omega_R} &= \frac{-\phi_i(1-v)}{v} < 0 && (3.19)\\
\frac{\partial \ln m_i}{\partial \ln \omega_R} &= \frac{-\phi_i(1-v)}{v} < 0 && (3.20)\\
\frac{\partial \ln r_i}{\partial \ln \omega_R} &= \frac{(1-v)(1-\phi_i)-1}{v} < 0 && (3.21)
\end{aligned}
$$

3.3 Empirical Implementation

3.3.1 Data

The primary data source used is EU KLEMS Growth and Productivity Accounts, measuring labor productivity, computerization intensity, and skill demand shifts for three different types of skilled workers during the period from 1970 to 2005. The growth rates of labor productivity, which is calculated as real gross output divided by total number of employees, in Table 3.15 are averaged annual growth rates for each sub-period. Similar

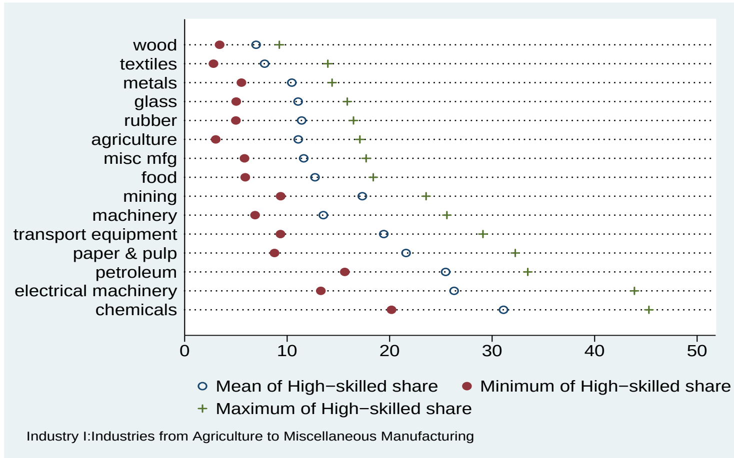

Figure 3.11: High-Skilled Workers' Share from Agriculture to Misc. Manufacturing: 1970-2005

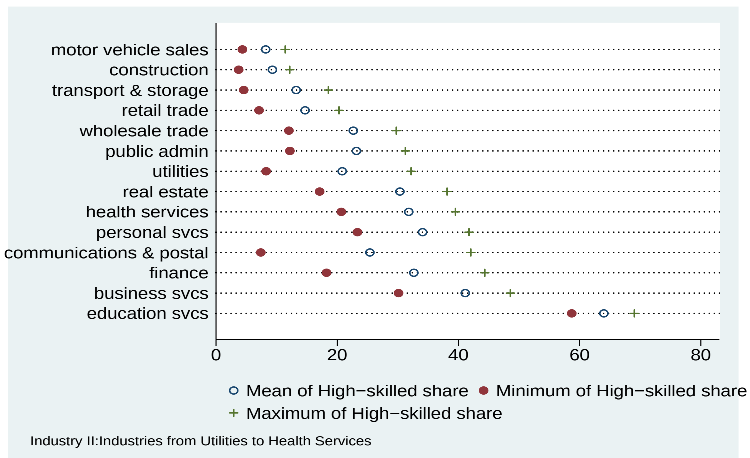

Figure 3.12: High-Skilled Workers' Share from Utilities to Health Service: 1970-2005

calculation methods are applied to the growth rate of computerization in Table 3.16, measured by three capital investments of computing equipment, software and communication equipment based on the real gross fixed capital formation data by industry. In the EU KLEMS Growth and Productivity Accounts, high-skilled workers are defined as those who have 16 years of schooling or more; middle-skilled workers have 12 years of schooling, including those with some college education, for a total of 12 to 15 years of schooling; and low-skilled workers have less than 12 years of schooling. Demand shifts for these three types of skilled workers are measured by each type of the skilled workers' employment share and

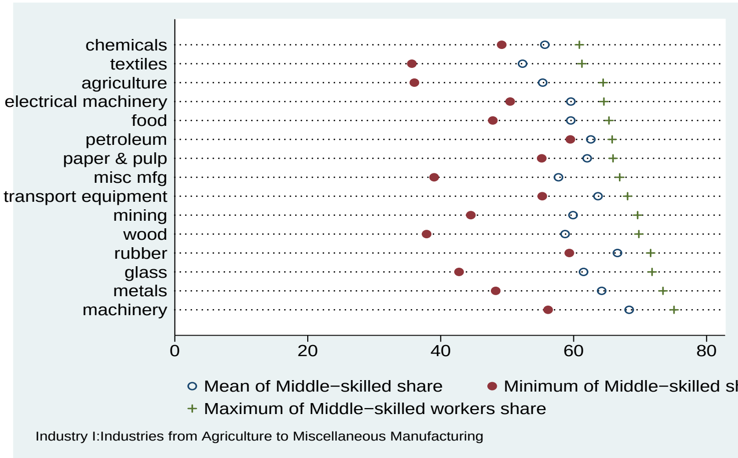

Figure 3.13: Middle-Skilled Workers' Share from Agriculture to Misc. Manufacturing: 1970-2005

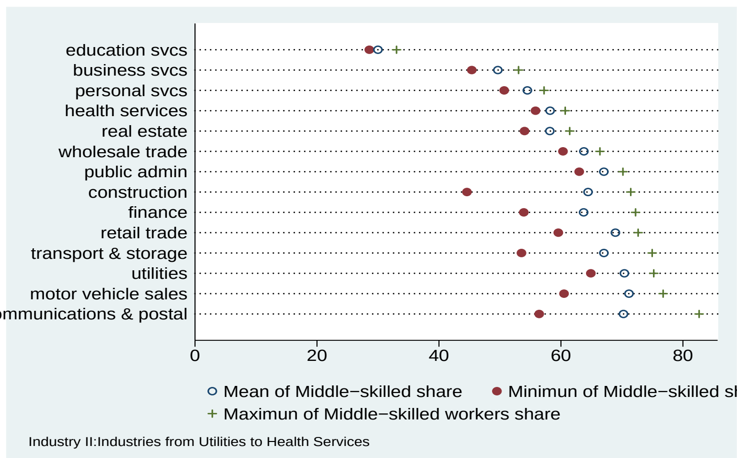

Figure 3.14: Middle-Skilled Workers' Share from Utilities to Health Service: 1970-2005

wage bill share. More detailed descriptive statistics for each industry are presented in the Appendix.

To present the diverging wage inequalities between top-half and bottom-half wage distributions in Figures 3.6 to 3.10, IPUMS Current Population Survey data are used as well. The industry classifications from the IPUMS Current Population Survey are recategorized into much broader classifications, 29 industries, to reconcile to industry classifications in the EU KLEMS Accounts. As described above, log real weekly wages for each year are regressed separately on variables of years of schooling, experience, experience squared, metro area,

Figure 3.15: Low-Skilled Workers' Share from Agriculture to Misc. Manufacturing: 1970-2005

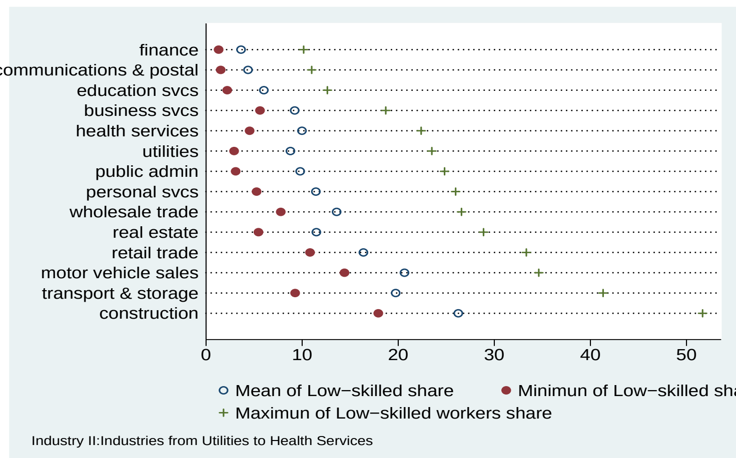

Figure 3.16: Low-Skilled Workers' Share from Utilities to Health Service: 1970-2005

gender, white, occupation, and industry using data on full-time, full-year wage workers age 25-55 with 2 to 48 years of potential labor market experience during the period from 1968 to 2007. Full-time and full-year workers are defined as those who worked 35 hours or more per week and forty-plus weeks in the previous year, respectively. A worker's log real weekly earnings are calculated as the logarithm of real annual earnings divided by the weeks worked during the previous year, and all earnings of workers are deflated by the Personal Consumption Expenditure Price Index (PCEPI). Earnings below 67 dollars per week in 1982 dollars (or below 125 dollars per week in 2005 dollars) are eliminated. The

Table 3.1: Descriptive Statistics for EU KLEMS Growth and Productivity: 1970-2005

Variables	Observations	Mean	Std. Dev.	Min	Max
Computerization Investment	1044	3902.28	9851.04	0.55	103127.28
Computerization Stocks	1044	12455.40	31320.24	1.02	269639.50
High-Skilled Employment Share	1044	21.01	13.31	2.81	69.02
Middle-Skilled Employment Share	1044	60.86	9.53	28.59	82.65
Low-Skilled Employment Share	1044	18.13	12.19	1.31	61.53
High-Skilled Worker Wage Share	1044	29.63	16.99	4.57	79.06
Middle-Skilled Worker Wage Share	1044	55.82	11.51	17.88	79.46
Low-Skilled Worker Wage Share	1044	14.55	11.40	0.72	55.88
Numbers of Employees	1044	4602.26	7298.44	115.00	51069.46
Real Gross Output	1044	428550.70	421881.60	47372.75	3031866.00

The data are from EU KLEMS Growth and Productivity Accounts from 1970 to 2005 and especially, computerization investment uses real gross fixed capital formation in 2005 dollars from EU KLEMS Database and computerization stocks are measured by real fixed capital stock in 2005 dollars from EU KLEMS Growth and Productivity Account during the period from 1970 to 2005. (in millions of U.S. dollars) Real Gross outputs are measured in millions of U.S. dollars and total number of employees are measured in thousands units. Demand shifts for different skill-types of workers are measured by employment share and wage share in which employment share is a share of a specific skill-type of workers in total number of employees and wage share means a share of a specific type of skilled workers in total wage bill.

CPS sample weight, which is person weight, is used for this analysis and observations for top-coded earners are multiplied by 1.5 following Katz and Murphy (1992) and Autor, Katz, and Kearney (2008).

3.3.2 Difference-in-Difference Estimates

In the late 1990s, rapid growth of computerization, strong productivity gains, and polarization patterns in employment and wage structure occurred simultaneously in the U.S. labor market, although there are variations across industries associated with their timing. To see whether increasing investments for computer-related assets affect large labor productivity gains and the polarization trends, the difference-in-difference empirical approach is used following Stiroh (2002). Based on industry level, this section investigates how industry characteristics associated with computerization affect the U.S. productivity revival and demand shifts for different skill-types of workers in the late 1990s. Then, based on Berman, Bound, and Griliches (1994) and Goldin and Katz (1996), the share equation for three types of skilled workers - high-skilled workers, middle-skilled workers, and low-skilled workers - is estimated using two-way fixed effect regressions over three different sub-periods.

3.3.2.1 Growth Rate of Labor Productivity

Even though descriptive statistics in Table 3.15 indicate a strong increase in the growth rates of labor productivity for the period from 1995 to 2000, the first empirical model illustrates the U.S. productivity revivals across industries in the post-1995 period by using difference-in-difference methods. Thus, the simple empirical model with the post-1995 dummy can be defined as

$$d \ln \mathrm{LP}_{it} = \beta_0 + \beta_1 \Phi + \epsilon_{it} \tag{3.22}$$

where $d \ln \mathrm{LP}_{it}$ is the annual growth rate of labor productivity in industry i at time t, and LP is calculated by real gross output divided by total number of employees. Φ is a post-1995 dummy indicating whether the observed period is prior to or post 1995. If the period is before 1995, then Φ is equal to zero; otherwise, it equals one. β_0 indicates annual growth rate of labor productivity in the period prior to 1995, β_1 indicates additional growth rate of labor productivity in the post-1995 period relative to before 1995. Since the error term ϵ_{it} can be heteroskedastic and correlated across industries, fixed effect regressions for heteroscedastic and correlated error term are used in the regression models from (3) to (6). For difference-in-difference estimates, since annual growth rates of computerization investment after 1995 increase sharply as shown in Table 3.16, the break point for the analysis is determined at 1995 following Stiroh (2002).

The next empirical specification is used to investigate the potential links between the fast growth rates of labor productivity in the late 1990s and the strong computer-related investments across industries. The main assumption applied is that if increasing investment for computerization assets is a driving force of large productivity gains in the late 1990s, industries with strong investment for computer-related assets should exhibit larger productivity gains than other industries, which are less computerized industries. Thus, the second empirical model showing the connection between computerization investments and labor productivity gains can be written as

$$d \ln \mathrm{LP}_{it} = \beta_0 + \beta_1 \Phi + \beta_2 \Gamma + \beta_3 \Phi\Gamma + \epsilon_{it} \tag{3.23}$$

where Γ is a dummy for computerization-intensified. β_0 indicates the growth rate of labor productivity for non-computerized industry in the period prior to 1995. Since β_1 represents additional growth rate of labor productivity for the non-computerized industry in the post-1995 period relative to prior to 1995, $\beta_0 + \beta_1$ indicates the growth rate of productivity for non-computerized industries in the post-1995 period. Furthermore, β_2 represents the additional growth rate of labor productivity in the period prior to 1995 for computerized industry. Thus, $\beta_0 + \beta_2$ represents the growth rate of labor productivity for computer-intensified industry in the period before 1995 and $\beta_0 + \beta_1 + \beta_2 + \beta_3$ indicates the labor productivity growth rate for computerized industry in the period after 1995.

Here investments for computerization assets are measured by three capital assets - computing equipment, software, and communication equipment. The computerized industry is defined based on the growth rate of computerization-real gross output intensity in 1995. That is, if the growth rate of computerization investment-output intensity in 1995 for an industry is larger than the median growth rate of the computerization investment-output intensity in 1995 over 29 industries, then Γ is equal to 1, indicating it is a computerization-intensified industry. The first and second empirical specifications use 6 estimation methods: OLS regression weighted by total number of employees in the regression model (1); OLS regression weighted by real gross output in the regression model (2); Fixed-effect regression weighted by total number of employees for heteroscedasticity in the regression model (3); Fixed-effect regression weighted by real gross output for heteroscedasticity in the regression model (4); Fixed-effect regression weighted by total number of employees for correlation in the regression model (5); and Fixed effect regression weighted by real gross output for correlation in the regression model (6)[6].

[6]Since there are variations across industries, all regressions with two different weights, total number of

Table 3.2: Acceleration of Annual Growth of Labor Productivity in the Post-1995 Period

Variables	Dependent variable: Annualized Growth of Labor Productivity					
	(1)	(2)	(3)	(4)	(5)	(6)
Post-1995 Dummy	0.0066***	0.0121***	0.0083**	0.0083***	0.0066*	0.0121***
	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.004)
Intercept	0.0095***	0.0116***	0.0089***	0.0131***	0.0095***	0.0116***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Weight by Employment	yes		yes		yes	
Weight by Real Gross Output		yes		yes		yes
Fixed Effect			yes	yes	yes	yes
Heteroskedastic			yes	yes		
Correlated					yes	yes
R-squared	0.0094	0.0232	0.2158	0.2798	0.0084	0.0212
Observations	1015	1015	1015	1015	1015	1015
Post-1995 Dummy	0.0023	0.0115***	0.0039	0.0052**	0.0023	0.0115***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Computerization Intensity	-0.0044^{*}	-0.0058^{*}	0.0000	0.0000	-0.0044	-0.0058^{*}
	(0.003)	(0.003)			(0.003)	(0.003)
Post-1995*Computerization	0.0127***	0.0015	0.0132*	0.0079	0.0127**	0.0015
	(0.004)	(0.005)	(0.007)	(0.005)	(0.005)	(0.005)
Intercept	0.0109***	0.0139***	0.0088***	0.0131***	0.0109***	0.0139***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Weight by Employment	yes		yes		yes	
Weight by Real Gross Output		yes		yes		yes
Fixed Effect			yes	yes	yes	yes
Heteroskedastic			yes	yes		
Correlated					yes	yes
R-squared	0.0172	0.0275	0.2241	0.2821	0.0162	0.0256
Observations	1015	1015	1015	1015	1015	1015

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Regressions (1) and (2) are estimated by ordinary least square with two weights: total number of employees and real gross output, respectively. Regressions (3) and (4) considers heteroskedasticity over industries based on fixed effect regression, while Regressions (5) and (6) are based on fixed effect regressions with correlated error structure. Regressions (1) to (6) are also estimated by two weights: total number of employees and the real gross output. This difference-in-difference estimation for growth rate of labor productivity is based on EU KLEMS Growth and Productivity Accounts from 1970 to 2005.

The upper panel of Table 3.2, illustrating the first empirical model with only a time dummy, shows annual growth rates for labor productivity increased from 0.66 percent to 1.21 percent in the post-1995 period. The bottom panel in Table 3.2, based on the

employees weight and real gross output weight, are applied here following Kahn and Lim (1998).

second empirical model, presents estimation results about the link between computerization and labor productivity growth. A comparison of non-computerized industry in the period prior to 1995 with non-computerized industry in the period post-1995 indicates that time effect for non-computerized industry is β_1. The comparison of prior and post 1995 in the computerized industry indicates that time effect for the computerized industry is $\beta_1 + \beta_3$. These comparisons suggest that the coefficient of interaction term by the post-1995 dummy and the computerization dummy, β_3, indicates an additional growth rate in labor productivity due to computerization characteristics of industry in the post-1995 period. It explains the link between increasing computerization and faster productivity growth.

For example, the bottom panel shows that additional acceleration in productivity growth rate, β_3, due to computerization, is 0.83 percent as a mean value with a range from 0.15 percent to 1.27 percent. Specifically, the estimations weighted by employment present significantly larger values than the regressions weighted by real gross output. In the post-1995 period, the model (3) shows the largest acceleration productivity growth rate due to computerization, 1.32 percent, and the model (1) and the model (5) show a 1.27 percent increase in labor productivity growth rate in computerized industry relative to non-computerized industries. Therefore, Table 3.2 shows that computerized industries experienced increases in labor productivity relative to non-computerized industries after the 1995 period, indicating there is a positive relationship between computerization and U.S. productivity revivals.

3.3.2.2 Demand Shifts for Different Skill-types of Workers

Observations from the U.S. labor market during the last decade show that with increasing computerization across industries demand shifts measured by employment share and wage bill share for high-skilled workers and for low-skilled workers have increased, while middle-skilled workers' shares have decreased. These key facts are consistent with the theoretical framework that when there are three types of skilled workers and four types of tasks (nonroutine cognitive tasks, which could be performed by high-skilled workers and middle-skilled workers; routine tasks such as routine cognitive tasks and routine manual tasks, which can be carried out by middle-skilled workers and computerization assets; non-routine manual tasks, which are performed by low-skilled workers) marginal workers from both edges in routine tasks switch their labor supply toward nonroutine cognitive tasks and nonroutine manual tasks with decreasing computerization cost.

Due to the decreasing price of computerization capital, increasing demand for production inputs of routine tasks, which are middle-skilled workers or computer-related capital, leads to an increase in the replacement of middle-skilled workers by computerization assets for routine cognitive and routine manual tasks. Therefore, with increasing investments in computerization, employment and wage bill shares of three different skill-types of workers should move toward polarization patterns such as increasing shares for high-skilled workers and for low-skilled workers and decreasing share of middle-skilled workers.

To see the impact of computerization on the labor market phenomena, relationships between computerization and increasing shares for high-skilled workers, decreasing shares for middle-skilled workers, and increasing shares for low-skilled workers will be analyzed respectively. For demand shifts of three types of skilled workers across industries in the late 1990s, the empirical model with the post-1995 dummy can be written as

$$d\mathrm{ES}_{it} = \beta_0 + \beta_1 \Phi + \epsilon_{it} \tag{3.24}$$

where $d\mathrm{ES}_{it}$ represents demand shifts for three types of skilled workers: high-skilled workers, middle-skilled workers, and low-skilled workers, in industry i at time t. Φ is a post-1995 dummy indicating whether the observed period is prior to or post 1995. Thus, if the period is prior to 1995, then Φ equals zero; otherwise, Φ is one. Similarly, β_0 indicates a demand shift for each type of skilled-worker in the period prior to 1995, and β_1 is an additional share change for high-skilled, middle-skilled, and low-skilled workers in the post-1995 relative to the previous period.

To see how employment share and wage bill share for each skill-type of worker in the late 1990s change with increasing computerization assets, the same break point for the time period in 1995 is used. In addition, to find whether there are possible connections between skill demand changes and large investments for computerization assets across industries after 1995, the second empirical model can be written as

$$dES_{it} = \beta_0 + \beta_1\Phi + \beta_2\Gamma + \beta_3\Phi\Gamma + \epsilon_{it} \tag{3.25}$$

where Γ is a dummy for computerization-intensity. β_0 indicates demand shifts for different types of skilled workers in non-computerized industry during the period prior to 1995. Since β_1 presents an additional share change for non-computerized industry in the post-1995 period relative to prior to 1995, $\beta_0 + \beta_1$ indicates demand shifts for high-skilled workers, middle-skilled workers, and low-skilled workers in a non-computerized industry in the post-1995 period. Also, since β_2 is the additional share change for j type of workers in the period prior to 1995 due to computerization characteristic for industry, $\beta_0 + \beta_2$ equals the share shifts for three types of skilled workers for a computer-intensified industry in the period before 1995. Thus, $\beta_0 + \beta_1 + \beta_2 + \beta_3$ indicates demands shifts, measured by share changes in total employment and total wage bill, for high-skilled, middle-skilled, and low-skilled workers in computerized industry during the period post-1995.

Table 3.3 and Table 3.4, based on the employment share's change and the wage bill share's change, respectively, present the estimation results for demand shifts for high-skilled workers. Each table consists of two panels: the first empirical specification with only a time dummy and the second empirical specification with time and computerization dummies. Both the upper panels in Table 3.3 and Table 3.4 show that demand for high-skilled workers has decreased since 1995. The lower panels, however, indicate that in the post-1995 period, computerized industry has experienced increasing demand for high-skilled workers, measured by employment share and wage bill share, and the increasing demand shift for high-skilled worker due to computerization are clearly presented in Table 3.4.

Second, for middle-skilled workers' demand shifts, which are also measured by em-

Table 3.3: Changes of Employment Share for High-Skilled Workers in the Post-1995 Period

Variables	Dependent variable: Demand Shifts for High-Skilled Workers					
	(1)	(2)	(3)	(4)	(5)	(6)
I. Time Dummy						
Post-1995 Dummy	−0.0948	−0.1174	−0.0906***	−0.1489***	−0.0948	−0.1174
	(0.065)	(0.074)	(0.031)	(0.048)	(0.151)	(0.136)
Intercept	0.4790***	0.5071***	0.4776***	0.5194***	0.4790***	0.5071***
	(0.038)	(0.046)	(0.011)	(0.019)	(0.087)	(0.083)
Weight by Employment	yes		yes		yes	
Weight by Real Gross Output		yes		yes		yes
Fixed Effect			yes	yes	yes	yes
Heteroskedastic			yes	yes		
Correlated					yes	yes
R-squared	0.0021	0.0025	0.0219	0.0251	0.0005	0.0006
Observations	1015	1015	1015	1015	1015	1015
II. Time and Computerization						
Post-1995 Dummy	−0.1001	−0.1072	−0.0972***	−0.1543**	−0.1001	−0.1072
	(0.080)	(0.095)	(0.031)	(0.065)	(0.210)	(0.186)
Computerization Intensity	−0.0953	−0.0801	0.0000	0.0000	−0.0953	−0.0801
	(0.081)	(0.095)			(0.136)	(0.114)
Post-1995*Computerization	0.0203	−0.0290	0.0194	0.0136	0.0203	−0.0290
	(0.136)	(0.152)	(0.074)	(0.096)	(0.238)	(0.187)
Intercept	0.5104***	0.5391***	0.4776***	0.5195***	0.5104***	0.5391***
	(0.046)	(0.060)	(0.011)	(0.019)	(0.120)	(0.115)
Weight by Employment	yes		yes		yes	
Weight by Real Gross Output		yes		yes		yes
Fixed Effect			yes	yes	yes	yes
Heteroskedastic			yes	yes		
Correlated					yes	yes
R-squared	0.0040	0.0040	0.0219	0.0251	0.0023	0.0022
Observations	1015	1015	1015	1015	1015	1015

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Regressions (1) and (2) are estimated by ordinary least square with two weights: total number of employees and real gross output, respectively. Regressions (3) and (4) consider heteroskedasticity over industries based on the fixed effect regression, while regressions (5) and (6) are based on the fixed effect regressions with a correlated error structure. Regression (1) to regression (6) are also estimated by two weights: total number of employees and real gross output. The upper panel entitled 'I. Time dummy' shows the first empirical estimation results with only a time dummy and the lower panel entitled 'II. Time and Computerization' presents the second empirical estimation results with time and computerization dummies.

ployment share and wage bill share, the top panels in Table 3.5 and in Table 3.6 show that decreasing demand for middle-skilled workers is much larger than decreasing demand for high-skilled workers, with mean values being -0.5607 for employment share and -0.4652 for wage bill share with a range from -0.5491 to -0.5757 for the middle-skilled workers'

Table 3.4: Changes of Wage Bill Share for High-Skilled Workers in the Post-1995 Period

Variables	Dependent variable: Demand Shifts for High-Skilled Workers					
	(1)	(2)	(3)	(4)	(5)	(6)
I. Time Dummy						
Post-1995 Dummy	−0.0553	−0.1290	−0.0472	−0.1685**	−0.0553***	−0.1290***
	(0.098)	(0.115)	(0.053)	(0.071)	(0.002)	(0.003)
Intercept	0.5794***	0.6550***	0.5766***	0.6705***	0.5794***	0.6550***
	(0.058)	(0.072)	(0.018)	(0.028)	(0.001)	(0.002)
Weight by Employment	yes		yes		yes	
Weight by Real Gross Output		yes		yes		yes
Fixed Effect			yes	yes	yes	yes
Heteroskedastic			yes	yes		
Correlated					yes	yes
R-squared	0.0003	0.0012	0.0173	0.0159	0.0003	0.0012
Observations	1015	1015	1015	1015	1015	1015
II. Time and Computerization						
Post-1995 Dummy	−0.0680	−0.1313	−0.0551	−0.1880*	−0.0680	−0.1313
	(0.121)	(0.148)	(0.046)	(0.098)	(0.303)	(0.302)
Computerization Intensity	0.0698	0.0114			0.0698	0.0114
	(0.123)	(0.148)			(0.197)	(0.194)
Post-1995*Computerization	0.0330	0.0063	0.0234	0.0491	0.0330	0.0063
	(0.207)	(0.236)	(0.135)	(0.140)	(0.341)	(0.316)
Intercept	0.5564***	0.6504***	0.5765***	0.6707***	0.5564***	0.6504***
	(0.070)	(0.093)	(0.018)	(0.028)	(0.173)	(0.185)
Weight by Employment	yes		yes		yes	
Weight by Real Gross Output		yes		yes		yes
Fixed Effect			yes	yes	yes	yes
Heteroskedastic			yes	yes		
Correlated					yes	yes
R-squared	0.0010	0.0012	0.0173	0.0159	−0.0001	−0.0001
bservations	1015	1015	1015	1015	1015	1015

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Regressions (1) and (2) are estimated by ordinary least square with two weights: total number of employees and real gross output, respectively. Regressions (3) and (4) consider heteroskedasticity over industries based on the fixed effect regression, while regressions (5) and (6) are based on the fixed effect regressions with a correlated error structure. Regression (1) to regression (6) are also estimated by two weights: total number of employees and real gross output. The upper panel entitled 'I. Time dummy' shows the first empirical estimation results with only a time dummy and the lower panel entitled 'II. Time and Computerization' presents the second empirical estimation results with time and computerization dummies.

employment share and a range from -0.3942 to -0.4996 for the wage bill share's change of middle-skilled workers. In the bottom panels, the changes of share in employment and wage bill for middle-skilled workers due to computerization are on average -0.2482 with a range from -0.2256 to -0.2646 and on average -0.2470 with a range from -0.2295 to -0.2603,

Table 3.5: Changes of Employment Share for Middle-Skilled Workers in the Post-1995 Period

Variables	Dependent variable: Demand Shifts for Middle-Skilled Workers					
	(1)	(2)	(3)	(4)	(5)	(6)
I. Time Dummy						
Post-1995 Dummy	-0.5712^{***}	-0.5757^{***}	-0.5491^{***}	-0.5212^{***}	-0.5712^{***}	-0.5757^{***}
	(0.076)	(0.086)	(0.051)	(0.068)	(0.158)	(0.159)
Intercept	0.2745^{***}	0.2772^{***}	0.2669^{***}	0.2558^{***}	0.2745^{***}	0.2772^{***}
	(0.045)	(0.054)	(0.018)	(0.027)	(0.093)	(0.100)
Weight by Employment	yes		yes		yes	
Weight by Real Gross Output		yes		yes		yes
Fixed Effect			yes	yes	yes	yes
Heteroskedastic			yes	yes		
Correlated					yes	yes
R-squared	0.0530	0.0421	0.0987	0.0869	0.0529	0.0421
Observations	1015	1015	1015	1015	1015	1015
II. Time and Computerization						
Post-1995 Dummy	-0.4839^{***}	-0.4848^{***}	-0.4647^{***}	-0.4184^{***}	-0.4839^{**}	-0.4848^{**}
	(0.093)	(0.110)	(0.056)	(0.082)	(0.214)	(0.195)
Computerization Intensity	0.2541^{***}	0.2762^{**}			0.2541	0.2762^{*}
	(0.095)	(0.110)			(0.164)	(0.151)
Post-1995*Computerization	-0.2646^{*}	-0.2256	-0.2490^{**}	-0.2598^{*}	-0.2646	-0.2256
	(0.160)	(0.176)	(0.106)	(0.130)	(0.278)	(0.240)
Intercept	0.1909^{***}	0.1667^{**}	0.2676^{***}	0.2550^{***}	0.1909	0.1667
	(0.054)	(0.070)	(0.017)	(0.025)	(0.124)	(0.123)
Weight by Employment	yes		yes		yes	
Weight by Real Gross Output		yes		yes		yes
Fixed Effect			yes	yes	yes	yes
Heteroskedastic			yes	yes		
Correlated					yes	yes
R-squared	0.0597	0.0481	0.1009	0.0889	0.0596	0.0481
Observations	1015	1015	1015	1015	1015	1015

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Regressions (1) and (2) are estimated by ordinary least square with two weights: total number of employees and real gross output, respectively. Regressions (3) and (4) consider heteroskedasticity over industries based on the fixed effect regression, while regressions (5) and (6) are based on the fixed effect regressions with a correlated error structure. Regression (1) to regression (6) are also estimated by two weights: total number of employees and real gross output. The upper panel entitled 'I. Time dummy' shows the first empirical estimation results with only a time dummy and the lower panel entitled 'II. Time and Computerization' presents the second empirical estimation results with time and computerization dummies.

respectively.

Third, the upper panels in Tables 3.7 and 3.8 show that since 1995 demand for low-skilled workers has increased, which is measured by employment share in Table 3.7 and wage bill share in Table 3.8. The lower panels present that change of employment share

Table 3.6: Changes of Wage Bill Share for Middle-Skilled Workers in the Post-1995 Period

Variables	Dependent variable: Demand Shifts for Middle-Skilled Workers					
	(1)	(2)	(3)	(4)	(5)	(6)
I. Time Dummy						
Post-1995 Dummy	-0.4996^{***}	-0.4602^{***}	-0.4773^{***}	-0.3942^{***}	-0.4996^{***}	-0.4602^{**}
	(0.099)	(0.116)	(0.063)	(0.081)	(0.193)	(0.201)
Intercept	0.0807	0.0538	0.0730^{***}	0.0279	0.0807	0.0538
	(0.058)	(0.073)	(0.022)	(0.032)	(0.114)	(0.123)
Weight by Employment	yes		yes		yes	
Weight by Real Gross Output		yes		yes		yes
Fixed Effect			yes	yes	yes	yes
Heteroskedastic			yes	yes		
Correlated					yes	yes
R-squared	0.0247	0.0152	0.0618	0.0510	0.0247	0.0152
Observations	1015	1015	1015	1015	1015	1015
II. Time and Computerization						
Post-1995 Dummy	-0.4126^{***}	-0.3680^{**}	-0.3946^{***}	-0.2922^{***}	-0.4126	-0.3680
	(0.122)	(0.149)	(0.048)	(0.099)	(0.263)	(0.262)
Computerization Intensity	0.1844	0.2570^{*}			0.1844	0.2570
	(0.123)	(0.149)			(0.184)	(0.190)
Post-1995*Computerization	-0.2603	-0.2295	-0.2443^{*}	-0.2581	-0.2603	-0.2295
	(0.208)	(0.238)	(0.139)	(0.156)	(0.315)	(0.306)
Intercept	0.0200	-0.0490	0.0737^{***}	0.0271	0.0200	-0.0490
	(0.071)	(0.094)	(0.019)	(0.030)	(0.151)	(0.160)
Weight by Employment	yes		yes		yes	
Weight by Real Gross Output		yes		yes		yes
Fixed Effect			yes	yes	yes	yes
Heteroskedastic			yes	yes		
Correlated					yes	yes
R-squared	0.0270	0.0181	0.0631	0.0521	0.0270	0.0181
Observations	1015	1015	1015	1015	1015	1015

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Regressions (1) and (2) are estimated by ordinary least square with two weights: total number of employees and real gross output, respectively. Regressions (3) and (4) consider heteroskedasticity over industries based on the fixed effect regression, while regressions (5) and (6) are based on the fixed effect regressions with a correlated error structure. Regression (1) to regression (6) are also estimated by two weights: total number of employees and real gross output. The upper panel entitled 'I. Time dummy' shows the first empirical estimation results with only a time dummy and the lower panel entitled 'II. Time and Computerization' presents the second empirical estimation results with time and computerization dummies.

for low-skilled workers due to computerization in the post-1995 period is on average 0.2456 with a range from 0.2296 to 0.2546 and the wage bill share's change for low-skilled workers is on average 0.2218 with a range from 0.2089 to 0.2273.

These estimation results from Tables 3.3 to 3.8 imply that computerized industries

Table 3.7: Changes of Employment Share for Low-Skilled Workers in the Post-1995 Period

Variables	Dependent variable: Demand Shifts for Low-Skilled Workers					
	(1)	(2)	(3)	(4)	(5)	(6)
I. Time Dummy						
Post-1995 Dummy	0.6660^{***}	0.6931^{***}	0.6397^{***}	0.6701^{***}	0.6660^{***}	0.6931^{***}
	(0.055)	(0.063)	(0.057)	(0.064)	(0.149)	(0.147)
Intercept	-0.7536^{***}	-0.7843^{***}	-0.7445^{***}	-0.7752^{***}	-0.7536^{***}	-0.7843^{***}
	(0.033)	(0.040)	(0.020)	(0.025)	(0.088)	(0.094)
Weight by Employment	yes		yes		yes	
Weight by Real Gross Output		yes		yes		yes
Fixed Effect			yes	yes	yes	yes
Heteroskedastic			yes	yes		
Correlated					yes	yes
R-squared	0.1250	0.1062	0.1650	0.1358	0.1227	0.1037
Observations	1015	1015	1015	1015	1015	1015
II. Time and Computerization						
Post-1995 Dummy	0.5840^{***}	0.5920^{***}	0.5619^{***}	0.5727^{***}	0.5840^{***}	0.5920^{***}
	(0.068)	(0.081)	(0.049)	(0.050)	(0.140)	(0.137)
Computerization Intensity	-0.1588^{**}	-0.1962^{**}			-0.1588^{*}	-0.1962^{*}
	(0.069)	(0.081)			(0.096)	(0.111)
Post-1995*Computerization	0.2442^{**}	0.2546^{**}	0.2296	0.2462^{*}	0.2442	0.2546
	(0.117)	(0.129)	(0.144)	(0.140)	(0.159)	(0.175)
Intercept	-0.7013^{***}	-0.7058^{***}	-0.7452^{***}	-0.7745^{***}	-0.7013^{***}	-0.7058^{***}
	(0.040)	(0.051)	(0.020)	(0.023)	(0.083)	(0.088)
Weight by Employment	yes		yes		yes	
Weight by Real Gross Output		yes		yes		yes
Fixed Effect			yes	yes	yes	yes
Heteroskedastic			yes	yes		
Correlated					yes	yes
R-squared	0.1303	0.1116	0.1683	0.1389	0.1280	0.1092
Observations	1015	1015	1015	1015	1015	1015

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Regressions (1) and (2) are estimated by ordinary least square with two weights: total number of employees and real gross output, respectively. Regressions (3) and (4) consider heteroskedasticity over industries based on the fixed effect regression, while regressions (5) and (6) are based on the fixed effect regressions with a correlated error structure. Regression (1) to regression (6) are also estimated by two weights: total number of employees and real gross output. The upper panel entitled 'I. Time dummy' shows the first empirical estimation results with only a time dummy and the lower panel entitled 'II. Time and Computerization' presents the second empirical estimation results with time and computerization dummies.

experienced increasing demands for high-skilled workers and for low-skilled workers and decreasing demand for middle-skilled workers relative to other less computerized industries in the post-1995 period. It supports the implications from the combined theoretical framework that due to cheaper computerization costs, middle-skilled workers are displaced from

Table 3.8: Changes of Wage Bill Share for Low-Skilled Workers in the Post-1995 Period

Variables	Dependent variable: Demand Shifts for Low-Skilled Workers					
	(1)	(2)	(3)	(4)	(5)	(6)
I. Time Dummy						
Post-1995 Dummy	0.5549^{***}	0.5892^{***}	0.5245^{***}	0.5628^{***}	0.5549^{***}	0.5892^{***}
	(0.059)	(0.066)	(0.057)	(0.059)	(0.139)	(0.141)
Intercept	-0.6601^{***}	-0.7088^{***}	-0.6496^{***}	-0.6984^{***}	-0.6601^{***}	-0.7088^{***}
	(0.034)	(0.041)	(0.020)	(0.023)	(0.083)	(0.090)
Weight by Employment	yes		yes		yes	
Weight by Real Gross Output		yes		yes		yes
Fixed Effect			yes	yes	yes	yes
Heteroskedastic			yes	yes		
Correlated					yes	yes
R-squared	0.0812	0.0739	0.1381	0.1186	0.0794	0.0717
Observations	1015	1015	1015	1015	1015	1015
II. Time and Computerization						
Post-1995 Dummy	0.4806^{***}	0.4994^{***}	0.4497^{***}	0.4802^{***}	0.4806^{***}	0.4994^{***}
	(0.072)	(0.084)	(0.051)	(0.053)	(0.117)	(0.112)
Computerization Intensity	-0.2542^{***}	-0.2684^{***}			-0.2542^{**}	-0.2684^{**}
	(0.073)	(0.084)			(0.100)	(0.114)
Post-1995*Computerization	0.2273^{*}	0.2232^{*}	0.2209^{*}	0.2089^{*}	0.2273	0.2232
	(0.123)	(0.134)	(0.121)	(0.118)	(0.164)	(0.179)
Intercept	-0.5764^{***}	-0.6014^{***}	-0.6502^{***}	-0.6977^{***}	-0.5764^{***}	-0.6014^{***}
	(0.042)	(0.053)	(0.017)	(0.020)	(0.069)	(0.072)
Weight by Employment	yes		yes		yes	
Weight by Real Gross Output		yes		yes		yes
Fixed Effect			yes	yes	yes	yes
Heteroskedastic			yes	yes		
Correlated					yes	yes
R-squared	0.0921	0.0834	0.1410	0.1208	0.0903	0.0813
Observations	1015	1015	1015	1015	1015	1015

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Regressions (1) and (2) are estimated by ordinary least square with two weights: total number of employees and real gross output, respectively. Regressions (3) and (4) consider heteroskedasticity over industries based on the fixed effect regression, while regressions (5) and (6) are based on the fixed effect regressions with a correlated error structure. Regression (1) to regression (6) are also estimated by two weights: total number of employees and real gross output. The upper panel entitled 'I. Time dummy' shows the first empirical estimation results with only a time dummy and the lower panel entitled 'II. Time and Computerization' presents the second empirical estimation results with time and computerization dummies.

routine tasks by computerized assets, and demand shifts for high-skilled workers and for low-skilled workers, measured by changes in employment share and in wage bill share, have increased due to increasing movements of middle-skilled workers from routine tasks toward nonroutine cognitive tasks and nonroutine manual tasks.

3.3.3 Share Equation Estimates for Three Types of Skilled Workers

This section tries to show how demand for different skill-types of workers changes due to increasing computerization using share equation estimates, derived from translog cost function for high-skilled workers, middle-skilled workers, and low-skilled workers. It is based on skill upgrading literature within industry, which shows variations of nonproduction workers' share within-industry in the manufacturing industries due to labor-saving technological change, capital-skill complementarity hypothesis, or skill-biased technological change (Berman, Bound, Griliches, 1994; Goldin and Katz, 1996; Machine and Van Reenen, 1998).

Following Goldin and Katz (1996), the empirical specification for demand shifts for three types of skilled workers can be written as

$$d\mathrm{S}_{it} = \beta_0 + \beta_1 d\ln \mathrm{C}_{it} + \beta_2 d\ln(RelWage)_{it} + \epsilon_{it} \tag{3.26}$$

where i is an indicator of industry with $i = 1, 2, \dots, 29$; $d\mathrm{S}_{it}$ represents a change of each skill-type of workers' employment share or wage bill share; C_{it} indicates computerization intensity in the industry i at time t, which is calculated by two measurements: (i) computer-related capital stocks divided by total number of employees and (ii) computer-based capital stocks divided by real gross output. The relative wage term, $(RelWage)_{it}$, can be used for this empirical model, but it will be dropped since this term is likely to be endogenous. Instead, Y_{it}, which is real gross output of industry i at time t, is included. Thus, the empirical model for share equation estimates can be defined as

$$d\mathrm{S}_{it} = \beta_0 + \beta_1 d\ln \mathrm{C}_{it} + \beta_2 d\ln \mathrm{Y}_{it} + \epsilon_{it} \tag{3.27}$$

Tables 3.9 to 3.14 present six estimation results for computerization impacts on the changes of each skilled worker's shares in total employment and total wages. As measurements of computerization, computer-related assets such as computing equipment, soft-

Table 3.9: Computerization Impact on Demand Shifts Measured by Employment Share for High-Skilled Workers: 1970-2005

Variables	Fixed-Effect Regression			Fixed-Effect Regression with Weights					
	70-80	80-95	95-05	70-80	70-80	80-95	80-95	95-05	95-05
I. Total Number of Employment									
Computerization Intensity	0.2116	0.7753**	0.3658	0.3400	0.2990	1.0045	0.7534	−1.1926	0.2501
	(0.236)	(0.337)	(1.685)	(0.289)	(0.314)	(0.596)	(0.455)	(1.592)	(2.448)
Real Gross Output	−3.5641***	1.3953	−2.5478	−4.2959***	−4.3326***	−1.3127	−0.0776	−1.6505	−3.3600
	(0.914)	(1.257)	(2.725)	(0.998)	(1.092)	(1.542)	(1.491)	(2.939)	(2.074)
Intercept	0.7884***	0.6845***	0.7947***	0.7583***	0.5833***	0.0978	0.5300*	0.8610***	0.8038**
	(0.174)	(0.188)	(0.250)	(0.098)	(0.134)	(0.283)	(0.291)	(0.277)	(0.349)
R-squared	0.1727	0.1175	0.0527	0.2815	0.2275	0.2434	0.2041	0.1784	0.1289
Observations	290	464	319	290	290	464	464	319	319
II. Real Gross Output									
Computerization Intensity	0.2604	0.7120*	0.3300	0.1468	0.2047	0.7876	0.5986	−1.8970	0.0247
	(0.258)	(0.394)	(1.888)	(0.343)	(0.368)	(0.545)	(0.427)	(1.720)	(2.490)
Real Gross Output	−3.3774***	1.8085	−2.3173	−4.2780***	−4.2389***	−0.9303	0.2369	−2.6488	−3.3096
	(0.934)	(1.275)	(2.926)	(0.999)	(1.117)	(1.565)	(1.493)	(3.164)	(2.497)
Intercept	0.7819***	0.7011***	0.7979***	0.7767***	0.5965***	0.1337	0.5560*	0.9536***	0.8304**
	(0.176)	(0.204)	(0.261)	(0.100)	(0.126)	(0.284)	(0.295)	(0.272)	(0.350)
R-squared	0.1731	0.1171	0.0527	0.2798	0.2268	0.2419	0.2032	0.1818	0.1288
Observations	290	464	319	290	290	464	464	319	319
Weight by Employment				yes		yes		yes	
Weight by Real Gross Output					yes		yes		yes
Industry Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Computerization assets are measured by real fixed capital stocks at 2005 prices from the EU KLEMS Growth and Productivity Accounts from 1970 to 2005. The two computerization intensity variables are measured by (i) computerization divided by total number of employees for computerization-employment intensity in the upper panel and (ii) computerization divided by real gross output for computerization-output intensity in the bottom panel. Specification I in the upper panel uses computerization-employment intensity and specification II in the bottom panel uses computerization-output intensity. Based on three different time periods; 1970-1980, 1980-1995, and 1995-2005, all estimations used two-way fixed effect regressions without weights and with two weights of total number of employees and real gross output.

Table 3.10: Computerization Impact on Demand Shifts Measured by Wage Bill Share for High-Skilled Workers: 1970-2005

Variables	Fixed-Effect Regression			Fixed-Effect Regression with Weights					
	70-80	80-95	95-05	70-80	70-80	80-95	80-95	95-05	95-05
I. Total Number of Employment									
Computerization Intensity	0.9609**	0.9410	−0.4965	0.8669	1.3933**	0.6562	0.3686	−0.2740	0.7297
	(0.396)	(0.695)	(2.631)	(0.584)	(0.554)	(0.590)	(0.577)	(1.714)	(3.559)
Real Gross Output	−4.8733***	−0.4608	2.2349	−6.0802***	−5.7643***	−4.8267**	−3.6437	3.0574	1.8200
	(1.546)	(2.193)	(3.838)	(1.575)	(2.001)	(2.157)	(2.234)	(3.749)	(3.911)
Intercept	0.9000***	0.7686**	0.5473	0.6405***	0.7012**	−0.0378	0.6137	0.5328	0.2702
	(0.269)	(0.300)	(0.475)	(0.144)	(0.279)	(0.372)	(0.423)	(0.398)	(0.624)
R-squared	0.2517	0.1346	0.0893	0.3257	0.2939	0.2878	0.2402	0.1125	0.1002
Observations	290	464	319	290	290	464	464	319	319
II. Real Gross Output									
Computerization Intensity	1.1523**	1.1268	0.0743	0.6269	1.2661**	0.4114	0.3993	−1.9970	0.5970
	(0.447)	(0.885)	(2.919)	(0.654)	(0.594)	(0.573)	(0.650)	(1.981)	(3.693)
Real Gross Output	−4.0544**	0.3019	2.2613	−5.7774***	−5.0102**	−4.6853**	−3.3764	2.1994	2.2438
	(1.553)	(2.385)	(3.396)	(1.514)	(1.996)	(2.216)	(2.342)	(3.676)	(2.814)
Intercept	0.8730***	0.7205**	0.4722	0.6616***	0.7316**	0.0082	0.6038	0.7353*	0.2830
	(0.268)	(0.302)	(0.495)	(0.152)	(0.267)	(0.359)	(0.408)	(0.374)	(0.622)
R-squared	0.2540	0.1357	0.0892	0.3233	0.2917	0.2873	0.2403	0.1147	0.1001
Observations	290	464	319	290	290	464	464	319	319
Weight by Employment				yes		yes		yes	
Weight by Real Gross Output					yes		yes		yes
Industry Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Computerization assets are measured by real fixed capital stocks at 2005 prices from the EU KLEMS Growth and Productivity Accounts from 1970 to 2005. The two computerization intensity variables are measured by (i) computerization divided by total number of employees for computerization-employment intensity in the upper panel and (ii) computerization divided by real gross output for computerization-output intensity in the bottom panel. Specification I in the upper panel uses computerization-employment intensity and specification II in the bottom panel uses computerization-output intensity. Based on three different time periods; 1970-1980, 1980-1995, and 1995-2005, all estimations used two-way fixed effect regressions without weights and with two weights of total number of employees and real gross output.

ware, and communication equipment are divided by total number of employees and real gross output for each industry. The estimation results for each computerization intensity, computerization-employment intensity and computerization-output intensity, are presented in the top panel and bottom panel, respectively. In addition, to investigate demand shifts for three types of skilled workers over the period from 1970 to 2005 due to increasing computerization, the entire period was divided into three sub-periods; the period from 1970 to 1980, the period from 1980 to 1995, and the period from 1995 to 2005.

For high-skilled workers, the estimation results from the first period (1970 to 1980) and the second period (1980 to 1995) in Table 3.9 and Table 3.10 show that computerization intensity has a positive effect on demand for high-skilled workers measured by employment share and wage bill share. However, in the period from 1995 to 2005, both computerization intensities of fixed effect regressions with weights and without weights show mixed effects on the demand shifts for high-skilled workers. From fixed effect regression without weights, computerization intensity has a positive impact on employment share for high-skilled workers but mixed effects on wage bill share for high-skilled workers. In addition, regressions weighted by total number of employees show that computerization intensity has a negative effect on employment share and on wage bill share, while computerization increases the demand shifts for high-skilled workers based on the estimation results with real gross output weight in Table 3.9 and Table 3.10.

Second, estimation results for middle-skilled workers in Tables 3.11 and 3.12 present mixed effects of computerization on changes in employment share and wage bill share for middle-skilled workers depending on the time period. In the period from 1970 to 1980, all regressions exhibit a mixed effect of computerization on the demand shift for middle-skilled workers. For demand shifts measured by the employment share, computerization shows a mixed impact but a negative impact on wage bill share for middle-skilled workers in the 1970s. In the period from 1980 to 1995, both computerization intensities have a negative impact on employment share for middle-skilled workers, but they show positive effects on demand shifts measured by wage bill share for middle-skilled workers. The fixed-effect

Table 3.11: Computerization Impact on Demand Shifts Measured by Employment Share for Middle-Skilled Workers: 1970-2005

Variables	Fixed-Effect Regression			Fixed-Effect Regression with Weights					
	70-80	80-95	95-05	70-80	70-80	80-95	80-95	95-05	95-05
I. Total Number of Employment									
Computerization Intensity	0.0289	−0.3274	−0.8851	−0.0763	0.0919	−0.6858	−0.8114**	0.6716	−2.0445
	(0.397)	(0.432)	(2.090)	(0.405)	(0.426)	(0.423)	(0.377)	(1.761)	(2.987)
Real Gross Output	2.9205**	−0.0705	3.4994	3.6028***	2.9265*	1.5301	−0.4275	3.1427	3.9118*
	(1.105)	(1.350)	(2.915)	(1.123)	(1.531)	(1.065)	(1.372)	(3.404)	(2.245)
Intercept	0.0665	1.0163***	−0.7623**	0.3149***	1.0445***	1.1978***	0.9369***	−0.9850***	−0.7882*
	(0.235)	(0.231)	(0.343)	(0.105)	(0.359)	(0.194)	(0.249)	(0.278)	(0.398)
R-squared	0.0659	0.1000	0.0969	0.2860	0.2375	0.2643	0.2141	0.1372	0.1373
Observations	290	464	319	290	290	464	464	319	319
II. Real Gross Output									
Computerization Intensity	−0.0440	−0.2640	−1.4306	0.0911	0.0591	−0.6041	−0.6853**	1.1557	−1.6908
	(0.404)	(0.407)	(2.103)	(0.464)	(0.571)	(0.400)	(0.327)	(1.721)	(2.806)
Real Gross Output	2.8692**	−0.2085	2.5310	3.7250***	2.9513*	1.1992	−0.8095	3.7401	2.7146
	(1.140)	(1.371)	(2.941)	(1.332)	(1.666)	(1.050)	(1.340)	(3.337)	(2.585)
Intercept	0.0726	0.9998***	−0.6844*	0.2981***	1.0489***	1.1879***	0.9175***	−1.0474***	−0.8217**
	(0.234)	(0.236)	(0.359)	(0.107)	(0.366)	(0.200)	(0.259)	(0.261)	(0.374)
R-squared	0.0660	0.0999	0.0982	0.2860	0.2375	0.2640	0.2135	0.1383	0.1363
Observations	290	464	319	290	290	464	464	319	319
Weight by Employment				yes		yes		yes	
Weight by Real Gross Output					yes		yes		yes
Industry Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Computerization assets are measured by real fixed capital stocks at 2005 prices from the EU KLEMS Growth and Productivity Accounts from 1970 to 2005. The two computerization intensity variables are measured by (i) computerization divided by total number of employees for computerization-employment intensity in the upper panel and (ii) computerization divided by real gross output for computerization-output intensity in the bottom panel. Specification I in the upper panel uses computerization-employment intensity and specification II in the bottom panel uses computerization-output intensity. Based on three different time periods; 1970-1980, 1980-1995, and 1995-2005, all estimations used two-way fixed effect regressions without weights and with two weights of total number of employees and real gross output.

Table 3.12: Computerization Impact on Demand Shifts Measured by Wage Bill Share for Middle-Skilled Workers: 1970-2005

Variables	Fixed-Effect Regression			Fixed-Effect Regression with Weights					
	70-80	80-95	95-05	70-80	70-80	80-95	80-95	95-05	95-05
I. Total Number of Employment									
Computerization Intensity	−0.4264	0.1319	−0.2628	−0.5691	−0.8974	0.1271	0.0478	−0.2612	−2.3493
	(0.472)	(0.560)	(2.954)	(0.440)	(0.550)	(0.481)	(0.443)	(1.730)	(3.972)
Real Gross Output	2.7023*	1.9504	−2.6848	2.6368	2.5659	4.7214***	2.7286	−2.4175	−1.9126
	(1.470)	(1.572)	(4.133)	(1.986)	(2.024)	(1.661)	(1.680)	(4.051)	(4.156)
Intercept	0.0476	1.0359***	−0.4138	0.2997***	0.6762	1.2526***	0.9392***	−0.5294	−0.1115
	(0.299)	(0.272)	(0.547)	(0.100)	(0.403)	(0.277)	(0.310)	(0.378)	(0.666)
R-squared	0.0962	0.1079	0.0697	0.2496	0.2236	0.2464	0.1886	0.0994	0.1083
Observations	290	464	319	290	290	464	464	319	319
II. Real Gross Output									
Computerization Intensity	−0.5357	0.0519	−1.5965	−0.2971	−0.9524	0.1480	0.0086	1.0420	−2.3051
	(0.463)	(0.555)	(3.023)	(0.515)	(0.707)	(0.434)	(0.412)	(1.961)	(3.941)
Real Gross Output	2.3155	1.9519	−3.7335	2.5545	1.9407	4.8206***	2.7172*	−2.0493	−3.4793
	(1.469)	(1.530)	(3.569)	(2.080)	(2.180)	(1.570)	(1.567)	(3.898)	(3.014)
Intercept	0.0617	1.0567***	−0.2320	0.2742**	0.6702	1.2466***	0.9471***	−0.6783*	−0.1052
	(0.295)	(0.270)	(0.549)	(0.104)	(0.415)	(0.276)	(0.309)	(0.354)	(0.648)
R-squared	0.0967	0.1079	0.0710	0.2485	0.2239	0.2464	0.1886	0.1000	0.1086
Observations	290	464	319	290	290	464	464	319	319
Weight by Employment				yes		yes		yes	
Weight by Real Gross Output					yes		yes		yes
Industry Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Computerization assets are measured by real fixed capital stocks at 2005 prices from the EU KLEMS Growth and Productivity Accounts from 1970 to 2005. The two computerization intensity variables are measured by (i) computerization divided by total number of employees for computerization-employment intensity in the upper panel and (ii) computerization divided by real gross output for computerization-output intensity in the bottom panel. Specification I in the upper panel uses computerization-employment intensity and specification II in the bottom panel uses computerization-output intensity. Based on three different time periods; 1970-1980, 1980-1995, and 1995-2005, all estimations used two-way fixed effect regressions without weights and with two weights of total number of employees and real gross output.

regressions without weight and with real gross weight indicate that both computerization-employment intensity and computerization-output intensity have a negative impact on demand shifts for middle-skilled workers in the period from 1995 to 2005.

Table 3.13 and Table 3.14, third, show computerization impact on demand shifts for low-skilled workers for which these shifts are measured by employment share changes and wage bill changes in three different time periods; 1970-1980, 1980-1995, and 1995-2005. For the first period (1970 to 1980), all estimation results from fixed effect regressions without weights and with weights show a positive impact of computerization intensity on employment share change and wage bill share change for low-skilled workers. Even though the period from 1980 to 1995 presents a mixed effect on demand shifts for low-skilled workers - a positive effect on the employment share for low-skilled workers only in the fixed regression weighted by the real gross output -, the other estimation results support the negative impact of computerization on the demand shifts for low-skilled workers. By contrast, in the post-1995 period, the estimation results show that both computerization intensities have a positive effect on employment share change and wage bill share change for low-skilled workers.

In the share equation estimates seen in Tables 3.9 to 3.14, computerization impacts on demands shifts from high-skilled workers and middle-skilled workers do not show clear trends of increasing demand for high-skilled workers and decreasing demand for middle-skilled workers. However, computerization effects on the demand shifts for low-skilled workers clearly present that in the prior to 1995 period computerization growth decreased employment share and wage bill share for low-skilled workers, but after 1995 increasing computerization raised the demand shift for low-skilled workers, measured by employment share change and wage bill share change.

The regression results focusing on low-skilled workers provide empirical evidence supporting the comparative statics from the theoretical framework. Cheaper computerization costs and increasing relative wages of nonroutine tasks (nonroutine cognitive tasks and nonroutine manual tasks) led marginal workers from both edges, above-average and below-

Table 3.13: Computerization Impact on Demand Shifts Measured by Employment Share for Low-Skilled Workers: 1970-2005

Variables	Fixed-Effect Regression			Fixed-Effect Regression with Weights					
	70-80	80-95	95-05	70-80	70-80	80-95	80-95	95-05	95-05
I. Total Number of Employment									
Computerization Intensity	−0.2404	−0.4479	0.5194	−0.2637	−0.3909	−0.3187	0.0580	0.5210	1.7944**
	(0.378)	(0.406)	(0.788)	(0.525)	(0.410)	(0.477)	(0.288)	(0.712)	(0.862)
Real Gross Output	0.6436	−1.3248	−0.9516	0.6932	1.4061	−0.2174	0.5051	−1.4922	−0.5517
	(1.094)	(1.104)	(1.514)	(0.859)	(1.272)	(1.043)	(1.100)	(1.567)	(1.288)
Intercept	−0.8549***	−1.7008***	−0.0325	−1.0732***	−1.6278***	−1.2956***	−1.4669***	0.1241	−0.0156
	(0.219)	(0.194)	(0.220)	(0.134)	(0.351)	(0.196)	(0.152)	(0.123)	(0.151)
R-squared	0.0970	0.1535	0.1788	0.3325	0.2401	0.2762	0.2090	0.1468	0.1453
Observations	290	464	319	290	290	464	464	319	319
II. Real Gross Output									
Computerization Intensity	−0.2164	−0.4480	1.1006**	−0.2379	−0.2638	−0.1835	0.0867	0.7413	1.6660**
	(0.341)	(0.420)	(0.535)	(0.546)	(0.474)	(0.482)	(0.334)	(0.628)	(0.625)
Real Gross Output	0.5081	−1.6000	−0.2137	0.5530	1.2876	−0.2689	0.5726	−1.0913	0.5950
	(1.127)	(1.248)	(1.614)	(1.011)	(1.323)	(1.199)	(1.218)	(1.563)	(1.517)
Intercept	−0.8545***	−1.7009***	−0.1135	−1.0748***	−1.6454***	−1.3216***	−1.4735***	0.0937	−0.0087
	(0.217)	(0.209)	(0.220)	(0.133)	(0.359)	(0.203)	(0.165)	(0.119)	(0.142)
R-squared	0.0968	0.1535	0.1808	0.3323	0.2395	0.2757	0.2090	0.1478	0.1452
Observations	290	464	319	290	290	464	464	319	319
Weight by Employment				yes		yes		yes	
Weight by Real Gross Output					yes		yes		yes
Industry Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Computerization assets are measured by real fixed capital stocks at 2005 prices from the EU KLEMS Growth and Productivity Accounts from 1970 to 2005. The two computerization intensity variables are measured by (i) computerization divided by total number of employees for computerization-employment intensity in the upper panel and (ii) computerization divided by real gross output for computerization-output intensity in the bottom panel. Specification I in the upper panel uses computerization-employment intensity and specification II in the bottom panel uses computerization-output intensity. Based on three different time periods; 1970-1980, 1980-1995, and 1995-2005, all estimations used two-way fixed effect regressions without weights and with two weights of total number of employees and real gross output.

Table 3.14: Computerization Impact on Demand Shifts Measured by Wage Bill Share for Low-Skilled Workers: 1970-2005

Variables	Fixed-Effect Regression			Fixed-Effect Regression with Weights					
	70-80	80-95	95-05	70-80	70-80	80-95	80-95	95-05	95-05
I. Total Number of Employment									
Computerization Intensity	−0.5345	−1.0728*	0.7593	−0.2978	−0.4960	−0.7832	−0.4164	0.5352	1.6197**
	(0.433)	(0.555)	(0.613)	(0.622)	(0.479)	(0.510)	(0.449)	(0.707)	(0.716)
Real Gross Output	2.1710*	−1.4896	0.4499	3.4434***	3.1984**	0.1053	0.9151	−0.6399	0.0927
	(1.167)	(1.431)	(1.338)	(1.170)	(1.214)	(1.299)	(1.402)	(1.435)	(1.045)
Intercept	−0.9476***	−1.8045***	−0.1335	−0.9402***	−1.3774***	−1.2148***	−1.5529***	−0.0034	−0.1588
	(0.193)	(0.227)	(0.181)	(0.157)	(0.336)	(0.218)	(0.200)	(0.101)	(0.120)
R-squared	0.1500	0.2146	0.1323	0.3406	0.2839	0.2742	0.2376	0.1359	0.1295
Observations	290	464	319	290	290	464	464	319	319
II. Real Gross Output									
Computerization Intensity	−0.6167	−1.1787	1.5222***	−0.3298	−0.3137	−0.5593	−0.4079	0.9551*	1.7081***
	(0.431)	(0.744)	(0.384)	(0.608)	(0.576)	(0.536)	(0.536)	(0.559)	(0.493)
Real Gross Output	1.7389	−2.2538	1.4723	3.2228**	3.0695**	−0.1353	0.6592	−0.1501	1.2355
	(1.209)	(1.701)	(1.373)	(1.339)	(1.297)	(1.497)	(1.636)	(1.332)	(1.190)
Intercept	−0.9347***	−1.7772***	−0.2403	−0.9359***	−1.4018***	−1.2548***	−1.5509***	−0.0570	−0.1778*
	(0.186)	(0.215)	(0.162)	(0.155)	(0.345)	(0.215)	(0.193)	(0.090)	(0.098)
R-squared	0.1505	0.2158	0.1358	0.3407	0.2830	0.2724	0.2376	0.1379	0.1318
Observations	290	464	319	290	290	464	464	319	319
Weight by Employment				yes		yes		yes	
Weight by Real Gross Output					yes		yes		yes
Industry Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Computerization for information and communication technology is measured by real fixed capital stocks at 2005 prices from the EU KLEMS Growth and Productivity Accounts from 1970 to 2005. The two computerization intensity variables are measured by (i) computerization divided by the total number of employees for computerization-employment intensity in the upper panel and (ii) computerization divided by the real gross output for computerization-output intensity in the bottom panel. Specification I in the upper panel uses computerization-employment intensity, and specification II in the bottom panel uses computerization-output intensity. Based on three different time periods; 1970-1980, 1980-1995, and 1995-2005, all estimations used two-way fixed effect regressions without weights and with the two weights of the total number of employees and the real gross output.

average, in the routine tasks (routine cognitive tasks and routine manual tasks) to move toward nonroutine cognitive tasks and nonroutine manual tasks. In addition, the decreasing price of computerization assets increases relative demand for production inputs of routine tasks to nonroutine tasks, so cheaper computerization assets replace middle-skilled workers for routine tasks. Therefore, strong investments in computer-based technology across industries in the late 1990s led to increased productivity growth across industries; employment polarization with increasing demand shifts for high-skilled workers and low-skilled workers and decreasing demand shifts for middle-skilled workers; and diverged evolutions of wage inequalities between top-half wage distribution and bottom-half wage distribution in U.S. labor market.

3.4 Concluding Remarks

In the late 1990s, a strong increase in U.S. productivity and divergent wage inequalities emerged between upper-tail wage distribution and lower-tail wage distribution across industries. For the U.S. productivity revival, Stiroh (2002) shows that strong investments in computer-related assets brought sharp increases in productivity growth over industries in the late 1990s. Also, associated with two phenomena in the U.S. labor market - polarization trends in employment and wage structure - Autor, Katz, and Kearney (2006) argue that heterogeneous demand shifts for different skill-types of workers, due to the decreasing price of computer-related capital, are key factors in the new wage structure such as a secular rise in top-half wage inequality and compression in bottom-half wage inequality over the total economy during the last 15 years.

This paper documents, first, the stylized facts of polarization trends in employment, based on growth rates of employment shares for three different types of skilled workers across industries, and divergent wage evolution between the top-half and the bottom-half wage distribution by industry level. Then, to discover the mechanism beneath these labor market observations, combined theoretical framework, which is built on the theoretical frameworks in Autor, Katz, and Kearney (2006) and Autor, Levy and Murnane (2003), shows how rapid adoptions of computerization affect the demand shifts for three different skill-types of workers and how these demand shifts are accompanied by wage polarization trends in the wage differentials of upper-tail and lower-tail wage distribution.

Based on the integrated theoretical framework, empirical analysis in this paper provides the empirical evidence that strong investment in computer-related technology is a driving force for large increases in productivity growth and employment polarization pattern with divergent wage inequality in the U.S. labor market. That is, as predicted in the theoretical framework, due to increasing computerization, middle-skilled workers have been replaced from routine tasks, so that two measurements of demand shifts, employment share and wage bill share, of high-skilled workers for nonroutine cognitive tasks and of low-skilled workers for nonroutine manual tasks have increased, while demand shifts for middle-skilled workers have decreased. These heterogeneous demand changes for different types of skilled workers explain the polarization patterns in employment and in wage inequality: increasing wage inequality in the upper-tail wage distribution and decreasing wage inequality in the lower-tail wage distribution in the U.S. labor market.

3.5 Appendix

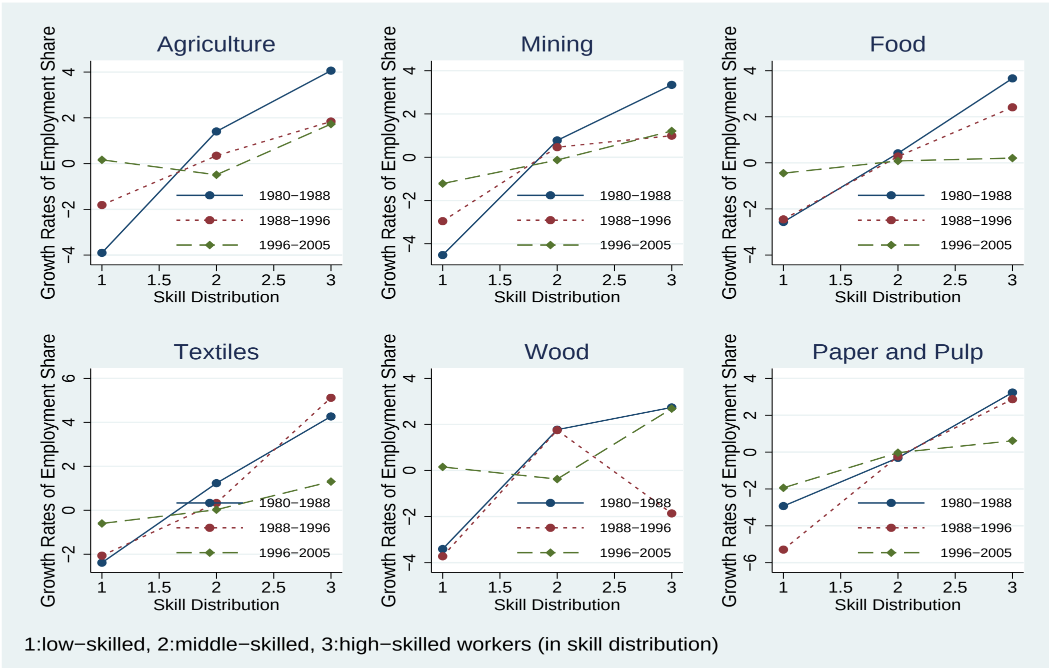

Figure 3.17: Annual Growth Rates of Employment Share among Three Types of Workers I

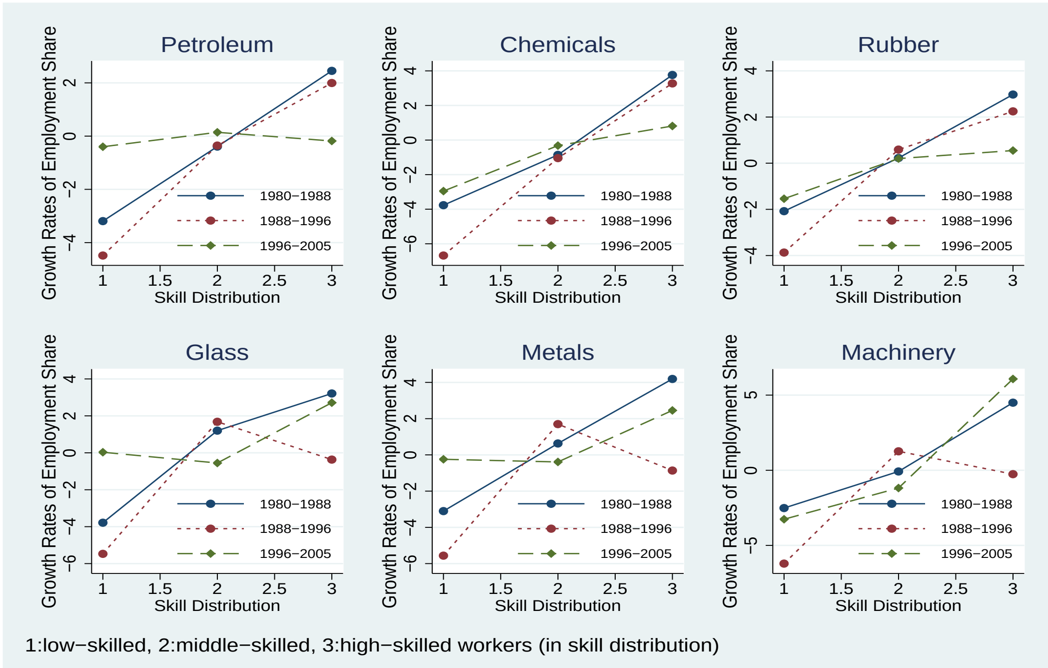

Figure 3.18: Annual Growth Rates of Employment Share among Three Types of Workers II

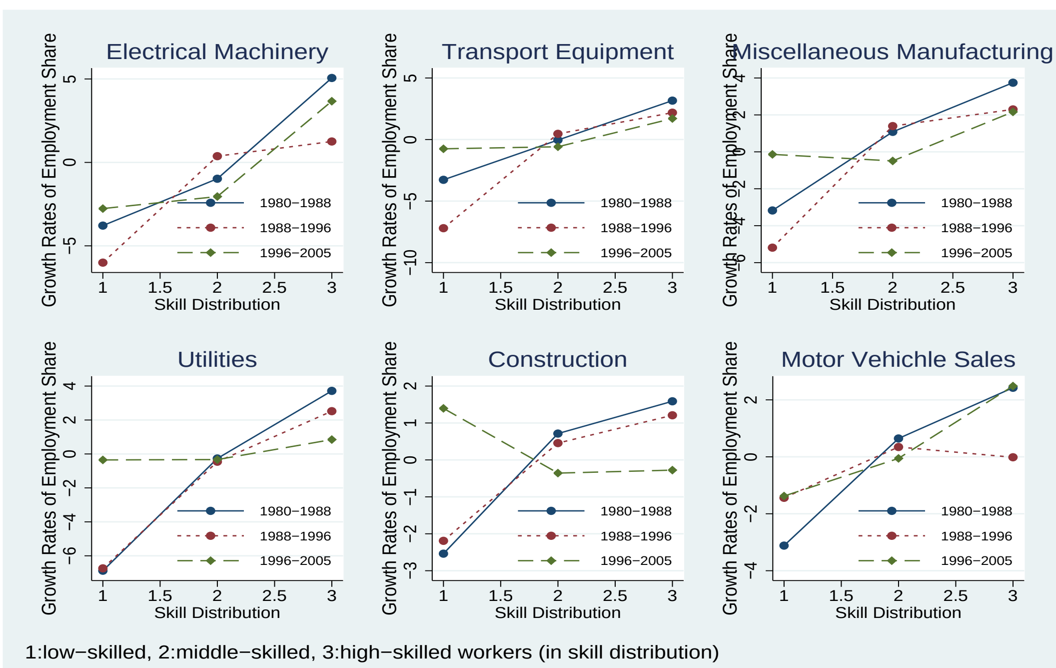

Figure 3.19: Annual Growth Rates of Employment Share among Three Types of Workers III

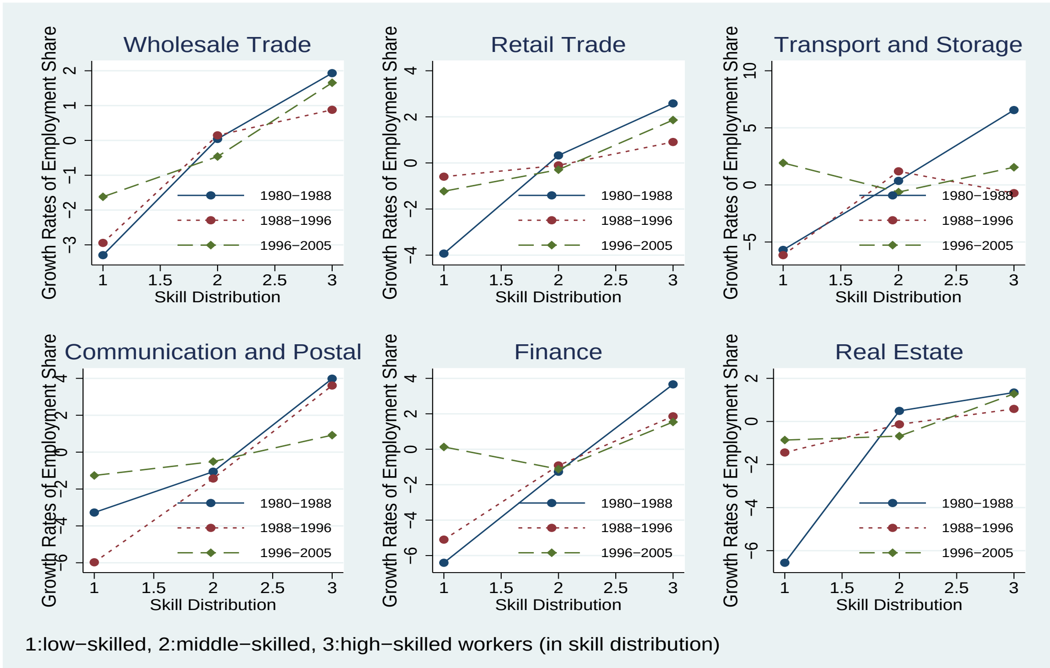

Figure 3.20: Annual Growth Rates of Employment Share among Three Types of Workers IV

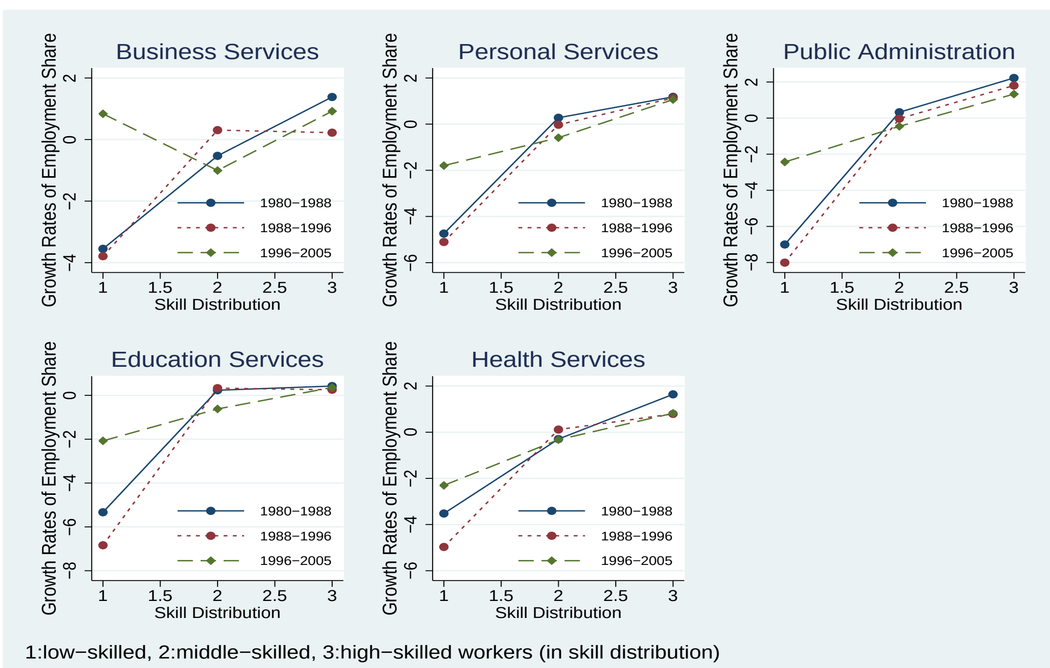

Figure 3.21: Annual Growth Rates of Employment Share among Three Types of Workers V

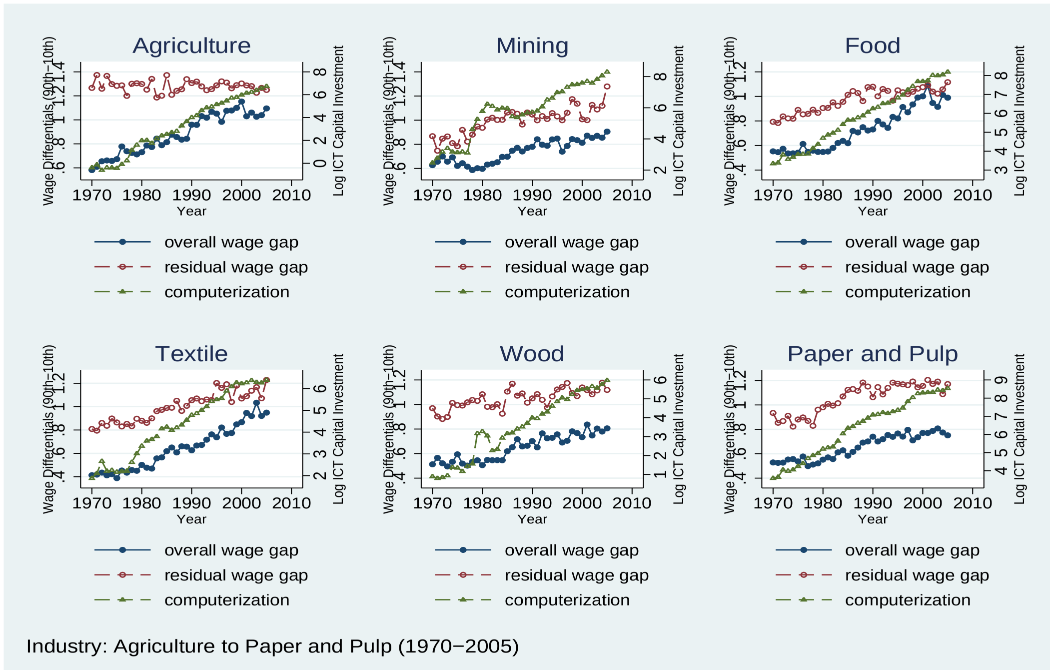

Figure 3.22: Trends in Information and Communication Technology and Wage Differentials I

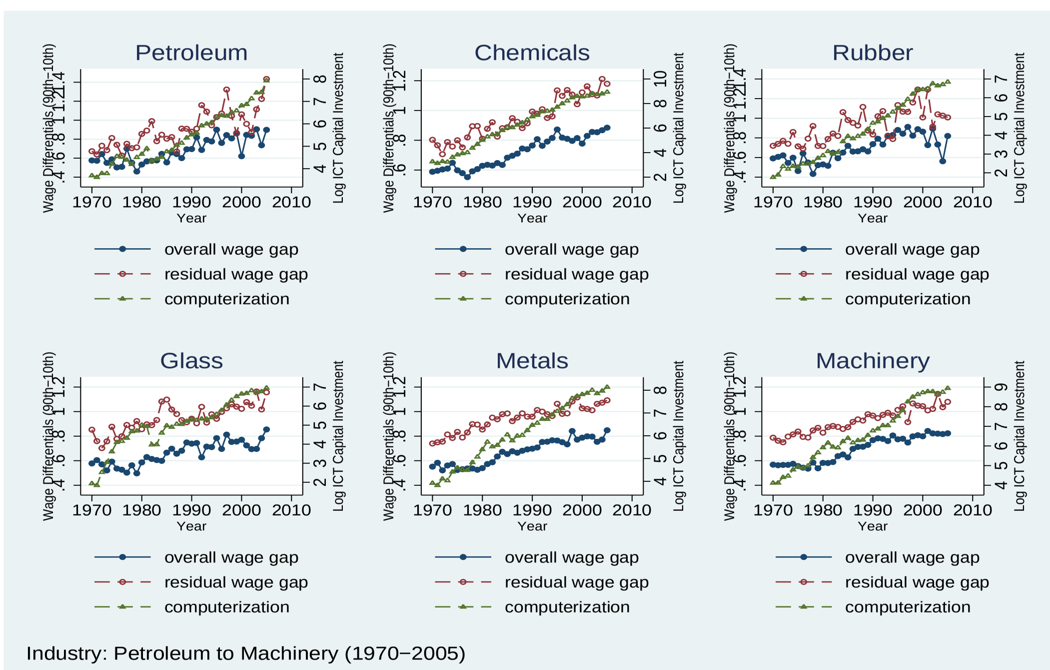

Figure 3.23: Trends in Information and Communication Technology and Wage Differentials II

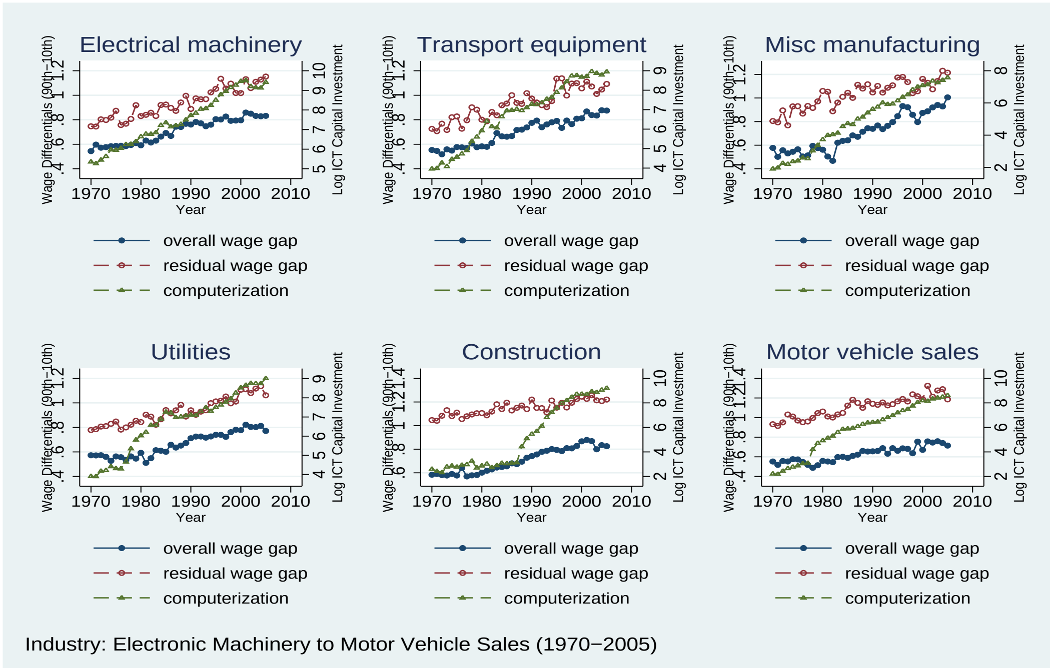

Figure 3.24: Trends in Information and Communication Technology and Wage Differentials III

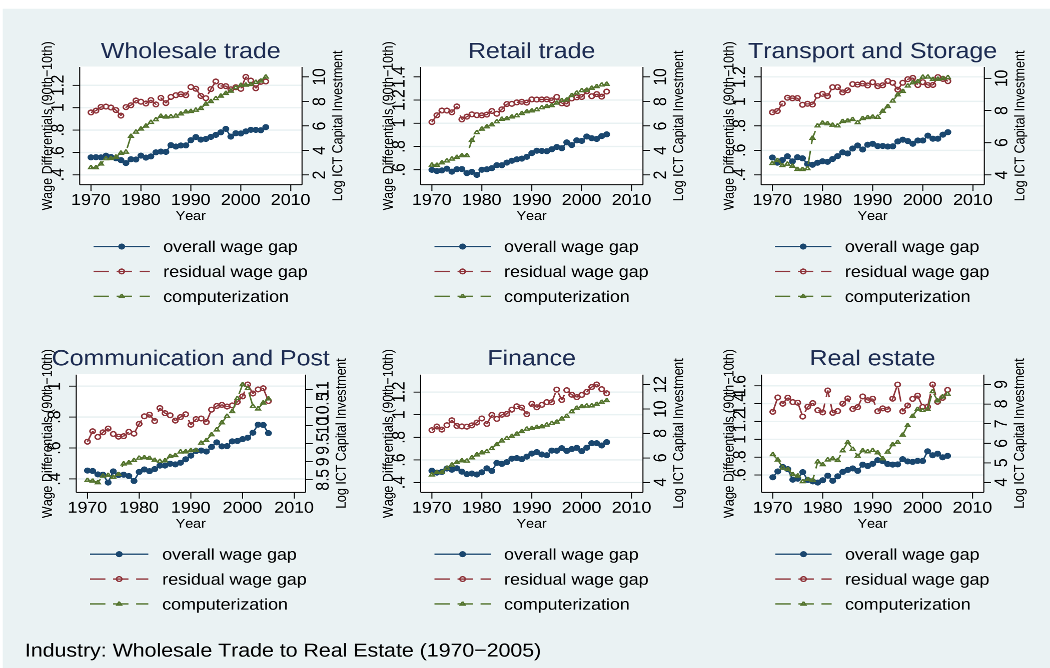

Figure 3.25: Trends in Information and Communication Technology and Wage Differentials IV

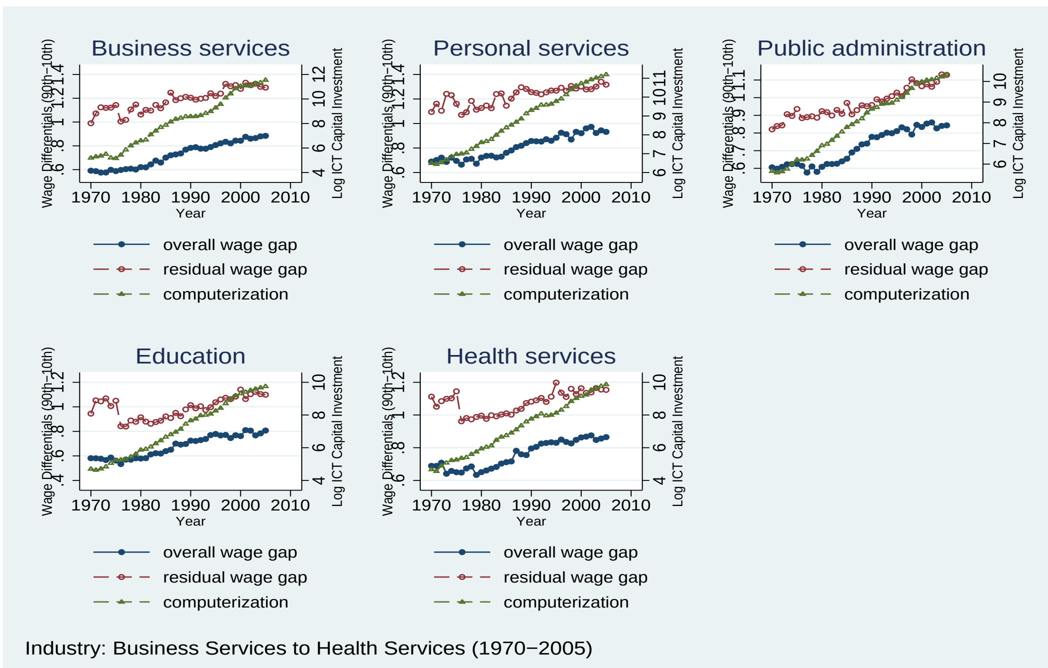

Figure 3.26: Trends in Information and Communication Technology and Wage Differentials V

Table 3.15: Labor Productivity Growth Rates and Differences Focusing on Period Prior to 1995 and Post-1995 Period at Industry Level

Industry	Annualized Growth Rates				Differences	
	1970-1995	1995-2000	2000-2005	1995-2005	1970-2000†	1970-2005‡
Agriculture, Hunting, Forestry, and Fishing	0.0112	0.0044	0.0254	0.0149	−0.0067	0.0038
Mining and Quarrying	0.0023	0.0280	−0.0088	0.0096	0.0258	0.0074
Food, Beverages and Tobacco	0.0230	0.0152	0.0185	0.0168	−0.0078	−0.0061
Textiles, Textile, Leather and Footwear	0.0304	0.0533	0.0180	0.0357	0.0230	0.0053
Wood and of Wood and Cork	0.0174	−0.0086	0.0109	0.0012	−0.0260	−0.0163
Pulp, Paper, Printing and Publishing	0.0132	0.0181	0.0197	0.0189	0.0049	0.0057
Coke, Refined Petroleum and Nuclear Fuel	0.0239	0.0403	0.0133	0.0268	0.0164	0.0029
Chemicals and Chemical Products	0.0208	0.0220	0.0228	0.0224	0.0012	0.0016
Rubber and Plastics	0.0265	0.0271	0.0290	0.0281	0.0005	0.0015
Other Non-Metallic Mineral	0.0166	0.0411	0.0231	0.0321	0.0245	0.0156
Basic Metals and Fabricated Metal	0.0157	0.0352	0.0226	0.0289	0.0195	0.0132
Machinery, Nec	0.0162	0.0349	0.0508	0.0428	0.0187	0.0267
Electrical and Optical Equipment	0.0755	0.1593	0.0627	0.1110	0.0838	0.0355
Transport Equipment	0.0254	0.0530	0.0375	0.0452	0.0276	0.0198
Manufacturing, Nec and Recycling	0.0190	0.0432	0.0464	0.0448	0.0242	0.0258
Electricity, Gas and Water Supply	0.0029	0.0332	−0.0003	0.0164	0.0303	0.0135
Construction	−0.0059	−0.0079	0.0017	−0.0031	−0.0020	0.0028
Sales and Maintenance of Motor Vehicles and Motorcycles	0.0178	0.0328	0.0337	0.0332	0.0151	0.0155
Wholesale Trade and Commission Trade	0.0289	0.0228	0.0244	0.0236	−0.0061	−0.0053
Retail Trade, except of Motor Vehicles and Motorcycles	0.0028	0.0282	0.0436	0.0359	0.0254	0.0331
Transport and Storage	0.0138	−0.0016	0.0219	0.0101	−0.0154	−0.0036
Post and Communication	0.0441	0.0156	0.0911	0.0534	−0.0284	0.0093
Financial Intermediation	0.0264	0.0558	0.0118	0.0338	0.0294	0.0074
Real Estate Activities	0.0064	0.0045	0.0214	0.0130	−0.0019	0.0065
Renting and Other Business Activities	−0.0171	0.0080	0.0257	0.0168	0.0251	0.0339
Community Social and Personal Services	0.0054	0.0069	0.0046	0.0057	0.0014	0.0003
Public Administration, Defense, Compulsory Social Security	0.0093	0.0078	−0.0034	0.0022	−0.0015	−0.0071
Education	0.0039	0.0026	0.0026	0.0026	−0.0013	−0.0013
Health and Social Work	−0.0052	0.0121	0.0160	0.0140	0.0173	0.0192
Mean	0.0162	0.0272	0.0237	0.0254	0.0109	0.0092
Median	0.0162	0.0228	0.0219	0.0224	0.0151	0.0065
Standard Deviation	0.0171	0.0312	0.0209	0.0220	0.0217	0.0130

Labor productivity is defined as real gross output divided by the total numbers of employees from 1970 to 2005 using data from EU KLEMS Growth and Productivity Accounts. †Differences for 1970-2000 are calculated using the annualized growth rate for 1995-2000 minus the growth rate for 1970-1995. ‡Similarly, differences for 1970-2005 are measured by the growth rate for 1995-2005 minus the growth rate for 1970-1995.

Table 3.16: Growth Rates of Computerization and Differences Focusing on Period Prior to 1995 and Post-1995 Period at Industry Level

Industry	Annualized Growth Rates				Differences	
	1970-1995	1995-2000	2000-2005	1995-2005	1970-2000†	1970-2005‡
Agriculture, Hunting, Forestry, and Fishing	0.2214	0.1665	0.1503	0.1584	−0.0549	−0.0630
Mining and Quarrying	0.1808	0.1223	0.1407	0.1315	−0.0585	−0.0493
Food, Beverages and Tobacco	0.1394	0.1734	0.0996	0.1365	0.0340	−0.0029
Textiles, Textile, Leather and Footwear	0.1445	0.1464	0.0331	0.0897	0.0019	−0.0548
Wood and of Wood and Cork	0.1587	0.1271	0.0970	0.1121	−0.0316	−0.0467
Pulp, Paper, Printing and Publishing	0.1500	0.1906	0.0482	0.1194	0.0406	−0.0306
Coke, Refined Petroleum and Nuclear Fuel	0.1050	0.0987	0.2228	0.1608	−0.0063	0.0558
Chemicals and Chemical Products	0.1782	0.1678	0.0758	0.1218	−0.0103	−0.0564
Rubber and Plastics	0.1469	0.2006	0.0802	0.1404	0.0537	−0.0065
Other Non-Metallic Mineral	0.1455	0.2139	0.0626	0.1383	0.0684	−0.0072
Basic Metals and Fabricated Metal	0.1263	0.1478	0.0637	0.1057	0.0216	−0.0205
Machinery, Nec	0.1359	0.2410	0.0439	0.1424	0.1050	0.0065
Electrical and Optical Equipment	0.1260	0.1922	−0.0103	0.0909	0.0662	−0.0350
Transport Equipment	0.1576	0.1555	0.0542	0.1048	−0.0021	−0.0528
Manufacturing, Nec and Recycling	0.1695	0.1887	0.0966	0.1427	0.0192	−0.0269
Electricity, Gas and Water Supply	0.1442	0.2035	0.0969	0.1502	0.0592	0.0060
Construction	0.2001	0.2253	0.0969	0.1611	0.0252	−0.0390
Sales and Maintenance of Motor Vehicles and Motorcycles	0.1998	0.1971	0.0842	0.1407	−0.0026	−0.0591
Wholesale Trade and Commission Trade	0.2254	0.2159	0.1355	0.1757	−0.0095	−0.0497
Retail Trade, except of Motor Vehicles and Motorcycles	0.2026	0.2025	0.1052	0.1539	−0.0001	−0.0487
Transport and Storage	0.1706	0.2193	−0.0047	0.1073	0.0487	−0.0633
Post and Communication	0.0560	0.2507	−0.0786	0.0861	0.1947	0.0301
Financial Intermediation	0.1725	0.2522	0.0980	0.1751	0.0797	0.0026
Real Estate Activities	0.0249	0.3248	0.1673	0.2460	0.2999	0.2211
Renting and Other Business Activities	0.1637	0.3517	0.0991	0.2254	0.1879	0.0617
Community Social and Personal Services	0.1315	0.1892	0.0941	0.1417	0.0577	0.0102
Public Administration, Defense, Compulsory Social Security	0.1377	0.1760	0.0702	0.1231	0.0382	−0.0146
Education	0.1423	0.2116	0.0871	0.1493	0.0693	0.0070
Health and Social Work	0.1385	0.2046	0.1430	0.1738	0.0661	0.0353
Mean	0.1516	0.1985	0.0846	0.1415	0.0469	−0.0100
Median	0.1469	0.1971	0.0941	0.1407	0.0382	−0.0205
Standard Deviation	0.0425	0.0535	0.0575	0.0363	0.0757	0.0568

Computerization is defined as three capital investments associated with computer-based technology, computing equipment, software and communication equipment for 1970 to 2005 using data from EU KLEMS Growth and Productivity Accounts. †Differences for 1970-2000 are calculated by annualized growth rate for 1995-2000 minus the growth rate for 1970-1995. ‡Similarly, differences for 1970-2005 are measured by growth rate for 1995-2005 minus the growth rate of 1970-1995.

Table 3.17: Descriptive Statistics by Industry from EU KLEMS Accounts I: 1970-2005

Agriculture	Observations	Mean	Std. Dev.	Min	Max
Computerization Stocks	36	402.27	601.34	1.02	2205.42
Computerization Investment	36	151.64	226.86	0.55	847.11
High-Skilled Employment Share	36	11.08	4.10	3.03	17.10
Middle-Skilled Employment Share	36	55.34	7.65	36.04	64.44
Low-Skilled Employment Share	36	33.57	11.55	21.79	60.90
High-Skilled Wage Share	36	17.68	6.32	5.89	27.40
Middle-Skilled Wage Share	36	55.31	5.14	45.21	64.40
Low-Skilled Wage Share	36	27.01	10.86	12.45	48.89
Numbers of Employees	36	1915.89	232.76	1535.00	2341.00
Real Gross Output	36	272347.97	64929.28	179905.25	400809.88
Mining	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Computerization Stocks	36	2405.43	2605.62	25.11	9844.86
Computerization Investment	36	828.70	1007.10	11.84	4052.76
High-Skilled Employment Share	36	17.34	3.97	9.37	23.56
Middle-Skilled Employment Share	36	59.91	6.04	44.53	69.63
Low-Skilled Employment Share	36	22.76	9.53	11.72	46.10
High-Skilled Wage Share	36	26.17	5.41	17.02	34.09
Middle-Skilled Wage Share	36	54.11	6.49	37.77	66.25
Low-Skilled Wage Share	36	19.72	10.73	6.69	42.29
Numbers of Employees	36	722.00	175.64	533.00	1160.00
Real Gross Output	36	173996.45	6877.45	164107.45	191955.45
Food	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Computerization Stocks	36	2392.69	2940.10	72.77	10143.04
Computerization Investment	36	854.08	1062.87	28.37	3620.44
High-Skilled Employment Share	36	12.72	3.76	5.91	18.40
Middle-Skilled Employment Share	36	59.57	5.03	47.83	65.31
Low-Skilled Employment Share	36	27.71	8.58	18.94	46.25
High-Skilled Wage Share	36	20.41	6.93	9.56	31.37
Middle-Skilled Wage Share	36	57.80	3.20	49.67	62.41
Low-Skilled Wage Share	36	21.79	8.81	12.41	40.77
Numbers of Employees	36	1751.67	64.00	1647.00	1909.00
Real Gross Output	36	402167.91	69413.30	284491.78	515913.03
Textiles	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Computerization Stocks	36	552.04	620.68	14.70	1857.48
Computerization Investment	36	184.67	208.17	6.60	599.96
High-Skilled Employment Share	36	7.80	3.45	2.81	13.97
Middle-Skilled Employment Share	36	52.32	8.04	35.66	61.25
Low-Skilled Employment Share	36	39.88	11.07	28.82	61.53
High-Skilled Wage Share	36	15.79	7.50	5.43	28.68
Middle-Skilled Wage Share	36	51.66	6.25	38.70	59.51
Low-Skilled Wage Share	36	32.55	12.66	18.56	55.88
Numbers of Employees	36	1921.06	578.04	734.00	2747.00
Real Gross Output	36	138955.56	16631.89	99036.40	165079.25

Table 3.18: Descriptive Statistics by Industry from EU KLEMS Accounts II: 1970-2005

Wood	Observations	Mean	Std. Dev.	Min	Max
Computerization Stocks	36	251.30	308.69	6.45	1046.61
Computerization Investment	36	91.09	110.86	2.24	396.93
High-Skilled Employment Share	36	6.97	1.70	3.41	9.24
Middle-Skilled Employment Share	36	58.71	10.16	37.88	69.81
Low-Skilled Employment Share	36	34.32	11.66	22.33	58.11
High-Skilled Wage Share	36	11.48	3.85	4.57	18.17
Middle-Skilled Wage Share	36	58.70	9.11	43.01	69.38
Low-Skilled Wage Share	36	29.82	12.65	15.42	52.42
Numbers of Employees	36	744.53	64.03	570.00	857.00
Real Gross Output	36	97001.81	15866.11	66081.40	118995.03
Paper and Pulp	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Computerization Stocks	36	4172.28	4796.67	86.99	15500.91
Computerization Investment	36	1438.65	1629.18	36.44	5106.32
High-Skilled Employment Share	36	21.60	6.96	8.76	32.26
Middle-Skilled Employment Share	36	62.03	2.51	55.20	65.92
Low-Skilled Employment Share	36	16.36	8.41	7.78	36.04
High-Skilled Wage Share	36	28.96	9.18	12.53	42.77
Middle-Skilled Wage Share	36	57.92	2.83	52.37	62.84
Low-Skilled Wage Share	36	13.12	7.97	4.85	31.52
Numbers of Employees	36	2043.72	196.69	1730.00	2294.00
Real Gross Output	36	311027.47	56370.47	205902.64	386600.50
Petroleum	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Computerization Stocks	36	1138.03	1361.07	85.47	5796.93
Computerization Investment	36	443.91	589.15	37.46	2776.61
High-Skilled Employment Share	36	25.46	5.43	15.62	33.48
Middle-Skilled Employment Share	36	62.59	1.41	59.50	65.80
Low-Skilled Employment Share	36	11.95	5.35	6.68	23.20
High-Skilled Wage Share	36	33.95	7.59	20.65	45.01
Middle-Skilled Wage Share	36	56.41	2.51	51.34	60.39
Low-Skilled Wage Share	36	9.64	5.71	3.56	20.89
Numbers of Employees	36	162.89	28.87	115.00	205.00
Real Gross Output	36	145056.42	16990.20	112337.91	173316.91
Chemicals	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Computerization Stocks	36	5185.13	6728.02	63.14	21416.63
Computerization Investment	36	1918.81	2436.89	23.09	7654.83
High-Skilled Employment Share	36	31.11	8.51	20.18	45.30
Middle-Skilled Employment Share	36	55.67	3.17	49.18	60.86
Low-Skilled Employment Share	36	13.22	6.58	5.43	26.13
High-Skilled Wage Share	36	41.81	10.84	26.90	59.81
Middle-Skilled Wage Share	36	48.30	5.57	37.43	55.26
Low-Skilled Wage Share	36	9.89	6.17	2.76	22.61
Numbers of Employees	36	1041.39	46.65	930.00	1117.00
Real Gross Output	36	318077.28	57998.66	206957.17	416880.19

Table 3.19: Descriptive Statistics by Industry from EU KLEMS Accounts III: 1970-2005

Rubber	Observations	Mean	Std. Dev.	Min	Max
Computerization Stocks	36	585.82	799.02	12.40	2638.50
Computerization Investment	36	219.89	294.64	5.87	940.54
High-Skilled Employment Share	36	11.42	3.15	5.00	16.47
Middle-Skilled Employment Share	36	66.59	3.93	59.35	71.58
Low-Skilled Employment Share	36	21.99	6.95	13.60	35.65
High-Skilled Wage Share	36	18.03	5.99	5.52	27.34
Middle-Skilled Wage Share	36	64.19	2.16	60.43	67.27
Low-Skilled Wage Share	36	17.78	7.60	8.63	32.42
Numbers of Employees	36	834.92	114.74	625.00	1018.00
Real Gross Output	36	107394.46	41114.08	47372.75	169259.17
Glasses	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Computerization Stocks	36	831.81	860.67	16.08	2985.10
Computerization Investment	36	285.85	303.73	6.31	1051.35
High-Skilled Employment Share	36	11.07	3.12	5.03	15.87
Middle-Skilled Employment Share	36	61.49	8.94	42.76	71.80
Low-Skilled Employment Share	36	27.43	11.85	15.15	51.90
High-Skilled Wage Share	36	16.70	5.54	5.95	25.32
Middle-Skilled Wage Share	36	59.65	6.82	46.36	68.90
Low-Skilled Wage Share	36	23.65	12.05	10.01	47.70
Numbers of Employees	36	577.22	45.29	514.00	679.00
Real Gross Output	36	75286.34	13900.40	57259.54	104050.16
Metals	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Computerization Stocks	36	2724.68	2931.86	118.59	9608.21
Computerization Investment	36	943.21	1030.36	45.89	3421.39
High-Skilled Employment Share	36	10.46	2.61	5.54	14.39
Middle-Skilled Employment Share	36	64.22	7.68	48.27	73.44
Low-Skilled Employment Share	36	25.32	10.07	14.23	45.25
High-Skilled Wage Share	36	16.22	4.06	9.56	23.30
Middle-Skilled Wage Share	36	62.85	6.43	47.23	71.80
Low-Skilled Wage Share	36	20.93	10.01	9.14	41.58
Numbers of Employees	36	2294.23	339.83	1779.79	2913.74
Real Gross Output	36	355139.66	46204.03	280384.09	452344.09
Machinery	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Computerization Stocks	36	5370.03	6713.51	139.56	21287.38
Computerization Investment	36	1927.65	2436.48	61.62	7663.29
High-Skilled Employment Share	36	13.53	4.70	6.87	25.59
Middle-Skilled Employment Share	36	68.35	5.07	56.15	75.10
Low-Skilled Employment Share	36	18.11	8.65	7.19	36.98
High-Skilled Wage Share	36	20.32	7.11	10.94	38.20
Middle-Skilled Wage Share	36	64.87	4.10	55.81	71.64
Low-Skilled Wage Share	36	14.81	8.32	4.56	33.03
Numbers of Employees	36	1815.66	221.20	1329.63	2281.59
Real Gross Output	36	242071.91	39316.44	179577.45	327567.22

Table 3.20: Descriptive Statistics by Industry from EU KLEMS Accounts IV: 1970-2005

Electrical Machinery	Observations	Mean	Std. Dev.	Min	Max
Computerization Stocks	36	11579.48	12236.59	1073.96	36371.76
Computerization Investment	36	3832.36	4287.17	194.56	13531.86
High-Skilled Employment Share	36	26.29	8.68	13.29	43.88
Middle-Skilled Employment Share	36	59.58	3.16	50.45	64.55
Low-Skilled Employment Share	36	14.13	7.25	5.67	29.61
High-Skilled Wage Share	36	37.64	11.25	20.79	57.48
Middle-Skilled Wage Share	36	51.89	5.27	39.65	58.89
Low-Skilled Wage Share	36	10.46	6.77	2.78	24.25
Numbers of Employees	36	2842.15	321.83	2261.84	3359.49
Real Gross Output	36	456478.00	410678.72	73749.98	$1.34e{+}06$
Transport Equipment	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Computerization Stocks	36	6483.67	7586.15	120.54	23303.28
Computerization Investment	36	2297.01	2633.45	52.64	7856.29
High-Skilled Employment Share	36	19.43	6.11	9.35	29.11
Middle-Skilled Employment Share	36	63.66	3.12	55.28	68.11
Low-Skilled Employment Share	36	16.91	8.58	7.18	35.26
High-Skilled Wage Share	36	28.32	9.02	15.11	45.86
Middle-Skilled Wage Share	36	58.53	3.20	50.00	62.98
Low-Skilled Wage Share	36	13.15	7.91	3.93	29.53
Numbers of Employees	36	1839.54	128.85	1592.27	2067.00
Real Gross Output	36	419612.81	123256.38	247819.78	649173.75
Miscellaneous Manufacturing	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Computerization Stocks	36	1194.04	1528.64	14.77	5245.22
Computerization Investment	36	440.74	565.03	6.77	1951.35
High-Skilled Employment Share	36	11.62	3.65	5.84	17.71
Middle-Skilled Employment Share	36	57.72	8.06	39.01	66.93
Low-Skilled Employment Share	36	30.66	11.56	17.79	55.15
High-Skilled Wage Share	36	19.52	6.63	9.52	30.72
Middle-Skilled Wage Share	36	55.19	6.22	41.06	62.28
Low-Skilled Wage Share	36	25.29	12.50	11.21	49.41
Numbers of Employees	36	897.19	43.85	816.00	967.00
Real Gross Output	36	92868.09	24304.51	61012.77	143601.48
Utilities	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Computerization Stocks	36	6171.89	6214.58	161.07	22407.31
Computerization Investment	36	1916.90	2224.43	49.30	8221.18
High-Skilled Employment Share	36	20.82	6.80	8.27	32.18
Middle-Skilled Employment Share	36	70.40	2.70	64.90	75.22
Low-Skilled Employment Share	36	8.78	6.17	2.92	23.50
High-Skilled Wage Share	36	26.16	8.71	11.15	42.90
Middle-Skilled Wage Share	36	66.26	4.38	54.98	72.44
Low-Skilled Wage Share	36	7.58	5.89	2.01	21.22
Numbers of Employees	36	816.28	72.19	682.35	939.74
Real Gross Output	36	289008.06	23819.41	226872.53	320800.09

Table 3.21: Descriptive Statistics by Industry from EU KLEMS Accounts V: 1970-2005

Construction	Observations	Mean	Std. Dev.	Min	Max
Computerization Stocks	36	5148.65	8680.00	30.21	29357.11
Computerization Investment	36	1916.33	3001.68	10.23	10012.18
High-Skilled Employment Share	36	9.30	2.33	3.74	12.16
Middle-Skilled Employment Share	36	64.45	6.73	44.59	71.44
Low-Skilled Employment Share	36	26.25	8.97	17.92	51.68
High-Skilled Wage Share	36	12.79	3.86	5.04	18.75
Middle-Skilled Wage Share	36	64.71	6.30	46.79	71.44
Low-Skilled Wage Share	36	22.50	9.95	12.63	48.13
Numbers of Employees	36	5145.17	1148.56	3675.00	7540.00
Real Gross Output	36	708633.19	117094.73	521879.88	962976.88
Motor Vehicle Sales	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Computerization Stocks	36	3620.23	4673.57	36.34	16322.52
Computerization Investment	36	1229.40	1612.75	8.89	5523.62
High-Skilled Employment Share	36	8.19	1.95	4.35	11.41
Middle-Skilled Employment Share	36	71.16	4.07	60.50	76.75
Low-Skilled Employment Share	36	20.65	5.86	14.41	34.63
High-Skilled Wage Share	36	10.70	3.22	5.70	16.99
Middle-Skilled Wage Share	36	71.21	3.50	63.37	76.48
Low-Skilled Wage Share	36	18.08	6.37	10.52	30.22
Numbers of Employees	36	1856.40	557.66	1054.15	2703.87
Real Gross Output	36	145232.17	61328.54	70143.05	280713.84
Wholesale Trade	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Computerization Stocks	36	10454.90	14865.02	27.98	55528.49
Computerization Investment	36	3765.78	5506.87	13.45	22002.81
High-Skilled Employment Share	36	22.65	4.89	12.02	29.74
Middle-Skilled Employment Share	36	63.76	1.78	60.33	66.39
Low-Skilled Employment Share	36	13.59	5.61	7.78	26.58
High-Skilled Wage Share	36	31.85	7.55	16.46	44.30
Middle-Skilled Wage Share	36	58.07	3.07	50.19	63.22
Low-Skilled Wage Share	36	10.08	5.48	4.32	23.03
Numbers of Employees	36	5800.33	908.78	4089.00	7113.00
Real Gross Output	36	498508.75	209156.38	196513.70	861159.38
Retail Trade	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Computerization Stocks	36	7631.61	9984.16	57.51	36136.12
Computerization Investment	36	2622.37	3529.98	16.42	12262.52
High-Skilled Employment Share	36	14.69	3.74	7.10	20.29
Middle-Skilled Employment Share	36	68.93	3.02	59.57	72.65
Low-Skilled Employment Share	36	16.38	6.26	10.82	33.33
High-Skilled Wage Share	36	21.80	6.54	10.94	34.13
Middle-Skilled Wage Share	36	65.24	2.93	58.91	69.68
Low-Skilled Wage Share	36	12.95	6.01	6.96	29.07
Numbers of Employees	36	11608.53	2187.34	7742.49	14652.30
Real Gross Output	36	445470.38	135389.38	269425.69	783885.56

Table 3.22: Descriptive Statistics by Industry from EU KLEMS Accounts VI: 1970-2005

Transport and Storage	Observations	Mean	Std. Dev.	Min	Max
Computerization Stocks	36	24444.21	32989.21	583.47	105111.69
Computerization Investment	36	6557.37	8579.21	77.31	24146.77
High-Skilled Employment Share	36	13.22	4.51	4.57	18.54
Middle-Skilled Employment Share	36	67.04	5.88	53.53	74.96
Low-Skilled Employment Share	36	19.73	10.18	9.27	41.32
High-Skilled Wage Share	36	17.01	6.25	5.54	26.53
Middle-Skilled Wage Share	36	65.19	4.35	54.59	70.82
Low-Skilled Wage Share	36	17.80	10.08	7.21	38.31
Numbers of Employees	36	3446.33	670.07	2656.00	4589.00
Real Gross Output	36	369753.00	105451.85	220174.91	562097.50

Communications and Postal	Observations	Mean	Std. Dev.	Min	Max
Computerization Stocks	36	92873.82	68886.71	24456.77	237029.31
Computerization Investment	36	18446.36	17005.64	4544.94	68939.44
High-Skilled Employment Share	36	25.39	9.93	7.39	42.04
Middle-Skilled Employment Share	36	70.25	7.80	56.43	82.65
Low-Skilled Employment Share	36	4.37	2.49	1.52	10.99
High-Skilled Wage Share	36	30.91	12.57	11.31	54.38
Middle-Skilled Wage Share	36	65.55	10.67	44.47	79.46
Low-Skilled Wage Share	36	3.54	2.36	0.97	9.88
Numbers of Employees	36	1331.67	140.07	1123.00	1700.00
Real Gross Output	36	241035.94	115704.45	80836.98	512855.19

Finance	Observations	Mean	Std. Dev.	Min	Max
Computerization Stocks	36	23163.96	32182.45	238.95	114714.87
Computerization Investment	36	8979.60	12490.55	103.13	44325.28
High-Skilled Employment Share	36	32.64	8.24	18.23	44.35
Middle-Skilled Employment Share	36	63.72	6.11	53.91	72.24
Low-Skilled Employment Share	36	3.64	2.45	1.31	10.16
High-Skilled Wage Share	36	46.80	10.80	27.16	62.73
Middle-Skilled Wage Share	36	50.60	8.97	36.39	64.38
Low-Skilled Wage Share	36	2.61	2.10	0.72	8.45
Numbers of Employees	36	4938.39	1094.29	2994.00	6462.00
Real Gross Output	36	649491.94	334261.03	223294.50	1.31e+06

Real Estate	Observations	Mean	Std. Dev.	Min	Max
Computerization Stocks	36	3137.36	3685.82	913.66	14674.21
Computerization Investment	36	942.69	1487.32	57.56	5671.66
High-Skilled Employment Share	36	30.34	5.75	17.09	38.12
Middle-Skilled Employment Share	36	58.18	1.44	54.03	61.44
Low-Skilled Employment Share	36	11.48	6.19	5.45	28.88
High-Skilled Wage Share	36	42.13	8.81	25.16	53.99
Middle-Skilled Wage Share	36	50.27	4.17	43.58	57.68
Low-Skilled Wage Share	36	7.60	4.93	2.43	18.99
Numbers of Employees	36	1251.69	290.29	714.00	1750.00
Real Gross Output	36	854906.63	269583.06	439058.94	1.44e+06

Table 3.23: Descriptive Statistics by Industry from EU KLEMS Accounts VI: 1970-2005

Business Services	Observations	Mean	Std. Dev.	Min	Max
Computerization Stocks	36	45771.53	74557.63	562.11	269639.50
Computerization Investment	36	18231.42	29002.40	174.84	103127.28
High-Skilled Employment Share	36	41.12	5.17	30.11	48.57
Middle-Skilled Employment Share	36	49.65	1.75	45.38	53.05
Low-Skilled Employment Share	36	9.22	3.85	5.61	18.70
High-Skilled Wage Share	36	56.23	8.30	41.35	68.09
Middle-Skilled Wage Share	36	38.06	4.83	29.56	46.71
Low-Skilled Wage Share	36	5.71	3.64	2.31	14.05
Numbers of Employees	36	8765.71	4399.81	2893.17	15724.96
Real Gross Output	36	843892.50	408378.63	384378.69	$1.66e{+}06$

Personal Services	Observations	Mean	Std. Dev.	Min	Max
Computerization Stocks	36	49048.04	59345.86	3115.55	210038.75
Computerization Investment	36	17005.80	21450.75	631.64	73238.45
High-Skilled Employment Share	36	34.08	5.06	23.33	41.74
Middle-Skilled Employment Share	36	54.49	1.89	50.69	57.23
Low-Skilled Employment Share	36	11.43	6.20	5.26	25.97
High-Skilled Wage Share	36	47.93	5.34	37.66	56.49
Middle-Skilled Wage Share	36	44.86	1.73	41.02	47.86
Low-Skilled Wage Share	36	7.21	4.65	2.49	18.22
Numbers of Employees	36	37613.84	7453.66	26853.63	51069.46
Real Gross Output	36	$2.07e{+}06$	523577.63	$1.31e{+}06$	$3.03e{+}06$

Public Administration	Observations	Mean	Std. Dev.	Min	Max
Computerization Stocks	36	22680.15	26538.89	1149.94	89850.66
Computerization Investment	36	7905.56	9352.44	268.04	30841.17
High-Skilled Employment Share	36	23.17	5.44	12.18	31.24
Middle-Skilled Employment Share	36	67.04	2.03	62.99	70.17
Low-Skilled Employment Share	36	9.80	6.72	3.08	24.82
High-Skilled Wage Share	36	31.34	5.36	19.56	39.32
Middle-Skilled Wage Share	36	60.90	1.53	58.41	64.29
Low-Skilled Wage Share	36	7.77	5.62	2.10	21.11
Numbers of Employees	36	11517.43	923.03	10015.74	12951.42
Real Gross Output	36	711029.38	111099.64	528321.06	871424.81

Education Services	Observations	Mean	Std. Dev.	Min	Max
Computerization Stocks	36	10599.96	14099.47	445.82	48920.63
Computerization Investment	36	3901.14	5221.46	103.51	17239.86
High-Skilled Employment Share	36	63.99	2.78	58.70	69.02
Middle-Skilled Employment Share	36	29.99	1.19	28.59	33.05
Low-Skilled Employment Share	36	6.01	3.21	2.20	12.63
High-Skilled Wage Share	36	76.42	1.63	72.92	79.06
Middle-Skilled Wage Share	36	20.01	1.49	17.88	24.18
Low-Skilled Wage Share	36	3.57	1.96	1.35	7.51
Numbers of Employees	36	9203.89	2035.61	6094.00	12969.00
Real Gross Output	36	403426.69	101387.65	245344.75	590425.88

Table 3.24: Descriptive Statistics by Industry from EU KLEMS Accounts VII: 1970-2005

Health Services	Observations	Mean	Std. Dev.	Min	Max
Computerization Stocks	36	11191.46	14203.50	681.49	53685.24
Computerization Investment	36	3887.27	5368.60	96.29	19435.68
High-Skilled Employment Share	36	31.80	5.17	20.68	39.50
Middle-Skilled Employment Share	36	58.22	1.29	55.83	60.70
Low-Skilled Employment Share	36	9.98	5.38	4.53	22.38
High-Skilled Wage Share	36	54.07	5.72	45.45	64.13
Middle-Skilled Wage Share	36	40.56	3.15	33.85	47.22
Low-Skilled Wage Share	36	5.37	3.29	1.80	12.22
Numbers of Employees	36	8765.81	2729.56	4035.51	13282.57
Real Gross Output	36	593722.06	195728.25	297807.78	990330.69

1. Agriculture :: Agriculture, Hunting, Forestry, and Fishing; 2. Mining :: Mining and Quarrying; 3. Food :: Food, Beverages and Tobacco; 4. Textiles :: Textiles, Textile, Leather and Footwear; 5. Wood :: Wood and of Wood and Cork; 6. Paper & Pulp :: Pulp, Paper, Printing and Publishing; 7. Petroleum :: Coke, Refined Petroleum and Nuclear Fuel; 8. Chemicals :: Chemicals and Chemical Products; 9. Rubber :: Rubber and Plastics; 10. Glass :: Other Non-Metallic Mineral; 11. Metals :: Basic Metals and Fabricated Metal; 12. Machinery :: Machinery, Nec; 13. Electrical Machinery :: Electrical and Optical Equipment; 14. Transport Equipment :: Transport Equipment; 15. Misc. Manufacturing :: Manufacturing, Nec and Recycling; 16. Utilities :: Electricity, Gas and Water Supply; 17. Construction :: Construction; 18. Motor Vehicle Sales :: Sales and Maintenance of Motor Vehicles and Motorcycles; 19. Wholesale Trade :: Wholesale Trade and Commission Trade, except of Motor Vehicles and Motorcycles; 20. Retail Trade :: Retail Trade, except of Motor Vehicles and Motorcycles; 21. Transport & Storage :: Transport and Storage; 22. Communications & Postal :: Post and Communication; 23. Finance :: Financial Intermediation; 24. Real Estate :: Real Estate Activities; 25. Business Services :: Renting and Other Business Activities; 26. Personal Services :: Community Social and Personal Services; 27. Public Administration :: Public Administration, Defense, Compulsory Social Security; 28. Education Services :: Education; and 29. Health Services :: Health and Social Work.

Chapter 4

Conclusions

As introduced in Chapter 1, Rosen (1983) emphasizes that rate of returns of specialized knowledge increases with utilization of the skills, and technological changes increase relevant market size for the specialized knowledge. Specialization and production by the principle of comparative advantage, thus, originate from the increasing returns of utilization for the specialized knowledge. Chapter 2 suggests that heterogeneous impacts of information and communication technology on knowledge acquisition and utilization, which also effect the rate of returns for specific knowledge, are biased in the knowledge-based hierarchy, so that incentives for knowledge acquisition for workers are differentiated depending on specialized knowledge the worker has.

Chapter 2, first, presents between-group wage differentials among four occupational layers - managers, professionals, middle workers, and lower workers - with information and communication technological change. For advances in information technology, empirical analysis supports the comparative statics from theoretical framework hypothesizing that decreasing knowledge acquisition cost raises wage differentials between problem solvers and production workers such as managers and professionals, managers and middle workers, managers and lower workers, and middle workers and lower workers. Estimation results suggest advances in communication technology increase between-group wage differentials, managers and lower workers; professionals and middle workers; professionals and lower workers; and middle workers and lower workers. These results support the implications from theoretical frameworks that cheaper communication costs lead to an increase wage in differentials between problem solvers an production workers as well.

Moreover, decreasing wage differentials between managers and professionals and between managers and middle workers - though mixed - from advances in communication technology have an important implication for solving the SBTC hypothesis puzzle. Based on the sharp increases in investment for communication equipment and software in the late 1990s, which had a negative impact on wage differentials between managers and professionals and a mixed effect on wage differentials between managers and middle workers, cheaper communication costs might suppress the positive effect from investments in computing equipment on these two wage differentials. Therefore, the overall wage differential, which is measured by the wage differential between the 90th and the 10th percentiles, might be attenuated by decreasing wage differentials between managers and professionals and between manager and middle workers.

Second, Chapter 2 examines the predictions from the theoretical frameworks about impacts of information and communication technology on within-group wage differentials. Estimation results associated with information technology, wage differentials within managers as top problem solvers and within middle workers for production workers provide empirical evidence that decreasing knowledge acquisition costs increase within wage differentials for all workers based on four measurements of residual wage differentials for each group. For communication technology, Chapter 2 shows that advances in communication technology lead to a decrease within wage differentials for middle workers as production workers, while cheaper communication costs raise wage differentials within managers as problem solvers. These findings are consistent with the implications that cheaper communication cost acts as a wage equalizer among production workers, while it increases within wage differentials for top problem solvers due to the increasing returns of specialization.

Therefore, Chapter 2 supports the implications of Garicano (2000) and Garicano and Rossi-Hansberg (2006) that (i) decreasing knowledge costs raise wage differentials between problem solvers and production workers and within wage differentials for all occupational layers, (ii) advances in communication technology also increase between-group wage differentials, and (iii) cheaper communication cost acts as a wage equalizer among production workers but raises wage differentials within top problem solvers. The second and third implications illustrate the Superstar effect in Rosen (1981) in that due to available cheaper communication costs production workers acquire only basic knowledge and ask for solutions from the problem solvers when they confront difficult problems. The reduced incentive for knowledge acquisition due to advances in communication technology increases the dependency of production workers on problem solvers and thus leads to a centralization of top problem solvers in the knowledge hierarchy. Therefore, advances in communication technology increase wage differentials between problem solvers and production workers and within-group wage differentials for top problem solvers in the knowledge hierarchy.

Associated with specialization, Chapter 3 discusses workers' occupational choices for specialized knowledge among four types of workplace tasks: nonroutine cognitive tasks, routine cognitive tasks, routine manual tasks, and nonroutine manual tasks. Large investments for computerization caused by the decreasing price of computer-related capital change the workers' occupational choices and also demand for three different types of skilled workers: high-skilled, middle-skilled and low-skilled workers. When middle-skilled workers make their occupational choices between routine tasks and nonroutine manual tasks based on self-selection, the decreasing price of computerization and resulting increased relative efficiency unit between routine tasks and nonroutine manual tasks lead the middle-skilled workers, especially marginal workers below-average for routine tasks, to allocate their labor supply toward nonroutine manual tasks from routine tasks. Also, for middle-skilled workers between routine tasks and nonroutine cognitive tasks, the decreased relative efficiency unit between nonroutine cognitive tasks and routine tasks by decreasing computerization costs makes marginal workers above-average from routine tasks move toward nonroutine cognitive tasks.

Thus, due to increasing demand for production inputs for routine tasks with the price decline of computer-based capital and displacement of middle-skilled workers from routine tasks toward two nonroutine tasks, nonroutine cognitive and nonroutine manuals tasks, routine tasks will be carried out by computer-related capital more. Based on the combined theoretical frameworks from Autor, Katz, and Kearney (2006) and Autor, Levy and Murnane (2003), Chapter 3 empirically shows that rapid adoption of computer-related capital is a driving force of the U.S. productivity revival, employment polarization toward low-skilled workers and high-skilled workers, and divergent wage evolution between top-half and bottom-half wage differentials. First, difference-in-difference estimation methods show that computerized industries exhibit larger labor productivity gains than other less computerized industries. In addition, the increasing growth rate of computerization assets is positively related to demand shifts for high-skilled workers and low-skilled workers, but inversely related to demand shifts for middle-skilled workers, which are measured by employment share and wage bill share.

Second, share equation estimates for three types of skilled workers provide supportive empirical evidence for Autor, Katz, and Kearney (2006) and Autor, Levy and Murnane (2003) that due to increasing investments in computer-related capital, middle-skilled workers have been replaced from routine cognitive tasks and routine manual tasks, and employment share and wage bill share of high-skilled workers for nonroutine cognitive tasks and low-skilled workers for nonroutine manual tasks have been increased. These heterogeneous demand changes for different skill-types of workers corresponded well with the polarization patterns in employment share and the polarization trends in wage inequality.

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