Effects of Information Technology on Labor Demand and Technological Progress in Japanese Manufacturing: 1980-1998 *

Kazunori Minetaki
Fujitsu Research Institute

Kiyohiko G. Nishimura
Faculty of Economics, University of Tokyo

Masato Shirai
Department of Economics, University of Tokyo

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1 Introduction and Summary

The Japanese economy is 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. Rapid advance of information and communication technology may imply a drastic change in work place and job structure, which may alter the impact of aging work force. Technological advancement in information and communication

*We are grateful to Professor Miyagawa who kindly permitted us to use his disaggregate capital stock series in this paper.

technology may 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 is no research on the interrelationship between aging population and technological progress in information and communication technology. This paper is the first step to fill this gap. In this paper, we concentrate on the supply side and we explore interaction between information and communication technology and the composition of labor inputs. 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 stocks and various labor inputs. Second, we estimate contribution of information- and communication-related capital stocks and various labor inputs on the growth of the Japanese economy in the recent turbulent era (1980s and 1990s) and explore possible correlation on technological progress in the form of the total factor productivity growth on the one hand, and rapid accumulation of information- and communication-related capital stocks and compositional changes in labor inputs on the other hand.

The natural framework of the measurement of factor substitutability 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 competitive factor markets. Although the latter assumption is relatively benign in the Japanese industries, the former one 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 that all capital stocks are quasi-fixed nor all labor inputs are perfectly variable. We disaggregate capital stocks and labor inputs into quasi-fixed parts and variable ones, and assume production capacity is determined by quasi-fixed factors and capacity utilization is determined by variable factors. Under the assumption of homogeneity of the production-capacity function and the capital-utilization function 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 growth of the total factor productivity without imposing a perfect competition assumption on product markets. This is particularly important, since most of the Japanese industries are not competitive (see Nishimura, Ohkusa and Ariga (1999)). The traditional approach assuming perfect competition may result in wrong estimates of technological progress (see Nishimura and Shirai (2000)).

In Section 3, we briefly explain data used in the paper. We proceed in two steps. First, we construct a time series of information-technology capital stocks (we hereafter call it IT stocks) based on Base-Year *Input Output Tables* and other primary government statistics, and break down capital stocks into IT stocks and other capital stocks (non-IT stocks). The non-IT stocks are further decomposed into *structure* and (non-IT) *equipment.* Many researchers in the United States have pointed out that the structure part of capital stocks move very differently from the equipment part (see for example, Gordon (1990) and DeLong and Summers (1992)). The difference is also argued to be important in understanding the contribution of capital stocks in economic growth However, the difference has been largely overlooked in empirical research in Japan except for a recent seminal study by Miyagawa and Shiraishi (2000). Second, we disaggregate labor inputs into *production* workers' and *non-production* workers' ones. Moreover, both production and non-production workers are further disaggregated into young workers (no older than forty years) and old workers (the rest). We construct these disaggregate labor inputs data from a partly unpublished data set of the *Basic Survey of Wage Structure*. We concentrate our attention on manufacturing.

Sections 4 and 5 report the main result of this paper. In Section 4, using the data explained in Section 3, we estimated tranlsog variable-cost functions. In particular, we examined what factors of production can be treated as quasi-fixed. We found that the result of translog cost function estimation was inconsistent with the hypothesis of structure capital stocks and non-production workers were variable inputs. Instead, the result suggested that IT stocks, equipment, and production workers were likely to be variable inputs. The empirical result also showed that IT stocks and production labor were substitutable to a large extent in IT-intensive industries such as Chemical, Electric Machinery, and Instruments, while the substitutability is not so strong in less IT-intensive idustries. The substitutability between IT and production workers in IT-intensive industries was very strong in the 1980s and somewhat subdued in the 1990s. Though the substitutability was relatively small in the 1980s in other less IT-intensive industries, there seem to be significant increase in the 1990s. This implies that the pressure from aging production work force may be effectively mitigated by an increase in IT capital stocks.

In Section 5, we examined TFP growth between 1981 and 1998 in the framework developed in Section 3, and estimated the contribution of IT capital stocks and the effect of changing age structure of labor force in TFP growth. Because of technical problems in constructing labor input series, we restricted our attention to eight out of eleven industries. The result revealed the prolonged slump of the 1990s was not merely a demand-driven phenomenon, but the supply side played a substantial role. The TFP growth declined substantially between the 1980s and 1990s. We then examined the relationship between the TFP growth rate on the one hand and IT capital growth. We found a very strong correlation between them, suggesting a strong externality effect of IT capital stocks. This has an important implication on the future of the Japanese economy countering the pressure of aging population. To promote IT investment may be very effective to increase TFP growth and thus ultimately to boost the Japanese economy. As for the effect of "maturing" labor force on TFP growth, we had rather mixed results. In the 1980s, the TFP growth was apparently positively correlated with "maturing" non-production labor force. That is, the TFP growth was increased as the ratio of old non-production workers to the total non-production workers was increased. This suggested that the increased average skill among workers due to "maturing" labor force had a positive effect to improve productivity. However, the relationship changed in the 1990s, and we no longer had such positive relationship. The nature of TFP growth apparently changed to be neutral with respect to "maturing" labor force.

2 Quasi-Fixed Factors, Variable Cost Function and TFP Measurement

2.1 Production Function: Production-Capacity Function and Capacity-Utilization Function

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

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

where x_i is the ith variable factor and z_j is the jth quasi-fixed factor. 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. F **is multiplicatively separable between variable factors** $(x_1, ..., x_i, ..., x_n)$ **and quasi-fixed factors** $\left(z_1, ..., z_j, ..., z_m\right)$ **:**

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

The function $S\left(z_1, ..., z_j, ..., z_m\right)$ may be interpretedas the *production-capacity* function. The quasi-fixed factors $\left(z_1, ..., z_j, ..., z_m\right)$ are needed for a production capacity of S. Using this production capacity, actual output is produced by consuming variable factors $(x_1, ..., x_i, ..., x_n)$. 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 equipments 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 equipments, 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 $G = G(x_1, ..., x_i, ..., x_n)$.

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

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

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

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

$$C_V(p_1, ..., p_i, ...p_n, Y, S) = \underset{x_1,\cdots,x_n}{Min} \sum_{i=1}^{n} p_i x_i \quad \text{subject to } Y = G(x_1, ..., x_i, ..., x_n) S \tag{2}$$

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

$$C_V(p_1, ..., p_n, Y, S) = c_v(p_1, ..., p_n) \left(\frac{Y}{S}\right)^{1/k} \tag{3}$$

where c_v is homogeneous of degree one in prices defined in the Appendix (8). Consequently, using Shepherd's Lemma, we have

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

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

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

Moreover, (3) means that

$$\frac{Y}{C_V} \frac{\partial C_v}{\partial Y} = \frac{Y}{C_V} \lambda = \frac{1}{k} \tag{4}$$

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

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

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

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

where p_y is the price of output, Θ denotes other market conditions determining competitiveness of the industry in qeustion. The term $J \geq 0$ is the fixed cost that is independent of the quasi-fixed factors. This optimization implies which is

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

where

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

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

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

Next, consider the determination of quasi-fixed factors. 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 put today. In the following analsys, we assume that quasi-fixed factor inputs must be determined one period before production for simplicity. It is straightfoward 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.[1] Thus, our formulation is perfectly consistent with the time-to-build formulation of investment.

Under the simplifying assumption of the one-period-advance determination, the quasi-fixed inputs must be determined by the following (expected) net profit maximization

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

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.

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

[1]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 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.

cost C_S be such that.

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

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

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

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

$$\underset{z_1,..,z_m}{Max} \quad E_{-1} \quad net \ \ profit=E_{-1}\left[\pi_{gross}(S)-c_s\left(q_{-1,1},..,q_{-1,m}\right)S^{1/(1-k)}-J\right].$$

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.

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

2.4 TFP Measurement

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

Let us now consider the measurement of the total factor productivity. Let A denote the sate of production knowledge determining production efficiency such that

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

Then, the technological progress in the discrete time, which is the rate of change in the total factor productivity, is defined by

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

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 approxiamte relation

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

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

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

Since the variable cost shares and quasi-fixed cost shares are observable, the TFP growth 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 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

$$TC^L\left(p_1,\ldots,p_n,q_{-1,1},..,q_{-1,m},Y,A\right) = \underset{x_1,\ldots,x_n,z_1,\ldots,z_m}{Min} \quad \sum_{i=1}^{n} p_i x_i + \sum_{j=1}^{m} q_{-1,j} z_j \quad \text{s.t.} \quad (7).$$

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

$$\underset{Y_L}{Max} \quad p_y\left(Y^L;\Theta\right)Y^L - TC^L\left(p_1,\ldots,p_n,q_{-1,1},..,q_{-1,m},Y^L,A\right) - J$$

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

$$C_V^L = \sum_{i=1}^{n} p_i x_i^L = \lambda^L k Y^L; \text{ and } C_S^L = \sum_{j=1}^{m} q_{-1,j} z_j^L = \lambda^L (1-k) Y^L$$

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 the entire sample period in the empirical analysis of Section 5.

3 IT 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 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 stocks), and break down capital stocks into IT 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 production workers' and non-production workers' inputs. Moreover, both production and non-production workers are further disaggregated into young workers (no older than forty years) and old workers (the rest). The details of the procedure are explained in an unpublished Appendix (which is available from the authors upon request).

IT Stocks, (Non-IT) Equipment, and Structure 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 equipments 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 prepackaged, custom, and ownaccount software, the Japanese definition only includes custom software. This definitional difference of IT software must be kept in mind in the following analysis.

The Ministry of International Trade and Industry (MITI) 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.[2] 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 MITI.[3]. The IT capital stock is then constructed by applying the perpetual inventory method. In constructing 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.[4] As for the IT software investment deflator, we use the price index of communication services (1985-1995) and software development (1995-1998) in the Corporate Service Price Index compiled by the Bank of Japan. These two series are linked at 1995. Before 1984, there is no price index for IT software. Consequently, we are obliged to estimate the IT software price index between 1980 and 1984 by using a regression equation explaining IT software price index by several economic variables, which we estimate using data between 1985 and 1998.

In their seminal work, Miyagawa and Shiraishi (2000) construct detailed industry-by-industry capital stock series for manufacturing, in which structure capital stocks and equipment ones (including IT stocks) are separately estimated. In the following analysis, we use the Miyagawa-Shiraishi series of structure capital stocks.[5] Finally, we subtract our IT capital

[2]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.

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

[4]An alternative is to use the Wholesale Price Index of IT products published by the Bank of Japan (BOJ). However, this price index of IT 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 BOJ 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. Taking this in mind, we adopt Shreyer's index instead of the BOJ index in this paper.

[5]To be precise, the Miyagawa-Shiraishi series end in 1996. We extend their data to 1998 by using unpublished

stocks from Miyagawa-Shiraishi equipment capital stocks to get non-IT equipment capital stocks. In the following, we simply use the term "equipment capital stocks" for non-IT ones to simplify notations.

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):

$$UCC_{it} = \frac{1 - u_t z_{it}}{1 - u_t}(r_t + \delta_{it} - \frac{q_{it} - q_{i,t-1}}{q_{it}})q_{it}$$

where UCC_{it} is the user cost of the ith capital stocks, r_t the required nominal rate of return, δ_{it} is the ith capital stocks' depreciation rate, q_{it} their price, 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).

Production and Non-Production Labor Inputs We construct disaggregate labor input data from a partly unpublished data set of the *Basic Survey of Wage Structure.* 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. The survey also includes age information of these workers. We define workers over forty years of age as old workers and those under forty years as young workers. 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. Combining the estimated number of employed workers[6] for each industry with industry-wise work-hour

data of the Japan Center for Economic Research which use the same methodology as Miyagawa and Shiraishi.

[6]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*

data,[7] we construct labor input data for young production workers, old production workers, young non-production workers, and old non-production workers. Hourly wage data for each category are then derived by compensation data of the *Basic Survey* divided by total work hours obtained earlier.[8]

Eleven Manufacturing Industries Under Consideration In this paper, we concentrate our attention on manufacturing. We break down manufacturing into thirteen industries, following the System of National Accounts. Table 1 shows industries we consider. Among thirteen industries in the manufacturing sector, we exclude "other 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 industries we consider are eleven out of thirteen SNA manufacturing industries. The total sample period is 1980-1998. The starting year 1980 is chosen since IT stock estimates before 1980 become problematic because of the reliability issue of our data sources.

Descriptive statistics of factor inputs are shown in Table 2 for each industry in two subperiods 1980-1989 and 1990-1998. Time profile of the share of IT stocks in the total capital stock is shown in Figure 1, and that of the ratio of production-worker labor inputs to the total labor inputs is depicted in Figure 2. The table and figures show a substantial increase in IT stocks in almost all industries. The increase is apparently accelerated after 1995. They also show a slow but steady increase of non-production workers relative to production workers.

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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 production and non-production workers, we postulate the breakdown is the same as that of employees in the following analysis.

[7]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*.

[8]For self-employed and family workers, we adopt the method of Kuroda et al (1996). See the unpublished Appendix for details.

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

In this section, we examine the impact of the advancement of IT on labor inputs. In particular, we explore whether IT stocks are substitutes or complements of labor inputs, and whether the magnitude of such substitutability/complemetarity has changed between the 1980s and 1990s. To our knowledge, this is the first attempt of this kind.[9]

Since our concern is whether IT and labor inputs are substitute or not, we use a translog cost function approach. Let n be the number of variable inputs. In the empirical analysis, we assume that c_v has a translog functional form such that

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

In order that C_V is a cost function, c_v should be non-decreasing and homogeneous of degree one in $(p_1,...,p_n)$. As usual, we impose the following restrictions on parameters to satisfy these requirements.

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

Under these restrictions, we immediately get the cost share function such that

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

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

There is one remaining requirement on C_V that C_V should be concave in $\left(p_1, ..., p_3\right)$. This is satisfied if c_v is concave. In general, the concavity requirement on c_v is not neatly represented by restrictions on the parameters β_i and γ_{ij}. Thus, we estimate the share function imposing only homogeneity of degree one, and then examine whether the estimated parameters imply the concavity of cost function locally around the sample mean of input prices.

It should be noted that concavity property of cost functions depends on the assumption that the decision maker can freely choose factor inputs and minimizes the cost by appropriately

[9] 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.

adjusting factor inputs to their price changes. Thus, if some factors are fixed, 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 may suggest that some factors are not variable but fixed.

We use IT stocks as factor 1 of the above framework[10]. Since structure capital stocks is a likely candidate of quasi-fixed capital stocks and that non-production workers is possible quasi-fixed labor inputs, we proceed in the following three steps.

In the first step, we assume all factors including structure and non-production workers are variable, and estimate share functions of the following type by pooling eleven industries from 1980 to 1998 and by letting Primary and Fabric Metal industries as "base industries" (that is, no-industry-dummy industries). The estimation method is the Full Information Maximum Likelihood.

$$\begin{aligned} \frac{p_i x_i}{C_V} &= \beta_i + \sum_l \beta_{il} IND_l + \beta_{i90} D_{90} \\ &\quad + \sum_j \gamma_{ij} \log \frac{p_j}{p_{IT}} \\ &\quad + \sum_l \gamma_{iil} IND_l \log \frac{p_i}{p_{IT}} + \sum_l \gamma_{ii90} IND_l D_{90} \log \frac{p_i}{p_{IT}} + \gamma_{ii90} D_{90} \log \frac{p_i}{p_{IT}} \end{aligned}$$

Here IND_l is the lth industry dummy, D_{90} is the period dummy for 1990-1998. The above specification allows that both the intercept and slope of the own-price effect may be different among industries and between subperiods. We start to estimate above share functions with all dummy variables except for base industries. Then, dummy variables are dropped if they are statistically insignificant. The result is reported in Table 3.

In the second step, we exclude structure capital stocks and re-estimate share functions by the same procedure as in the first step, on the assumption that IT stock, equipment, non-production workers, and production workers are variables. The result is found in Table 4. In the third step, we consider only IT stock, equipment and production workers are variable, and re-estimate share functions in the same way. The final result is shown in Table 5. In every case, the period dummy D_{90} is significant, which implies a structural change between the 1980s and 1990s.

Let us now examine what factors of production should be treated as quasi-fixed. We

[10]This implicitly assumes that the IT stocks are always variable inputs.

examine three cases: (1) all inputs including structure and non-production workers were variable factors (Table 3) (2) inputs except structure were variable (Table 4) and (3) only IT stocks, equipment, and production workers were variable (Table 5). We find that the estimated function does not satisfy concavity in many periods in Case (1)[11] and in some periods especially in the 1980s in Case (2) [Table 6]. These results suggest that structure and non-production labor are generally quasi-fixed. In fact, if excluded these two factors, the estimated function do satisfy concavity requirement in Case (3) [Table 7]. Thus, IT stocks, equipment, and production workers are likely to be variable inputs, whereas structure and non-production workers especially in 1990s may better be considered as quasi-fixed.

We then computed Allen's elasticity of substitution in Case (3) in Table 7. The result reported in this table shows that IT stocks on the one hand, and both equipment and production workers on the other hand, are generally substitutes. Moreover, the magnitude of the substitutability is increased substantially from the 1980s to the 1990s in many industries. Especially in Stone&Clay, Primary Metal, Fabricated Metal,and Paper and Pulp, the elasticity of substitution between IT capital stock and production worker is substantially increased. This implies that the pressure from aging production work force may be effectively mitigated by an increase in IT capital stocks, and that the effectiveness of IT capital stocks in substituting labor inputs have been increased recently. Also, the elasticity of substitution between IT capital stock and Non IT equipment is increased from the 1980s to the 1990s in Food, Textile, Stone and Clay, Primary Metal, Fabricated Metal, General Machinery, Transport Machinery, and Paper and Pulp.

Moreover, the result reported in Table 6 suggests that non-production workers once considered as quasi-fixed in the 1980s becomes apparently variable in the 1990s (though a more thorough analysis is needed to verify this claim). Thus, the results in this section show that rapid advancement of IT technology and vigorous IT capital stock formation may be a key to counter the negative effect of labor shortage caused by aging population. This seems important both in the production and non-production divisions.

[11] It is obvious from the result of Table 3, thus not reported in this paper.

5 IT Stocks, Production/Non-Production Labor, and Technological Progress: 1980-1998

In this section, we first examine value-added and TFP growth between 1981 and 1998 in the framework developed in Section 3, and estimate the contribution of IT capital stocks and the effect of changing age structure of labor force in growth. The main results are summarized in three tables (Tables 8 through 10). Because of a technical problem in constructing labor input series, we are obliged to restrict our attention further to eight industries out of eleven industries of Section 4. The industries we consider are, General Machinery, Electric Machinery, Transportation Equipment, Instruments, Fabric Metal, Stone & Clay, Chemicals, and Paper & Pulp.

The results reveal a remarkable contrast between the 1980s and the 1990s. All eight industries showed a very high rate of value-added growth in the 1980s, especially in the boom period of 1985-1989. Then, after the crash of the stock and real estate markets around 1990, the growth rate declined substantially and in some industries fell into the negative region. This decline was not simply attributed to a slump in demand and resulting decrease in factor inputs. The TFP growth also declined substantially in many industries (Table 8). Thus, the prolonged slump of the 1990s was not merely a demand-driven phenomenon, but the supply side played a substantial role.

There were, however, notable exceptions for the general pattern of declining TFP growth. The 1995-98 rate of TFP growth in Electric Machinery and Instruments was almost the same as in the 1980s. These two industries were among industries having a consistently high rate of IT capital formation both in the 1980s and 1990s (Table 9). This suggests a possible linkage of IT capital formation and TFP growth. The linkage is not likely to be realized in the short run, since Chemicals having an accelerating rate of IT capital formation in the 1990s, still showed a dismal performance.

Reflecting changing age structure of labor force, contribution of young workers in value-added growth was declined substantially (Table 9 and Table 10). The effect was more prominent in the production labor. A stark contrast was found between young production workers and old non-production workers until recently. Despite a higher wage rate, labor inputs of old non-production workers kept increasing. This was one important factor making fixed costs keep increasing throughout the whole sample period (Table 8), and imposed pressure on firms' profitability. Although this trend seemed to be halted recently (1995-98), it is too early to tell its future direction.

Let us now examine relationship between the technological progress on the one hand, and IT innovation and "maturing" labor force (that is, an increase in the average age of workers) on the other hand. We construct a panel data set of TFP growth rates for eight industries in four subperiods (1981-1984, 1985-1989, 1990-1994, 1995-1998). We then estimate an equation explaining the TFP growth rate by (1) the ratio of old production workers' labor inputs to the total production labor inputs ($POLD$), (2) the ratio of old non-production workers' labor inputs to the total non-production labor inputs ($NPOLD$), (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. These explanatory variables are all the period average for the specific subperiod.

$$\begin{aligned} TFP\ Growth \quad = \quad & Const. + \left(\beta_{POLD} + \delta_{POLD} * DUMMY\right) * POLD \\ & + \left(\beta_{NPOLD} + \delta_{NPOLD} * DUMMY\right) * NPOLD \\ & + \beta_{PROFIT} * PROFIT + \beta_{ITK} * ITK + \beta_{EQ} * EQ + \alpha_i + \varepsilon_{it} \end{aligned}$$

Here we allow the possibility of structural change around 1990 by including a coefficient dummy variable $DUMMY$ for the 90's. We estimate both the fixed effect model and the random effect model, and select one of them according to the Hausman test.

Table 11 shows the result. The random effect model is chosen by the Hausman test, so that we report only the random effect model here. This table reveals that there is statistically significant positive correlation between IT capital stocks and TFP growth for all industry in all subperiods. This result strongly suggests that IT capital stocks contribute to growth not only as factor inputs, but also through their network-externality effect. In contrast, the non-IT equipment capital stocks do not have such an externality effect. Finally, a pure profit does not have significant effect on TFP growth.

Let us now turn to the issue of TFP growth and the "maturing" labor force. Here "maturing" means an increase of the average age of workers and (supposedly) accompanying increase in their skill. Here we examine whether TFP growth has positive correlation with the ratio of old workers' labor inputs to the total labor inputs. The table shows that TFP growth was positively correlated to the ratio of old non-production workers' labor inputs to the total non-production labor inputs. This suggests that the increased average skill among non-production workers due to "maturing" had a positive effect to improve productivity in the 1980s. However, the relationship changed in the 1990s, and we no longer had such positive relationship. The nature of TFP growth apparently changed to be neutral with respect to "maturing". Moreover, there was no correlation between TFP growth and the ratio of old production workers' labor inputs to the total production labor inputs.

References

[1] Delong, J. Bradford and Lawrence Summers. (1992), "Equipment Investment and Economic Growth: How Strong Is the Nexus?", *Brookings Papers on Economic Activity*, 2, pp. 157-199.

[2] Gordon, Robert J. (1990), *The Measurement of Durable Goods Prices*, A National Bureau of Economic Research Monograph series, Chicago: University of Chicago Press.

[3] Jorgenson, Dale W. and Kevin J. Stiroh (1999), "Information Technology and Growth," *American Economic Review* 89, pp. 109-115.

[4] Jorgenson, Dale W. and Kevin J. Stiroh (2000), "Raising the Speed Limit: US Economic Growth in the Information Age," Discussion Paper No. 261, OECD, also in *Brookings Papers on Economic Activity*.

[5] Kuroda, M., K. Shinpo, K. Nomura and N. Kobayashi (1997), *KEO Data Base - The Measurement of Output, Capital and Labor -* , Tokyo: Keio Economic Obsevatory.

[6] Miyagawa, T. and S. Shiraishi (2000), "Why did Economic Growth Decline in Japan ? : An Analysis Using New Capital Stocks Data Categorized by asset," *JCER Discussion Paper*, no 62. (in Japanese)

[7] Nishimura, Kiyohiko G., Yasushi Ohkusa, and Kenn Ariga, (1999) "Estimating the Mark-up Over Marginal Cost: A Panel Analysis of Japanese Firms 1971-1994," *International Journal of Industrial Organization*, 17 (1999), 1077-1111.

[8] Nishimura, Kiyohiko G., and Masato Shirai, (2000) *Fixed Cost, Imperfect Competition and Bias in Technology Measurement: Japan and the United States*, Discussion Paper No. 273, OECD.

[9] Schreyer, Paul, (2000) "The Contribution of Information and Communication Technology to Output Growth: A Study of the G7 Countries", STI working paper 2000/2, OECD

[10] Suruga, T. and K. Hashimoto (1996), On the Substitution between Labor Differentiated by Educational Attainment and Capital : The Case of Japanese Manufacturing Industries, *Journal of the Japan Statistical Society*, 26, pp. 255-267. (in Japanese)

Appendix A: Derivation of (3)

From Assumption 2, we have

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

Consequently, we obtain

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

Thus, 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

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

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

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

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

$$h = h\left(\frac{p_2}{p_1}, ..., \frac{p_n}{p_1}\right)$$

be the solution of

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

Note that h is a function of only the relative variable input prices. 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

$$C_V(p_1, ..., p_n, Y, S) = \left(1 + \sum_{i=2}^{n} \frac{p_i}{p_1} \tilde{v}_i^*\left(\frac{p_2}{p_1}, ..., \frac{p_n}{p_1}\right)\right) \frac{p_1}{h^{1/k}} \left\{\frac{Y}{S}\right\}^{1/k}$$

where

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

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

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

where c_v is homogeneous of degree one in prices such that

$$c_v\left(p_1,...,p_n\right) = \left(1+\sum_{i=2}^{n}\frac{p_i}{p_1}\widetilde{v_i^*}\left(\frac{p_2}{p_1},...,\frac{p_n}{p_1}\right)\right)p_1\left\{h\left(\frac{p_2}{p_1},...,\frac{p_n}{p_1}\right)\right\}^{-1/k}. \tag{8}$$

Table 1: Industries under Study

Manufacturing Indsutries	Abbreviation	
Food and Kindred Products	Food	IND1
Textile Mill Products and Apparel	Textile	IND2
Chemicals	Chemicals	IND3
Stone, Clay, Glass	Stone & Clay	IND4
Primary Metal	Pri. Metal	IND5
Fabricated Metal	Fab. Metal	IND6
Machinery, Non-electrical	Gen. Machinery	IND7
Electrical Machinery	Elec. Machinery	IND8
Transportation Equipment and Ordnance	Trans. Equipment	IND9
Instruments	Instruments	IND10
Paper and Allied Products	Paper & Pulp	IND11
(Excluded)		
Petroleum and Coal Products	Petro. & Coal	
Miscellaneous Manufacturing	Misc. Manufac.	

Table 2
Average Growth Rate of Factors

Industry	IND 1:Food		IND 2:Textile		IND 3: Chemicals	
Period	**80'S**	**90'S**	**80'S**	**90'S**	**80'S**	**90'S**
IT	18.24%	17.38%	4.82%	13.16%	15.01%	17.02%
Non-IT	4.05%	4.42%	2.45%	2.61%	2.16%	3.24%
Pro. Worker	1.07%	-0.89%	-0.92%	-6.93%	-1.06%	-2.40%
Non-Pro. Worker	1.00%	-0.09%	-2.05%	-3.28%	0.72%	-2.66%
Industry	**IND 4:Stone & Clay**		**IND 5:Pri. Metal**		**IND 6:Fab. Metal**	
Period	**80'S**	**90'S**	**80'S**	**90'S**	**80'S**	**90'S**
IT	12.99%	16.93%	14.37%	13.41%	25.09%	9.00%
Non-IT	4.58%	3.61%	1.35%	1.29%	4.72%	4.19%
Pro. Worker	-1.69%	-3.47%	-1.76%	-4.05%	-0.30%	-3.18%
Non-Pro. Worker	-0.23%	-2.22%	-1.51%	-2.35%	1.17%	-1.65%
Industry	**IND 7:Gen. Machinery**		**IND 8:Elec. Machinery**		**IND 9:Trans. Machinery**	
Period	**80'S**	**90'S**	**80'S**	**90'S**	**80'S**	**90'S**
IT	12.51%	11.65%	20.96%	13.41%	16.88%	13.29%
Non-IT	6.48%	4.98%	13.25%	7.53%	8.37%	5.79%
Pro. Worker	1.58%	-2.40%	4.17%	-3.44%	0.42%	-2.17%
Non-Pro. Worker	1.95%	-0.09%	5.23%	-1.19%	1.27%	0.70%
Industry	**IND 10:Instruments**		**IND 11:Paper & Pulp**			
Period	**80'S**	**90'S**	**80'S**	**90'S**		
IT	23.74%	15.27%	6.10%	10.05%		
Non-IT	11.66%	5.53%	2.20%	3.31%		
Pro. Worker	-1.41%	-3.16%	-0.55%	-2.04%		
Non-Pro. Worker	3.04%	-1.89%	0.77%	-1.77%		

Notes: annual rate. 80'S = 1981-1989, 90'S = 1990-1998.

Table 3. Five Variable-Input Case
(IT, Non IT Equipment, Structure, Non Production Worker, Production Worker)

	Coefficient	t-Statistic	Prob.
β_1	-0.020073	-0.919779	0.3580
β_{13} for industry dummy 3	-0.196832	-31.58534	0.0000
β_{17} for industry dummy 7	-0.134233	-4.427157	0.0000
β_{18} for industry dummy 8	-0.073908	-16.79912	0.0000
β_{19} for industry dummy 9	-0.118580	-4.129246	0.0000
β_{110} for industry dummy 10	-0.093476	-7.866170	0.0000
$\beta_{111}$for industry dummy11	0.030017	7.807151	0.0000
β_1 (90) for 90's dummy	- 0.132918	-9.573749	0.0000
γ_{EE}	-0.057569	-6.073287	0.0000
γ_{ES}	-0.060884	-13.02049	0.0000
γ_{EW}	0.026365	2.906723	0.0038
γ_{EB}	0.122078	13.78827	0.0000
γ_{EE} (90) for 90's dummy	-0.063242	-5.880461	0.0000
β_2	0.144375	9.897034	0.0000
β_{23} for industry dummy 3	-0.098138	-36.88628	0.0000
β_{27} for industry dummy 7	-0.098410	-6.308114	0.0000
β_{28} for industry dummy 8	-0.091284	-30.13002	0.0000
β_{29} for industry dummy 9	-0.096443	-6.471931	0.0000
β_{211} for industry dummy 11	-0.029080	-18.00283	0.0000
β_2(90) for 90's dummy	-0.044630	-8.153077	0.0000
γ_{SS}	0.046553	6.666378	0.0000
γ_{SW}	0.047428	4.774247	0.0000
γ_{SB}	-0.024212	-2.967857	0.0031
γ_{SS2} for industry dummy 2	0.065674	10.62094	0.0000
γ_{SS4} for industry dummy 4	0.010579	3.653296	0.0003
γ_{SS10} for industry dummy 10	0.078033	9.363314	0.0000
β_3	0.271365	12.62147	0.0000
β_{32} for industry dummy 2	-0.120893	-27.01903	0.0000
β_{33} for industry dummy 3	0.270868	42.45515	0.0000
β_{37} for industry dummy 7	0.177074	10.93062	0.0000
β_{38} for industry dummy 8	0.108266	23.30479	0.0000
β_{39} for industry dummy 9	0.099556	5.799898	0.0000
β_{310} for industry dummy 10	0.103417	14.25911	0.0000
β_3(90) for 90's dummy	0.061604	8.200590	0.0000
γ_{WW}	0.309131	28.39854	0.0000
γ_{WB}	-0.375674	-105.6797	0.0000
β_4	0.628802	31.44561	0.0000
β_{42} for industry dummy 2	0.151109	32.08733	0.0000
β_{47} for industry dummy 7	0.056704	1.857611	0.0636
β_{49} for industry dummy 9	0.105878	3.608911	0.0003
β_{410} for industry dummy 10	0.107568	4.989460	0.0000
β_4(90) for 90's dummy	0.071393	6.238187	0.0000
γ_{BB}	0.267040	25.25089	0.0000
γ_{BB10} for industry dummy 10	-0.055692	-7.243858	0.0000

Log Likelihood	2424.451
Adjusted R-squared for Share Equation of equipment	0.487186
Adjusted R-squared for Share Equation of structure	0.608072
Adjusted R-squared for Share Equation of non production worker	0.892203
Adjusted R-squared for Share Equation of production worker	0.424490

Table 4. Four Variable-Input Case
(IT, Non IT Equipment, Non Production Worker, Production Worker)

	Coefficient	t-Statistic	Prob.
β_1	0.222919	8.636626	0.0000
β_{11} for industry dummy 1	-0.084279	-8.308653	0.0000
β_{12} for industry dummy 2	-0.042725	-1.688817	0.0918
β_{13} for industry dummy 3	-0.197716	-17.66903	0.0000
β_{14} for industry dummy 4	-0.035867	-3.030720	0.0025
β_{17} for industry dummy 7	-0.164603	-5.158225	0.0000
β_{18} for industry dummy 8	-0.200361	-13.22537	0.0000
β_{19} for industry dummy 9	-0.159861	-4.521855	0.0000
β_{110} for industry dummy 10	-0.127973	-5.864365	0.0000
$\beta_1(90)$ for 90's dummy	-0.100366	-6.420363	0.0000
γ_{EE}	-0.058467	-4.206264	0.0000
γ_{EW}	0.000749	0.080532	0.9358
γ_{EB}	0.072530	8.653534	0.0000
γ_{EE7} for industry dummy 7	-0.064371	-3.240157	0.0013
γ_{EE8} for industry dummy 8	0.078216	18.14761	0.0000
γ_{EE10} for industry dummy 10	0.015778	1.865926	0.0626
γ_{EE} (90) for 90's dummy	-0.020472	-3.303075	0.0010
β_2	0.295056	16.35369	0.0000
β_{21} for industry dummy 1	0.085976	8.411988	0.0000
β_{23} for industry dummy 3	0.255964	27.61677	0.0000
β_{28} for industry dummy 8	0.238347	16.28566	0.0000
β_{210} for industry dummy 10	0.137984	5.415574	0.0000
$\beta_2(90)$ for 90's dummy	0.033862	3.946461	0.0001
γ_{WW}	-0.068888	-2.224579	0.0265
γ_{WB}	0.041364	1.388480	0.1655
γ_{WW7} for industry dummy 7	0.075277	13.39061	0.0000
γ_{WW9} for industry dummy 9	0.044751	6.562700	0.0000
γ_{WW10} for industry dummy 10	0.019843	2.539345	0.0114
γ_{WW} (90) for 90's dummy	0.006419	2.532172	0.0116
β_3	0.495038	39.76700	0.0000
β_{32} for industry dummy 2	0.045058	1.762326	0.0785
β_{34} for industry dummy 4	0.042487	3.210108	0.0014
β_{37} for industry dummy 7	0.077272	3.017283	0.0027
β_{39} for industry dummy 9	0.149293	4.476589	0.0000
$\beta_3(90)$ for 90's dummy	0.039194	3.704594	0.0002
γ_{BB}	-0.093929	-2.904765	0.0038
γ_{BB3} for industry dummy 3	-0.036872	-17.15735	0.0000
γ_{BB7} for industry dummy 7	-0.056617	-7.753393	0.0000
γ_{BB8} for industry dummy 8	-0.033071	-18.97840	0.0000
γ_{BB9} for industry dummy 9	-0.047873	-6.807424	0.0000
γ_{BB10} for industry dummy 10	-0.039992	-5.286405	0.0000

Log Likelihood	1736.219
Adjusted R-squared for share equation of equipment	0.420181
Adjusted R-squared for share equation of non production worker	0.860096
Adjusted R-squared for share equation of production worker	0.610782

Table5. Three Variable-Input Case
(IT, Non IT Equipment, Production Worker), Estimation Result

	Coefficient	t-Statistic	Prob.
β_1	0.254162	29.91000	0.0000
β_{11} for industry dummy 1	-0.089767	-2.512734	0.0124
β_{17} for industry dummy 7	-0.163845	-2.959143	0.0033
β_{19} for industry dummy 9	-0.133962	-4.274423	0.0000
$\beta_{111}$for industry dummy 11	0.090085	2.426683	0.0157
β_1(90) for 90's dummy	-0.117820	-7.045339	0.0000
γ_{EE}	-0.079741	-9.249374	0.0000
γ_{EB}	0.085056	13.35323	0.0000
γ_{EE3} for industry dummy 3	0.081914	4.889429	0.0000
$\gamma_{EE\ 8}$ for industry dummy 8	0.161210	23.62385	0.0000
γ_{EE10} for industry dummy 10	0.111046	8.224363	0.0000
γ_{EE} (90) for 90's dummy	-0.038617	-5.476398	0.0000
β_3	0.728667	95.19742	0.0000
β_{31} for industry dummy 1	0.163233	8.755118	0.0000
β_{33} for industry dummy 3	0.009893	4.097604	0.0001
β_{34} for industry dummy 4	0.162732	2.870670	0.0043
β_{37} for industry dummy 7	0.070242	10.62478	0.0000
β_{38} for industry dummy 8	0.123731	3.922856	0.0001
β_{39} for industry dummy 9	0.100823	7.647653	0.0000
$\beta_{310}$for industry dummy 10	-0.088368	-2.292880	0.0224
β_3(90) for 90's dummy	0.085999	5.014459	0.0000
γ_{BB}	-0.080090	-12.30651	0.0000
γ_{BB3} for industry dummy 3	-0.085473	-15.29256	0.0000
γ_{BB8} for industry dummy 8	-0.068750	-27.01605	0.0000
γ_{BB10} for industry dummy 10	-0.061238	-14.65970	0.0000

Log Likelihood	1007.091
Adjusted R-squared for share equation of equipment	0.407779
Adjusted R-squared for share equation of production worker	0.365242

Notations for Tables 3 to 5.

E: Non-IT Equipment Capital Stocks
S: Structure Capital Stocks
W: Non Production Worker
B: Production Worker

Estimation Method: FIML

Table 6
Examining Concavity of Estimated Translog Cost Function: Four-Factor Case

Four Factors = IT, Equipment, Production Worker, Non-Production Worker

Industry	IND 1:Food		IND 2:Textile		IND 3: Chemicals	
Period	80'S	90'S	80'S	90'S	80'S	90'S
Concavity	NO	OK	NO	OK	OK	OK
Industry	**IND 4:Stone & Clay**		**IND 5:Pri. Metal**		**IND 6:Fab. Metal**	
Period	80'S	90'S	80'S	90'S	80'S	90'S
Concavity	NO	OK	OK	OK	NO	OK
Industry	**IND 7:Gen. Machine**		**IND 8:Elec. Machine**		**IND 9:Trans. Machinery**	
Period	80'S	90'S	80'S	90'S	80'S	90'S
Concavity	OK	OK	NO	NO	OK	OK
Industry	**IND 10:Instruments**		**IND 11:Paper & Pulp**			
Period	80'S	90'S	80'S	90'S		
Concavity	OK	OK	OK	OK		

Notes: OK ＝Sufficient conditions of strict concavity are satisfied.
OK(*) = One condition is not satisfied but its deviation is negligible.
NO = More than two conditions are violated. Concavity is evaluated at the average input prices.

Table 7
Concavity of Traonslog Cost Function
and Substitutability/Complementarity With IT Capital

Three Factors = IT, Equipment, Production Worker

Industry	IND 1:Food		IND 2:Textile		IND 3: Chemicals	
Period	80'S	90'S	80'S	90'S	80'S	90'S
Concavity	OK	OK	OK	OK	OK	OK
Substitutability/Complementarity: Allen's Elasticity of Substitution						
IT & Equipment	0.82539	2.1794	0.02159	5.0745	-3.6877	-0.21182
IT & Production Labor	0.92295	0.93217	0.51384	0.71962	4.2678	2.3996

Industry	IND 4:Stone & Clay		IND 5:Pri. Metal		IND 6:Fab. Metal	
Period	80'S	90'S	80'S	90'S	80'S	90'S
Concavity	OK(*)	OK	OK	OK	OK	OK
Substitutability/Complementarity: Allen's Elasticity of Substitution						
IT & Equipment	-2. 2119	7.6099	0.02678	4.8652	-0.00196	4.8971
IT & Production Labor	-0.99414	0.4283	0.28393	0.62941	0.38306	0.67903

Industry	IND 7:Gen. Machine		IND 8:Elec. Machine		IND 9:Trans. Machinery	
Period	80'S	90'S	80'S	90'S	80'S	90'S
Concavity	OK	OK	OK(*)	OK	OK	OK
Substitutability/Complementarity: Allen's Elasticity of Substitution						
IT & Equipment	-0.30128	8.0603	-4.6353	-1.8946	0.15616	5.0271
IT & Production Labor	0.59629	0.71401	2.1393	1.7116	0.67323	0.80518

Industry	IND 10:Instruments		IND 11:Paper & Pulp	
Period	80'S	90'S	80'S	90'S
Concavity	OK(*)	OK	OK	OK
Substitutability/Complementarity: Allen's Elasticity of Substitution				
IT & Equipment	-6.4159	-1.7658	0.26053	4.4072
IT & Production Labor	2.8878	2.0123	0.30968	0.57185

Notes: OK ＝Sufficient conditions of strict concavity are satisfied.
OK(*) = One condition is not satisfied but its deviation is negligible.
NO = More than two conditions are violated. Concavity is evaluated at the average input prices.

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

(%)

	Paper & Pulp	Chemicals	Stone & Clay	Fab. Metal	Gen. Machinery	Elec. Machinery	Trans. Equipment	Instruments
Whole Sample Period: 1981-98								
Value Added	2.888	4.432	1.622	3.278	2.793	8.368	2.173	2.096
Variable Inputs	1.309	0.952	0.318	0.413	0.759	2.558	1.164	0.551
Quasi Fixed Inputs	0.299	0.460	0.198	0.409	0.879	1.623	0.734	0.709
Total Factor Productivity	1.291	2.951	1.042	2.494	1.285	4.260	0.276	0.908
1980s: 1981-1989								
Value Added	6.040	8.172	4.664	5.978	6.437	12.151	3.969	5.019
Variable Inputs	1.589	0.573	0.601	0.936	1.680	4.000	1.723	0.710
Quasi Fixed Inputs	0.534	0.676	0.233	0.561	1.196	3.067	0.668	1.464
Total Factor Productivity	3.936	6.876	3.698	4.437	3.585	5.102	1.598	2.886
1990s: 1990-1998								
Value Added	-0.170	0.822	-1.331	0.646	-0.726	4.713	0.409	-0.745
Variable Inputs	1.030	1.331	0.036	-0.108	-0.153	1.136	0.607	0.392
Quasi Fixed Inputs	0.064	0.244	0.163	0.258	0.564	0.201	0.800	-0.040
Total Factor Productivity	-1.286	-0.830	-1.546	0.587	-0.963	3.424	-1.028	-1.032
Sub-Periods								
1981-84								
Value Added	4.726	8.246	3.656	4.606	7.133	14.431	2.024	4.340
Variable Inputs	1.465	0.134	-0.232	0.021	1.647	5.134	1.503	0.525
Quasi Fixed Inputs	0.419	1.148	0.359	-0.222	1.137	4.188	0.835	1.048
Total Factor Productivity	2.864	6.937	3.249	4.749	4.258	5.126	-0.309	2.733
1985-1989								
Value Added	7.103	8.114	5.477	7.088	5.884	10.360	5.551	5.565
Variable Inputs	1.688	0.927	1.271	1.675	1.706	3.101	1.900	0.858
Quasi Fixed Inputs	0.627	0.300	0.132	1.193	1.243	2.178	0.534	1.797
Total Factor Productivity	4.802	6.827	4.059	4.189	3.049	5.083	3.150	3.009
1990-1994								
Value Added	0.457	2.344	-0.037	3.093	-2.123	3.812	0.989	-3.708
Variable Inputs	2.135	1.634	0.781	0.177	-0.574	0.890	0.780	0.014
Quasi Fixed Inputs	0.328	1.660	0.892	0.749	1.266	0.902	1.479	0.299
Total Factor Productivity	-2.024	-0.990	-1.728	2.240	-2.585	2.083	-1.287	-3.900
1995-1998								
Value Added	-0.949	-1.049	-2.924	-2.331	1.050	5.851	-0.311	3.087
Variable Inputs	-0.334	0.954	-0.888	-0.462	0.376	1.445	0.392	0.866
Quasi Fixed Inputs	-0.266	-1.498	-0.741	-0.353	-0.307	-0.669	-0.042	-0.463
Total Factor Productivity	-0.356	-0.630	-1.319	-1.442	1.102	5.125	-0.703	2.673
Cost Share of Variable Inputs								
81-89	0.643	0.466	0.631	0.611	0.542	0.500	0.612	0.523
90-98	0.641	0.441	0.606	0.590	0.488	0.490	0.586	0.470

Notes: The average in this table is the geometric average.
The sum of input contributions and TFP growth may not add up to value added growth.

Table 9
Contribution of Variable Inputs to Growth in Value Added: 1981-98

	Paper & Pulp	Chemicals	Stone & Clay	Fab. Metal	Gen. Machinery	Elec. Machinery	Trans. Equipment	Instruments
IT Capital								
Total Sample Period	0.083	0.501	0.067	0.107	0.104	0.861	0.215	0.517
81-89	0.056	0.296	0.041	0.116	0.095	0.846	0.190	0.463
90-98	0.110	0.707	0.093	0.098	0.113	0.876	0.241	0.570
Sub-Period								
81-84	0.008	0.147	0.018	0.070	0.049	0.554	0.085	0.372
85-89	0.094	0.416	0.060	0.153	0.132	1.080	0.274	0.537
90-94	0.114	0.541	0.050	0.155	0.103	0.772	0.239	0.348
95-98	0.105	0.915	0.146	0.026	0.126	1.007	0.243	0.848
Equipment								
Total Sample Period	1.243	0.563	1.171	0.963	0.801	1.412	1.404	1.126
81-89	1.219	0.534	1.492	1.200	1.053	1.700	1.702	1.447
90-98	1.267	0.592	0.850	0.725	0.549	1.125	1.107	0.806
Sub-Period								
81-84	0.995	0.346	1.507	1.159	1.029	1.607	1.763	1.239
85-89	1.398	0.685	1.480	1.233	1.073	1.775	1.652	1.614
90-94	1.939	0.943	1.260	0.988	0.806	1.403	1.586	1.134
95-98	0.435	0.156	0.339	0.398	0.229	0.778	0.512	0.397
Production Labor, Young (under 40)								
Total Sample Period	-0.071	-0.192	-0.398	-0.487	-0.219	0.034	-0.404	-0.951
81-89	-0.036	-0.385	-0.652	-0.551	-0.072	0.770	-0.419	-1.185
90-98	-0.106	0.002	-0.142	-0.422	-0.366	-0.696	-0.389	-0.717
Sub-Period								
81-84	-0.224	-0.516	-0.998	-1.097	-0.232	1.878	-0.640	-1.280
85-89	0.115	-0.280	-0.376	-0.112	0.056	-0.108	-0.243	-1.108
90-94	-0.093	-0.025	-0.299	-0.510	-0.805	-1.040	-0.635	-1.025
95-98	-0.123	0.036	0.055	-0.313	0.187	-0.263	-0.081	-0.331
Production Labor, Old (over 40)								
Total Sample Period	0.055	0.081	-0.514	-0.163	0.080	0.261	-0.044	-0.136
81-89	0.349	0.129	-0.266	0.174	0.610	0.690	0.258	-0.012
90-98	-0.238	0.033	-0.762	-0.499	-0.447	-0.166	-0.345	-0.261
Sub-Period								
81-84	0.687	0.158	-0.727	-0.107	0.806	1.107	0.300	0.205
85-89	0.079	0.106	0.104	0.400	0.454	0.357	0.225	-0.185
90-94	0.171	0.182	-0.227	-0.445	-0.671	-0.236	-0.408	-0.430
95-98	-0.746	-0.152	-1.427	-0.566	-0.165	-0.078	-0.266	-0.048

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

Table 10
Contribution of Quasi Fixed Inputs to Growth in Value Added: 1981-98

	Paper & Pulp	Chemicals	Stone & Clay	Fab. Metal	Gen. Machinery	Elec. Machinery	Trans. Equipment	Instruments
Structure								
Total Sample Period	0.122	0.176	0.327	0.342	0.471	0.501	0.364	0.767
81-89	0.012	0.138	0.295	0.274	0.445	0.606	0.336	0.903
90-98	0.233	0.215	0.360	0.410	0.498	0.397	0.393	0.633
Sub-Period								
81-84	-0.039	0.186	0.302	0.259	0.472	0.586	0.361	0.865
85-89	0.053	0.099	0.290	0.286	0.423	0.622	0.315	0.933
90-94	0.400	0.326	0.532	0.669	0.734	0.650	0.627	0.987
95-98	0.025	0.076	0.144	0.088	0.203	0.082	0.101	0.191
Non-Production Labor, Young (under 40)								
Total Sample Period	0.015	-0.203	-0.212	-0.139	-0.063	0.277	-0.058	-0.379
81-89	0.094	-0.322	-0.256	-0.173	-0.066	0.963	-0.145	0.033
90-98	-0.065	-0.085	-0.168	-0.106	-0.060	-0.405	0.030	-0.789
Sub-Period								
81-84	0.028	-0.134	-0.283	-0.583	-0.279	1.666	-0.078	-0.057
85-89	0.147	-0.472	-0.233	0.157	0.105	0.404	-0.198	0.105
90-94	-0.171	0.455	-0.104	0.028	0.108	-0.260	0.017	-0.558
95-98	0.067	-0.756	-0.248	-0.273	-0.270	-0.587	0.047	-1.077
Non-Production Labor, Old (Over 40)								
Total Sample Period	0.163	0.493	0.084	0.207	0.479	0.859	0.428	0.333
81-89	0.430	0.867	0.196	0.461	0.820	1.506	0.476	0.541
90-98	-0.103	0.121	-0.027	-0.045	0.140	0.217	0.380	0.124
Sub-Period								
81-84	0.431	1.105	0.344	0.101	0.950	1.938	0.552	0.273
85-89	0.429	0.676	0.078	0.749	0.716	1.161	0.415	0.757
90-94	0.100	0.880	0.466	0.053	0.441	0.514	0.839	-0.116
95-98	-0.356	-0.819	-0.641	-0.168	-0.235	-0.152	-0.190	0.426

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

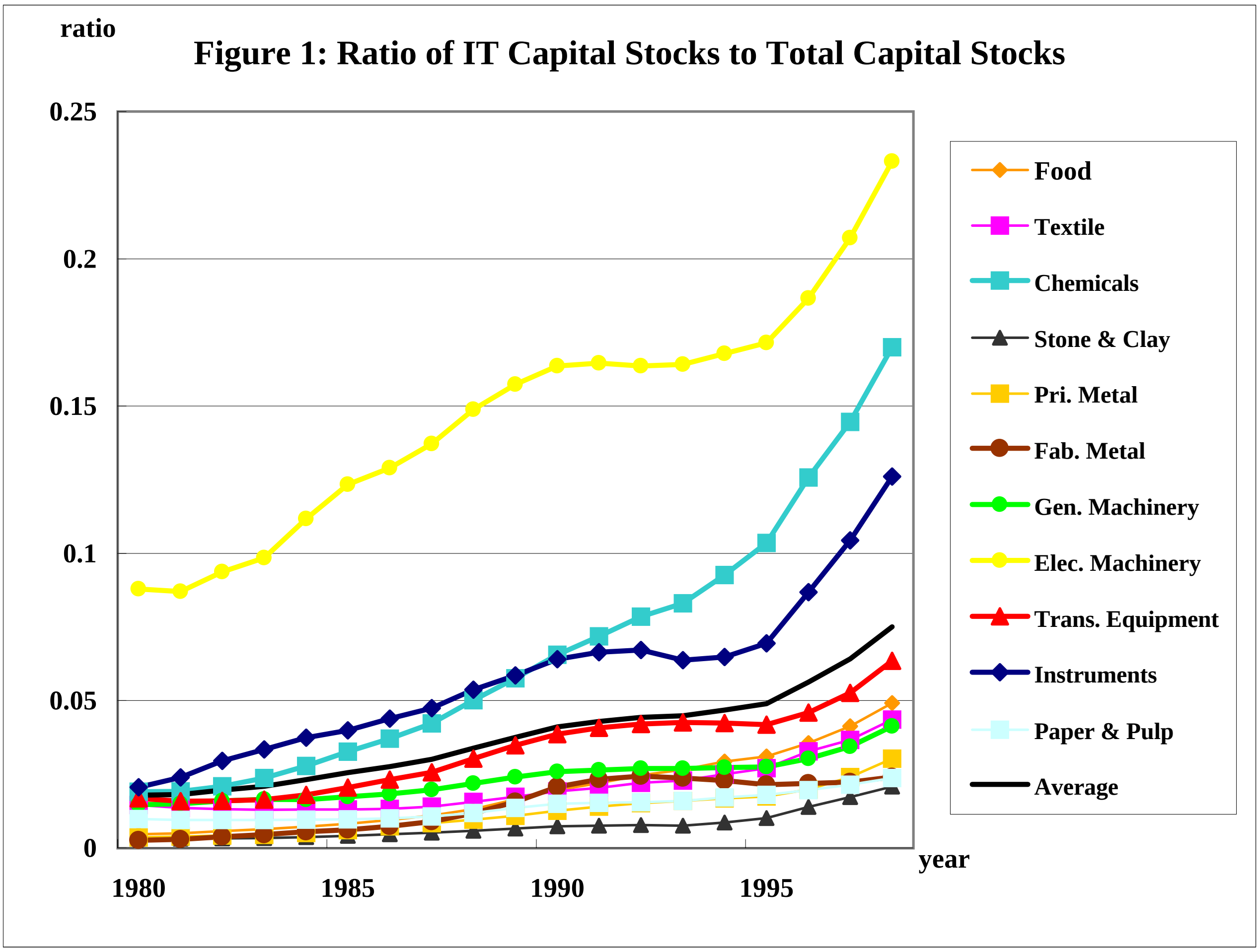
Table 11
TFP Growth, Old Workers and IT

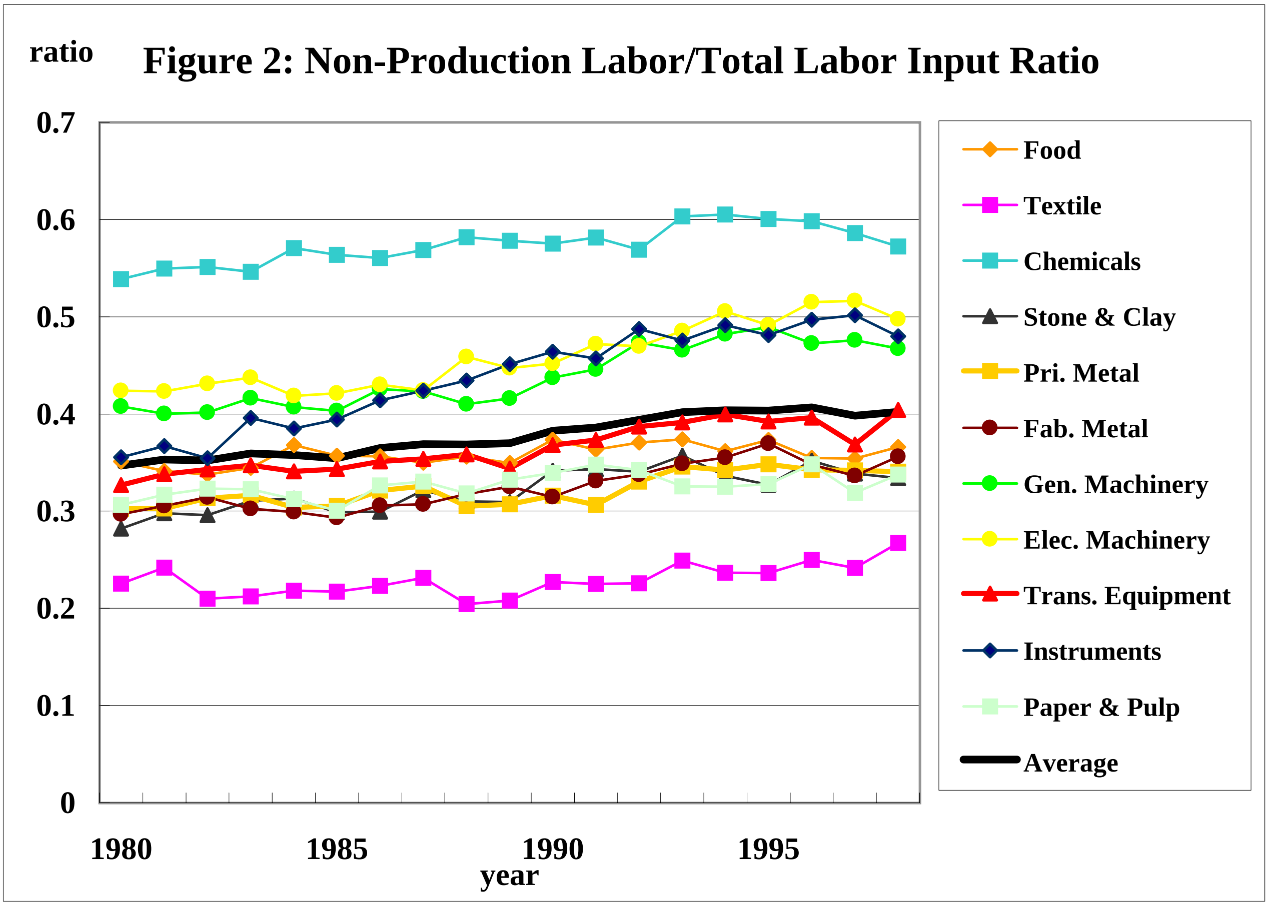
Depending Variable = TFP Growth

Coefficient	Estimate	Standard Error	t-statistic	P-value
Const.	-2.335	3.477	-0.672	0.502
β_{POLD}	0.079	0.062	1.270	0.204
δ_{POLD}	0.053	0.042	1.265	0.206
β_{NPOLD}	0.494	0.141	3.507	0.000
δ_{NPOLD}	-0.463	0.088	-5.280	0.000
β_{PROFIT}	-1.768	2.094	-0.845	0.398
β_{ITK}	0.358	0.089	4.032	0.000
β_{EQ}	-0.083	0.061	-1.369	0.171

	Adj.R^2		D.W. ratio
	0.717		1.780

Hausman Test	Value		p-Value
	1.196		0.991


ratio
Figure 1: Ratio of IT Capital Stocks to Total Capital Stocks
0.25
0.2
0.15
0.1
0.05
0
1980
1985
1990
1995
year
Food
Textile
Chemicals
Stone & Clay
Pri. Metal
Fab. Metal
Gen. Machinery
Elec. Machinery
Trans. Equipment
Instruments
Paper & Pulp
Average



ratio
Figure 2: Non-Production Labor/Total Labor Input Ratio
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1980
1985
1990
1995
year
Food
Textile
Chemicals
Stone & Clay
Pri. Metal
Fab. Metal
Gen. Machinery
Elec. Machinery
Trans. Equipment
Instruments
Paper & Pulp
Average