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Effects of Information Technology and Aging Work Force on Labor Demand and Technological Progress in Japanese Industries: 1980-1998

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[1]We are grateful to past discussants and participants of the ESRI confererences for helpful commnets, and to Professor Miyagawa and his research associates who kindly permitted us to use their disaggregate capital stock series in this paper. The order of authors in the tilte page is based on their age.

Abstract

The purpose of this paper is two-folds. First, we examine the direction and the magnitude of substitutability or complementarity between information- and communication-related capital stock and various labor inputs to know about differential impacts of information and communication technology on labor demand. In this way, we can obtain information about what segments of workers information and communication technology can effectively substutute for. Second, we estimate contribution of information- and communication-related capital stock and various labor inputs on the value-added growth of the Japanese economy in the recent turbulent era (1980s and 1990s) and explore factors determining technological progress. In particular, we investigate whether rapid accumulation of information-related capital stock has a positive effect on technological progress, examining IT externality. We also discern the effect of compositional changes in labor inputs on technological progress, examining the inflexibility issue and IT-induced technological obsolescence issue.

Three remarkable facts emerge from our result with respect to substitutability/complementarity issues. First, IT capital stocks are shown to be significant substitutes for young workers with a low education level, whereas old workers with a low education level are consistently quasi-fixed in all industries under investigation. Second, IT capital stocks have complementary relationship with workers with a high education level in many industries. Third, workers with a high education level and those with a low education level are substitutes. These all suggest that IT investment and human capital accumulation are of utmost importance to overcome possible shortage (in relative terms) of young workers with a low education level caused by rapidly aging population.

As for IT externality, we find at first positive correlation between IT stocks and technological progress in manufacturing, suggesting a strong externality effect of IT capital stocks. In the first glance it is very promising, since this suggests that this IT externality can be used for boosting productivity growth. However, the correlation is not robust. First, if non-manufacturing industries are included, the correlation vanishes. Second, if “Electrical Machinery” is excluded from the sample of manufacturing, the correlation also vanishes. Thus, we fail to discern clear-cut evidence for IT externality. Thus, the proposition that IT

“revolution” can pop up productivity growth and can counter the pressure of aging population is not supported by our data, although investment in IT-producing industries is surely an important driving force for economic growth through substitution effects.

As for the effect of labor force composition on the rate of technological progress, the results do not support that the “inflexible old worker” hypothesis of productivity slowdown. There is no correlation between the rate of technological progress and the ratio of old workers with low education in the total labor inputs. However, the results suggest that information technology development in the 1990s has a negative impact on the past strength of the Japanese economy: productivity increase through high-education workers’ learning by doing. In manufacturing industries where Japan has been strong, the rate of technological progress in the 1980s has positive (though weak) correlation with “maturing” high-education labor force. That is, the ratio of old well-educated workers in the total labor inputs has a positive (though weak) effect on technological progress. This suggests that the increased average skill among well-educated workers due to longer experience has a positive effect to improve productivity. However, the relationship changes significantly in the 1990s, and we have rather negative relationship. The nature of technological progress apparently changed adversely.

1 Introduction and Summary

The Japanese economy has been suffering from a prolonged recession since the collapse of asset markets in 1990, and at the same time she has been in the midst of a fundamental change driven by two economic forces: aging population and rapid progress in information and communication technology. Population aging has attracted much discussion, mostly with respect to their impacts on the macroeconomic future of the Japanese economy in such issues as sustainable pension and health care systems and the optimal policy mix of debts and taxes to finance government expenditure. Technological progress in information and communication has also been a hot issue both politically and economically, but most discussion has been concentrated on its microeconomic impacts on the Japanese industries. However, these two factors may interact each other in a very important way, and have a confounding effect on the economy. Rapid advance of information and communication technology may imply a drastic change in production technology, work place and job structure, which may alter the impact of aging work force. Technological advancement in information and communication technology may also change "consumption technology" of the general public, especially those who have been handicapped by physical problems before. Old people are among those handicapped, and thus information and communication technology may bring about a sizable change in the economy's demand structure.

To our knowledge, however, there are few studies on the interrelationship between aging population and technological progress in information and communication technology, and their joint impacts on the economy.[1] The purpose of the project to which our subproject belongs is to fill this gap. In this paper, we concentrate on the supply side of economy,[2] and explore interaction between information and communication technology and the composition of labor inputs and their combined effect on economic growth.

Casual observations suggest that workers and firms can benefit from information and communication technology. In manufacturing (especially machinery) industries, industrial robots have played an important role to promote so-called factory automation (FA), which had been brought by hardware and software investment in information and communication

[1] A notable exception is Hiromatsu et al (2001).

[2] Demand-side effects are discussed in the papers of Yoshikawa and others.

technology. Likewise, the automobile industry has succeeded in shortening the development period of automobiles substantially, relying on computer-aided design (CAD) software. In non-manufacturing industries, growing utilization of video-scanned data or so-called point-of-sales (POS) systems in the retail industry and automatic teller machines (ATM) in banking and securities industries signify this trend.

Moreover, technological progress in the work place may depend on externality in information and communication technology such as network effects as the literature of endogenous growth suggests (IT externality). If this is the case, information and communication technology investment may play a vital role to keep the economy growing, in spite that the supply of young workers is getting smaller as population aging continues. In fact, some may argue that dismal performance of the Japanese economy stems from insufficient investment in information and communication technology. This view is often further strengthened by comparison between the revival of the U. S. economy with strong information technology investment and the dismal performance of the Japanese economy with, for example, delayed development in the Internet.[3]

Changes brought by information technology, however, may not always be beneficial to all workers and firms. Computers are based on digital technology and software running on them can be flawlessly copied. This makes compiling and transfer of knowledge easier and much of once tacit knowledge becomes explicit. Skills, once learned from long experience, may be replaced by software in NC machines, customer-relationship management (CRM) software, and so on. Many Japanese workers and firms have been heavily dependent on non-transferrable, relation-specific tacit knowledge of producing good products and keeping good customer relations. They may find that their knowledge and skills are replaced by software and hardware powered by information and communication technology development, and that they lose their comparative advantage in management and production. If this is the case, we will find an adverse effect on information technology development.[4]

Sweeping diffusion of information technology may also have distributional effects. In

[3]The effort of the past and present governments to promote information techonology is clearly based on this belief. See, for example, the *e-Japan* program of the Koizumi government.

[4]There is now sizable literature on this effect in Japanese industries, though most are written in Japanese. See Morita and Nishimura (2001) and references therein.

utilizing information and communication technology, workers should have sufficient knowledge about computer and communication hardware and software. This suggests that information and communication innovations are likely to demand well-educated, skilled workers as a complementary factor to information and communication capital stocks, while these capital stocks tend to replace less-educated, unskilled workers. Thus, we should expect differential impacts of information and communication technology in the work place. Moreover, if old workers have problems in embracing new technology, overall aging of work force may have negative impact on productivity growth.

The purpose of this paper is consequently two-folds. First, we examine the direction and the magnitude of substitutability or complementarity between information- and communication-related capital stock and various labor inputs to know about differential impacts of information and communication technology on labor demand. In this way, we can obtain information about what segments of workers information and communication technology can effectively substutute for. Second, we estimate contribution of information- and communication-related capital stock and various labor inputs on the value-added growth of the Japanese economy in the recent turbulent era (1980s and 1990s) and explore factors determining technological progress. In particular, we investigate whether rapid accumulation of information-related capital stock has a positive effect on technological progress, examining IT externality. We also discern the effect of compositional changes in labor inputs on technological progress, examining the inflexibility issue and IT-induced technological obsolescence issue.

In examining complementarity/substitutability between factors of production, the natural framework is a translog cost function. This functional form is flexible enough to allow both substitutability and complementarity and widely used in the literature. There is, however, an important caveat in applying the translog cost function approach to the Japanese industries. The translog cost function approach assumes cost minimization coupled with perfect variability of inputs and factor-price taking behavior. Although the factor-price-taking behavioral assumption is relatively benign in the Japanese industries, the perfect-input-variability assumption is problematic. It is often argued that some factors of production, especially some parts of capital stocks are not completely variable but fixed in the short run ("quasi-fixed"). Buildings and factories are typical examples. Moreover, because Japanese firms keep long-term stable relationship with their workers, some parts of workers are often considered as "fixed" and some of labor inputs are not sensitive to changes in economic conditions. Personnels in the corporate headquarters are often considered as such quasi-fixed labor inputs. Even production workers often have long-run stable employment relationship with the firm, and hiring and firing may not be as easy as the translog cost function approach assumes. Thus, it is not all that clear that the translog cost function approach is appropriate for an analysis of substitutability of all factors, though it may be so for a subset of the factors.

To tackle this problem, we develop in Section 2 a theory of production-capacity functions coupled with capacity-utilization functions. The theory explicitly incorporates quasi-fixed nature of some of capital stocks and labor inputs. In this theory, *we do not presuppose that capital stocks are quasi-fixed and labor inputs are variable inputs.* The argument in the previous paragraph shows that we cannot say *a priori* that all capital stocks are quasi-fixed nor all labor inputs are perfectly variable.[5] Whether particular factors are quasi-fixed or not is an empirical question. Thus, we disaggregate capital stocks and labor inputs into finer categories, some of which are quasi-fixed and others are variable. We then assume that production capacity is determined by quasi-fixed factors and that capacity utilization is determined by variable factors. Under the assumption of homogeneity of production-capacity functions and capital-utilization functions coupled with "long-run" constant returns to scale, we are able to show that variable cost shares are independent of output and production capacity, and that basic properties of variable cost functions can be inferred from the estimated variable cost share functions without knowledge of output and production capacity. Moreover, we show that this theory allows to estimate the rate of technological progress without imposing a perfect competition assumption on product markets. This is particularly important, since most of the Japanese industries are not competitive (see Ariga et al (1999) and Nishimura et al (1999)[6]). The traditional approach assuming perfect competition may result in wrong estimates of technological progress (see Nishimura and Shirai (2000)).

In Section 3, we explain data used in this paper, since this data set is one of main

[5]In this respect, our approach is different from the quasi-fixed-capital literature (see, for example, Morrison (1992) and Flaig and Steiner (1993)), which assume *a priori* that all capital goods are quasi-fixed and all labor inputs are variable. However, at the same time, we have to pay for this versatile setting: we are obliged to assume homotheticity and constant returns to scale whereas the above authors do not.

[6]Examining a large panel of firms, they find non-neglible deviation from perfect competition in almost all industries in Japan.

contributions of this paper. We develop an industry-wise disaggregate data set of capital stocks and labor inputs. First, as for capital stocks, we construct a time series of industry-wise information-technology capital stock (we hereafter call it IT capital stocks) based on Base-Year *Input Output Tables* and other primary government statistics. Here we use the SNA classification of industries. Our approach differs substantially from previous studies such as Miyagawa et al (2001), and we carefully compile our IT capital stock data to make them internationally comparable. In particular, we include software capital stocks in IT capital stocks and use an internationally comparable imputation method for price deflators of IT products following Schreyer (2000), while others use the Bank of Japan's Price Indexes which are somewhat problematic with respect to their reliability. We then make our IT capital stocks consistent with Miyagawa et al's other disaggregate capital stock data. In this way, we have five series of capital stocks for each industry: structure, buildings, transportation machines, machines and tools, and IT capital stocks. Second, we construct disaggregate labor inputs data from a partly unpublished data set of the *Basic Survey of Wage Structure.* In particular, we disaggregate industry-wise labor inputs into several sub-groups. We have three dimensions. In all industries, we have the age (young [no older than forty years] or old [older than forty years]), and the educational attainment (high education level [with a junior college degree or higher] or low education level [with a high school diploma or lower]). In the case of manufacturing industries, we have an additional dimension, that production/non-production difference.[7]. In this way, we are able to construct industry-wise data of disaggregate capital and labor inputs in the eleven SNA-level manufacturing and five SNA-level non-manufacturing industries, except for three problematic industries ("Petroleum and Coal", "Miscellaneous Manufacturing", "Utilities" and "Real Estate"). These problematic industries are either heavily regulated ("Petroleum and Coal" and "Utilities"), their data are somewhat artificial (imputed rents are included in "Real Estate"), or they are uncontrollably heterogeneous ("Miscellaneous Manufacturing"). In addition, there is a problem in "Finance and Insurance" after 1993 because of severe non-performing loan problems, so that we use their data until 1992.

[7] In the paper presented at the 2001 Spring ESRI conference, we only consider one type (production vs. non-production) and only manufacturing industries. In this paper, we are able to add two additional dimensions, which has greatly improved our results. See the next footnote.

Sections 4 and 5 report the main result of this paper. In Section 4, using the data explained in Section 3, we estimate translog variable-cost functions for each industry[8]. In particular, we examine what factors of production can be treated as quasi-fixed. As for capital stocks, we find that the result of translog cost function estimation is consistent with the hypothesis of structure, buildings, transportation machines, and machines and tools are quasi-fixed. In contrast, IT capital stocks are shown to be variable in all industries. As for labor inputs, young workers with a low education level are robustly shown to be variable inputs in all industries. We also find that workers with a high education level are variable inputs in the cases of “Food”, “Textile”, “Fabricated Metal”, “General Machinery (1990’s)”, “Electrical Machinery”, “Instruments”, “Finance and Insurance (–92)”, and “Services”. In contrast, old workers with a low education level are robustly shown to be quasi-fixed. In manufacturing industries where the production/non-production classification is available, production workers are shown to be variable. We also find the difference between the 1980s and the 1990s. The ratio of quasi-fixed factor costs in the total cost is increased from the 1980s to the 1990s, except for General Machinery. This means that Japanese industries lose “flexibility” in economic fluctuations. This may be behind the poor performance of Japanese firms in the prolonged downturn of the 1990s.

Three remarkable facts emerge from our result with respect to substitutability/complementarity issues. First, IT capital stocks are shown to be significant substitutes for young workers with a low education level, whereas old workers with a low education level are consistently quasi-fixed in all industries under investigation. Second, IT capital stocks have complementary relationship with workers with a high education level in many industries. Third, workers with a high education level and those with a low education level are substitutes.

In Section 5, we examine the rate of technological progress between 1981 and 1998 in the framework developed in Section 3. We estimate the effect of IT capital stocks and that of changing age structure of labor force on technological progress using a panel of eleven manufacturing and four non-manufacturing industries in four half-decades. The result suggests

[8] In the previous version presented at the 2001 Spring ESRI conference, we pool all industry data. However, one may argue that implicit assumption behind pooling that all industries have the same quasi-fixed factors and the same variable factors is too restrictive. Taking this possible criticism in mind, we analyze each industry separately in this version.

that the prolonged slump of the 1990s is not merely a demand-driven phenomenon, but the supply side plays a substantial role. The rate of technological progress declines substantially between the 1980s and 1990s. We then examines three possible explanations of the productivity slow down: (i) inflexibility of old workers in adopting information technology, (2) technological and managerial obsolescence brought by information technology development, and (3) insufficient investment in information technology that fails to realize IT externality. At first, we find positive correlation between IT stocks and technological progress in manufacturing, suggesting a strong externality effect of IT capital stocks, supporting the third view. In the first glance it is very promising, since this suggests that this IT externality can be used for boosting productivity growth.[9] However, the correlation is not robust. First, if non-manufacturing industries are included, the correlation vanishes. Second, if "Electrical Machinery" is excluded from the sample of manufacturing, the correlation also vanishes. Thus, we fail to discern clear-cut evidence for IT externality.[10] Thus, the proposition that IT "revolution" can pop up productivity growth is not supported by our data, although investment in IT-producing industries is surely an important driving force for economic growth through substitution effects.

As for the effect of labor force composition on the rate of technological progress, the results do not support that the "inflexible old worker" hypothesis of productivity slowdown. There is no correlation between the rate of technological progress and the ratio of old workers with low education in the total labor inputs. However, the results suggest that information technology development in the 1990s has a negative impact on the past strength of the Japanese economy: productivity increase through high-education workers' learning by doing. In manufacturing industries where Japan has been strong, the rate of technological progress in the 1980s has positive (though weak) correlation with "maturing" high-education labor force. That is, the ratio of old well-educated workers in the total labor inputs has a positive (though weak) effect on technological progress. This suggests that the increased average skill among well-educated workers due to longer experience has a positive effect to improve productivity. However, the relationship changes significantly in the 1990s, and we have rather negative relationship. The nature of technological progress apparently changed adversely.

[9] This was our first reading of the result in the previous version presented at the 2001 Spring ESRI conference.
[10] The same result is obtained in the United States. See Stiroh (2001).

Finally, there are some policy implications. The improved data set we compiled in this paper shows in Section 4 that IT capital stocks are an important substitute for young, low-education workers. These results strongly suggest that IT investment is an effective way to counter prospective shortage of young workers because of population aging. The results also imply that, in order to strengthen this effect of IT investment, it is necessary to improve the educational level of labor force, since otherwise IT investment's impact may be seriously hindered by the shortage of complementary high-education labor inputs. The necessity is all the more apparent if one consider substitutability between high-education and low-education labor inputs.

The results of Section 5, however, shows that the hope that many economists as well as politicians have with respect to "IT revolution," in which externality in IT technology greatly enhances productivity, is not supported by the data. The productivity gain in IT-producing industries ("Electrical Machinery" in our sample) is remarkable, but this is rather an industry-specific phenomenon and not "revolution" that changes all industries. On the contrary, our result suggests a negative indirect effect of information technology. The advent of information technology may change comparative technological and managerial advantage drastically, and the past strength of the Japanese manufacturing based on workers' learning by doing in work place (such as Total Quality Circle (TQC) and on-the-job/off-the-job training) may be substantially reduced as digital software such as knowledge management systems improves and becomes easily transferred across the international border.

In this respect, Japan needs thorough examination of her productivity slowdown in the 1990s, especially of the strength and weakness in technology and management. As our data suggest, technology and management are not independent. One form of management (including work organization and personnel management) may be efficient to one form of technology but not for other forms. Management styles are often stable in the long run and there may be mismatch of management and current technology.[11] Moreover, technology itself is not exogenous. The past history of technological development shows importance of the government in enhancing particular types of technological development. Although the government cannot choose technology for the economy obviously, it can provide a menu of possible ones and to influence the choice of the market. However, in doing so, appetence

[11] See Nishimura and Tamai (2001) for a model of long-run rigidity of management styles.

between technology and management should be properly taken into consideration.

2 Quasi-Fixed Factors, Variable-Cost Function and Measurement of Technological Change

2.1 Production Function: Production Capacity and Capacity Utilization

Let us consider a general form of production function, with n variable factors of production and m quasi-fixed factors:

$$Y = F\left(x_1, \ldots, x_i, \ldots, x_n; z_1, \ldots, z_j, \ldots, z_m; A\right)$$

where x_i is the ith variable factor and z_j is the jth quasi-fixed factor. The term A denotes the state of production technology. We make two assumptions on the production function. Firstly, we assume that the production function can be decomposed into a "capacity" part and a "utilization" part. Secondly, both parts are assumed to be homothetic and the overall production function exhibits constant returns to scale.

Assumption 1 (Capacity and Utilization) *F is multiplicatively separable between variable factors $(x_1, \ldots, x_i, \ldots, x_n)$ and quasi-fixed factors $\left(z_1, \ldots, z_j, \ldots, z_m\right)$:*

$$Y = F\left(x_1, \ldots, x_i, \ldots, x_n; z_1, \ldots, z_j, \ldots, z_m; A\right) = G\left(x_1, \ldots, x_i, \ldots, x_n; A\right) S\left(z_1, \ldots, z_j, \ldots, z_m; A\right) \tag{1}$$

The function $S\left(z_1, \ldots, z_j, \ldots, z_m; A\right)$ may be interpreted as the *production-capacity* function. The quasi-fixed factors $\left(z_1, \ldots, z_j, \ldots, z_m\right)$ are needed for a production capacity of S. Using this production capacity, actual output is produced by consuming variable factors $(x_1, \ldots, x_i, \ldots, x_n)$. G is then has an natural interpretation, that is, the *capacity-utilization function*, which is the production level Y divided by the production capacity S. For example, consider an oil refinery firm. The firm's production capacity is, say, S gallons per day. In order to realize this capacity, the firm has oil tanks and other large refinery equipment which are fixed in the short run. The firm has maintenance workers and management teams to run the factory of this size. They are also fixed in the short run. Using this refinery system, the firm produces the actual refinery products by consuming crude oil, services of trucks and other equipment, and labor of factory workers. They are all variable in the short run. In order to produce 100G% of the S gallon capacity, a combination of these inputs is needed, which is determined by $G = G(x_1, \ldots, x_i, \ldots, x_n; A)$.

Assumption 2 (Homogeneity) *G is homogeneous of degree k in $(x_1, \ldots, x_i, \ldots, x_n)$, and S is homogeneous of degree $1-k$ in $\left(z_1, \ldots, z_j, \ldots, z_m\right)$.*

An immediate consequence of this assumption is that F is homogeneous of degree one in all inputs $\left(x_1, \ldots, x_i, \ldots, x_n; z_1, \ldots, z_j, \ldots, z_m\right)$. Thus, we implicitly assumes that production exhibits constant returns to scale "in the long run" where quasi-fixed factors are optimally adjusted.[12]

Quasi-fixed factors are fixed in the short run but variable in the long run. To build a specific production capacity in the future, quasi-fixed factors must be inputted at the present time. We assume that quasi-fixed factor inputs must be determined one period before production. It is straightforward to extend our analysis to the case where some quasi-fixed factor inputs must be determined well in advance before production, though it becomes cumbersome in notations. Thus, our formulation is consistent with the time-to-build formulation of investment.

Assumption 3 (Timing of Quasi-Fixed Factor Determination) *Quasi-fixed factors must be determined one period before production.*

2.2 Variable Cost Function under the Capacity-cum-Utilization Framework

In this section, we show that under Assumptions 1 and 2, the share of a variable factor of production in the total variable cost, which we hereafter call the variable cost share, is independent of the level of output and production capacity. This property has an important

[12]Basu (1997) shows that constant returns to scale is a good description of production technology in the long run of U. S. manufacturing establishments. Although many empirical studies of production function in Japan show deviation from constant returns, they are mostly concerned with the short run in the end, or long-run adjustment of various factors of production (including ability of managers) is not explicitly incorporated. There are few empirical studies about the relevance of this neoclassical constant-returns-to-scale assumption in the long run, where all physical and managerial adjustment is completed. We make the long-run constant returns assumption in this paper partly because production technology itself is not much different between Japan and the United States, and partly because the assumption allows us to identify cost function parameters from available data.

implication in empirical analysis: the variable cost share function can be estimated without knowledge of production capacity.

The variable cost function corresponding to the production function F is defined as

$$C_V(p_1,\ldots,p_i,\ldots p_n,Y,S;A) = \underset{x_1,\ldots,x_n}{Min} \sum_{i=1}^{n} p_i x_i \qquad \text{subject to } Y = G(x_1,\ldots,x_i,\ldots,x_n;A)S \qquad (2)$$

With some calculation (see Appendix A) we have multiplicatively separable variable cost function such that

$$C_V(p_1,\ldots,p_n,Y,S;A) = c_v(p_1,\ldots,p_n;A)\left(\frac{Y}{S}\right)^{1/k} \qquad (3)$$

where c_v is homogeneous of degree one in prices defined in the Appendix A (see equation (10) there). Consequently, using Shepherd's Lemma, we have

$$\frac{p_i x_i}{C_V} = \frac{p_i}{c_v(p_1,\ldots,p_n;A)} \frac{\partial c_v(p_1,\ldots,p_n;A)}{\partial p_i},$$

which implies that *the variable cost share is independent of the level of production Y and the level of production capacity S.*

Under Assumption 2, we have a neat relation between the variable-cost share and the curvature of the capacity-utilization function, which we utilize later in this paper. The cost minimization (2) implies

$$p_i = \lambda \frac{\partial G}{\partial x_i} S \qquad \text{for } i = 1,\ldots,n \quad \text{and } \lambda = \frac{\partial C_V}{\partial Y}$$

Moreover, (3) means that

$$\frac{Y}{C_V}\frac{\partial C_V}{\partial Y} = \frac{Y}{C_V}\lambda = \frac{1}{k} \qquad (4)$$

Using the above result, we have the following formula relating the cost share and the curvature of the production function

$$\frac{p_i x_i}{C_V} = \frac{1}{C_V}\lambda\frac{\partial G}{\partial x_i}Sx_i = \frac{1}{kY}\frac{\partial G}{\partial x_i}Sx_i = \frac{1}{kGS}\frac{\partial G}{\partial x_i}Sx_i = \frac{1}{k}\left(\frac{x_i}{G}\frac{\partial G}{\partial x_i}\right). \qquad (5)$$

In empirical analysis of Section 4, we postulate that c_v has a translog functional form.

2.3 Quasi-Fixed Factor Inputs and Capacity Cost Function

In this section, we explain output and quasi-fixed factor determination for completeness. Output is determined by the gross profit π_{gross} maximization

$$\underset{Y}{Max} \quad \pi_{gross} = p_Y(Y;\Theta)Y - c_v(p_1,...,p_n;A)\left\{\frac{Y}{S}\right\}^{1/k} - J(A)$$

where p_Y is the price of output, Θ denotes other market conditions determining competitiveness of the industry in question. The term $J \geq 0$ is the fixed cost that is independent of the quasi-fixed factors. The fixed cost J depends on the state of production technology A. This optimization implies

$$p_Y = \mu MC; \quad MC \equiv c_v\left(\frac{1}{S}\right)^{1/k}\frac{1}{k}(Y)^{(1/k)-1}$$

where

$$\mu = \mu(\Theta) \equiv \left(1 + \frac{Y}{p_Y}\frac{\partial p_Y}{\partial Y}\right)^{-1}.$$

is a mark-up over marginal cost, which may be different from unity. Thus, we allow imperfect competition in our framework. Then, the gross profit is, with some calculation

$$\pi_{gross} = \pi_{gross}(S) \equiv \left\{(\mu k)^k - 1\right\}(\mu k)^{\frac{1}{1-k}} p_Y^{\frac{1}{1-k}} c_v^{-\frac{k}{1-k}} S^{\frac{1}{1-k}}.$$

We have made the assumption of one-period-advance determination of quasi-fixed factors (Assumption 3). Then, the quasi-fixed inputs are determined by the following (expected) net profit maximization

$$\underset{z_1,..,z_m}{Max} \quad E_{-1} \quad net\ profit = E_{-1}\left[\pi_{gross}\left(S\left(z_1,..,z_j,...,z_m;A\right)\right) - \sum_{j=1}^{m} q_{-1,j}\ z_j - J(A)\right]$$

where the quasi-fixed factors' prices $\{q_{-1,j}\}$ are those in the previous period and expectation E_{-1} is taken using information available in the previous period. It is straightforward to extend our analysis to the case where some quasi-fixed factor inputs must be determined well in advance before production, though it becomes cumbersome in notations.[13]

[13] For example, consider the case of two quasi-fixed factor inputs. The following analysis does not change if one factor is must be determined, say, two periods before production, while the firm can determine the other

Like the variable-input optimization, the quasi-fixed-input optimization is decomposed into two steps. The first one is the "capacity cost" minimization. For Given S, let the capacity cost C_S be such that.

$$C_S\left(q_{-1,1},..,q_{-1,j},...,q_{-1,m},S;A\right) = Min \quad \sum_{j=1}^{m} q_{-1,j}\ z_j \quad \text{subject to } S = S\left(z_1,..,z_j,....,z_m;A\right)$$

The optimization implies

$$q_{-1,j} = \rho\frac{\partial S}{\partial z_j} \qquad \text{for } j = 1,...,m \quad \text{and } \rho = \frac{\partial C_S}{\partial S}.$$

and

$$C_S\left(q_{-1,1},..,q_{-1,m};A\right) = c_s\left(q_{-1,1},..,q_{-1,m};A\right) S^{1/(1-k)}.$$

In the second step, we determine the optimum capacity using this capacity cost function, such that

$$\underset{S}{Max} \quad E_{-1} \quad net\ \ profit = E_{-1}\left[\pi_{gross}(S) - c_s\left(q_{-1,1},..,q_{-1,m};A\right) S^{1/(1-k)} - J(A)\right].$$

This maximization determines the optimum capacity S, which in turn determines the quasi-fixed factors.

Note that $S(z_1,..,z_m)$ is homogeneous of degree $1-k$ in $(z_1,...,z_m)$. Then, using a similar argument to the output elasticity of variable cost, we have the following relationship between capacity cost share and the curvature of the production-capacity function S.

$$\frac{q_{-1,j}\ z_j}{C_S} = \frac{1}{1-k}\left(\frac{z_j}{S}\frac{\partial S}{\partial z_j}\right). \tag{6}$$

factor one period before production, so long as the production capacity function is multiplicatively separable such that

$$S = S^1(z_1)\, S^2(z_2)$$

where S^1 and S^2 are homogeneous of degree k' and k'' and $k' + k'' = 1-k$. We then have three-period sequential expected profit maximization to determine z_1 and z_2, instead of two-period expected profit maximization described in the text.

2.4 Measurement of Technological Progress

We show in this section that under Assumptions 1 and 2, the rate of technological progress can be estimated without making any assumption on competitiveness of industries in question.[14] This is a major departure from the technological-progress measurement literature where perfect competition is almost always assumed.[15]

Let us now consider the measurement of technological progress. Let A denote the sate of production technology determining production efficiency such that

$$Y = F\left(x_1, \ldots, x_i, \ldots, x_n; z_1, \ldots, z_j, \ldots, z_m, A\right) = G\left(x_1, \ldots, x_i, \ldots, x_n, A\right) S\left(z_1, \ldots, z_j, \ldots, z_m, A\right). \qquad (7)$$

As usual, we define the rate of technological progress is the output growth which cannot be attributable to factor inputs. Thus, the rate of technological progress RTP_t is defined by

$$RTP_t = \left[\frac{1}{F}\frac{\partial F}{\partial A}\right]_t \Delta A_t = \left[\frac{1}{GS}\left(\frac{\partial G}{\partial A}S + G\frac{\partial S}{\partial A}\right)\right]_t \Delta A_t,$$

where a suffix t denotes the period, $[X]_t$ is the value of X at the period t, and $\Delta x_t = x_{t+1} - x_t$.

With some calculation, we have the following approximate relation

$$\frac{\Delta Y_t}{Y_t} \approx \sum_{i=1}^{n}\left[\frac{x_i}{G}\frac{\partial G}{\partial x_i}\right]_t \Delta x_{t,i} + \sum_{j=1}^{m}\left[\frac{z_j}{S}\frac{\partial S}{\partial z_j}\right]_t \Delta z_{t,j} + RTP_t,$$

Since we have (5) and (6), we obtain

$$RTP_t \approx \frac{\Delta Y_t}{Y_t} - k\left(\sum_{i=1}^{n}\frac{p_{t,i}x_{t,i}}{[C_V]_t}\frac{\Delta x_{t,i}}{x_{t,i}}\right) - (1-k)\left(\sum_{j=1}^{m}\frac{q_{t-1,j}\ z_{t,j}}{[C_S]_t}\frac{\Delta z_{t,j}}{z_{t,j}}\right)$$

Since the variable cost shares and quasi-fixed cost shares are observable, the rate of technological progress is calculated from the above formula if we know k. Thus the remaining task is to estimate k.

Let us consider the "steady-state", in which no uncertainty exists. In our framework, only difference between variable and quasi-fixed inputs is that quasi-fixed inputs must be

[14] In fact, Shirai (2001) uses this framework to estimate industry mark-ups.

[15] We do not use the term TFP growth here. Precisely speaking, TFP is defined as a ratio of the Divisia index of outputs and that of inputs. Although TFP growth is equal to the rate of technological progress if all factors are variable under perfect competition and constant returns to scale, it is not in more general cases. We do not assume that all variables are variable nor competition is perfect.

determined one period before when future is still uncertain. Then, if there is no uncertainty in the future, the sequential optimization described in the previous sections is equivalent to the following one-shot two-step problem. Firstly, for given Y the "steady-state total cost function" is defined by

$$TC^{L}\left(p_{1},...,p_{n},q_{-1,1},..,q_{-1,m},Y,A\right)=\underset{x_{1},...,x_{n},z_{1},...,z_{m}}{Min}\quad\sum_{i=1}^{n}p_{i}x_{i}+\sum_{j=1}^{m}q_{-1,j}z_{j}\quad\text{s.t.}\quad(7).$$

Then, the optimum steady-state output, Y^L, is determined by

$$\underset{Y_{L}}{Max}\quad p_{y}\left(Y^{L};\Theta\right)Y^{L}-TC^{L}\left(p_{1},...,p_{n},q_{-1,1},..,q_{-1,m},Y^{L},A\right)-J\left(A\right)$$

Since the steady-state total cost minimization implies

$$p_{i}=\lambda^{L}\frac{\partial G}{\partial x_{i}}S;\ \text{ and }\ q_{-1,j}=\lambda^{L}G\frac{\partial S}{\partial z_{j}},$$

we have

$$C_{V}^{L}=\sum_{i=1}^{n}p_{i}x_{i}^{L}=\lambda^{L}kY^{L};\ \text{ and }\ C_{S}^{L}=\sum_{j=1}^{m}q_{-1,j}z_{j}^{L}=\lambda^{L}\left(1-k\right)Y^{L}$$

Consequently, we have

$$k=\frac{C_{V}^{L}}{C_{V}^{L}+C_{S}^{L}}=\frac{C_{V}^{L}}{TC^{L}}.$$

Thus, k is the variable cost's share in the total cost in the steady state of no uncertainty.

If we knew the period in which there were no uncertainty, we could infer k from the variable cost's share of that period. Since we do not *a priori* know the period of the least uncertainty, we approximate k by the time average of the variable cost's share over a relevant period[16] in the empirical analysis of Section 5.

3 Data: IT Capital Stocks and Disaggregate Factor Inputs

Since our study differs from the literature in its disaggregation of both capital stocks and labor inputs, it is worthwhile to briefly explain data sources and the way we construct these

[16] The meaning of this "relevant period" will be explained in Section 5.

disaggregate factor input series. We proceed in two steps. First, we construct a time series of information-technology capital stocks (we hereafter call it IT capital stocks), and break down capital stocks into IT capital stocks and other capital stocks (non-IT stocks). Then, non-IT stocks are further decomposed into structure and non-IT equipment. Second, we disaggregate labor inputs into well-educated workers (with a college or higher degree) and less-educated ones (with a high school diploma or lower). Moreover, both well-educated and less-educated workers are further disaggregated into young (no older than forty years) and old workers (the rest). In manufacturing, those labor inputs are divided into production and non-production workers.

3.1 Capital Stocks

IT Capital Stocks. We follow Jorgenson and Stiroh (2000) as close as possible in defining IT capital stocks. IT capital stocks consist of IT hardware and IT software. IT hardware include computer equipment such as office computers and related instruments, and communication equipment such as terminal, switching, and transmitting devices. The definition of IT hardware is the same between the United States and Japan. However, while the U.S. definition of IT software includes pre-packaged, custom, and own-account software, the Japanese definition only includes custom software. This definitional difference of IT software must be kept in mind in the following analysis[17].

The Ministry of Economy, Trade and Industry (METI), which was Ministry of International Trade and Industry (MITI) before January 2001, reports Fixed Capital Formation Matrices every five years in the *Base Year Input Output Tables*, which show industry-by-industry formation of above-mentioned disaggregate capital stocks.[18] We further disaggregate these five-year time-aggregate series into annual series by utilizing IT expenditure data of the *Information Technology Survey* conducted by the METI[19]. Then IT capital stock are

[17]We are now starting a project that examines possible biases which the Japanese definitional deviation has on GDP and TFP growth analysis..

[18]In the case of IT software, only 1995 Fixed Capital Formation Matrices of the *Base-Year Input Output Tables* report industry-by-industry data. We extrapolate the series before 1995 by using the *Information Technology Survey* described below.

[19]The Bureau of Research of the Economic Planning Agency followed a similar procedure in their *Policy Effectiveness Analysis Report* No.4, October 2000.

constructed by applying the perpetual inventory method. In doing so, we need IT investment deflators. As for the IT hardware capital stock series, we use IT hardware investment deflators of Schreyer (2000), who studies the contribution of information and communication technology to output growth in G7 countries by using the same definition of IT hardware as ours.[20] As for the IT software investment deflator, we assume that the ratio of the hardware deflator to the software one is the same between Japan and the United States, and construct the software deflator from Schreyer's hardware deflator relying on the U. S. data reported in Jorgenson and Stiroh (2000)[21].

Structure and (non-IT) equipment. In his seminal work (reported in Miyagawa and Shiraishi (2000)), Miyagawa constructed detailed industry-by-industry capital stock series for manufacturing, in which structure capital stocks and equipment ones (including IT stocks) were separately estimated. Since then, Miyagawa and his associates extended their series by including non-manufacturing and by disaggregating structure and equipment further (Miyagawa, Ito and Harada 2001). In his data, there are five categories of capital stocks: (i) IT, (ii) machines and tools, (iii) transportation machines, (iv) buildings, and (v) structure.

In the following analysis, we use our estimate of IT capital stocks described in the previous paragraph, rather than Miyagawa's. There are several reasons for this choice. First, Miyagawa IT capital stocks do not include software. Second, Miyagawa and his associates use as the IT hardware price deflator the Wholesale Price Index of IT hardware products published by the Bank of Japan. However, this price index of IT hardware products such as computers is known to be plagued by a problem of inadequate decoupling of hardware prices and accompanying software prices in both mainframe and personal computers. Because of this and other problems, the Wholesale Price Index of computers do not show a sharp decline of IT product prices between 1995 and 2000, a stark contrast to the movement of U.S. counterparts. This is why we adopt Schreyer's index instead of the Wholesale Price

[20] An alternative is to use the Wholesale Price Index of IT hardware products published by the Bank of Japan. However, this price index has serious problems described below.

[21] As for the IT software investment deflator, the only available one is reported in the Corporate Service Price Index compiled by the Bank of Japan, which is the price index of software development. However, this index is available only for recent three years (1995-1998). Thus, we are obliged to use the imputation method described in the text.

Index in the first place. For other components of capital stocks, we use Miyagawa's series.

As for the estimate of the rental price of these disaggregate capital stocks, we use the following Jorgensonian user-cost formula (except for the investment tax credit, since there is no investment tax credit in Japan):

$$UCC_{it} = \frac{1 - u_t z_{it}}{1 - u_t}(\rho_t + \delta_{it})q_{it}$$

where UCC_{it} is the user cost of the ith capital stocks, ρ_t the dividend yield of Tokyo Stock Exchange, δ_{it} is the ith capital stocks' depreciation rate, u_t the marginal corporate income tax rate, and z_{it} the ith capital stocks' capital consumption allowance. We use the long-term prime rate for the proxy of required nominal rate of return. Marginal corporate income tax rate, capital consumption allowance, and other variables except for the depreciation rate for IT stocks are constructed by using the *Survey on Corporate Activities*, the *Annual Statistical Report of Local Governments*, and the *Financial Statements Statistics of Corporations*. As to the depreciation rate of IT stocks, since we do not have sufficient data to estimate it in Japan, we use the Bureau of Economic Analysis figure for the U.S. IT stocks reported in the *Survey of Current Business* (May, 1997).

3.2 Labor Inputs

We construct disaggregate labor input data from a partly unpublished data set of the *Basic Survey of Wage Structure.* There are three dimensions in this disaggregation.

Production versus Non-Production: Manufacturing Industries. In manufacturing industries, the *Basic Survey* distinguishes non-production workers from production workers, and estimate the number of those workers in each industry. Production workers include those who engage in operation at production sites. Non-production workers are supervisory, clerical and technical workers. However, there are no comparable data in non-manufacturing industries.

Age and Education: All Industries. The survey also includes rather detailed age information of workers both in manufacturing and non-manufacturing industries. Using this detailed information, we define workers over forty years of age as old workers and those under forty years as young ones, although other categorization is also possible.[22] In contrast, as to the educational level of workers, the survey contain only incomplete information. Thus, we only have two categories: well-educated workers with a college degree or a higher one (including a degree from junior colleges, higher professional schools, universities, and graduate schools) and less-educated workers with a high school diploma or a lower one (including a diploma from high schools, junior high schools and elementary schools).

These disaggregate data were published for each industry until 1988, but the publication was ceased at that time. Fortunately, we obtain data after 1989 from the Ministry of Labor on the personal basis.

Combining the estimated number of employed workers[23] for each industry with industry-wise work-hour data,[24] we construct for all industries labor input data of four categories: (i) young with low education, (ii) young with high education, (iii) old with low education, and (iv) old with high education. In the case of manufacturing, we have finer classification: each of four categories is divided into (a) production workers and (b) non-production workers. Thus, we have eight categories in manufacturing. Hourly wage data for each category are then derived by compensation data [25] divided by total work hours obtained earlier.[26]

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[22]Shirai is now investigating possible connection between male-female composition on the one side and wage and productivity difference on the other side.

[23]There are three kinds of employed workers: employees, self-employed, and family workers. The *Basic Survey* contains information only for employees. Thus, we supplement the *Basic Survey* with the *Annual Report on the Labor Force Survey* which contains information about the latter two. Since there is no information about the breakdown of self-employed and family workers into various subcategories we consider, we postulate the breakdown is the same as that of employees in the following analysis. We follow Kuroda et al (1997) here.

[24]For employees, the *Basic Survey* has work hour information. For the self-employed and family workers, we use the *Annual Report on the Labor Force Survey*.

[25]The Basic Survey wage income data do not exactly correspond to the SNA-based compensation data. Thus, we first estimate wage payments of each worker type using the Basic Survey data, and divide the SNA total compensation of employees into compensation for each worker type relying on this obtained distribution of wage income.

[26]For self-employed and family workers, we adopt the method of Kuroda et al (1997). See their unpublished Appendix for details.

3.3 Industries under Investigation

We consider both manufacturing and non-manufacturing industries using the System of National Accounts (SNA) classification in our analysis. Table 1 shows industries we consider. We break down manufacturing into thirteen industries, following the SNA. Among thirteen industries in the manufacturing sector, we exclude Miscellaneous Manufacturing since this is not a homogeneous industry, and "Petroleum and Coal" since it is known that this industry's data on prices and quantities are problematic in nature because of heavy government interventions and regulations. Thus, the manufacturing industries we consider are eleven out of thirteen SNA manufacturing industries.

As for non-manufacturing, there are seven SNA industries. Among them, Real Estate and Utilities are problematic. Real Estate industry's output includes imputed rents of owner-occupied houses which are very sizable in Japan. Thus, its movement does not represent Real Estate industry's activities properly, so that we exclude it. In addition, Utilities are a heavily regulated industry and this industry may deviate from cost minimizing behavior that we postulate in Section 2, because of rent-seeking behavior and political influence often found in this industry. Consequently, we are concerned remaining five non-manufacturing industries.[27]

The sample period is 1980-1998 except for Finance and Insurance. The starting year 1980 is chosen since IT stock estimates before 1980 become problematic because of the reliability issue of our data sources. Finance and Insurance's data after 1992 are problematic, since so-called non-performing loan problems mar value-added data of this industry. Thus, we are obliged to use 1980-1992 data for Finance and Insurance.[28]

Descriptive statistics of factor inputs are shown in Table 2 for each industry in two sub-periods 1980-1989 and 1990-1998. Time profile of the share of IT capital stocks in the total capital stocks is shown in Figure 1, and that of the ratios of high-education labor inputs, old labor inputs, and non-production labor inputs to the total labor inputs is depicted in Figures

[27] In fact, we applied the same procedure to these excluded industries alongside with other industries. We found that these industries' estimated cost functions did not satisfy concavity requirement nor even monotonicity requirement, no matter what set of inputs was chosen as variable inputs.

[28] We applied the same procedure to the 1990s Finance data but estimated cost functions did not satisfy concavity requirement nor even monotonicity requirement, no matter what set of inputs was chosen as variable inputs.

2.1 through 2.3.

Table 2 (1) and 2 (2), and Figure 2.1 show a substantial increase in IT capital stocks in almost all industries in the total sample period. However, there is significant difference among industries. In fact, we can easily identify two groups. The first one, which can be denoted as *IT-intensive industries*, shows a rapid accumulation of IT capital stocks in the 1980s and keeps its lead in the 1990s. This IT intensive industries consist of five industries: Electrical Machinery and Instruments in manufacturing, and Finance and Insurance, Transportation and Communication, and Service in non-manufacturing. This is exactly the same industries that Striroh (2001) found IT-intensive in the United States.[29] Other remaining eleven industries are IT non-intensive industries. As for other types of capital stocks, there is no such salient difference among industries.

As for labor inputs, industrial difference is wide. However, time profile of the ratio of old workers to the total, that of high-education labor to the total and that of production labor to non-production labor in the case of manufacturing, show little change in this industrial difference.

4 Substitutability Between IT Capital Stocks and Labor Inputs: 1980-1998

In this section, we examine the impact of the advancement of IT on demand for labor inputs. In particular, we explore whether IT stocks are substitutes or complements of various labor inputs, and whether the magnitude of such substitutability or complementarity has changed between the 1980s and 1990s. To our knowledge, this is the first attempt of this kind.[30]

In order to examine substitutability or complementarity, we have to determine what factors are variable, and what factors are quasi-fixed. If some factors are variable, cost minimization implies their input prices are equal to their marginal product and this information is utilized

[29] Stiroh (2001) classified those industries IT intensive in which the ratio of IT capital stocks to the total is above the average of all industries in 1985-9 just before the acceleration of IT investment in the 1990s. Using the same criterion, we identify these five industries as IT-intensive ones.

[30] There are several attempts to discern substitutability/complementarity between various labor inputs and capital stocks. See Suruga and Hashimoto (1996) for a survey. However, no attempt is made to examine substitutability/complementarity between IT stocks and labor inputs.

to calculate substitutability or complementarity by estimating cost functions. However, if one factor is variable but another is quasi-fixed, the standard procedure cannot be applied since the quasi-fixed factor's input price is no longer equal to its marginal product.

As explained in Section 1, it is not appropriate in the Japanese economy to assume *a priori* that all factor inputs are variable, nor that capital stocks are quasi-fixed and labor inputs are variable. Rather, we let data determine what factor inputs are variable, using the framework of Section 2.

4.1 Translog Multiplicably-Separable Variable-Cost Function

Since our concern is to detect substitutability or complementarity between factor inputs, we should use a flexible function form for cost functions allowing both substitutability and complementarity. For this purpose , we use a translog cost function. Let n be the number of variable inputs. We assume that c_v in (3) has a translog functional form such that

$$\log c_v(p_1,..,p_n;A) = \alpha(A) + \sum_{i=1}^{n} \beta_i(A) \log p_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij}(A) \log p_i \log p_i.$$

In order that C_V is a cost function, c_v should be non-decreasing and homogeneous of degree one in $(p_1,...,p_n)$. Appendix B shows in (12) that the following restrictions on parameters of c_v are sufficient to satisfy these requirements.

$$\sum_{i=1}^{n} \beta_i(A) = 1, \sum_{i=1}^{n} \gamma_{ij}(A) = 0, \sum_{j=1}^{n} \gamma_{ij}(A) = 0.$$

Under these restrictions, we immediately get the cost share function (see (13) in Appendix B) such that

$$\frac{p_i x_i}{C_V} = \beta_i(A) + \sum_{j=2}^{n} \gamma_{ij}(A) \left(\log p_j - \log p_1\right).$$

for $i = 2,...,$ which can be estimated by using information about variable-factor shares and variable-input prices.

There is one remaining requirement on C_V that C_V should be concave in $(p_1,...,p_n)$.[31] This is satisfied if and only if c_v is concave. It should be noted that concavity property

[31] In general, the concavity requirement on cost functions is not neatly represented by restrictions on the parameters β_i and γ_{ij}. Thus, the share function is customerly estimated by imposing only homogeneity of degree one, and then it is examined whether the estimated parameters imply the concavity of cost function locally around the sample mean of input prices.

of cost functions depends on the assumption that the decision maker can freely choose factor inputs and minimizes the cost by appropriately adjusting factor inputs to their price changes. That is, the concavity is a necessary condition that factors $(x_1,...,x_n)$ are variable ones. Thus, if some factors are fixed in the short run, an estimated cost function assuming these factors as variable ones may not exhibit concavity property. In other words, if an estimated cost function fails to exhibit concavity property, this suggest that some factors are not variable but fixed. We use this property to examine whether a particular factor input is quasi-fixed or not.

Let us now consider the effect of a change in production technology, which is represented by a change in A. As it is well known, Hicks-neutral technological progress A_H such that $G(x_1,...,x_i,...,x_n,A_H) = A_H G^*(x_1,...,x_i,...,x_n)$ for some G^* does not affect β_i and γ_{ij}. However, non-Hicks-neurtal technological change may change either or both of β_i and γ_{ij}. There is no a priori reason to assume that technological change is Hicks neutral so that we should take the effect of the change in A on $\beta_i(A)$ and $\gamma_{ij}(A)$ explicitly into consideration.

In fact, our sample period 1980-1998 is a very turbulent period. The 1980s is the heyday of the Japanese economy, with decent economic growth and booming asset markets without inflation. In contrast, the 1990s is the dismal decade with flat growth and collapsed asset markets. Thus, the composition of industry products may be different making value-added production technology different between the two periods. Moreover, information technology has rather different effects on work place. There are two waves of IT innovation in the Japanese economy: the first in the mid 1980’s and the second in the 1990’s. Typical examples of IT innovation in the 1980’s are FA (Factory Automation) and CAD (Computer Aided Design)in manufacturing, particularly in machinery, industries, POS (Point of Sales) systems in the Wholesale and Retail Trade industry, and ATM (Automatic Teller Machine) and CD (Cash Dispenser) in Finance and Insurance Industry. In the early 1990’s, personal computers become widespread in the office, and the Internet becomes popular after 1993. These IT innovations allegedly change so-called white-color jobs. Moreover, CRM (Customer Relationship Management) and SCM (Supply Chain Management) software is introduced and it is often argued to have a great impact on the organization of many firms. This also suggests that value-added production technology may be changed between 1980s and 1990s.

In order to take possible non-Hicks-neutral changes in production technology, we employ a period-dummy framework such that

$$\frac{p_i x_i}{C_V} = \left(\beta_i + \sum_k \beta^I_{i,s_k} D^I_{i,s_k}\right) + \left(\sum_{j=2}^{n} \left(\gamma_{ij} + \sum_k \gamma^S_{ij,s_k} D^S_{i,s_k}\right)\right) \left(\log p_j - \log p_1\right) \tag{8}$$

for $i = 2, \ldots$. Here D^I_{i,s_k} is the intercept period-dummy and D^S_{i,s_k} is the slope period-dummy, representing effects of (non-Hicks-neutral) technological change in period s_k, which are 0 before s_k, and 1 after s_k. Here the symmetry of γ_{ij} should be properly taken in estimation. The above specification allows that either or both of the intercept and the slope may be different between before and after the technological change.

4.2 Identification of Variable Factor Inputs and Estimation of Variable Cost Parameters: A Heuristic Approach

As explained in the previous section, we have five categories of capital stocks ("IT", "machines and tools", "transportation machines", "buildings", and "structure"). Moreover, we have four categories of labor inputs ("young with low education", "young with high education", "old with low education", and "old with high education"). In the case of manufacturing, we have further decomposition in which each category can be divided into non-production and production subcategories. Thus, there are many possibilities of input combination that we must test whether the estimated cost function including these inputs satisfies monotonicity and concavity requirements in order to determine which factors can be considered as variable inputs. In contrast, the data is annual and we have only nineteen years in our sample. Moreover, industry difference is supposed to be large so that simple pooling of all industries to cope with the small sample problem may not be appropriate.[32] These problems are further compounded by possibility that technological change may make some factor inputs from variable to quasi-fixed or vice versa.

In order to cope with these problems, we proceed in a heuristic way. As a starting point, we postulate the order of "quasi-fixedness." As for capital stocks,. we assume that

[32] In an earlier version of this paper (presented in the 2001 spring conference), we tried pooling in manufacturing industries and got qualitatively similar results to ones obtained in this paper. However, the results are sensitive to small changes in the data. For example, if one industry is dropped from the sample, then the estimate of cost function parameters changes substantially.

structure capital ("structure" and "buildings") are more likely to be quasi-fixed than non-IT equipment ("machines and tools" and "transportation machines" [mostly automobiles]), while these non-IT equipment is more likely to be quasi-fixed than IT capital stocks. In fact, Fraumeni (1997) reports that the service life of IT capital stocks is roughly 3-5 years, that of machines/tools and automobiles is 8-15 years, and that of structure capital is more than 20 years, suggesting that "mobility" or "quasi-fixedness" of these capital stocks accord with our assumption.[33] As for labor inputs, we postulate young workers with low education are more likely to be quasi-fixed than any other workers. Other than that, we make no assumption about the order of "quasi-fixedness" with respect to labor inputs. We also assume that young workers with low education is the least "quasi-fixed" among all factor inputs except for IT capital stocks. We then choose IT capital stocks as factor 1 of the regression equation (8).[34] This turns out to be satisfactory since estimated cost functions (of some form) with IT capital stocks as factor 1 exhibit concavity in all industries.

Then, we employ the following three-steps procedure industry by industry. We briefly summarize our procedure and the detail is given in Appendix C.

In the first step, we choose variable inputs. For all industries, we have two labor-input dimensions (young/old, and high-education/low-education) and thus four types of labor inputs. This four-labor-types case is the baseline case. We estimate (8), and examine whether estimated cost function parameters are consistent with the concavity requirement. In this step, we ignore technological change and thus estimate (8) without period dummies. The estimation method is Full Information Maximum Likelihood and the estimation period is from 1980 to 1998. Since we ignore technological change, we do not expect sharp results but we should get "reasonably" good results in which all estimated γ_{ii}'s are negative at least with marginal statistical significance to satisfy the concavity requirement, although they may not be significant under standard levels of significance (5% or 1%). We apply this procedure

[33] Moreover, our preliminary study presented in the ESRI 2001 spring conference, which is based on pooling of manufacturing industries, suggests that IT capital stocks are likely to be variable.

[34] IT price movement is far greater than other factor input price movements. If we take IT capital stocks as factor 1, we have reasonably similar magnitude of relative price fluctuation among other factors, whereas if we choose another factor input, we get wide difference in fluctuation between the relative price of IT and that of other factors. This is one reason we choose IT capital stocks as factor 1 in share-equation estimation. In fact, we tried "young with low education," but the result was unsatisfactory.

starting from five factor inputs (explained in Appendix), and if the result is unsatisfactory, we drop some of factors until we get satisfactory results. In the end, we are able to identify variable inputs for all industries. Moreover, the list of variable factors is unique to each industry, that is, only one combination of factor inputs is chosen by this procedure.

In the second step, we re-estimate (8) with period dummies signifying technological change. As explained earlier, there is a good reason that the impact of information technology may be different between the 1980s and the 1990s. Thus, we consider both the intercept and slope dummies of the 1990s. In addition, there might be an additional industry-specific technological change. In fact, in some manufacturing industries such as Fabricated Metal, IT capital stocks' contribution is first sharply increased and then decreased (hump-shaped) some time in the 1990s, while IT capital stocks' contribution is increasing overall in industries such as Chemicals. The former may have another technological change later in the 1990s, inducing less reliance on IT stocks. In the case of Finance and Insurance, and Transportation and Communication, the hump-shape movement is found in the 1980s. This suggests there might be technological change in the mid-1980s in these industries. Taking these observations into account, we consider additional intercept and slope dummies of the mid-1990s for manufacturing industries with hump-shaped IT contribution. In the case of Finance and Insurance and Transportation and Communication, we consider the mid-1980 dummies instead of the mid-1990 dummies.

Upon deciding the number of period dummies (that is, technological changes), we estimate (8) with these period dummies, drop insignificant intercept and/or slope dummies, re-estimate the equations, and examine whether estimated coefficients are consistent with the concavity requirement. With respect to the timing of technological change, we use the following heuristic search procedure. For possible technological change from the 1980s to the 1990s, we assume that the change takes place in 1990 as a starting point. For possible technological change in the mid-1990s (mid-1980s), we assume that the change takes place in 1995 (1985). We then move the point of change around the initial point to see whether this gives us a sharper estimation (in terms of statistical significance of γ_{ii}) keeping the concavity requirement still satisfied. If we have a sharper result we choose this specification, and if otherwise we stick to the original specification.

The step 3 is taken only for manufacturing industries. For these industries, we have one more dimension with respect to labor input types, that is, production workers and non-production workers. Production workers are factory workers engaging in production, while non-production workers are supervisory, clerical and technical workers. Their activities are different from each other's so that aggregating these workers may lead to misleading results. Basically, we repeat Steps 1 and 2 for finer labor input data of manufacturing. However, there is problem of seeming multicolinearity. To avoid this problem, we aggregate young and old in production workers. Thus, we consider six types of labor inputs ("production workers with low education", "production workers with high education", "non-production young workers with low education", "non-production young workers with high education", "non-production old workers with low education", and "non-production young workers with high education.").

4.3 Age, Education Level, and IT Stocks

Tables 3 through 7 report the results of the previous section's procedure.. Table 3.1 shows the periods of (non-Hicks-neutral) technological change detected in the above procedures in the baseline case of four labor input types. In most baseline cases, the concavity requirement (derived in Appendix B.3) is satisfied at the average input price of the relevant period.[35] In a few industries the concavity requirement is not strictly satisfied for some sub-periods, but the deviation is rather small.[36]. Table 3.2 shows the result for the extended case of six labor inputs in manufacturing industries. Because of the seeming multicolinearity problem explained earlier, we get satisfactory results for only five out of eleven manufacturing industries.

Table 4.1 and 4.2 shows what factor inputs are variable in each industry. As expected, Table 4.1 reveals that *IT capital stocks and young workers with low education are shown to be variable in all industries*. In the case of manufacturing industries, Table 4.2 indicates that IT capital stocks and production workers with low education are variable., when production/non-

[35]Here we are again heuristic: we calculate (24), (25) and (26) in the four factor-input case (and corresponding terms in other cases) at the average input price vector of the relevant period, and examine whether sign conditions are satisfied or not. If sign conditions are satisfied at the average price vector, we consider that the estimated cost function satisfies the concavity requirement.

[36]Here "small deviation" means in the case of four factor inputs that one or two of (24), (25) and (26) may violate sign conditions but there deviation is rather small in absolute terms. Qualitatively the same criterion applies to other cases.

production difference is explicitly considered. The result of share equation estimation is reported in Table 5.1 for the baseline case and in Table 5.2 for the extended case in manufacturing. Coefficients of these estimated share equations are statistically significant and the equations have high adjusted R squares and no sign of autocorrelation. One exception is Electrical Machinery in the baseline case, showing strong error autocorrelation. However, it has high adjusted R squares and no sign of error autocorrelation in the extended case. Thus, so long as Electrical Machinery is concerned, we ignore the baseline case and instead rely on the extended case.

These tables also show a striking result. In all industries, *old workers with low education are shown consistently to be quasi-fixed*. Labor economists associate an education level with a skill level, and often use an education level as proxy of a skill level.[37] If this association is reasonable, then old workers with low education are unskilled labor and they are likely to be variable. However, this is not supported by our data. The result reported in Table 5.1 is rather consistent with firm-specific team-oriented skills that must be learned through a long period. To work for a particular firm for a long period enables old workers with low education to be more productive and cooperative to one another than young workers of the same education level. Because of this labor-productivity difference and externality in workplace, the firm considers them as quasi-fixed factors, rather than variable factors that can be freely adjusted to current economic conditions.

Table 4.1 also shows that *workers with high education are variable in almost half of all industries*. Young well-educated workers are variable factors in Food, Textile, Fabricated Metal, General Machinery (90s), and Finance and Insurance (–92), and old well-educated workers are variable factors in Instruments, Finance and Insurance (–92), and Services (non-production well-educated workers in the case of Electrical Machinery). This may seem puzzling at the first sight since a popular concept of “life-long employment” in Japan is often associated with this segment of labor force. As the word “life-long employment” suggests it, well-educated workers are usually considered to be quasi-fixed.

However, this may not be surprising if one takes account of the effect of IT technology development. In Table 6, we calculate Allen-Uzawa’s elasticity of substitution. *In all cases*

[37] “It is standard in the literature to define the level of labor skill on the basis of the level of workers’ education.” (Krusell et al (2000, p. 1033).)

where high-education-level labor is variable inputs, IT capital stocks and high-education-level are complements, rather than substitutes. Thus, a rapid increase in IT investment reported in Table 2 induces more demand for well-educated workers capable of using IT productively. Casual observation suggests that these well-educated workers specialized in information technology, such as system engineers and the like, are "mobile" and different from the stereo-type image of "life-long-ly employed" workers with high education. In fact, in General Machinery, young workers with high education are quasi-fixed in the 1980s, but they become variable inputs in the 1990s. Thus, the result in Table 4.1 and 4.2 may indicate a deep effect of information technology on well-educated work force, making them variable inputs rather than quasi-fixed. In contrast, but not surprisingly, *young workers with high education are substitutes for young workers with low education* in industries where both are variable inputs.

Table 6 also shows difference between IT-intensive industries and non-IT-intentive ones. As explained in Section 3, Electrical Machinery, Instruments, Finance and Insurance, Transportation and Communication, and Services are IT-incentive industries. Among them, the Transportation and Communication industry has only IT and young workers with low education as variable factors, and the Finance and Insurance industry's data are reliable only before 1992. In remaining three IT-intensive industries, *old well-educated workers (non-production old well-educated workers), rather than young well-educated workers, are complements of IT capital stocks.* However, we are so far unable to explain this difference.

Let us now turn to the issue of dynamics in the effect of IT advancement. Table 6 also shows how substitutability/complementarity evolves in the long run.[38] From Table

[38]Recently, Morishima's elasticity of substitution (see Murota (1977), Kuga (1979) and Blackorby and Russell (1989)) rather than Allen-Uzawa's elasticity of substitution, is utilized in the literature (see, for example, Stiroh (2000)). However, we still reports Allen-Uzawa's elasticity of substitution, since (a) Allen-Uzawa's and Morishima's are the same in two factor cases (many industries in our sample fall into this category) and (b) substitutability/complementarity is obvious in Allen-Uzawa's but not in Morishima's.

In fact, we also calculate Morishima's elasticity of substitution for three variable factor cases, and find an interesting result. Morishima's elasticity shows a stark asymmetry in the effect of IT-wage relative-price change. If IT price decreases while other prices are unchanged, then Morishima's elasticity is positive and greater than unity, showing that the relative share of IT increases in all industries in which high-education labor is complements to IT stocks in the baseline case (except for Electrical Machinery but this industry's estimate in the baseline case is not reliable as explained in the text.) In contrast, in these industries, if hourly wage of high-education labor

6, we see that *the Allen-Uzawa's elasticity of substitution between IT and young workers with low education is decreased from the 1980's to 1990's* in many industries except for Fabricated Metal and Instrument. Similarly, the degree of complementarity between well-educated workers and IT capital stocks is also diminished. In contrast, substitutability between well-educated workers and less-educated workers does not change.

Finally, let us examine the overall change of "quasi-fixedness" of factor inputs. In Table 7, the share of variable costs in the total production cost (that is, the sum of variable costs and quasi-fixed factors' costs) is shown for the 1980s and 1990s. *The variable cost share is decreased, substantially in some cases, from the 1980s to the 1990s, except for General Machinery* where the number of variable inputs is increased. This is one cause of poor performance of Japanese firms in the 1990s, when demand is very weak.

5 IT Stocks, Human Capital, and Technological Progress: 1980-1998

In this section, we first examine sectoral value-added growth and examine contribution of each input to economic growth between 1981 and 1998. Then we derive the rate of technological progress in the framework developed in Section 3. We confirm sharp decline of the rate of technological progress from the 1980s to the 1990s. Then, we investigate possible causes of the decline of technological progress mentioned in Section 1 by examining factors determining the rate of technological growth and their dynamic change. Industries under consideration are eleven manufacturing industries and four non-manufacturing industries (excluding Finance).[39]

As explained in Section 3, we approximate the prodution-function parameter k by the long-run ratio of the variable cost to the total cost. In doing so, we allow k may be different between the 1980s and 1990s. This is obvious in General Machinery in which the number of variable inputs is changed. Although it is not obvious in other industries, we assume that k is changed to take account of difference often pointed out between the two periods and approximate k_{1980} by the 1980's average variable-cost-total-cost ratio, and k_{1990}

decreases while other prices are unchanged, the Morishima's elasticity is negative implying that the relative share of IT stocks increases.

[39]We exclude Finance and Insurance becasuse their data after 1993 are problematic.

by the 1990's variable-cost-to-total-cost ratio. We then further divide the two decades into four sub-periods (1981-84, 1985-89, 1990-94, 1995-98).

5.1 Value Added Growth and Contribution of Inputs to Growth

Let us first examine sectoral value-added growth (see Table 8 and Figure 3). The results reveal a remarkable contrast between the 1980s and the 1990s. Most industries show a very high rate of value-added growth in the 1980s. Then, after the crash of the stock and real estate markets around 1990, the growth rate declines substantially and in some industries fall into the negative region especially in the latest period of 1995-1998. In eleven manufacturing industries, the following six industries have a negative rate of value added growth in the latest period (Textile - 9.50%, Paper and Pulp - 0.64%, Chemicals - 0.99%, Stone and Clay -3.26%, Primary Metal -2.43%, and Fabricated Metal - 2.30%). In four machinery industries, Transportation Equipment also has a negative growth rate (- 0.28%) in that period. However, other three machinery industries experience a higher rate of value added growth in the latter half of the 90's than in the first half (General Machinery 1.11%, Electrical Machinery 5.99%, and Instruments 3.13% in 1995-98). In four non-manufacturing industries under investigation, Construction and Trade have a negative rate of value added growth in the latest period (respectively - 4.04% and - 0.64%). The two broken-line graphs drawn in Figure 3 show a nominal GDP[40] share of each industry. A thick broken-line is the nominal GDP share in 1980,while the dotted one is that in 1998. These graphs show that the GDP share of Primary Metal and Trade decline sharply from 1980 to 1998, while that of Services rises sharply.

The following simple regression of value-added growth on the 1990s dummy confirms a sharp decline of value-added growth from the 1980s to the 1990s. Regressing the sub-period-average value-added growth in four subperiods on a constant and the 1990s dummy, we obtain

$$\begin{aligned} Value-Added\ \ Growth &= \underset{(7.711)}{4.773} - \underset{(-5.116)}{4.479} \times 90sDummy \\ R^2 &= 0.311, \quad No.\ of\ \ Obs. = 60 \end{aligned}$$

[40]It should be reminded that we include software in GDP, while 1968SNA-based GDP does not.

where $t-$value is in parenthesis. The 1990s dummy is very significant. However, a similar simple regression (not reported here) with a manufacturing dummy reveals that there is no statistically significant difference between manufacturing and non-manufacturing.

Tables 9 and 10 show each input's contribution to value added growth. To save space, we aggregate structure and buildings to structure capital, and machines and tools and transportation machines into equipment capital. As for labor inputs, we report the four-labor-inputs case (young with low education, young with high education, old with low education, and old with high education) since production/non-production classification is not available for non-manufacturing.

Table 9 shows that IT stock's contribution to value added growth is always positive except for Fabricated Metal in the latter half of the 90's, and the same is true for (non-IT) equipment. In contrast, structure's contribution to value-added growth is small and becomes negative in the latter half of the 90's in four industries (Textile, Stone and Clay, Primary Metal, Instruments). This clearly shows that industrial growth gravitates from physical expansion to internal upgrading of equipment (both IT-related and non-IT related.)

Table 10 reveals a remarkable contrast between low and high education workers in the 1990s. Let us start with young workers. In the 1990s, the contribution of young workers with low education is negative in all industries under consideration, regardless of the level of value added growth. In contrast, the contribution of young workers with high education to value added growth is all positive except for Textile and Instruments in the1990's. Many industries now experience the effect of population aging, and upgrade their work force with respect to the education level. As for old workers, this upgrading is far more sweeping. In the 1990s, all industries but Service have a negative contribution of old workers with low education, while that of old workers with high education is positive in all industries in the same period. Thus, although old workers with low education are quasi-fixed as shown in Section 4, their inputs are adjusted in the long run by natural attrition and/or by employment adjustment. They are quasi-fixed but variable in the long run.

5.2 Technological Progress, IT Externality, and IT-Induced Skill Obsolescence

As explained in the previous sub-section, the rate of value-added growth declined substantially in 1990s. This decline was not simply attributed to a slump in demand and resulting decrease in factor inputs. The rate of technological progress also declines substantially in many industries. The prolonged slump of the 1990s is not merely a demand-driven phenomenon, but the supply side plays a substantial role.

In Table 8, the rate of technological growth, which is the residual of the value-added growth that is not attributed to inputs' contribution is shown for the total sample period, for the 1980s and 1990s, and for four subperiods (1981-1984, 1985-1989, 1990-1994, 1995-1998). Figure 4 shows changes between subperiods in a concise way, as well as the ratio of IT stocks' share in the total capital stock in the 1881-1984 period and the 1995-1998 period.

Table 8 and Figure 4 indicate there is a downward shift in technological progress from the 1980s to the 1990s. To see this, we regress the sub-period-average rates of technological progress on a constant and the 1990s dummy and get (9).

$$\begin{aligned} \textit{Technological Progress} &= \underset{(4.672)}{2.315} - \underset{(-3.733)}{2.616} \times 90s\textit{Dummy} \\ R^2 &= 0.194, \quad No.\ of\ Obs. = 60 \end{aligned} \tag{9}$$

The coefficient for the 1990s dummy is negative and statistically significant, suggesting a downward shift. When a dummy representing manufacturing industries included, the coefficient of this dummy is statistically insignificant. Thus, the shift occurs both in manufacturing and non-manufacturing in the same way.

There are, however, a few exceptions for the general pattern of declining rate of technological progress. The 1995-98 rate of technological progress in Electrical Machinery and Instruments is almost the same as in the 1980s. These two industries are among industries having a high rate of IT capital formation both in the 1980s and 1990s (Table 9 and figure 4). However, this does not necessarily suggest a possible linkage between IT capital formation and the rate of technological progress, since Services has a higher rate of IT capital formation and their rate of technological progress are negative even in the latter half of 90s (Figure 4). The relationship between the technological progress and IT capital stocks is more subtle, and we need to examine the issue using more formal analysis.

Before proceeding with a formal analysis, let us review several possible factors that may influence the rate of technological progress.

First, there is a strong argument that information and communication technology capital stocks have positive externality. Computers are connected with each other by the LAN and/or the Internet. Their productivity increases more than proportionally as the number of computers increases. The value of software is increased more than proportionally as the number of users increases. It is often argued that this kind of externality is present in IT capital stocks. And some argue that the U. S. productivity increase found in Jorgenson and Stiroh (2000) and Oliner and Sichel (2000) and others[41] partly stems from this externality. So-called "New Economy" argument is based on this kind of argument.[42] If there is externality in IT capital stocks, the growth residual (that is, the rate of technological progress) must be correlated with IT capital stocks in some way.

Second, casual observation shows that there is "digital divide" between the young and the old. Rapid and ever-changing information and communication technology produces a generational gap. The old, who are skeptical about the "new and improved" technological gadgets, may be slow in adopting new technology. If such inflexibility is present in the work place, then technological progress due to information and communication technology may be lower in industries having more old workers than young workers.

Third, let us ignore the effect of information technology development for a while and consider more conventional factors influence productivity. Skills obtained by learning by doing and on-the-job training are often considered to be the most important determinant of productivity. So-called Toyota Production System combining Kanban (Just-in-Time) and TQC (Total Quality Circle) clearly recognizes this importance. Long-run knowledge about jobs and coworkers greatly enhances improvement of the worker's productivity in team production. This is externality in work place, and one worker's productivity is positively related to his coworkers' productivity. If this is important in production, industries with many old workers having long experience must show higher growth residual (technological progress). However, as explained in Section 1, this productivity advantage may be eroded by the advance of information technology, which makes this tacit knowledge obsolete. Thus, if this factor is important, we expect a positive correlation between the ratio of old workers and the growth residual before the rapid increase of information capital stocks, and a negative correlation

[41] Many microeconomic studies find a large economic impact from IT use in firms. See the surveys of Brynjolfsson and Yang (1996) and Brynjolfsson and Hitt (2000).

[42] Stiroh (1999) reviews the new economy literature.

after it.

Fourth, there is a classical Schumpeterian argument that technological development is often carried out by monopolistic firms. If this is the case, there must be a positive correlation between pure profits and the growth residual. In contrast, there may be a counter-argument that monopoly firms do not have market pressure to innovate so that there must be a negative correlation. Finally, there is a strong arguement that the impact of capital stocks is different between structure and equipment.[43] We will also consider this possibility.

To examine the validity of the above arguments, we employ panel data of fifteen industries and four subperiods explained earlier. We then estimate an equation explaining the growth residual, or equivalently, the rate of technological progress, by (1) the ratio of old workers with low education to the total labor inputs (OL), (2) the ratio of old workers with high education to the total labor inputs (OH), (3) the ratio of a net profit to the total cost ($PROFIT$), (4) the ratio of IT stocks to the total capital stocks (ITK), and (5) the ratio of the non-IT equipment capital stocks to total capital stocks (EQ) in the following way.

$$\begin{aligned} Technological\ Progress &= Const. + \left(\beta_{OL} + \delta_{OL} * 90sDUMMY\right) * OL \\ &\quad + \left(\beta_{OH} + \delta_{OH} * 90sDUMMY\right) * OH \\ &\quad + \beta_{PROFIT} * PROFIT + \beta_{ITK} * ITK + \beta_{EQ} * EQ + \varepsilon_{it} \end{aligned}$$

Here we allow the possibility of structural change due to IT development around 1990 by including a coefficient dummy variable $90sDUMMY$ for the 90's.

We estimate both the fixed effect model and the random effect one. In addition, since explanatory variables may be endogenously determined so that they may be correlated with error terms, we also employ Generalized Method of Moments.[44]

Table 11 through 14 report the results. In all cases the random effect model is chosen by the Hausman test, so that we report only the random effect model here. In the case of

[43] See Gordon (1990) and De Long and Summers (1992).

[44] Instruments we use are (1) constant, (2) $90sDUMMY$, (3) the ratio of the old (over 40) in the total population, (4) the ratio of college and junior college graduates in the total 20-24 year old population of 1951-1955, 1956-1960, 1961-1965, 1966-1970, (5) population growth, (6) one-year-lagged value-added growth, (7) one-year-lagged capital/labor ratio, (8) one-year-lagged ITK, (9) one-year-lagged EQ. Hansen's overidentifying restrictions test (Hansen (1982)) shows that our choice is reasonable. We also tried other macroeconomic variables but the result is not satisfactory because of seeming multicolinearity.

GMM, the coefficient of $90sDUMMY * OL$, δ_{OL}, is not statistically significant and to include this variable makes other estimates deteriorate, we exclude it in all of Tables 11 through 14. Similar problems occur for $PROFIT$ so that we also exclude it in all of Tables 11 through 14 for GMM.

Table 11 is the case in which we use only manufacturing industries: the number of observations, NOB, is 44. Table 11 shows that β_{OH}, δ_{OH}, and β_{ITK} are statistically 10%-, 5%-, and 1%-level significant. Thus, the result supports the existence of IT externality, a positive effect of long experience of old workers on productivity growth in the high-education segment in the 1980s, and a negative IT effect (obsolescence effect) on long experience in the 1990s. In contrast, there is no effect of the old's inflexibility, no pure-profit effect, nor externality in (non-IT) equipment. Qualitatively the same result is obtained for all industries reported in Table 14. However, these results are influenced by manufacturing industries. In fact, when sample industries are four non-manufacturing industries, no variable has explanatory power with respect to rate of technological progress (Table 13).

Moreover, the IT externality effect is not robust. Let us exclude Electrical Machinery from these eleven manufacturing industries to restrict sample industries to ten manufacturing industries (NOB is 40). The result is reported in Table 12. The coefficient β_{ITK} is now statistically insignificant. In contrast, the obsolescence effect of IT (δ_{OH}) is still statistically significant. Thus, the result of this section shows that IT's effects are mostly concentrated in Electrical Machinery, which is IT-producing industry, and there is no general IT externality.

The result of this paper is consistent with Stiroh (2001)'s result about the U. S. manufacturing industries. He uses U. S. manufacturing industries data from 1973 to 1999 to estimate correlation between IT capital intensity and the rate of technological progress. His results suggest the primary impact of IT is through traditional capital-deepening and provide little evidence that IT capital formation is responsible to accelerate the rate of technological progress in the United States.

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A Derivation of Multiplicably-Separable Variable-Cost Function (3)

From Assumption 2, we have

$$Y = G(x_1, \ldots, x_i, \ldots, x_n; A)\, S = G\left(1, \frac{x_2}{x_1}, \ldots, \frac{x_n}{x_1}; A\right) x_1^k S$$

Consequently, we obtain

$$C_V(p_1, \ldots, p_n, Y, S; A) = \underset{x_1, \ldots, x_n}{Min} \quad \left(1 + \sum_{i=2}^{n} \frac{p_i x_i}{p_1 x_1}\right) p_1 x_1 \qquad \text{subject to} \quad \frac{Y}{x_1^k S} = G\left(1, \frac{x_2}{x_1}, \ldots, \frac{x_n}{x_1}; A\right).$$

Then, the cost minimization has three steps. In the first step, for given x_1 and Y, the ratios $\{x_i / x_1\}$ are optimized. Let v_i^* be the resulting optimum ratio, such that

$$\left(\frac{x_i}{x_1}\right)^* = v_i^*\left(\frac{p_2}{p_1}, \ldots, \frac{p_n}{p_1}, \frac{Y}{x_1^k S}; A\right) \qquad \text{for } i = 2, \ldots, n$$

In the second step, the optimal x_1^* is implicitly determined by

$$\frac{Y}{x_1^k S} = G\left(1, v_2^*\left(\frac{p_2}{p_1}, \ldots, \frac{p_n}{p_1}, \frac{Y}{x_1^k S}; A\right), \ldots, v_n^*\left(\frac{p_2}{p_1}, \ldots, \frac{p_n}{p_1}, \frac{Y}{x_1^k S}; A\right)\right)$$

Finally, the optimal x_i^* is determined by $x_i^* = v_i^* x_1^*$.

Let us now show that the variable cost function C_V has a multiplicatively separable between relative prices on the one hand, and output and production capacity on the other. Let h such that

$$h = h\left(\frac{p_2}{p_1}, \ldots, \frac{p_n}{p_1}; A\right)$$

be the solution of

$$h = G\left(1, v_2^*\left(\frac{p_2}{p_1}, \ldots, \frac{p_n}{p_1}, h; A\right), \ldots, v_n^*\left(\frac{p_2}{p_1}, \ldots, \frac{p_n}{p_1}, h; A\right)\right).$$

Note that h is a function of only the relative variable input prices (and the state of production technology A). Then we have $Y / \left(x_1^k S\right) = h$, which in turn implies

$$x_1 = \left\{\frac{Y}{hS}\right\}^{1/k}$$

Substituting these results into the variable cost function, we have

$$C_V\left(p_1,\ldots,p_n,Y,S\right)=\left(1+\sum_{i=2}^{n}\frac{p_i}{p_1}\widetilde{v_i^*}\left(\frac{p_2}{p_1},\ldots,\frac{p_n}{p_1};A\right)\right)\frac{p_1}{h^{1/k}}\left\{\frac{Y}{S}\right\}^{1/k}$$

where

$$\widetilde{v_i^*}\left(\frac{p_2}{p_1},\ldots,\frac{p_n}{p_1};A\right)=v_i^*\left(\frac{p_2}{p_1},..,\frac{p_n}{p_1},h\left(\frac{p_2}{p_1},\ldots,\frac{p_n}{p_1};A\right);A\right)$$

Consequently, under Assumptions 1 and 2, we have multiplicatively separable variable cost function (3) such that

$$C_V\left(p_1,\ldots,p_n,Y,S;A\right)=c_v\left(p_1,\ldots,p_n;A\right)\left(\frac{Y}{S}\right)^{1/k}$$

where c_v is homogeneous of degree one in prices such that

$$c_v\left(p_1,\ldots,p_n;A\right)=\left(1+\sum_{i=2}^{n}\frac{p_i}{p_1}\widetilde{v_i^*}\left(\frac{p_2}{p_1},\ldots,\frac{p_n}{p_1};A\right)\right)p_1\left\{h\left(\frac{p_2}{p_1},\ldots,\frac{p_n}{p_1};A\right)\right\}^{-1/k}. \qquad (10)$$

B Multiplicably-Separable Translog Variable-Cost Function, Share Equations and Elasticity of Substitution

We are concerned with the following form of n-factor multiplicably-separable variable cost functions.

$$C_V\left(p_1,\ldots,p_n,Y,S;A\right)=c_v\left(p_1,\ldots,p_n;A\right)\left(\frac{Y}{S}\right)^{1/k} \qquad (11)$$

We assume that a translog approximation of c_v at $\overline{p}=\left(\overline{p_1},\ldots,\overline{p_n}\right)$ is a good approximation. In many applications of translog functions and in many textbooks, prices are normalized through appropriate choice of units, either by setting a particular year's price equal to unity or by making the average price equal to unity, and then set $\overline{p}=\left(1,\ldots,1\right)$. This makes exposition simple and straightfoward in the traditional share equation estimation.

In this paper, however, we do not normalized prices and we let $\overline{p}$ be the average price vector. Thus, we have $\overline{p}\neq\left(1,\ldots,1\right)$ in general in this paper. We take this procedure since parameter estimation are not invariant with respect to normalization. We we get sharper results without normalization than with normalization.

Taking logarithm of c_v and then taking a second-order Taylor expansion of $\ln c_v$ with respect to $\ln p_i$ around $p = \overline{p}$, we have

$$\ln c_v(p_1, ..., p_n; A) = \alpha(A) + \sum_{i=1}^{n} \beta_i(A) \ln p_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij}(A) \ln p_i \ln p_j$$

where

$$\alpha(A) = \ln c_v(\overline{p_1}, ..., \overline{p_n}) - \sum_{i=1}^{n} \left.\frac{\partial \ln c_v}{\partial \ln p_i}\right|_{p=\overline{p}} (\ln \overline{p_i}) + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \left.\frac{\partial^2 \ln c_v}{\partial \ln p_i \partial \ln p_j}\right|_{p=\overline{p}} (\ln \overline{p_i}) \left(\ln \overline{p_j}\right);$$

$$\beta_i(A) = \left.\frac{\partial \ln c_v}{\partial \ln p_i}\right|_{p=\overline{p}} - \sum_{j=1}^{n} \left.\frac{\partial^2 \ln c_v}{\partial \ln p_i \partial \ln p_j}\right|_{p=\overline{p}} \left(\ln \overline{p_j}\right);$$

and

$$\gamma_{ij}(A) = \left.\frac{\partial^2 \ln c_v}{\partial \ln p_i \partial \ln p_j}\right|_{p=\overline{p}}.$$

Note that all these parameters depend on the state of production technology A.

Let us examine the requirement that the cost function is homogeneous of degree one in input prices. Since C_V has the form (11), it is obvious that c_v should be homonegeneous of degree one in input prices. As usual, this implies

$$\begin{aligned}
\ln c_v(\lambda p_1, ..., \lambda p_n; A) &= \alpha(A) + \sum_{i=1}^{n} \beta_i(A)(\ln \lambda + \ln p_i) + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij}(A)(\ln \lambda + \ln p_i)\left(\ln \lambda + \ln p_j\right) \\
&= \alpha(A) + \left(\sum_{i=1}^{n} \beta_i(A)\right) \ln \lambda + \sum_{i=1}^{n} \beta_i(A) \ln p_i + \frac{1}{2} \sum_{j=1}^{n} \left\{ \left(\sum_{i=1}^{n} \gamma_{ij}(A)\right) \ln \lambda \right\} \ln p_j \\
&\quad + \frac{1}{2} \sum_{i=1}^{n} (\ln p_i) \left\{ \left(\sum_{j=1}^{n} \gamma_{ij}(A)\right) \ln \lambda \right\} + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij}(A)(\ln p_i)\left(\ln p_j\right) \\
&= \ln \lambda c_v(p_1, ..., p_n; A) = \ln \lambda + \alpha(A) + \sum_{i=1}^{n} \beta_i(A) \ln p_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij}(A) \ln p_i \ln p_j
\end{aligned}$$

As in the standard case, we have the following requirement:

$$\sum_{i=1}^{n} \beta_i(A) = 1, \quad \sum_{i=1}^{n} \gamma_{ij}(A) = 0, \quad \sum_{j=1}^{n} \gamma_{ij}(A) = 0, \quad \gamma_{ij}(A) = \gamma_{ji}(A) \text{ for all } i \text{ and } j \qquad (12)$$

B.1 Regression Equations: Share Functions

Although our formulation of cost function deviates slightly from the standard one, we have the same form of share functions. To see this, note that

$$\ln c_v(p_1,...,p_n;A) = \ln\left[p_1 \cdot c_v\left(1,\frac{p_2}{p1},...,\frac{p_n}{p_1};A\right)\right] = \ln p_1 + \left[\sum_{i=2}^{n}\beta_i(A)\ln\frac{p_i}{p_1} + \frac{1}{2}\sum_{i=2}^{n}\sum_{j=2}^{n}\gamma_{ij}(A)\ln\frac{p_i}{p_1}\ln\frac{p_j}{p_1}\right]$$

$$= \ln p_1 + \sum_{i=2}^{n}\beta_i(A)(\ln p_i - \ln p_1) + \frac{1}{2}\sum_{i=2}^{n}\sum_{j=2}^{n}\gamma_{ij}(A)\ln(\ln p_i - \ln p_1)\left(\ln p_j - \ln p_1\right)$$

Let x_i be the quantity of the ith input. Then, we get

$$\frac{\partial C_V}{\partial p_i} = x_i = \left(\frac{\partial c_v}{\partial p_i}\right)\left(\frac{Y}{S}\right)^{1/k}$$

Combining these two relations, we get the following representation of share functions, for $i = 2,...,n$

$$\begin{aligned} s_i = \frac{p_i x_i}{C_v} &= \frac{p_i x_i}{c_v(p_1,...,p_n)\left(\frac{Y}{S}\right)^{1/k}} = \frac{p_i}{c_v(p_1,...,p_n)}\left(\frac{\partial c_v}{\partial p_i}\right) \\ &= \frac{d\ln c_v}{d\ln p_i} = \beta_i(A) + \sum_{j=2}^{n}\gamma_{ij}(A)(\ln p_i - \ln p_1) \end{aligned} \tag{13}$$

These equations are regression equations from which the following parameters of the cost function can be retrieved

$$\left(\beta_i(A), \gamma_{ij}(A)\middle|\ i,j = 2,...,n\right).$$

From these estimated $\beta_i(A)$ and $\gamma_{ij}(A)$, the rest of parameters are calculated using the homogeneity relations (12).

B.2 First and Second Order Derivatives

To avoid heavy notations, we hereafter supress "(A)" in α, β_i, and γ_{ij}.

(1) First order derivate. It is immediate to have

$$\frac{\partial c_v}{\partial p_i} = \left(\frac{c_v}{p_i}\right)\left(\frac{\partial \ln c_v}{\partial \ln p_i}\right) = \left(\frac{c_v}{p_i}\right)\left(\beta_i + \sum_{j=1}^{n}\gamma_{ij}\ln p_j\right). \tag{14}$$

(2) Second-order derivative. Note that

$$\frac{\partial \ln c_v}{\partial \ln p_i} = \beta_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j$$

Thus we have

$$\begin{aligned}
\frac{\partial}{\partial \ln p_i}\left(\frac{\partial \ln c_v}{\partial \ln p_i}\right) = \gamma_{ii} &= p_i \frac{\partial}{\partial p_i}\left(\frac{p_i}{c_v}\frac{\partial c_v}{\partial p_i}\right) \\
&= p_i \left[\left\{\frac{\partial}{\partial p_i}\left(\frac{p_i}{c_v}\right)\right\}\frac{\partial c_v}{\partial p_i} + \frac{p_i}{c_v}\frac{\partial}{\partial p_i}\left(\frac{\partial c_v}{\partial p_i}\right)\right] \\
&= p_i \left[\left\{\left(\frac{c_v - p_i \frac{\partial c_v}{\partial p_i}}{c_v^2}\right)\right\}\frac{\partial c_v}{\partial p_i} + \frac{p_i}{c_v}\left(\frac{\partial^2 c_v}{\partial p_i^2}\right)\right] \\
&= \left(1 - \frac{p_i}{c_v}\frac{\partial c_v}{\partial p_i}\right)\frac{p_i}{c_v}\frac{\partial c_v}{\partial p_i} + \frac{p_i^2}{c_v}\left(\frac{\partial^2 c_v}{\partial p_i^2}\right)
\end{aligned}$$

which implies

$$\frac{\partial^2 c_v}{\partial p_i^2} = \frac{c_v}{p_i^2}\left[\gamma_{ii} + \left(\frac{\partial \ln c_v}{\partial \ln p_i} - 1\right)\frac{\partial \ln c_v}{\partial \ln p_i}\right] \tag{15}$$

Similarly, we have

$$\begin{aligned}
\frac{\partial}{\partial \ln p_j}\left(\frac{\partial \ln c_v}{\partial \ln p_i}\right) = \gamma_{ij} &= p_j \frac{\partial}{\partial p_j}\left(\frac{p_i}{c_v}\frac{\partial c_v}{\partial p_i}\right) \\
&= p_j \left[\left\{\frac{\partial}{\partial p_j}\left(\frac{p_i}{c_v}\right)\right\}\frac{\partial c_v}{\partial p_i} + \frac{p_i}{c_v}\frac{\partial}{\partial p_j}\left(\frac{\partial c_v}{\partial p_i}\right)\right] \\
&= p_j \left[\left\{p_i\left(-\frac{1}{c_v^2}\frac{\partial c_v}{\partial p_j}\right)\right\}\frac{\partial c_v}{\partial p_i} + \frac{p_i}{c_v}\partial\frac{\partial^2 c_v}{\partial p_i \partial p_j}\right] \\
&= -\left(\frac{p_j}{c_v}\frac{\partial c_v}{\partial p_j}\right)\frac{p_i}{c_v}\frac{\partial c_v}{\partial p_i} + \frac{p_i p_j}{c_v}\partial\frac{\partial^2 c_v}{\partial p_i \partial p_j}
\end{aligned}$$

$$\frac{\partial^2 c_v}{\partial p_i \partial p_j} = \frac{c_v}{p_i p_j}\left[\gamma_{ij} + \left(\frac{\partial \ln c_v}{\partial \ln p_j}\right)\frac{\partial \ln c_v}{\partial \ln p_i}\right] \tag{16}$$

The above discussion reveals the following simple characterization of the second derivatives. Let η_i be the input-price elasticity of the cost function:

$$\eta_i = \frac{\partial \ln c_v}{\partial \ln p_i} = \beta_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j.$$

As it has been shown, in the translog case, the input-price elasticity happens to be equal to the cost share of the inputs.

$$\eta_i = \frac{\partial \ln c_v}{\partial \ln p_i} = \frac{p_i x_i}{C_V} = s_i$$

Then we have

$$z_{ii} = \frac{\partial^2 c_v}{\partial p_i^2} = \frac{c_v}{p_i^2}\widetilde{z_{ii}} \tag{17}$$

where

$$\widetilde{z_{ii}} = \gamma_{ii} + (\eta_i - 1)\,\eta_i \tag{18}$$

and

$$z_{ij} = \frac{\partial^2 c_v}{\partial p_i \partial p_j} = \frac{c_v}{p_i p_j}\widetilde{z_{ij}} \qquad i \neq j \tag{19}$$

where

$$\widetilde{z_{ij}} = \gamma_{ij} + \eta_i \eta_j \tag{20}$$

B.3 Cost-Function Requirements

By construction, homogeneity of degree one with respect to input prices is satisfied. The remaining requirements are monotonicity and cocavity.

(1) Monotonicity. The monotonicity requirement is satisfied if

$$\frac{\partial c_v}{\partial p_i} > 0.$$

Since $c_v > 0$ and $p_i > 0$, we have from (14)

$$sgn\left(\frac{\partial c_v}{\partial p_i}\right) = sgn\left(\frac{\partial \ln c_v}{\partial \ln p_i}\right) = sgn\left(\frac{p_i x_i}{C_v}\right) = sgn\left(\beta_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j\right)$$

Consequently, if the share is positive for the range of variables we observe, then monotonicity is satisfied.

(2) Concavity. The concavity requirement is satisfied if for all i and j, the following reltions are satisfied,.in the case of four varaible case,

$$z_{ii} < 0; \tag{21}$$

$$\det \begin{bmatrix} z_{ii} & z_{ij} \\ z_{ji} & z_{jj} \end{bmatrix} > 0; \tag{22}$$

$$\det \begin{bmatrix} z_{ii} & z_{ij} & z_{ik} \\ z_{ji} & z_{jj} & z_{jk} \\ z_{ki} & z_{kj} & z_{kk} \end{bmatrix} < 0. \tag{23}$$

The concavity requirement in the general case of n is analogously derived. Since n is atmost four in this paper, we examine the four-factor case here.

Note that since $c_v > 0$ and $p_i > 0$, we have

$$sgn(z_{ii}) = sgn\left(\frac{c_v}{p_i^2}\widetilde{z_{ii}}\right) = sgn(\widetilde{z_{ii}})$$

$$\begin{aligned}
sgn\left(\det \begin{bmatrix} z_{ii} & z_{ij} \\ z_{ji} & z_{jj} \end{bmatrix}\right) &= sgn\left[z_{ii}z_{jj} - z_{ij}^2\right] = sgn\left[\frac{c_v}{p_i^2}\widetilde{z_{ii}}\frac{c_v}{p_j^2}\widetilde{z_{jj}} - \left(\frac{c_v}{p_ip_j}\right)^2\left(\widetilde{z_{ij}}\right)^2\right] \\
&= sgn\left[\left(\frac{c_v}{p_ip_j}\right)^2\left\{\widetilde{z_{ii}}\widetilde{z_{jj}} - \left(\widetilde{z_{ij}}\right)^2\right\}\right] = sgn\left[\left\{\widetilde{z_{ii}}\widetilde{z_{jj}} - \left(\widetilde{z_{ij}}\right)^2\right\}\right] \\
&= sgn\left(\det \begin{bmatrix} \widetilde{z_{ii}} & \widetilde{z_{ij}} \\ \widetilde{z_{ji}} & \widetilde{z_{jj}} \end{bmatrix}\right)
\end{aligned}$$

$$\begin{aligned}
sgn\left(\det \begin{bmatrix} z_{ii} & z_{ij} & z_{ik} \\ z_{ji} & z_{jj} & z_{jk} \\ z_{ki} & z_{kj} & z_{kk} \end{bmatrix}\right) &= sgn\left(z_{ii}z_{jj}z_{kk} + z_{ji}z_{kj}z_{ik} + z_{ij}z_{jk}z_{ki} - z_{ik}z_{jj}z_{ki} - z_{jk}z_{kj}z_{ii} - z_{ij}z_{ji}z_{kk}\right) \\
&= sgn\begin{pmatrix} \frac{c_v}{p_i^2}\widetilde{z_{ii}}\frac{c_v}{p_j^2}\widetilde{z_{jj}}\frac{c_v}{p_k^2}\widetilde{z_{kk}} + \frac{c_v}{p_jp_i}\widetilde{z_{ji}}\frac{c_v}{p_kp_j}\widetilde{z_{kj}}\frac{c_v}{p_ip_k}\widetilde{z_{ik}} + \frac{c_v}{p_ip_j}\widetilde{z_{ij}}\frac{c_v}{p_jp_k}\widetilde{z_{jk}}\frac{c_v}{p_kp_i}\widetilde{z_{ki}} \\ \\ -\frac{c_v}{p_jp_k}\widetilde{z_{ik}}\frac{c_v}{p_j^2}\widetilde{z_{jj}}\frac{c_v}{p_kp_i}\widetilde{z_{ki}} - \frac{c_v}{p_jp_k}\widetilde{z_{jk}}\frac{c_v}{p_kp_j}\widetilde{z_{kj}}\frac{c_v}{p_i^2}\widetilde{z_{ii}} - \frac{c_v}{p_ip_j}\widetilde{z_{ij}}\frac{c_v}{p_jp_i}\widetilde{z_{ji}}\frac{c_v}{p_k^2}\widetilde{z_{kk}} \end{pmatrix} \\
&= sgn\left(\left[\frac{c_v^3}{p_i^2p_j^2p_k^2}\right]\left[\widetilde{z_{ii}}\widetilde{z_{jj}}\widetilde{z_{kk}} + \widetilde{z_{ji}}\widetilde{z_{kj}}\widetilde{z_{ik}} + \widetilde{z_{ij}}\widetilde{z_{jk}}\widetilde{z_{ki}} - \widetilde{z_{ik}}\widetilde{z_{jj}}\widetilde{z_{ki}} - \widetilde{z_{jk}}\widetilde{z_{kj}}\widetilde{z_{ii}} - \widetilde{z_{ij}}\widetilde{z_{ji}}\widetilde{z_{kk}}\right]\right) \\
&= sgn\left(\det \begin{bmatrix} \widetilde{z_{ii}} & \widetilde{z_{ij}} & \widetilde{z_{ik}} \\ \widetilde{z_{ji}} & \widetilde{z_{jj}} & \widetilde{z_{jk}} \\ \widetilde{z_{ki}} & \widetilde{z_{kj}} & \widetilde{z_{kk}} \end{bmatrix}\right)
\end{aligned}$$

Thus, the concavity requirements (21) through (23) are equivalnet to the following conditions:

$$\widetilde{z_{ii}} < 0 \tag{24}$$

$$\det \begin{bmatrix} \widetilde{z_{ii}} & \widetilde{z_{ij}} \\ \widetilde{z_{ji}} & \widetilde{z_{jj}} \end{bmatrix} > 0 \tag{25}$$

$$\det \begin{bmatrix} \widetilde{z_{ii}} & \widetilde{z_{ij}} & \widetilde{z_{ik}} \\ \widetilde{z_{ji}} & \widetilde{z_{jj}} & \widetilde{z_{jk}} \\ \widetilde{z_{ki}} & \widetilde{z_{kj}} & \widetilde{z_{kk}} \end{bmatrix} < 0 \tag{26}$$

It should be noted here that c_v is not identifiable from data. Although the expression of z_{ii} and z_{ij} in (17) and (19) contain this unobservable c_v, the expression of $\widetilde{z_{ii}}$ and $\widetilde{z_{ij}}$ in (18) and (20) consists of all observable (estimatable) parameters. Thus, (24) through (26) can be used to examine whether the observed “cost function” actually satisfies the concavity requirements.

B.4 Elasticity of Substititions

Allen-Uzawa’s Elasticity of Substitution (AES) is defined as

$$AES_{ij} = \frac{C_V \frac{\partial^2 C_V}{\partial p_i \partial p_j}}{\frac{\partial C_V}{\partial p_j}\frac{\partial C_V}{\partial p_i}}$$

Since we have from (11), (14), (15) and (16),

$$\frac{C_V \frac{\partial^2 C_V}{\partial p_i \partial p_j}}{\frac{\partial C_V}{\partial p_j}\frac{\partial C_V}{\partial p_i}} = \frac{c_v \frac{\partial^2 c_v}{\partial p_i \partial p_j}}{\frac{\partial c_v}{\partial p_j}\frac{\partial c_v}{\partial p_i}} = \frac{\frac{p_i p_j}{c_v}\frac{\partial^2 c_v}{\partial p_i \partial p_j}}{\frac{p_j}{c_v}\frac{\partial c_v}{\partial p_j}\frac{p_i}{c_v}\frac{\partial c_v}{\partial p_i}} = \frac{\frac{p_i p_j}{c_v}\frac{\partial^2 c_v}{\partial p_i \partial p_j}}{\frac{\partial \ln c_v}{\partial \ln p_j}\frac{\partial \ln c_v}{\partial \ln p_i}} = \frac{\frac{p_i p_j}{c_v} z_{ij}}{\eta_i \eta_j},$$

we obtain the following neat expression of AES in our model by substituting (17) and (19) into the above expression

$$AES_{ij} = \frac{\frac{p_i p_j}{c_v} z_{ij}}{\eta_i \eta_j} = \frac{1}{\eta_i \eta_j}\frac{p_i p_j}{c_v}\left(\frac{c_v}{p_i p_j}\widetilde{z_{ij}}\right) = \frac{1}{\eta_i \eta_j}\left(\widetilde{z_{ij}}\right) = \frac{1}{\eta_i \eta_j}\left(\gamma_{ij} + \eta_i \eta_j\right) = \frac{\gamma_{ij}}{\eta_i \eta_j} + 1.$$

Morishima’s Elasticity of Substitution (MES) is defined as

$$MES_{ij} = \frac{p_i \frac{\partial^2 C_V}{\partial p_i \partial p_j}}{\frac{\partial C_V}{\partial p_j}} - \frac{p_i \frac{\partial^2 C_V}{\partial^2 p_i}}{\frac{\partial C_V}{\partial p_i}}.$$

Note that we have from (11), (14), (15) and (16),

$$\frac{p_i \frac{\partial^2 C_V}{\partial p_i \partial p_j}}{\frac{\partial C_V}{\partial p_j}} - \frac{p_i \frac{\partial^2 C_V}{\partial^2 p_i}}{\frac{\partial C_V}{\partial p_i}} = \frac{p_i \frac{\partial^2 c_v}{\partial p_i \partial p_j}}{\frac{\partial c_v}{\partial p_j}} - \frac{p_i \frac{\partial^2 c_v}{\partial^2 p_i}}{\frac{\partial c_v}{\partial p_i}} = \frac{p_i \frac{\partial^2 c_v}{\partial p_i \partial p_j}}{\frac{\partial c_v}{\partial p_j}} - \frac{p_i \frac{\partial^2 c_v}{\partial^2 p_i}}{\frac{\partial c_v}{\partial p_i}};$$

$$\frac{p_i \frac{\partial^2 c_v}{\partial p_i \partial p_j}}{\frac{\partial c_v}{\partial p_j}} = \frac{p_i \frac{c_v}{p_i p_j}\left[\gamma_{ij} + \left(\frac{\partial \ln c_v}{\partial \ln p_j}\right)\frac{\partial \ln c_v}{\partial \ln p_i}\right]}{\left(\frac{c_v}{p_j}\right)\left(\frac{\partial \ln c_v}{\partial \ln p_j}\right)} = \frac{\gamma_{ij} + \left(\frac{\partial \ln c_v}{\partial \ln p_j}\right)\frac{\partial \ln c_v}{\partial \ln p_i}}{\frac{\partial \ln c_v}{\partial \ln p_j}} = \frac{\gamma_{ij} + \eta_j \eta_i}{\eta_j} = \frac{\gamma_{ij}}{\eta_j} + \eta_i;$$

and

$$\frac{p_i \frac{\partial^2 c_v}{\partial^2 p_i}}{\frac{\partial c_v}{\partial p_i}} = \frac{p_i \frac{c_v}{p_i^2}\left[\gamma_{ii} + \left(\frac{\partial \ln c_v}{\partial \ln p_i} - 1\right)\frac{\partial \ln c_v}{\partial \ln p_i}\right]}{\left(\frac{c_v}{p_i}\right)\left(\frac{\partial \ln c_v}{\partial \ln p_i}\right)} = \frac{[\gamma_{ii} + (\eta_i - 1)\,\eta_i]}{\eta_i} = \frac{\gamma_{ii}}{\eta_i} + (\eta_i - 1)\,.$$

Thus, we obtain

$$MES_{ij} = \frac{\gamma_{ij}}{\eta_j} + \eta_i - \left[\frac{\gamma_{ii}}{\eta_i} + (\eta_i - 1)\right] = \frac{\gamma_{ij}}{\eta_j} - \frac{\gamma_{ii}}{\eta_i} + 1.$$

C Estimation of Variable-Cost Function Parameters with Technological Change in Section 4

In this Appendix, we explain in detail the heuristic procedure we take in Section 4 to determine what inputs are variable, and to estimate traslog variable cost function parameters allowing technological change.

- **Step 1. Choice of Variable Inputs.**
  - *Substep 1.1. (5 factor inputs)* (i) Take all four types of labor inputs and "machines and tools" as variable inputs and estimate (8) without period dummies. Some of estimated γ_{ii}'s are positive and statistically significant, implying the concavity requirement is not likely to be satisfied. (ii) Then, take all four types of labor inputs and "transportation machines" as variable inputs and estimate (8) without period dummies. Some of estimated γ_{ii}'s are positive and statistically significant, implying the concavity requirement is not likely to be satisfied. So, we proceed to the next substep.

- *Substep 1.2. (4 factor inputs)* (i) Drop all capital stocks except for IT stocks. Take all four types of labor inputs as variable inputs and estimate (8) without period dummies. Some of estimated γ_{ii}'s are positive and statistically significant, implying the concavity requirement is not likely to be satisfied. (ii) Keep "machines and tools" and drop one of three labor inputs (young with high education, old with low education, and old with high education). Estimate (8) without period dummies. Some of estimated γ_{ii}'s are positive and statistically significant, implying the concavity requirement is not likely to be satisfied. (iii) Then Keep "transportation machines" and drop one of three labor inputs. Estimate (8) without period dummies. Some of estimated γ_{ii}'s are positive and statistically significant, implying the concavity requirement is not likely to be satisfied. So, we proceed to the next substep.

- *Substep 1.3. (3 factor inputs.)* Drop all capital stocks except for IT stocks and keep young workers with low education. Then drop one of remaining three labor inputs. Estimate (8) without period dummies. We examine whether all estimated γ_{ii}'s are negative with some statistical significance. In this step, eight out of senteen industries show all negative γ_{ii}'s with marginal statistical significance. They are Food, Textile, Fabricated Metal, Electrical Machinery, Instruments, Finance and Insurance, and Service.[45] These eight industries are likely to have sharper results if we consider period dummies explicitly based on technological change. Thus, we move to Step 2 for these industries. For remaining nine industries we proceed to the next substep.

- *Substep 1.4 (2 factor inputs).* Drop all capital stocks except for IT stocks, keep young workers with low education, drop two of remaining three labor inputs, estimate (8) without period dummies. We examine whether estimated γ_{ii} are negative with some statistical significance. Nine industries out of remaining ten industries have estimated γ_{ii} that are all negative with marginal statistical significance. We then move to Step 2 for these industries for the same reason as nine indsutries in Substep 3. Then, there is only General Machinery left. We

[45]Moreover, the combination of chosen labor inputs is unique to each industry in this category. That is, there is only one combination of labor inputs that have all negative γ_{ii}'s with some statistical significance.

proceed to the next substep for General Machinery.

– *Substep 1.5 (Period difference).* The failure of Substeps 1.1-1.4 in General Machinery suggests that there may be a break in the number of quasi-fixed factors between the 1980s and the 1990s. Then, we divide the total sample period into the two periods, and re-apply Substeps 1.1-1.4 for each subperiod. Then, the result suggests that General Machinery has two variable factors in the 1980s and three variable factors in the 1990s. We then proceed to Step 2.

• **Step 2. Estimation of Share Equations with Period Dummies.**

– *Substep 2.1. (identifying the possible number of technological changes).* For each industry, the possible number of technological changes is identified. As explained in the text, there may be a technological change between the 1980s and the 1990s because the usage of information technology is different between the two periods. (In the case of General Machinery, we found in Step 1 that the number of quasi-fixed factors is different between the 1980s and 1990s, already implying a break in production technology.) In addition, there may be an additional technological change for specific industry. To identify technological changes for each industry, we look at Table 9, which reports IT stocks' contribution to value-added growth for the entire sample period and for each half-decade. We find two types of industries: (1) IT stocks' contribution is monotonously increasing from half-decade to half-decade (Textile, Chemicals, Trade, and Services). or increasing overall, though there is minor setback on the way (Stone and Clay, Instruments, and Trade); and (2) Its movement from half-decade to half-decade is hump-shaped (first increasing then decreasing) in the 1990s (Food, Paper and Pulp, Primary Metal, Fabricated Metal, General Machinery, Electrical Machinery, Trasportation Equipment, Construction). The category-(2) industries may have technological change inducing less reliance on IT capital stocks. We allow possibility of one additional technological change in the mid-1990s for (2). In addition, since IT contribution in Finance and Transportation and Communication show a big jump in the mid-1980s, we also consider possibility of technological change in the mid-1980s for these two industries.

- *Substep 2.2. (searching of timing of technological change)*. For the technological change between the 1980s and 1990s, we first set 1990 as the year of change. For industry-specific technological change suggested in the previous substep, we set 1995 for the change in 1990s and 1985 for the change in the 1980s. Upon deciding the number of period dummies (that is, technological changes), we estimate (8) with these period dummies, drop insignificant intercept and/or slope dummies, re-estimate the equations, and examine whether estimated coefficients are consistent with the concavity requirement. We then move the point of change around the initial point to see whether this gives us a sharper estimation (in terms of statistical significance of γ_{ii}), still keeping the concavity requirement satisfied. In the end, many period dummies are not statistically significant. For example, the Instruments and Trade have no siginificant period dummies, implying no non-Hicks neurtral technological changes. Similarly, although Construction, General Machinery, Electrical Machinery and Food have hump-shaped IT contribution in the mid-1990s, corresponding period dummies are not statistically significant. The results are reported in Tables 3.1, 4.1 and 5.1.

• **Step 3. Manufacturing Industries.**

  - For manufacturing industries, we have one more dimension with respect to labor input types, that is, production workers and non-production workers. This means we have eight types of labor inputs. Basically, we repeat Steps 1 and 2 for finer labor input data of manufacturing. However, there is problem of seeming multicolinearity, and consequently some form of aggregation is necessary. We tried all sensible aggregation possibilities, and found aggregating young and old of production workers and using six types of labor inputs (production worker with low education, production worker with high education, non-production young workers with low education, non-production young workers with high education, non-production old workers with low education, non-production old workers with low education) resulted in satisfactory results. The results are reported in Tables 3.2, 4.2, and 5.2.

Table 1: Industries under Study

SNA Sector	Abbreviation
Manufacturing Industries	
Food and Kindred Products	Food
Textile Mill Products	Textile
Paper and Allied Products	Paper & Pulp
Chemicals	Chemicals
Stone, Clay, Glass	Stone & Clay
Primary Metal	Pri. Metal
Fabricated Metal	Fab. Metal
Machinery, Non-electrical	Gen. Machinery
Electrical Machinery	Elec. Machinery
Transportation Equipment and Ordnance	Trans. Equipment
Instruments	Instruments
Non manufacturing Industries	
Construction	Construc.
Trade	Trade
Finance and Insurance	Finance
Transportation and Communications	Trans. & Commu.
Services	Services
(Excluded)	
Petroleum and Coal Products	Petro. & Coal
Miscellaneous Manufacturing	Misc. Manufac.
Utilities	Utilities
Real Estate	Real Estate

Table 2. (1)
Average Growth Rate of Factors: Manufacturing

Industry	Food		Textile		Paper & Pulp	
Period	80'S	90'S	80'S	90'S	80'S	90'S
IT	24.43%	16.48%	22.60%	14.08%	16.75%	10.09%
Equipment	8.38%	3.69%	5.90%	4.98%	4.15%	5.10%
Structure	2.91%	2.45%	-0.24%	-0.27%	3.52%	3.45%
Young, Low Education Level	-0.92%	-2.11%	-4.12%	-12.32%	-0.49%	-1.59%
Old, Low Education Level	3.08%	-0.26%	1.47%	-6.79%	2.42%	-1.47%
Young, High Education Level	2.86%	4.28%	-0.40%	-2.25%	3.59%	2.24%
Old, High Education Level	5.44%	1.75%	5.19%	0.98%	4.84%	3.57%

Industry	Chemicals		Stone & Clay		Pri. Metal	
Period	80'S	90'S	80'S	90'S	80'S	90'S
IT	28.54%	16.88%	17.65%	15.73%	16.96%	12.46%
Equipment	3.63%	4.65%	6.75%	3.15%	1.36%	3.12%
Structure	1.20%	2.50%	1.43%	0.66%	1.68%	2.48%
Young, Low Education Level	-4.05%	-2.39%	-4.31%	-2.24%	-2.25%	-3.42%
Old, Low Education Level	1.51%	-0.10%	-0.68%	-2.32%	2.87%	-2.75%
Young, High Education Level	1.88%	2.34%	1.29%	1.09%	1.63%	1.93%
Old, High Education Level	5.44%	1.75%	5.15%	2.66%	5.62%	1.70%

Industry	Fab. Metal		Gen. Machinery		Elec. Machinery	
Period	80'S	90'S	80'S	90'S	80'S	90'S
IT	30.57%	8.12%	27.11%	11.45%	29.11%	13.33%
Equipment	9.68%	6.59%	10.73%	5.20%	16.89%	7.65%
Structure	1.62%	2.14%	3.02%	2.27%	8.96%	4.03%
Young, Low Education Level	-2.78%	-2.83%	-1.30%	-3.33%	2.49%	-4.93%
Old, Low Education Level	0.97%	-1.87%	2.91%	-1.89%	6.27%	-1.13%
Young, High Education Level	1.78%	1.12%	3.24%	2.21%	6.87%	0.76%
Old, High Education Level	5.78%	3.15%	7.02%	3.98%	8.44%	4.21%

Industry	Trans. Equipment		Instruments	
Period	80'S	90'S	80'S	90'S
IT	30.16%	12.67%	26.56%	14.49%
Equipment	10.60%	5.02%	14.20%	4.74%
Structure	4.62%	2.94%	1.73%	-0.85%
Young, Low Education Level	-2.16%	-2.43%	-4.43%	-6.18%
Old, Low Education Level	1.50%	-1.18%	0.56%	-1.80%
Young, High Education Level	2.61%	2.47%	2.81%	-1.57%
Old, High Education Level	4.90%	5.58%	5.11%	4.12%

Notes: Annual rate. 80'S = 1981-1989, 90'S = 1990-1998.
Young = under 40
Old = over 40
Low Education Level = with high school or lower education
High Education Level = with junior college or higher education

Table 2. (2)
Average Growth Rate of Factors: Non-Manufacturing

Industry	Construction		Trade	
Period	80'S	90'S	80'S	90'S
IT	12.04%	14.77%	14.94%	11.81%
Equipment	3.66%	1.65%	6.97%	2.34%
Structure	3.88%	4.19%	3.96%	4.32%
Young, Low Education Level	-2.41%	-0.71%	-3.00%	-4.20%
Old, Low Education Level	0.83%	-0.33%	2.34%	-0.26%
Young, High Education Level	1.70%	2.42%	3.68%	1.20%
Old, High Education Level	6.48%	5.70%	7.15%	4.37%

Industry	Finance		Trans. & Commu.		Services	
Period	80'S	90'S	80'S	90'S	80'S	90'S
IT	24.77%	n.a.	12.38%	12.67%	20.35%	18.15%
Equipment	8.44%	n.a.	8.55%	2.11%	8.95%	6.56%
Structure	2.36%	n.a.	3.30%	3.85%	7.14%	6.06%
Young, Low Education Level	-4.02%	n.a.	-1.92%	-1.83%	0.44%	-0.87%
Old, Low Education Level	2.00%	n.a.	3.27%	-0.16%	3.21%	0.58%
Young, High Education Level	5.69%	n.a.	2.85%	5.94%	6.04%	4.60%
Old, High Education Level	7.02%	n.a.	6.23%	5.43%	7.35%	6.53%

Notes: Annual rate. 80'S = 1981-1989, 90'S = 1990-1998.
Finance data are truncated at 1993. See Section 3.
Young = under 40
Old = over 40
Low Education Level = with high school or lower education
High Education Level = with junior college or higher education

Table 2. (3)
Average Growth Rate of Factors: Manufacturing, Production and Non-Production Labor

Industry	Food		Textile		Paper & Pulp	
Period	80'S	90'S	80'S	90'S	80'S	90'S
Production, Low Education Level	1.33%	-0.73%	-1.04%	-9.18%	0.83%	-1.36%
Production, High Education Level	6.31%	6.95%	6.59%	-0.38%	6.80%	6.90%
Non-Production, Young, Low Education Level	-1.71%	-3.90%	-5.10%	-9.43%	-0.32%	-2.36%
Non-Production, Old, Low Education Level	4.06%	-0.02%	0.49%	-5.36%	3.81%	-1.97%
Non-Production, Young, High Education Level	2.24%	3.90%	-1.80%	-2.24%	3.23%	1.05%
Non-Production, Old, High Education Level	4.96%	5.68%	3.36%	0.14%	3.93%	2.45%

Industry	Chemicals		Stone & Clay		Pri. Metal	
Period	80'S	90'S	80'S	90'S	80'S	90'S
Production, Low Education Level	-1.38%	-0.57%	-2.22%	-2.51%	0.71%	-2.98%
Production, High Education Level	2.42%	7.97%	4.01%	7.58%	6.23%	4.41%
Non-Production, Young, Low Education Level	-5.45%	-4.89%	-4.27%	-3.16%	-2.88%	-4.04%
Non-Production, Old, Low Education Level	2.63%	-0.08%	0.62%	-0.42%	2.75%	-2.32%
Non-Production, Young, High Education Level	1.98%	1.67%	1.03%	-0.10%	1.62%	1.28%
Non-Production, Old, High Education Level	5.29%	1.14%	4.92%	1.22%	4.57%	1.74%

Industry	Fab. Metal		Gen. Machinery		Elec. Machinery	
Period	80'S	90'S	80'S	90'S	80'S	90'S
Production, Low Education Level	-1.00%	-2.50%	0.96%	-2.82%	3.83%	-3.43%
Production, High Education Level	4.29%	4.96%	7.94%	5.03%	7.91%	2.47%
Non-Production, Young, Low Education Level	-3.08%	-2.12%	-2.54%	-3.42%	1.43%	-5.41%
Non-Production, Old, Low Education Level	2.57%	-1.22%	3.38%	-0.85%	8.23%	-0.52%
Non-Production, Young, High Education Level	1.60%	0.37%	2.62%	1.88%	6.82%	0.72%
Non-Production, Old, High Education Level	5.16%	2.25%	6.57%	3.31%	8.20%	3.83%

Industry	Trans. Equipment		Instruments	
Period	80'S	90'S	80'S	90'S
Production, Low Education Level	-0.47%	-2.20%	-3.34%	-4.03%
Production, High Education Level	6.14%	6.85%	-0.36%	3.01%
Non-Production, Young, Low Education Level	-3.54%	-2.11%	-2.70%	-7.24%
Non-Production, Old, Low Education Level	2.42%	0.67%	2.38%	-1.34%
Non-Production, Young, High Education Level	2.34%	2.03%	3.59%	-2.16%
Non-Production, Old, High Education Level	4.47%	4.90%	5.06%	3.78%

Notes: Annual rate. 80'S = 1981-1989, 90'S = 1990-1998.
Young = under 40
Old = over 40
Low Education Level = with high school or lower education
High Education Level = with junior college or higher education
Production = engaging operation at production sites
Non-Production = supervisory, clerical and technical

Table 3.1.
Technological Changes and Concavity of Cost Functions
1: Baseline Case (Four types of labor inputs)
A. Manufacturing

1. Food	80-89 OK	90-98 OK	
2. Textile	80-92 OK	93-98 OK	
3. Paper & Pulp	80-88 OK	89-92 OK*	93-98 OK*
4. Chemicals	80-89 OK	90-98 OK	
5. Stone & Clay	80-91 OK	92-98 OK	
6. Pri. Metal	80-87 OK	88-94 OK	95-98 OK
7. Fab. Metal	80-87 OK	88-93 OK	94-98 OK
8. Gen. Machinery	80-89 OK	90-98 OK	
9. Elec. Machinery	80-92 OK	93-98 OK	
10. Trans. Equipment	80-88 OK*	89-92 OK*	93-98 OK
11. Instruments	80-98 OK		

B. Non Manufacturing

12. Construction	80-89 OK	90-98 OK	
13. Trade	80-98 OK		
14. Finace & Insurance (--92)	80-84 OK	85-92 OK	
15. Transportation & Communication	80-85 OK	86-89 OK	90-98 OK
16. Services	80-89 OK	90-98 OK	

Notes:
Concavity is evaluated at the average input prices.
OK : Sufficient conditions of strict concavity are satisfied.
OK*: Conditions are not strictly satisfied, but their deviations are negligible.

Table 3.2.
Technological Changes and Concavity of Cost Functions
2: Exteded Case (Six types of labor inputs)
Manufacturing

<table>
<tr><td>3.
Paper & Pulp</td><td colspan="3">80-87
OK</td><td colspan="2">88-92
OK</td><td>93-98
OK</td></tr>
<tr><td>5.
Stone & Clay</td><td>80-84
OK</td><td colspan="4">85-92
OK</td><td>93-98
OK</td></tr>
<tr><td>7.
Fab. Metal</td><td colspan="2">80-86
OK</td><td colspan="2">87-88
OK</td><td colspan="2">89-98
OK</td></tr>
<tr><td>9.
Elec. Machinery</td><td>80-84
OK</td><td colspan="4">85-92
OK</td><td>93-98
OK</td></tr>
<tr><td>10.
Trans. Equipment</td><td colspan="2">80-86
OK</td><td colspan="2">87-88
OK*</td><td colspan="2">89-98
OK</td></tr>
</table>

Notes:
Concavity is evaluated at the average input prices.
OK : Sufficient conditions of strict concavity are satisfied.
OK*: Conditions are not strictly satisfied, but their deviations are negligible.
Six types of labor inputs are available in manufacturing only.

Table 4.1.
List of Variable Factor Inputs By Industry: All industries (Four types of labor inputs)

1. Industry with Three Variable Factor Inputs

Industry	Type of variable inputs
1. Food	IT : IT capital stocks YL : Young Worker with Low Education Level YH : Young Worker with High Education Level
2. Textile	IT : IT capital stocks YL : Young Worker with Low Education Level YH : Young Worker with High Education Level
7. Fab. Metal	IT : IT capital stocks YL : Young Worker with Low Education Level YH : Young Worker with High Education Level
8. Gen. Machinery (90s)	IT : IT capital stocks YL : Young Worker with Low Education Level YH : Young Worker with High Education Level
9. Elec. Machinery	IT : IT capital stocks YL : Young Worker with Low Education Level YH : Young Worker with High Education Level
11. Instruments	IT : IT capital stocks YL : Young Worker with Low Education Level OH : Old Worker with High Education Level
14. Finance & Insurance (--92)	IT : IT capital stocks YL : Young Worker with Low Education Level YH : Young Worker with High Education Level
16. Services	IT : IT capital stocks YL : Young Worker with Low Education Level OH : Old Worker with High Education Level

2. Industry with Two Variable Factor Inputs

Industry	Type of variable inputs
3. Paper & Pulp	IT : IT capital stocks YL : Young Worker with Low Education Level
4. Chemicals	IT : IT capital stocks YL : Young Worker with Low Education Level
5. Stone & Clay	IT : IT capital stocks YL : Young Worker with Low Education Level
6. Pri. Metal	IT : IT capital stocks YL : Young Worker with Low Education Level
8. Gen. Machinery (80s)	IT : IT capital stocks YL : Young Worker with Low Education Level
10. Trans. Equipment	IT : IT capital stocks YL : Young Worker with Low Education Level
12. Construction	IT : IT capital stocks YL : Young Worker with Low Education Level
13. Trade	IT : IT capital stocks YL : Young Worker with Low Education Level
15. Transportation & Commu	IT : IT capital stocks YL : Young Worker with Low Education Level

Notes:
Young = under 40, Old = over 40
Low Education Level = with high school or lower education
High Education Level = with junior college or higher education

Table 4.2.
List of Variable Factor Inputs By Industry: Manufacturing (Six types of labor inputs)

1. Industry with Four Variable Factor Inputs

Industry	Type of variable inputs	
9. Elec. Machinery	IT PL NPYH NPOH	: IT capital stocks : Production Worker with Low Education Level : Non-Production Young Worker with High Education Level : Non-Production Old Worker with High Education Level

2. Industry with Three Variable Factor Inputs

Industry	Type of variable inputs	
7. Fab. Metal	IT PL NPYH	: IT capital stocks : Production Worker with Low Education Level : Non-Production Young Worker with High Education Level
10. Trans. Equipment	IT PL NPOH	: IT capital stocks : Production Worker with Low Education Level : Non-Production Old Worker with High Education Level

3. Industry with Two Variable Factor Inputs

Industry	Type of variable inputs	
3. Paper & Pulp	IT PL	: IT capital stocks : Production Worker with Low Education Level
5. Stone & Clay	IT PL	: IT capital stocks : Production Worker with Low Education Level

Notes:
Young = under 40, Old = over40
Low Education Level = with high school or lower education
High Education Level = with junior college or higher education
Production = engaging operation at production sites
Non-Production = supervisory, clerical and technical

Table 5.1. (1)
Estimation of Cost Share Functions: Baseline Case (Four Types of Labor Inputs)
A. Manufacturing

1. Food (Period: 1980-1998) 1 = IT, 2 = YL, 3 = YH

	Coefficient	t-Statistic	Prob.
β_2	0.836835	86.47719	0.0000
β_3	0.159113	26.64262	0.0000
γ_{22}	-0.190435	-18.77942	0.0000
γ_{23}	0.078321	11.62105	0.0000
1990 Dummy for β_2	-0.045329	-4.22654	0.0002
1990 Dummy for γ_{23}	0.012446	3.157459	0.0035

Share Equation YL (Young Worker with Low Education Level)

Adjusted R-square	0.965777	
Q-statistics (H_0: no auto-correlation)	0.0907	(p-value: 0.763)

Share Equation YH (Young Worker with High Education Level)

Adjusted R-square	0.957404	
Q-statistics (H_0: no auto-correlation)	0.000006	(p-value: 0.994)

2. Textile (Period: 1980-1998) 1 = IT, 2 = YL, 3 = YH

	Coefficient	t-Statistic	Prob.
β_2	0.860119	97.78446	0.0000
β_3	0.117813	13.52187	0.0000
γ_{22}	-0.207041	-12.93283	0.0000
γ_{23}	0.079255	9.819605	0.0000
1993 Dummy for β_3	0.010277	1.816102	0.0784

Share Equation YL (Young Worker with Low Education Level)

Adjusted R-square	0.931533	
Q-statistics (H_0: no auto-correlation)	1.96651	(p-value: 0.161)

Share Equation YH (Young Worker with High Education Level)

Adjusted R-square	0.921065	
Q-statistics (H_0: no auto-correlation)	0.6695	(p-value: 0.413)

3. Paper & Pulp (Period: 1980-1998) 1 = IT, 2 = YL

	Coefficient	t-Statistic	Prob.
β_2	0.994474	197.9274	0.0000
γ_{22}	-0.02238	-5.825194	0.0000
1989 Dummy for β_2	-0.014646	-5.678358	0.0000
1993 Dummy for γ_{22}	0.003746	2.548571	0.0223

Share Equation YL (Young Worker with Low Education Level)

Adjusted R-square	0.945082	
Q-statistics (H_0: no auto-correlation)	0.4674	(p-value: 0.494)

Table 5.1. (2)
Estimation of Cost Share Functions: Baseline Case (Four Types of Labor Inputs)
A. Manufacturing (continued-1)
4. Chemical (Period: 1980-1998) 1 = IT, 2 = YL

	Coefficient	t-Statistic	Prob.
β_2	1.168784	78.76967	0.0000
γ_{22}	-0.147726	-17.39529	0.0000
1990 Dummy for β_2	0.133694	2.668878	0.0175
1990 Dummy for γ_{22}	-0.08189	-3.937875	0.0013

Share Equation YL (Young Worker with Low Education Level)

Adjusted R-square	0.989087	
Q-statistics (H_0: no auto-correlation)	0.3095	(p-value: 0.578)

5. Stone & Clay (Period: 1980-1998) 1 = IT, 2 = YL

	Coefficient	t-Statistic	Prob.
β_2	1.035082	164.6683	0.0000
γ_{22}	-0.036697	-7.748249	0.0000
1992 Dummy for γ_{22}	0.006052	2.937864	0.0097

Share Equation YL (Young Worker with Low Education Level)

Adjusted R-square	0.915275	
Q-statistics (H_0: no auto-correlation)	0.467	(p-value: 0.494)

6. Pri. Metal (Period: 1980-1998) 1 = IT, 2 = YL

	Coefficient	t-Statistic	Prob.
β_2	1.090819	65.21458	0.0000
γ_{22}	-0.097144	-8.389374	0.0000
1988 Dummy for β_2	-0.02254	-2.898441	0.0110
1995 Dummy for γ_{22}	0.017	5.358759	0.0001

Share Equation YL (Young Worker with Low Education Level)

Adjusted R-square	0.95987	
Q-statistics (H_0: no auto-correlation)	1.1795	(p-value: 0.2777)

Table 5.1 (3)

Estimation of Cost Share Functions: Baseline Case (Four Types of Labor Inputs)

A. Manufacturing (continued-2)

7. Fab. Metal (Period: 1980-1998) 1 = IT, 2 = YL, 3 = YH

	Coefficient	t-Statistic	Prob.
β_2	0.866233	80.60727	0.0000
β_3	0.131824	7.587936	0.0000
γ_{22}	-0.148852	-7.391223	0.0000
γ_{23}	0.064229	5.091403	0.0000
1988 Dummy for β_2	-0.01751	-2.884108	0.0070
1994 Dummy for β_3	0.016034	4.75823	0.0000

Share Equation YL (Young Worker with Low Education Level)

Adjusted R-square	0.951908	
Q-statistics (H_0: no auto-correlation)	1.1816	(p-value: 0.277)

Share Equation YH (Young Worker with High Education Level)

Adjusted R-square	0.923458	
Q-statistics (H_0: no auto-correlation)	0.7403	(p-value: 0.39)

8.1. Gen. Machinery (Period: 1980-1989) 1 = IT, 2 = YL

	Coefficient	t-Statistic	Prob.
β_2	1.043333	263.9369	0.0000
γ_{22}	-0.051775	-15.36908	0.0000

Share Equation YL (Young Worker with Low Education Level)

Adjusted R-square	0.905068	
Q-statistics (H_0: no auto-correlation)	1.1252	(p-value: 0.289)

8.2. Gen. Machinery (Period: 1990-1998) 1 = IT, 2 = YL, 3 = YH

	Coefficient	t-Statistic	Prob.
β_2	0.751362	45.29617	0.0000
β_3	0.190252	12.64918	0.0000
γ_{22}	-0.400227	-49.81038	0.0000
γ_{23}	0.301408	176.1062	0.0000
γ_{33}	-0.197548	-26.04773	0.0000

Share Equation YL (Young Worker with Low Education Level)

Adjusted R-square	0.884776	
Q-statistics (H_0: no auto-correlation)	0.8353	(p-value: 0.361)

Share Equation YH (Young Worker with High Education Level)

Adjusted R-square	0.86635	
Q-statistics (H_0: no auto-correlation)	1.2182	(p-value: 0.270)

Table 5.1. (4)
Estimation of Cost Share Functions: Baseline Case (Four Types of Labor Inputs)
A. Manufacturing (continued-3)

9. Elec. Machinery (Period: 1980-1998) 1 = IT, 2 = YL, 3 = YH

	Coefficient	t-Statistic	Prob.
β_2	0.870574	39.05199	0.0000
β_3	0.180672	9.015999	0.0000
γ_{22}	-0.43485	-8.302452	0.0000
γ_{23}	0.207779	3.885117	0.0005
γ_{33}	-0.111772	-2.036046	0.0501
1993's Dummy for γ_{22}	0.027052	3.911322	0.0004

Share Equation YL (Young Worker with Low Education Level)

Adjusted R-square	0.96984	
Q-statistics (H_0: no auto-correlation)	5.8219	(p-value: 0.016)

Share Equation YH (Young Worker with High Education Level)

Adjusted R-square	0.95655	
Q-statistics (H_0: no auto-correlation)	3.3269	(p-value: 0.068)

10. Trans. Equipment (Period: 1990-1998) 1 = IT, 2 = YL

	Coefficient	t-Statistic	Prob.
β_2	1.021142	103.2854	0.0000
γ_{22}	-0.037567	-5.963609	0.0000
1989's Dummy for β_2	-0.020381	-3.91411	0.0014
1993's Dummy for γ_{22}	0.004731	2.354335	0.0326

Share Equation YL (Young Worker with Low Education Level)

Adjusted R-square	0.942919	
Q-statistics (H_0: no auto-correlation)	1.7248	(p-value: 0.189)

11. Instruments (Period: 1980-1998) 1 = IT, 2 = YL, 3 = OH

	Coefficient	t-Statistic	Prob.
β_2	0.715623	32.99772	0.0000
β_3	0.173716	8.049934	0.0000
γ_{22}	-0.518429	-31.41078	0.0000
γ_{23}	0.311434	26.08083	0.0000
γ_{33}	-0.168416	-12.51788	0.0000

Share Equation YL (Young Worker with Low Education Level)

Adjusted R-square	0.973672	
Q-statistics (H_0: no auto-correlation)	0.5638	(p-value: 0.453)

Share Equation OH (Old Worker with High Education Level)

Adjusted R-square	0.96104	
Q-statistics (H_0: no auto-correlation)	2.405	(p-value: 0.121)

Notes:
Young = under 40
Old = over 40
Low Education Level = with high school or lower education
High Education Level = with junior college or higher education
Production = engaging operation at production sites
Non-Production = supervisory, clerical and technical

Table 5.1. (5)
Estimation of Cost Share Functions: Baseline Case (Four Types of Labor Inputs)
B. Non-Manufacturing

12. Construction (Period: 1980-1998) 1 = IT, 2 = YL

	Coefficient	t-Statistic	Prob.
β_2	1.029154	196.0772	0.0000
γ_{22}	-0.019982	-6.518501	0.0000
1990 Dummy for β_2	-0.003151	-2.803711	0.0134
1993 Dummy for γ_{22}	0.001269	3.283372	0.0050

Share Equation YL (Young Worker with Low Education Level)

Adjusted R-square	0.975001	
Q-statistics (H_0: no auto-correlation)	0.6697	(p-value: 0.413)

13. Trade (Period: 1980-1989) 1 = IT, 2 = YL

	Coefficient	t-Statistic	Prob.
β_2	1.065306	172.4378	0.0000
γ_{22}	-0.058105	-16.10721	0.0000

Share Equation YL (Young Worker with Low Education Level)

Adjusted R-square	0.951374	
Q-statistics (H_0: no auto-correlation)	3.2004	(p-value: 0.074)

14. Finance (Period: 1980-1992) 1 = IT, 2 = YL, 3 = YH

	Coefficient	t-Statistic	Prob.
β_2	0.446674	9.239858	0.0000
β_3	0.588524	13.81062	0.0000
γ_{22}	-1.339632	-55.07792	0.0000
γ_{23}	1.213711	196.4719	0.0000
γ_{33}	-1.145847	-40.17178	0.0000
1985 Dummy for β_2	-0.08055	-2.008003	0.0591
1985 Dummy for β_3	0.058565	2.035331	0.0560

Share Equation YL (Young Worker with Low Education Level)

Adjusted R-square	0.906977	
Q-statistics (H_0: no auto-correlation)	0.1292	(p-value: 0.719)

Share Equation YH (Young Worker with High Education Level)

Adjusted R-square	0.89295	
Q-statistics (H_0: no auto-correlation)	0.0044	(p-value: 0.947)

Table 5.1. (6)
Estimation of Cost Share Functions: Baseline Case (Four Types of Labor Inputs)
B. Non-Manufacturing (continued)

15. Trans. & Comm. (Period: 1980-1998) 1 = IT, 2 = YL

	Coefficient	t-Statistic	Prob.
β_2	1.347934	18.51695	0.0000
γ_{22}	-0.189788	-5.36855	0.0001
1990 Dummy for β_2	-0.031969	-2.336445	0.0338
1986 Dummy for γ_{22}	-0.009351	-2.634962	0.0187

Share Equation YL (Young Worker with Low Education Level)

Adjusted R-square	0.975456	
Q-statistics (H_0: no auto-correlation)	1.9338	(p-value: 0.164)

16. Services (Period: 1980-1998) 1 = IT, 2 = YL, 3 = OH

	Coefficient	t-Statistic	Prob.
β_2	0.475453	55.341	0.0000
β_3	0.331058	30.70933	0.0000
γ_{22}	-0.280723	-13.89209	0.0000
γ_{23}	0.132775	12.51075	0.0000
γ_{33}	-0.029039	-3.143733	0.0037
1990 Dummy for γ_{22}	0.180787	7.337514	0.0000
1990 Dummy for γ_{23}	-0.101925	-7.365514	0.0000
1990 Dummy for γ_{33}	0.06134	5.686303	0.0000

Share Equation YL (Young Worker with Low Education Level)

Adjusted R-square	0.984068	
Q-statistics (H_0: no auto-correlation)	1.0505	(p-value: 0.305)

Share Equation OH (Old Worker with High Education Level)

Adjusted R-square	0.971664	
Q-statistics (H_0: no auto-correlation)	1.7932	(p-value: 0.181)

Notes:
Young = under 40
Old = over 40
Low Education Level = with high school or lower education
High Education Level = with junior college or higher education

Table 5.2. (1)
Estimation of Cost Share Functions: Extended Case (Six Types of Labor Inputs)
Manufacturing

3. Paper & Pulp (Period: 1980-1998) 1 = IT, 2 = PL

	Coefficient	t-Statistic	Prob.
β_2	0.990677	985.9242	0.0000
γ_{22}	-0.007068	-8.845754	0.0000
1988 Dummy for β_2	-0.006371	-5.351275	0.0001
1993 Dummy for γ_{22}	0.001096	2.10594	0.0525

Share Equation PL (Production Worker with Low Education Level)

Adjusted R-square	0.905526	
Q-statistics (H_0: no auto-correlation)	1.7823	(p-value: 0.182)

5. Stone & Clay (Period: 1980-1998) 1 = IT, 2 = PL

	Coefficient	t-Statistic	Prob.
β_2	1.004978	750.0587	0.0000
γ_{22}	-0.010372	-10.20024	0.0000
1985 Dummy for β_2	-0.004029	-3.3947	0.0040
1993 Dummy for γ_{22}	0.001875	3.582348	0.0027

Share Equation PL (Production Worker with Low Education Level)

Adjusted R-square	0.863836	
Q-statistics (H_0: no auto-correlation)	2.6825	(p-value: 0.101)

7. Fab. Metal (Period: 1980-1998) 1 = IT, 2 = PL, 3 = NPYH

	Coefficient	t-Statistic	Prob.
β_2	0.872073	199.5942	0.0000
β_3	0.126904	14.67324	0.0000
γ_{22}	-0.126205	-26.38621	0.0000
γ_{23}	0.125612	21.99179	0.0000
γ_{33}	-0.129318	-11.26724	0.0000
1987 Dummy for β_2	-0.019657	-3.058593	0.0046
1989 Dummy for γ_{22}	-0.007073	-5.407896	0.0000
1987 Dummy for γ_{23}	0.005433	1.522482	0.1384

Share Equation PL (Production Worker with Low Education Level)

Adjusted R-square	0.826376	
Q-statistics (H_0: no auto-correlation)	0.8673	(p-value: 0.352)

Share Equation NPYH (Non-Production, Young Worker with High Education Level)

Adjusted R-square	0.576342	
Q-statistics (H_0: no auto-correlation)	2.6457	(p-value: 0.104)

Table 5.2. (2)
Estimation of Cost Share Functions: Extended Case (Six Types of Labor Inputs)
Manufacturing (continued)
9. Elec. Machinery (Period: 1980-1998) 1 = IT, 2 = PL, 3 = NPYH, 4 = NPOH

	Coefficient	t-Statistic	Prob.
β_2	0.556649	19.73215	0.0000
β_3	0.314969	27.31428	0.0000
β_4	0.218856	7.33154	0.0000
γ_{22}	-0.515423	-11.62932	0.0000
γ_{23}	0.130254	8.557887	0.0000
γ_{24}	0.179589	15.51856	0.0000
γ_{33}	-0.057329	-3.253348	0.0022
γ_{34}	-0.072841	-5.844739	0.0000
γ_{44}	-0.079084	-3.421994	0.0013
1985 Dummy for β_2	-0.159971	-4.034486	0.0002
1993 Dummy for β_3	0.018524	3.228834	0.0023
1985 Dummy for γ_{22}	0.137387	3.116263	0.0032

Share Equation PL (Production Worker with Low Education Level)

Adjusted R-square	0.97107	
Q-statistics (H_0: no auto-correlation)	0.00000008	(p-value: 0.979)

Share Equation NPYH (Non-Production, Young Worker with High Education Level)

Adjusted R-square	0.919207	
Q-statistics (H_0: no auto-correlation)	0.033	(p-value: 0.856)

Share Equation NPOH (Non-Production, Old Worker with High Education Level)

Adjusted R-square	0.952001	
Q-statistics (H_0: no auto-correlation)	0.848	(p-value: 0.357)

10. Trans. Equipment (Period: 1990-1998) 1 = PL, 2 = NPOH

	Coefficient	t-Statistic	Prob.
β_2	0.893444	116.4612	0.0000
β_3	0.086926	6.283634	0.0000
γ_{22}	-0.111079	-15.89312	0.0000
γ_{23}	0.058465	8.885717	0.0000
γ_{33}	-0.024328	-2.525586	0.0171
1989 Dummy for β_2	-0.008963	-3.514038	0.0014
1987 Dummy for β_3	-0.054495	-4.518324	0.0001
1987 Dummy for γ_{33}	0.020783	3.766634	0.0007

Share Equation PL (Production Worker with Low Education Level)

Adjusted R-square	0.939304	
Q-statistics (H_0: no auto-correlation)	0.4103	(p-value: 0.522)

Share Equation NPOH (Non-Production, Old Worker with High Education Level)

Adjusted R-square	0.925469	
Q-statistics (H_0: no auto-correlation)	0.2839	(p-value: 0.594)

Notes:
Young = under 40
Old = over 40
Low Education Level = with high school or lower education
High Education Level = with junior college or higher education
Production = engaging operation at production sites
Non-Production = supervisory, clerical and technical

Table 7.1. (1)

Substitutability/Complementarity : Allen's Elasticity of Substitution

1. Baseline Case (Four Types of Labor Inputs)

A. Manufacturing

1. Food		
	80-89	90-98
IT & YL	10.445	4.5166
IT & YH	-20.843	-5.4259
YL & YH	1.4537	1.4478

2. Textile		
	80-92	93-98
IT & YL	8.7841	3.9614
IT & YH	-22.269	-3.7831
YL & YH	1.5802	1.451

3. Paper & Pulp			
	80-88	89-92	93-98
IT & YL	1.6988	1.3986	1.3209

4. Chemicals		
	80-89	90-98
IT & YL	3.3424	2.2828

5. Stone & Clay		
	80-91	92-98
IT & YL	3.5543	1.9676

6. Pri. Metal			
	80-87	88-94	95-98
IT & YL	3.2555*	1.9228	1.6979

7. Fab. Metal			
	80-87	88-93	94-98
IT & YL	5. 8058	4. 1781	4. 7314
IT & YH	-10. 695	-6. 9642	-6. 3244
YL & YH	1. 3718	1. 3874	1. 3412

8. Gen. Machinery			
	80-89		90-98
IT & YL	3.5528	IT & YL	6.7831
		IT & YH	-8.6414
		YL & YH	2.3471

9. Elec. Machinery		
	80-92	93-98
IT & YL	5. 0917	3. 7034
IT & YH	-3. 1283	-0.73924
YL & YH	2. 1956	2. 1819

10. Trans. Equipment			
	80-88	89-92	93-98
IT & YL	2.6372	1.5929	1.4647

11. Instruments	
	80-98
IT & YL	4.9972
IT & OH	-7.6361
YL & OH	2.9774

Table 7.1. (2)
Substitutability/Complementarity : Allen's Elasticity of Substitution
1. Baseline Case (Four Types of Labor Inputs)

B. Non-Manufacturing

Construc.		
	80-89	90-98
IT & YL	3.7776	1.9186

Trade	
	80-98
IT & YL	3.4879

Finance		
	80-84	85-92
IT & YL	9.2824	5.2761
IT & YH	-4.5892	-0.58239
YL & YH	6.2053	6.9215

Trans. & Commu.			
	80-85	86-89	90-98
IT & YL	5.0983	3.269	2.301

Services		
	80-89	90-98
IT & YL	3.5142	2.188
IT & OH	-1.8956	0.058466
YL & OH	1.7061	1.1704

Notes: * = Concavity conditions are not satisfied but these deviations are negligible.
IT : IT Capital
E : Equipment
YL : Young Worker with Low Education Level
YH : Young Worker with High Education Level
OH : Old Worker with High Education Level
PL : Production Worker with Low Education Level
NPYH : Non-Production, Young Worker with High Education Level
NPOH : Non-Production, Old Worker with High Education Level

Table 7.2.

Substitutability/Complementarity : Allen's Elasticity of Substitution

2. Extended Case (Six Types of Labor Inputs)

3. Paper & Pulp			
	80-88	89-92	93-98
IT & PL	1.3885	1.2492	1.2051

5. Stone & Clay			
	80-84	85-92	93-98
IT & PL	3.584	1.9377	1.5853

7. Fab. Metal			
	80-86	87-88	89-98
IT & PL	1.1317	0.54435	1.1213
IT & NPYH	7.9238	-0.28935	0.33467
PL & NPYH	2.345	2.3504	2.2656

9. Elec. Machinery			
	80-84	85-92	93-98
IT & PL	9.7743	2.312	2.3064
IT & NPYH	0.98933	0.99594	0.99705
IT & NPOH	-4.8677	-0.96633	-0.30107
PL & NPYH	1.9889	2.1147	2.1627
PL & NPOH	3.2755	3.2609	3.1495

10. Trans. Equipment			
	80-86	87-88	89-98
IT & PL	5.8993	3.2891*	2.7259
IT & NPOH	-25.557	-15.664*	-8.5173
PL & NPOH	1.6276	1.5631*	1.4718

Table 7: Cost Share of Variable Inputs

(percentage points)

	Food	Textile	Paper & Pulp	Chemicals	Stone & Clay	
81-89	0.383	0.360	0.215	0.207	0.247	
90-98	0.329	0.265	0.180	0.162	0.193	
	Pri. Metal	Fab. Metal	Gen. Machinery	Elec. Machinery	Trans. Equipment	Instruments
81-89	0.190	0.397	0.284	0.515	0.307	0.432
90-98	0.143	0.334	0.322	0.430	0.229	0.348
	Construc.	Trade	Finance	Trans. & Commu.	Services	
81-89	0.284	0.331	0.499	0.274	0.344	
90-98	0.210	0.228	n.a.	0.228	0.330	

Notes: The average in this table is the geometric average.

The sum of input contributions and technological progress growth may not add up to value added growth.

Finance data in the 1990s are excluded because of data problems. See Section 3.

Table 8: Sources of Growth in Value Added: 1981-98

(percentage points)

	Food	Textile	Paper & Pulp	Chemicals	Stone & Clay	Pri. Metal	Fab. Metal	Gen. Machinery	Elec. Machinery	Trans. Equipment	Instruments	Construc.	Trade	Finance	Trans. & Commu	Services
Total Sample Period: 1981-98																
Value Added	2.288	-3.112	2.993	4.447	1.488	-0.149	3.285	2.803	8.396	2.179	2.105	2.246	2.132	n.a.	2.794	4.768
Variable Inputs	0.163	-1.733	-0.070	-0.070	-0.676	-0.209	-0.549	-0.283	1.267	-0.369	-0.486	-0.387	-0.880	n.a.	-0.042	1.726
Quasi Fixed Inputs	1.933	-0.171	2.033	1.847	0.299	1.056	0.848	2.101	2.973	2.282	1.238	1.400	2.030	n.a.	2.368	3.372
Technological Progress	0.088	-1.317	1.033	2.614	1.768	-0.967	3.002	1.132	4.242	0.277	1.443	1.241	0.972	n.a.	0.469	-0.348
1980s: 1981-89																
Value Added	2.782	-0.956	6.066	8.172	4.613	0.448	5.978	6.437	12.152	3.969	5.018	4.300	3.463	7.917	4.682	5.462
Variable Inputs	0.114	-1.152	0.022	-0.435	-1.017	-0.216	-0.607	-0.233	2.741	-0.427	-0.666	-0.667	-0.926	1.012	-0.240	1.719
Quasi Fixed Inputs	2.770	1.519	2.535	2.059	1.057	1.699	1.529	3.603	4.464	3.092	2.407	1.573	2.754	1.944	3.441	3.959
Technological Progress	-0.243	-1.387	3.515	6.498	4.391	-1.033	4.975	3.107	4.969	1.329	3.338	3.421	1.606	4.919	1.469	-0.241
1990s: 1990-98																
Value Added	1.796	-5.221	0.008	0.851	-1.544	-0.742	0.660	-0.706	4.765	0.420	-0.729	0.233	0.819	n.a.	0.940	4.078
Variable Inputs	0.211	-2.312	-0.161	0.296	-0.334	-0.201	-0.491	-0.333	-0.186	-0.311	-0.306	-0.105	-0.835	n.a.	0.156	1.733
Quasi Fixed Inputs	1.103	-1.833	1.534	1.636	-0.452	0.417	0.172	0.620	1.503	1.479	0.082	1.228	1.311	n.a.	1.306	2.788
Technological Progress	0.419	-1.248	-1.390	-1.128	-0.788	-0.902	1.066	-0.805	3.520	-0.765	-0.418	-0.894	0.343	n.a.	-0.521	-0.454
Sub-Period																
1981-84																
Value Added	3.810	-0.991	4.728	8.246	3.644	-4.403	4.606	7.133	14.435	2.024	4.340	0.041	1.907	5.409	4.632	6.300
Variable Inputs	-0.018	-0.831	-0.312	-0.455	-1.290	-0.034	-1.724	-0.559	4.293	-0.704	-0.888	-1.121	-0.655	1.472	-0.547	1.699
Quasi Fixed Inputs	2.679	1.526	2.354	1.972	0.597	2.383	0.477	4.029	5.329	3.206	2.482	0.518	3.496	2.497	3.866	4.316
Technological Progress	1.052	-1.672	2.695	6.711	3.949	-6.620	5.760	3.589	4.822	-0.475	2.758	0.640	-0.936	1.418	1.292	0.284
1985-89																
Value Added	1.967	-0.928	7.149	8.113	5.395	4.506	7.087	5.884	10.359	5.551	5.565	7.837	4.725	9.966	4.722	4.796
Variable Inputs	0.220	-1.407	0.289	-0.418	-0.798	-0.362	0.295	0.028	1.516	-0.205	-0.489	-0.303	-1.142	0.646	0.006	1.734
Quasi Fixed Inputs	2.843	1.513	2.680	2.128	1.427	1.154	2.379	3.264	3.777	3.000	2.347	2.425	2.164	1.504	3.103	3.675
Technological Progress	-1.266	-1.158	4.175	6.328	4.745	3.676	4.351	2.723	5.086	2.795	3.805	5.702	3.687	7.806	1.610	-0.660
1990-94																
Value Added	2.838	-1.651	0.527	2.343	-0.148	0.625	3.090	-2.133	3.798	0.988	-3.714	3.787	2.003	n.a.	0.878	5.119
Variable Inputs	0.170	-3.174	-0.205	0.300	-0.479	-0.481	-0.382	-0.677	-0.374	-0.506	-1.023	-0.035	-0.730	n.a.	-0.047	1.703
Quasi Fixed Inputs	2.770	-2.643	2.763	3.087	0.774	1.206	0.472	0.732	1.910	2.064	0.395	2.146	0.846	n.a.	1.357	3.330
Technological Progress	-0.134	3.978	-2.054	-1.077	-0.472	-0.114	3.068	-1.954	2.334	-0.592	-2.942	1.632	1.900	n.a.	-0.436	0.078
1995-98																
Value Added	0.508	-9.502	-0.636	-0.985	-3.261	-2.426	-2.298	1.106	5.986	-0.284	3.134	-4.038	-0.643	n.a.	1.017	2.792
Variable Inputs	0.263	-1.223	-0.105	0.291	-0.151	0.149	-0.627	0.100	0.051	-0.066	0.596	-0.193	-0.967	n.a.	0.412	1.770
Quasi Fixed Inputs	-0.943	-0.811	0.019	-0.149	-1.965	-0.559	-0.202	0.481	0.996	0.753	-0.307	0.092	1.896	n.a.	1.243	2.114
Technological Progress	1.115	-7.412	-0.554	-1.192	-1.182	-1.877	-1.382	0.649	5.022	-0.980	2.829	-3.963	-1.570	n.a.	-0.626	-1.116
Cost Share of Variable Inputs																
81-89	0.383	0.360	0.215	0.207	0.247	0.190	0.397	0.284	0.515	0.307	0.432	0.284	0.331	0.499	0.274	0.344
90-98	0.329	0.265	0.180	0.162	0.193	0.143	0.334	0.322	0.430	0.229	0.348	0.210	0.228	n.a.	0.228	0.330

Notes: The average in this table is the geometric average.

The sum of input contributions and technological progress growth may not add up to value added growth.

Finance data in the 1990s are excluded because of data problems. See Section 3.

Table 8: Sources of Growth in Value Added: 1981-98

(percentage points)

	Food	Textile	Paper & Pulp	Chemicals	Stone & Clay	Pri. Metal	Fab. Metal	Gen. Machinery	Elec. Machinery	Trans. Equipment	Instruments	Construc.	Trade	Finance	Trans. & Commu	Services
Total Sample Period: 1981-98																
Value Added	2.288	-3.112	2.993	4.447	1.488	-0.149	3.285	2.803	8.396	2.179	2.105	2.246	2.132	n.a.	2.794	4.768
Variable Inputs	0.163	-1.733	-0.070	-0.070	-0.676	-0.209	-0.549	-0.283	1.267	-0.369	-0.486	-0.387	-0.880	n.a.	-0.042	1.726
Quasi Fixed Inputs	1.933	-0.171	2.033	1.847	0.299	1.056	0.848	2.101	2.973	2.282	1.238	1.400	2.030	n.a.	2.368	3.372
Technological Progress	0.088	-1.317	1.033	2.614	1.768	-0.967	3.002	1.132	4.242	0.277	1.443	1.241	0.972	n.a.	0.469	-0.348
1980s: 1981-89																
Value Added	2.782	-0.956	6.066	8.172	4.613	0.448	5.978	6.437	12.152	3.969	5.018	4.300	3.463	7.917	4.682	5.462
Variable Inputs	0.114	-1.152	0.022	-0.435	-1.017	-0.216	-0.607	-0.233	2.741	-0.427	-0.666	-0.667	-0.926	1.012	-0.240	1.719
Quasi Fixed Inputs	2.770	1.519	2.535	2.059	1.057	1.699	1.529	3.603	4.464	3.092	2.407	1.573	2.754	1.944	3.441	3.959
Technological Progress	-0.243	-1.387	3.515	6.498	4.391	-1.033	4.975	3.107	4.969	1.329	3.338	3.421	1.606	4.919	1.469	-0.241
1990s: 1990-98																
Value Added	1.796	-5.221	0.008	0.851	-1.544	-0.742	0.660	-0.706	4.765	0.420	-0.729	0.233	0.819	n.a.	0.940	4.078
Variable Inputs	0.211	-2.312	-0.161	0.296	-0.334	-0.201	-0.491	-0.333	-0.186	-0.311	-0.306	-0.105	-0.835	n.a.	0.156	1.733
Quasi Fixed Inputs	1.103	-1.833	1.534	1.636	-0.452	0.417	0.172	0.620	1.503	1.479	0.082	1.228	1.311	n.a.	1.306	2.788
Technological Progress	0.419	-1.248	-1.390	-1.128	-0.788	-0.902	1.066	-0.805	3.520	-0.765	-0.418	-0.894	0.343	n.a.	-0.521	-0.454
Sub-Period																
1981-84																
Value Added	3.810	-0.991	4.728	8.246	3.644	-4.403	4.606	7.133	14.435	2.024	4.340	0.041	1.907	5.409	4.632	6.300
Variable Inputs	-0.018	-0.831	-0.312	-0.455	-1.290	-0.034	-1.724	-0.559	4.293	-0.704	-0.888	-1.121	-0.655	1.472	-0.547	1.699
Quasi Fixed Inputs	2.679	1.526	2.354	1.972	0.597	2.383	0.477	4.029	5.329	3.206	2.482	0.518	3.496	2.497	3.866	4.316
Technological Progress	1.052	-1.672	2.695	6.711	3.949	-6.620	5.760	3.589	4.822	-0.475	2.758	0.640	-0.936	1.418	1.292	0.284
1985-89																
Value Added	1.967	-0.928	7.149	8.113	5.395	4.506	7.087	5.884	10.359	5.551	5.565	7.837	4.725	9.966	4.722	4.796
Variable Inputs	0.220	-1.407	0.289	-0.418	-0.798	-0.362	0.295	0.028	1.516	-0.205	-0.489	-0.303	-1.142	0.646	0.006	1.734
Quasi Fixed Inputs	2.843	1.513	2.680	2.128	1.427	1.154	2.379	3.264	3.777	3.000	2.347	2.425	2.164	1.504	3.103	3.675
Technological Progress	-1.266	-1.158	4.175	6.328	4.745	3.676	4.351	2.723	5.086	2.795	3.805	5.702	3.687	7.806	1.610	-0.660
1990-94																
Value Added	2.838	-1.651	0.527	2.343	-0.148	0.625	3.090	-2.133	3.798	0.988	-3.714	3.787	2.003	n.a.	0.878	5.119
Variable Inputs	0.170	-3.174	-0.205	0.300	-0.479	-0.481	-0.382	-0.677	-0.374	-0.506	-1.023	-0.035	-0.730	n.a.	-0.047	1.703
Quasi Fixed Inputs	2.770	-2.643	2.763	3.087	0.774	1.206	0.472	0.732	1.910	2.064	0.395	2.146	0.846	n.a.	1.357	3.330
Technological Progress	-0.134	3.978	-2.054	-1.077	-0.472	-0.114	3.068	-1.954	2.334	-0.592	-2.942	1.632	1.900	n.a.	-0.436	0.078
1995-98																
Value Added	0.508	-9.502	-0.636	-0.985	-3.261	-2.426	-2.298	1.106	5.986	-0.284	3.134	-4.038	-0.643	n.a.	1.017	2.792
Variable Inputs	0.263	-1.223	-0.105	0.291	-0.151	0.149	-0.627	0.100	0.051	-0.066	0.596	-0.193	-0.967	n.a.	0.412	1.770
Quasi Fixed Inputs	-0.943	-0.811	0.019	-0.149	-1.965	-0.559	-0.202	0.481	0.996	0.753	-0.307	0.092	1.896	n.a.	1.243	2.114
Technological Progress	1.115	-7.412	-0.554	-1.192	-1.182	-1.877	-1.382	0.649	5.022	-0.980	2.829	-3.963	-1.570	n.a.	-0.626	-1.116
Cost Share of Variable Inputs																
81-89	0.383	0.360	0.215	0.207	0.247	0.190	0.397	0.284	0.515	0.307	0.432	0.284	0.331	0.499	0.274	0.344
90-98	0.329	0.265	0.180	0.162	0.193	0.143	0.334	0.322	0.430	0.229	0.348	0.210	0.228	n.a.	0.228	0.330

Notes: The average in this table is the geometric average.

The sum of input contributions and technological progress growth may not add up to value added growth.

Finance data in the 1990s are excluded because of data problems. See Section 3.

Table 9: Capital's Contribution to Value Added Growth: 1981-98

(percentage points)

	Food	Textile	Paper & Pulp	Chemicals	Stone & Clay	Pri. Metal	Fab. Metal	Gen. Machinery	Elec. Machinery	Trans. Equipment	Instruments	Construc.	Trade	Finance	Trans. & Commu	Services
Total Sample Period: 1981-98																
IT Capital	0.186	0.148	0.119	0.479	0.075	0.207	0.122	0.125	0.896	0.218	0.510	0.032	0.075	n.a.	0.381	0.814
Equipment	0.832	0.936	1.049	0.811	0.665	0.472	0.679	1.234	1.378	1.422	1.333	0.194	0.286	n.a.	0.967	1.371
Structure	0.138	-0.032	0.471	0.203	0.076	0.354	0.092	0.102	0.488	0.300	0.045	0.093	0.268	n.a.	0.400	0.566
1980s: 1981-89																
IT Capital	0.146	0.106	0.127	0.355	0.054	0.188	0.145	0.141	0.964	0.229	0.466	0.020	0.058	0.583	0.253	0.753
Equipment	1.153	0.887	0.940	0.774	0.949	0.291	0.719	1.636	1.687	1.841	1.802	0.302	0.450	0.278	1.589	1.560
Structure	0.162	-0.041	0.451	0.112	0.105	0.261	0.083	0.122	0.680	0.347	0.121	0.093	0.250	0.105	0.370	0.616
1990s: 1990-98																
IT Capital	0.226	0.190	0.110	0.604	0.095	0.225	0.098	0.109	0.828	0.207	0.555	0.045	0.092	n.a.	0.510	0.876
Equipment	0.513	0.985	1.158	0.848	0.383	0.653	0.640	0.834	1.069	1.005	0.866	0.086	0.122	n.a.	0.348	1.182
Structure	0.114	-0.022	0.491	0.294	0.047	0.448	0.100	0.081	0.296	0.252	-0.032	0.092	0.285	n.a.	0.430	0.516
Sub-Period																
1981-84																
IT Capital	0.102	0.074	0.098	0.249	0.027	0.070	0.089	0.097	0.705	0.151	0.370	0.007	0.027	0.349	0.043	0.625
Equipment	1.075	0.507	0.591	0.685	1.026	0.005	0.443	1.723	1.477	1.777	1.665	0.446	0.584	0.209	2.197	1.435
Structure	0.130	-0.209	0.164	-0.147	0.054	-0.051	0.020	0.087	0.824	0.234	0.321	0.132	0.292	0.144	0.491	0.720
1985-89																
IT Capital	0.182	0.132	0.150	0.440	0.076	0.284	0.190	0.175	1.172	0.293	0.543	0.030	0.083	0.771	0.421	0.856
Equipment	1.215	1.192	1.221	0.845	0.887	0.521	0.939	1.567	1.856	1.893	1.912	0.188	0.344	0.333	1.105	1.661
Structure	0.188	0.093	0.682	0.320	0.145	0.511	0.134	0.151	0.566	0.437	-0.038	0.063	0.217	0.074	0.273	0.533
1990-94																
IT Capital	0.255	0.173	0.138	0.537	0.064	0.229	0.181	0.132	0.830	0.243	0.385	0.050	0.080	n.a.	0.546	0.825
Equipment	0.781	1.075	1.446	0.803	0.347	0.662	0.798	0.988	1.251	1.138	1.148	0.089	0.126	n.a.	0.273	1.526
Structure	0.119	0.060	0.714	0.507	0.121	0.852	0.104	0.117	0.394	0.455	-0.022	0.119	0.355	n.a.	0.500	0.592
1995-98																
IT Capital	0.190	0.211	0.076	0.688	0.133	0.221	-0.006	0.079	0.825	0.162	0.767	0.038	0.107	n.a.	0.467	0.939
Equipment	0.179	0.873	0.800	0.904	0.427	0.642	0.442	0.642	0.843	0.841	0.516	0.083	0.119	n.a.	0.443	0.755
Structure	0.107	-0.126	0.214	0.028	-0.045	-0.055	0.095	0.036	0.173	0.000	-0.044	0.057	0.198	n.a.	0.342	0.420

Note: The average in this table is the geometric average.

Finance data in the 1990s are excluded because of data problems. See Section 3.

Table 10: Labor's Contribution to Value Added Growth: 1981-98

(percentage points)

	Food	Textile	Paper & Pulp	Chemicals	Stone & Clay	Pri. Metal	Fab. Metal	Gen. Machinery	Elec. Machinery	Trans. Equipment	Instruments	Construc.	Trade	Finance	Trans. & Commu	Services
Total Sample Period: 1981-98																
Low Education, Young (under 40)	-0.371	-1.777	-0.188	-0.549	-0.750	-0.416	-0.793	-0.517	-0.117	-0.587	-1.416	-0.419	-0.955	n.a.	-0.423	-0.008
Low Education, Old (over 40)	0.488	-1.157	0.126	0.160	-0.732	-0.047	-0.209	0.133	0.578	0.032	-0.185	0.089	0.228	n.a.	0.546	0.393
High Education, Young (under 40)	0.350	-0.094	0.162	0.237	0.073	0.090	0.125	0.277	0.496	0.193	0.055	0.308	0.525	n.a.	0.221	1.043
High Education, Old (over 40)	0.481	0.108	0.228	0.444	0.224	0.189	0.290	0.485	0.540	0.342	0.422	0.719	0.720	n.a.	0.236	0.919
1980s: 1981-89																
Low Education, Young (under 40)	-0.287	-1.223	-0.106	-0.790	-1.071	-0.405	-0.906	-0.374	0.882	-0.656	-1.523	-0.687	-0.984	-0.888	-0.493	0.098
Low Education, Old (over 40)	1.091	0.502	0.724	0.350	-0.339	0.805	0.404	0.980	1.442	0.446	0.127	0.309	0.524	0.563	1.152	0.658
High Education, Young (under 40)	0.259	-0.033	0.189	0.202	0.077	0.076	0.157	0.331	0.903	0.188	0.355	0.250	0.771	1.318	0.126	1.124
High Education, Old (over 40)	0.364	0.168	0.234	0.627	0.268	0.268	0.331	0.544	0.656	0.274	0.392	0.615	0.752	0.999	0.202	0.866
1990s: 1990-98																
Low Education, Young (under 40)	-0.456	-2.329	-0.271	-0.307	-0.428	-0.427	-0.680	-0.661	-1.105	-0.518	-1.308	-0.150	-0.927	n.a.	-0.354	-0.114
Low Education, Old (over 40)	-0.111	-2.789	-0.468	-0.031	-1.123	-0.891	-0.817	-0.706	-0.279	-0.381	-0.496	-0.131	-0.066	n.a.	-0.057	0.128
High Education, Young (under 40)	0.441	-0.155	0.135	0.273	0.070	0.105	0.094	0.223	0.092	0.199	-0.244	0.366	0.279	n.a.	0.315	0.963
High Education, Old (over 40)	0.599	0.048	0.222	0.261	0.180	0.110	0.248	0.426	0.424	0.411	0.452	0.822	0.688	n.a.	0.269	0.971
Sub-Period																
1981-84																
Low Education, Young (under 40)	-0.547	-1.081	-0.410	-0.704	-1.317	-0.103	-1.783	-0.656	2.233	-0.854	-1.456	-1.128	-0.682	-0.457	-0.590	0.280
Low Education, Old (over 40)	1.193	1.157	1.212	0.501	-0.849	1.871	-0.144	1.417	2.159	0.486	0.294	-0.487	0.851	1.190	0.762	0.695
High Education, Young (under 40)	0.427	0.178	0.174	0.225	0.043	0.192	-0.028	0.352	1.369	0.312	0.203	0.184	1.024	1.580	0.253	1.465
High Education, Old (over 40)	0.278	0.068	0.215	0.714	0.335	0.368	0.164	0.459	0.871	0.400	0.202	0.231	0.742	0.957	0.160	0.794
1985-89																
Low Education, Young (under 40)	-0.078	-1.336	0.139	-0.858	-0.874	-0.646	-0.198	-0.147	-0.186	-0.497	-1.578	-0.333	-1.225	-1.230	-0.415	-0.047
Low Education, Old (over 40)	1.009	-0.019	0.335	0.230	0.072	-0.040	0.844	0.631	0.873	0.414	-0.007	0.951	0.263	0.064	1.465	0.629
High Education, Young (under 40)	0.125	-0.203	0.202	0.184	0.103	-0.017	0.305	0.314	0.531	0.089	0.476	0.304	0.569	1.109	0.025	0.852
High Education, Old (over 40)	0.433	0.249	0.250	0.557	0.215	0.188	0.466	0.613	0.485	0.172	0.544	0.923	0.759	1.032	0.236	0.925
1990-94																
Low Education, Young (under 40)	-0.496	-2.968	-0.343	-0.236	-0.543	-0.709	-0.661	-0.980	-1.466	-0.750	-1.667	-0.085	-0.810	n.a.	-0.592	-0.101
Low Education, Old (over 40)	1.002	-3.419	0.059	0.392	-0.054	-0.639	-0.636	-0.768	-0.257	-0.185	-0.793	0.786	0.072	n.a.	-0.003	0.250
High Education, Young (under 40)	0.412	-0.350	0.110	0.688	0.080	0.142	0.101	0.178	0.265	0.173	0.079	0.211	-0.033	n.a.	0.323	0.964
High Education, Old (over 40)	0.867	-0.265	0.435	0.686	0.287	0.196	0.205	0.415	0.532	0.495	0.266	0.941	0.322	n.a.	0.264	0.979
1995-98																
Low Education, Young (under 40)	-0.405	-1.523	-0.182	-0.395	-0.284	-0.073	-0.704	-0.261	-0.652	-0.228	-0.856	-0.231	-1.073	n.a.	-0.055	-0.131
Low Education, Old (over 40)	-1.485	-1.996	-1.122	-0.557	-2.444	-1.206	-1.044	-0.627	-0.306	-0.625	-0.124	-1.267	-0.239	n.a.	-0.125	-0.025
High Education, Young (under 40)	0.478	0.089	0.167	-0.244	0.057	0.059	0.085	0.280	-0.124	0.231	-0.647	0.559	0.670	n.a.	0.304	0.962
High Education, Old (over 40)	0.265	0.440	-0.043	-0.269	0.046	0.002	0.301	0.440	0.288	0.305	0.684	0.674	1.147	n.a.	0.276	0.961

Note: The average in this table is the geometric average.

Finance data in the 1990s are excluded because of data problems. See Section 3.

Table 11: Technological Progress, Old Workers and IT (1)
Manufacturing, # of industries = 11, No. of Obs. = 44
Dependent Variable = Rate of Technological Progress

Parameter	Estimate	Standard Error	t-statistic	P-value
Constant				
Random Effects	0.349	4.957	0.070	0.944
GMM	0.860	4.141	0.208	0.836
β_{OL}				
Random Effects	0.011	0.081	0.137	0.891
GMM	0.018	0.051	0.356	0.722
OL 90sDummy				
Random Effects	0.015	0.036	0.426	0.670
GMM	n.a.	n.a.	n.a.	n.a.
β_{OH}				
Random Effects	0.644	0.370	1.740	0.082
GMM	0.660	0.430	1.535	0.125
OH 90sDummy				
Random Effects	-0.861	0.287	-2.995	0.003
GMM	-0.782	0.250	-3.125	0.002
β_{PROFIT}				
Random Effects	1.541	2.918	0.528	0.597
GMM	n.a.	n.a.	n.a.	n.a.
β_{ITK}				
Random Effects	0.515	0.226	2.282	0.022
GMM	0.392	0.153	2.568	0.010
β_{EQ}				
Random Effects	-0.045	0.056	-0.808	0.419
GMM	-0.046	0.036	-1.281	0.200

Specification Test	Value	P-value
Hausman (FE vs. RE)	10.353	0.169
Hansen	1.493	0.684

Note: n.a. denotes not applicable.
Hansen in specification test is Hansen's overidentifying restrictions test (Hansen 1982).

Table 12: Technological Progress, Old Workers and IT (2)

Manufacturing excluding Elec. Machinery, # of industries = 10, No. of Obs.=40
Dependent Variable = Rate of Technological Progress

Parameter	Estimate	Standard Error	t-statistic	P-value
Constant				
Random Effects	1.151	6.363	0.181	0.856
GMM	0.291	5.174	0.056	0.955
β_{OL}				
Random Effects	0.002	0.098	0.023	0.982
GMM	0.020	0.060	0.328	0.743
OL 90sDummy				
Random Effects	0.022	0.041	0.526	0.599
GMM	n.a.	n.a.	n.a.	n.a.
β_{OH}				
Random Effects	0.570	0.422	1.351	0.177
GMM	0.673	0.455	1.481	0.139
OH 90sDummy				
Random Effects	-0.898	0.313	-2.874	0.004
GMM	-0.745	0.279	-2.675	0.007
β_{PROFIT}				
Random Effects	2.147	3.259	0.659	0.510
GMM	n.a.	n.a.	n.a.	n.a.
β_{ITK}				
Random Effects	0.684	0.460	1.487	0.137
GMM	0.146	0.404	0.361	0.718
β_{EQ}				
Random Effects	-0.053	0.066	-0.806	0.421
GMM	-0.030	0.041	-0.744	0.457

Specification Test	Value	P-value
Hausman (FE vs. RE)	9.279	0.233
Hansen	1.815	0.612

Note: n.a. denotes not applicable.
Hansen in specification test is Hansen's overidentifying restrictions test (Hansen 1982).

Table 13: Technological Progress, Old Workers and IT (3)
Non-manufacturing, # of industries = 4, No. of Obs. = 16
Dependent Variable = Rate of Technological Progress

Parameter	Estimate	Standard Error	t-statistic	P-value
Constant				
Random Effects	-0.185	6.961	-0.027	0.979
GMM	-1.868	4.949	-0.377	0.706
β_{OL}				
Random Effects	0.083	0.212	0.392	0.695
GMM	0.089	0.138	0.644	0.520
OL 90sDummy				
Random Effects	-0.073	0.084	-0.871	0.383
GMM	n.a.	n.a.	n.a.	n.a.
β_{OH}				
Random Effects	-0.144	0.719	-0.201	0.841
GMM	0.184	0.624	0.295	0.768
OH 90sDummy				
Random Effects	0.043	0.368	0.116	0.908
GMM	-0.082	0.251	-0.326	0.744
β_{PROFIT}				
Random Effects	7.279	8.078	0.901	0.368
GMM	n.a.	n.a.	n.a.	n.a.
β_{ITK}				
Random Effects	0.144	0.359	0.401	0.689
GMM	-0.295	0.194	-1.522	0.128
β_{EQ}				
Random Effects	-0.050	0.148	-0.339	0.735
GMM	-0.014	0.086	-0.166	0.868

Specification Test	Value	P-value
Hausman (FE vs. RE)	3.975	0.409
Hansen	5.534	0.137

Note: n.a. denotes not applicable.
Hansen in specification test is Hansen's overidentifying restrictions test (Hansen 1982).

Table 14: Technological Progess, Old Workers and IT (4)
All Industries, # of Industries = 15, No. of Obs. = 60

Dependent Variable = Rate of Technological Progress

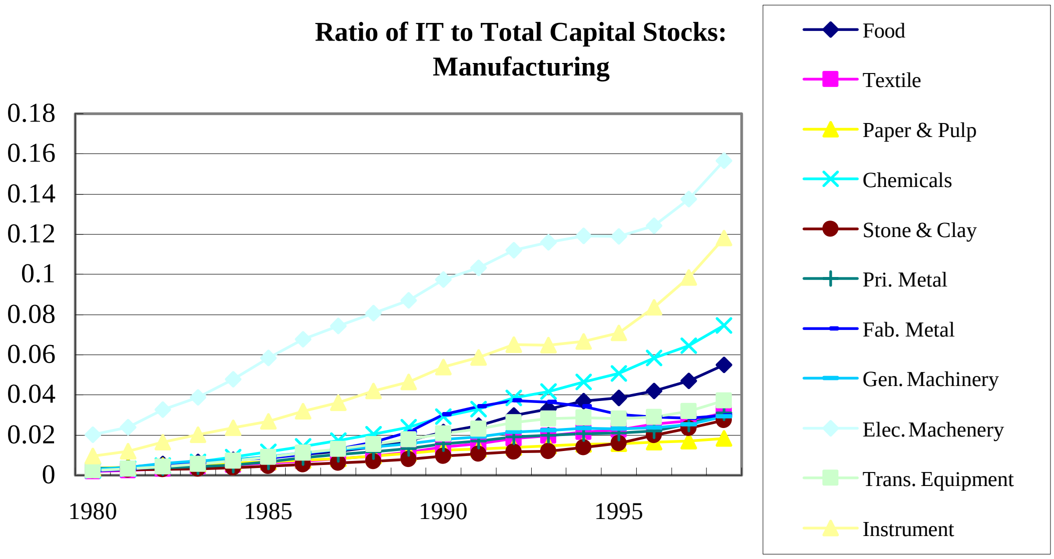
Parameter	Estimate	Standard Error	t-statistic	P-value
Constant				
Random Effects	0.514	3.285	0.157	0.876
GMM	1.253	3.914	0.320	0.749
β_{OL}				
Random Effects	-0.016	0.058	-0.275	0.783
GMM	-0.007	0.052	-0.143	0.886
OL 90sDummy				
Random Effects	-0.009	0.031	-0.277	0.781
GMM	n.a.	n.a.	n.a.	n.a.
β_{OH}				
Random Effects	0.116	0.287	0.402	0.688
GMM	0.514	0.433	1.188	0.235
OH 90sDummy				
Random Effects	-0.399	0.218	-1.826	0.068
GMM	-0.556	0.229	-2.424	0.015
β_{PROFIT}				
Random Effects	4.099	2.158	1.899	0.058
GMM	n.a.	n.a.	n.a.	n.a.
β_{ITK}				
Random Effects	0.280	0.140	1.991	0.046
GMM	0.031	0.146	0.212	0.832
β_{EQ}				
Random Effects	0.011	0.036	0.292	0.770
GMM	-0.018	0.030	-0.610	0.542

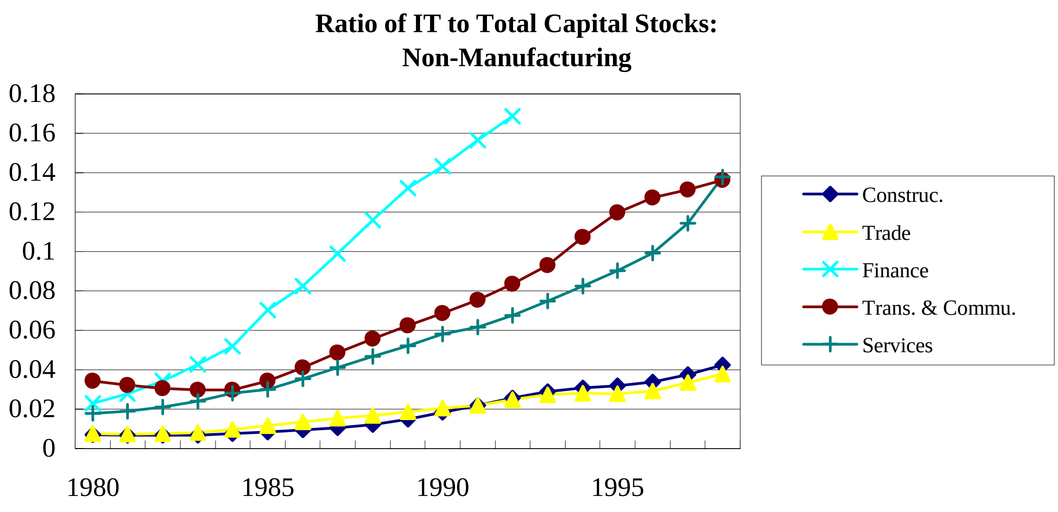
Specification Test	Value		P-value	
Hausman (FE vs. RE)	6.536		0.479	
Hansen	2.653		0.448	

Note: n.a. denotes not applicable.

Hansen in specification test is Hansen's overidentifying restrictions test (Hansen 1982).

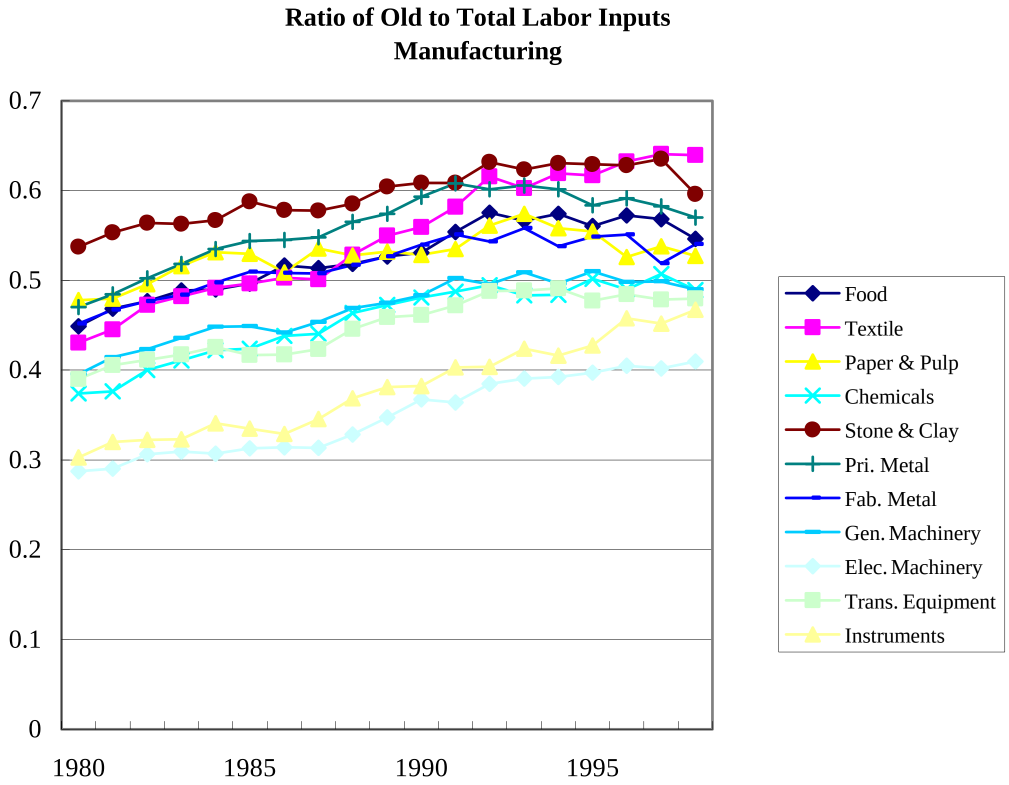
Figure 1. Ratio of IT to Total Capital Stocks

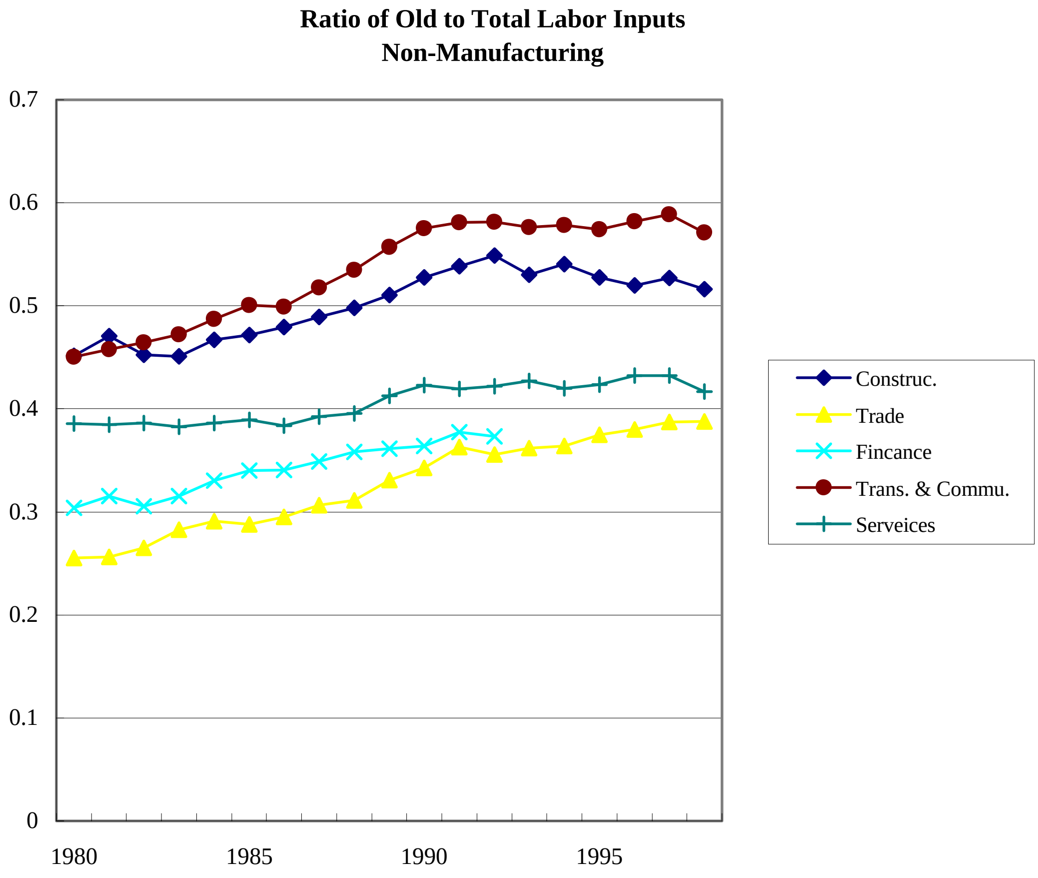




Note: Finance data are truncated at 1993. See Section 3.

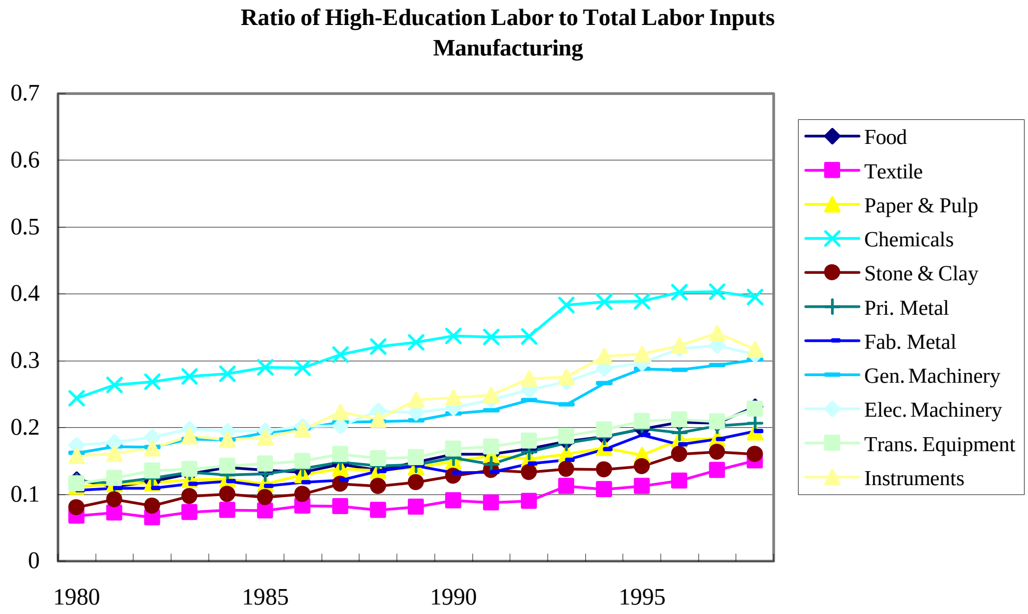
Figure 2.1. Ratio of Old to Total Labor Inputs

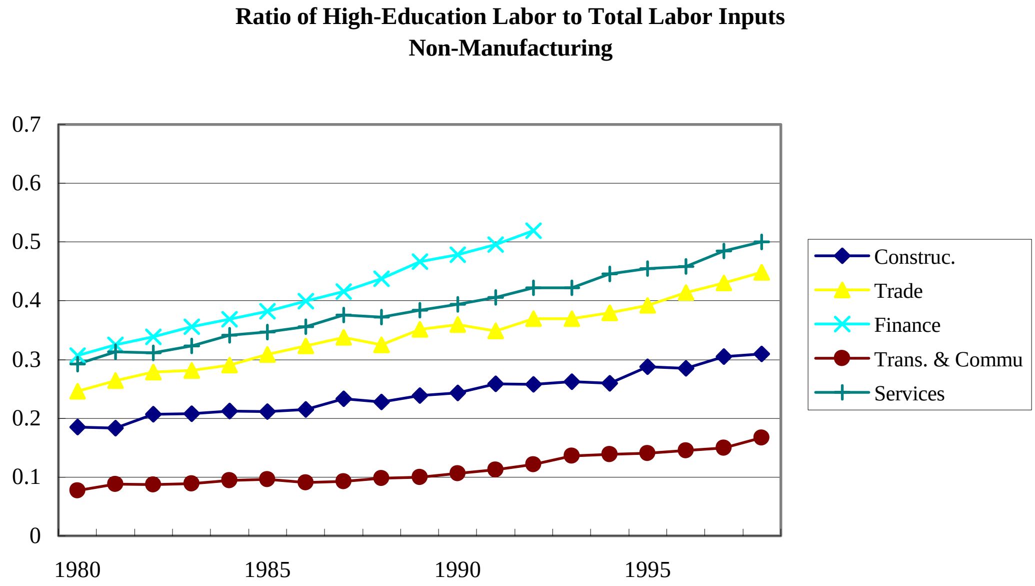




Note: Finance data are truncated at 1993. See Section 3.

Figure 2.2. Ratio of High-Education Labor to Total Labor Inputs





Note: Finance data are truncated at 1993. See Section 3.

Figure 2.3. Ratio of Non-Production Labor to Total Labor Inputs (Manufacturing Only)

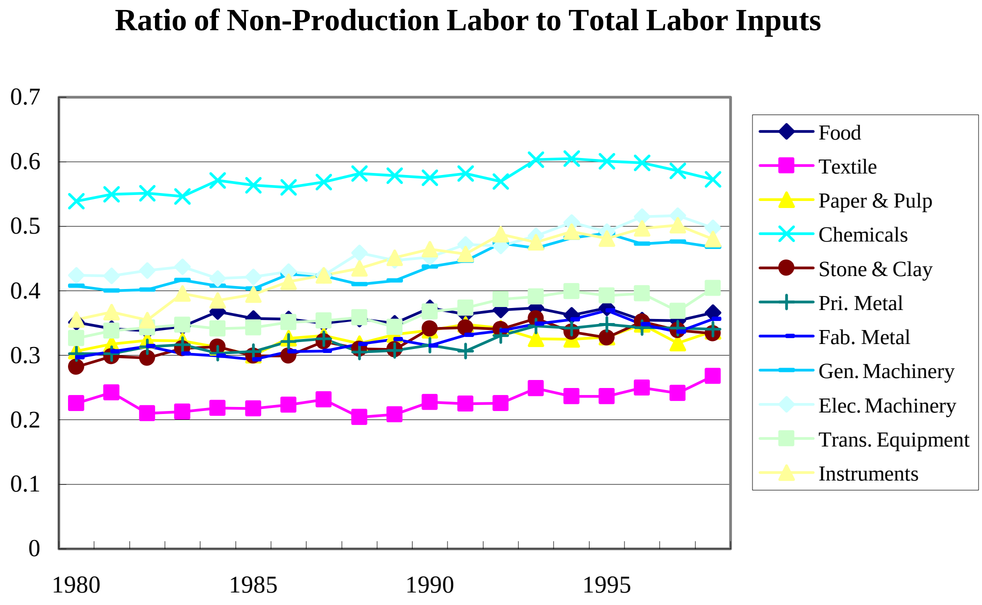


Figure 3 Value Added Growth and GDP Share

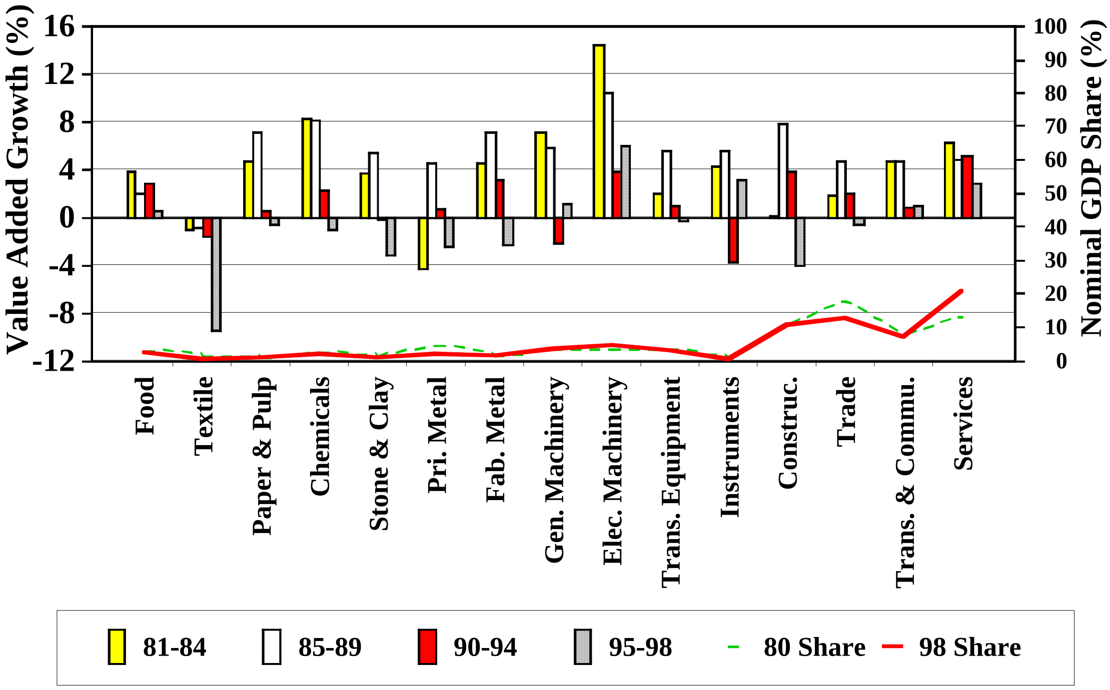


Figure 4 Technological Progress and IT Ratio