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A TEST OF SEPARABILITY AND RANDOM EFFECTS IN PRODUCTION FUNCTION WITH DECOMPOSED IT CAPITAL*

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Abstract

In productivity analysis, many studies have used real value-added function for estimating productivity. These studies have made explicit or implicit assumption that real value-added function exists. As real value-added is the residual of real gross output from real intermediate input through the double deflation method, the existence of real value-added function is not guaranteed automatically. In order to test this, we have used an additively strong separability test. We could not accept the existence of real value-added function from the data of 32 industries during the period of 1981-2002 in Korea. This means that it is more appropriate to use gross output based productivity rather than value-added based one.

In addition, in order to identify the contribution of IT investments, we have decomposed capital stock into IT capital stock and non-IT capital stock. We have failed to find the evidence that IT capital has increased productivity in the entire economy which supports the Solow (1987) paradox. However, when we decomposed the industries by IT capital intensity, there is a significant contribution of IT capital to gross output in the highly IT capital intensive industries. This phenomenon is related to the substitution elasticity between IT capital and non-IT capital.

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I. *Introduction*

Most empirical studies of productivity or production relationships have used the aggregate index of heterogeneous inputs. For example, capital is composed of several heterogeneous capitals: building and structure, machinery, vehicles, and so on. However, these individual capitals are combined as a single entity, simply by summing them into the aggregate index.

The real value-added can be also considered in this respect. It is the aggregate index of heterogeneous inputs: capital and labor. In the real production process, output is made by the inputs of capital, labor and intermediate materials. But the real value-added is assumed to be independent of the input of intermediate materials; that is, it is the function of only capital and labor. This assumption is referred to as the separability of real value-added from gross output. If this assumption is not accepted, the studies based on the real value-added might be incorrect and, instead, gross output as a measure of output is the proper concept. We have used the data of the 32 Korean industries and estimated the transcendental logarithmic (translog) gross output production function through the random effect model for the separability test.

In estimating production function, we have found that IT capital has contributed to the output production very little, and at times this contribution is even negative. Solow (1987) first noticed this trend, therefore it is called the Solow Paradox. It is believed that Information Technology has changed the production technology very much and that it has increased productivity. However, we cannot find any evidence supporting this belief.

The use of IT capital varies a great deal among industries. In general, it is used intensively in service sectors and IT producing sectors. Therefore, we divided the entire economy into several groups according to the level of IT intensity. We then estimated the contributions of IT capital separately for each group. We have found that there is no Solow Paradox in the industries which are highly IT capital intensive. Further, it seems to be related to the substitution elasticity between IT capital and non-IT capital.

The paper is organized as follows. In Section II, we have estimated gross output production function and tested separability. In Section III, we have estimated the contribution of IT capital, and Section IV concludes the paper.

II. *Separability Test in Gross Output Production Function*

The existence of the real value-added function is the basic assumption of the productivity analysis based on the real value-added accounting. That means that the real value-added function should not be affected by the change of intermediate inputs. The productivity analysis based on the real value-added does not consider the intermediate input. So, if the function is variant with the change of the intermediate inputs, the result of that analysis cannot be significant and it would be more appropriate to use the gross output production function which takes into account the intermediate input rather than the real value-added production function which does not. In this section, we will test the existence of the real value-added function in the form of additively strong separability by using a panel data of 32 industries over the period of 1981-2002.

1. Estimation of Gross Output Production Function

The translog gross output production function can give the second-order approximation of any twice differentiable production function (Berndt, 1990). It is a flexible functional form because there is no restriction in the substitutability between inputs. The general translog gross output production function with five inputs can be specified as follows:

$$\log Q = \log \beta_0 + \sum_{i=1}^{5} \beta_i \cdot \log X_i + \frac{1}{2} \cdot \sum_{i=1}^{5} \sum_{j=1}^{5} \beta_{ij} \cdot \log X_i \log X_j \tag{1}$$

where $X_1 = K$, $X_2 = IT$, $X_3 = L$, $X_4 = E$, $X_5 = M$ denotes non-IT capital stock, IT capital stock, labor input, energy input, and other intermediate material inputs respectively.

Eq.(1) can be estimated by both the economy-wide aggregate data and the sectoral data. When we use the economy-wide data, we can estimate production function through Zellner (1962)'s Seemingly Unrelated Regression (SUR) technique. The number of coefficients we will estimate is 31, which can be reduced to 21 using the symmetry condition. We usually generate share equations by differentiating $\log Q$ by $\log X_i (i=1, 2, ..., 5)$. There would be four independent share equations.[1]

$$S_i = \beta_i + \sum_{j=1}^{5} \beta_{ij} \log X_j \qquad i = 1, 2, 3, 4, 5 \tag{2}$$

(S_i: share ratio of i th input)

$$\sum \beta_i = 1, \ \ \beta_{ij} = \beta_{ji}, \ \ \sum_j \beta_{ij} = 0 \tag{3}$$

We can estimate the coefficients through SUR using these four equations (SUR1). We can also estimate the coefficients through SUR using the same four equations, along with another equation, the original production function (SUR2),[2] which can reduce the standard errors.

We have used the data of Pyo (2003) for the non-IT capital input and the data of Ha and Pyo (2004) for the IT capital input. Since Pyo's data includes both IT capital stock and non-IT capital stock, we have to subtract IT capital stock from Pyo's capital stock in order to obtain non-IT capital stock. Because our IT capital stock is the quality-adjusted one, we cannot directly subtract it from Pyo's capital stock. Therefore, we have estimated nominal non-IT capital stock by subtracting the nominal IT capital stock from the nominal Pyo's capital stock, and then we deflated it using implicit investment deflators. For the labor input, we have used the raw data file of the Survey Report on Wage Structure from the Ministry of Labor. Since this data does not include agriculture and government sectors, we had to use Economically Active Population Statistics for these two sectors. We have attached a table of reclassification of industries in Appendix.

The estimation results are shown in Table 1.

We can estimate the production function using the sectoral data.[3] As there can be an

[1] Because the sum of the share ratios should be 1, one equation is redundant.

[2] Yuhn (1991) have suggested this possibility, but we cannot reduce standards errors of most coefficients.

[3] We have attached the table of classification of industries in Appendix.

TABLE 1. ESTIMATION OF TRANSLOG GROSS OUTPUT PRODUCTION FUNCTION

	SUR1		SUR2	
β_1	0.1124***	(0.0083)	0.1113***	(0.0087)
β_2	0.0920***	(0.0021)	0.0888***	(0.0022)
β_3	0.2905***	(0.0066)	0.2745***	(0.0064)
β_4	0.1923***	(0.0084)	0.2082***	(0.0087)
β_5	0.3127***	(0.0088)	0.3172***	(0.0990)
β_{11}	0.0273***	(0.0033)	0.0320***	(0.0034)
β_{22}	0.0049***	(0.0004)	0.0050***	(0.0004)
β_{33}	−0.0403***	(0.0025)	−0.0348***	(0.0024)
β_{44}	0.0483***	(0.0035)	0.0536***	(0.0036)
β_{55}	−0.0403***	(0.0076)	−0.0558***	(0.0123)
β_{12}	−0.0194***	(0.0007)	−0.0188***	(0.0008)
β_{13}	0.0010	(0.0023)	0.0001	(0.0024)
β_{14}	−0.0170***	(0.0025)	−0.0176***	(0.0026)
β_{15}	0.0081**	(0.0032)	0.0043	(0.0152)
β_{23}	−0.0092***	(0.0006)	−0.0085***	(0.0006)
β_{24}	0.0153***	(0.0009)	0.0143***	(0.0009)
β_{25}	0.0084***	(0.0008)	0.008	(0.0055)
β_{34}	0.0271***	(0.0021)	0.0224***	(0.0020)
β_{35}	0.0213***	(0.0019)	0.0209***	(0.0039)
β_{45}	0.0024	(0.0035)	0.0226***	(0.0026)

*: significant at 10% level (standard error in parenthesis)
**: significant at 5% level
***: significant at 1% level

individual sector-specific effect in each data, this effect should be removed. In order to do it, we can use either the fixed effect model or the random effect model (Greene, 2003). The former removes the effect by dummy variables and the latter by stochastic error terms.

In estimating gross output production function through the fixed effect model, we have used the following translog production function.

$$\log Q_{it} = \sum_{k=1}^{5} \beta_k \log X_{it}^k + \frac{1}{2} \sum_{k=1}^{5} \sum_{l=1}^{5} \beta_{kl} \log X_{it}^k \log X_{it}^l + \alpha_i + \varepsilon_{it} \tag{4}$$

$$t = 1981, 1982, \ldots\ldots, 2002, \quad i = 1, 2, \ldots\ldots, 32$$

where $X^1 = K$, $X^2 = IT$, $X^3 = L$, $X^4 = E$, $X^5 = M$ denotes non-IT capital stock, IT capital stock, labor input, energy input, and other intermediate material inputs respectively. α_i is the dummy variable reflecting the specific effect in each industry i and ε_i reflects the net effects of the variables not included.[4]

The formula for estimation through the fixed effect model can be represented by the following equation:

[4] We have not included time dummies, because there was no time effects ($F(20,631) = 5.5011 < F_{0.95} = 1.57$) when we estimated the equation with industrial dummies and time dummies together.

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ \vdots \\ X_n \end{bmatrix} \cdot \beta + \begin{bmatrix} i & 0 & \cdots & \cdots & 0 \\ 0 & i & \cdots & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & \cdots & i \end{bmatrix} \cdot \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \vdots \\ \alpha_n \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

$$y = X\beta + D\alpha + \varepsilon \qquad (\mathrm{T}=22,\ \mathrm{n}=32) \tag{5}$$

where y_i is the logarithm of gross output, X_i is the logarithm of each input or their cross-product, and $i(T \times 1)$ is [1 1 ... 1]

The estimator Eq. (6) and the estimated asymptotic variance of β Eq. (7) are

$$\hat{\beta}_{Fixed} = [X' M_D X]^{-1} [X' M_D y]$$

$$M_D = I - D\ (D'D)^{-1} D' \tag{6}$$

$$\text{Est.Asy.Var}[\hat{\beta}_{Fixed}] = s^2 [X' M_D X]^{-1} \tag{7}$$

In the random effect model, we have used random error u_i and constant term α instead of the dummy variable α_i in the fixed effect model. So, we have the composite error term $\eta_{it} = u_i + \varepsilon_{it}$.[5] We assume the industry difference term u_i distributes randomly. We also assume that the two error terms follow the the general OLS assumptions and that there is no correlation between them.

The covariance matrix of each industry and the entire model are:

$$\Sigma = \begin{bmatrix} \sigma_\varepsilon^2 + \sigma_u^2 & \sigma_u^2 & \cdots & \cdots & \sigma_u^2 \\ \sigma_u^2 & \sigma_\varepsilon^2 + \sigma_u^2 & \cdots & \cdots & \sigma_u^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \sigma_u^2 & \sigma_u^2 & \cdots & \cdots & \sigma_\varepsilon^2 + \sigma_u^2 \end{bmatrix} \tag{8}$$

and

$$\Omega = I_n \otimes \Sigma \tag{9}$$

where σ_ε^2 and σ_u^2 denote the variance of ε_{it} and u_i, respectively.

Since Σ is unknown, we have first estimated it in the pooling model and then used the procedure of feasible GLS. The estimator of β is

$$\hat{\beta}_{Random} = [X'\hat{\Omega}^{-1} X]^{-1} [X'\hat{\Omega}^{-1} y] \tag{10}$$

The estimation results are shown in Table 2.

The difference among industries in the fixed effect model can be captured by α_i's. Therefore, we can test the existence of difference using the homogeneity test. The test statistic is

$$F(n-1,\ nT-n-K) = \frac{(R_{Fixed}^2 - R_{Pooled}^2) / (n-1)}{(1 - R_{Fixed}^2) / (nT-n-K)} \tag{11}$$

[5] Since we could not have found the time effects in Random Model considering individual and time effects simultaneously by the LM test ($X^2(1) = 0.05 < X_{0.95}^2 = 3.84$), we have not included the error term which is related to time.

TABLE 2. ESTIMATION OF GROSS OUTPUT PRODUCTION FUNCTION WITH PANEL DATA

	Fixed Effect Model[16]		Random Effect Model[17]	
β_1	0.8594***	(0.1380)	0.6710***	(0.0602)
β_2	−0.1770*	(0.0983)	−0.1746***	(0.0437)
β_3	0.5184**	(0.2441)	0.2855***	(0.1027)
β_4	0.5854***	(0.1970)	0.7675***	(0.0849)
β_5	0.5469**	(0.2228)	0.8397***	(0.0938)
β_{11}	0.0122***	(0.0045)	0.0165***	(0.0020)
β_{22}	−0.0001	(0.0031)	0.0025	(0.0014)
β_{33}	0.0250***	(0.0092)	0.0371***	(0.0038)
β_{44}	0.0550***	(0.0067)	0.0528***	(0.0028)
β_{55}	0.0593***	(0.0091)	0.0642***	(0.0040)
β_{12}	0.0086	(0.0097)	−0.0031	(0.0043)
β_{13}	−0.1215***	(0.0250)	−0.0917***	(0.0107)
β_{14}	−0.0874***	(0.0167)	−0.0900***	(0.0073)
β_{15}	0.0333*	(0.0176)	0.0219***	(0.0078)
β_{23}	0.0210	(0.0165)	0.0212***	(0.0074)
β_{24}	−0.0151	(0.0120)	−0.0046	(0.0052)
β_{25}	0.0032	(0.0139)	−0.0012	(0.0062)
β_{34}	0.0089	(0.0244)	−0.0013	(0.0105)
β_{35}	−0.0832**	(0.0360)	−0.1256***	(0.0153)
β_{45}	−0.1582***	(0.0297)	−0.1641***	(0.0120)
R^2	0.9912		0.8356	
R^2-adj	0.9905		0.8308	

*: significant at 10% level (standard error in parenthesis)
**: significant at 5% level
***: significant at 1% level

and we have rejected the hypothesis that there is no difference among industries ($F(31,652)=113.9>F_{0.95}=1.46$).

We can use Lagrange Multiplier Test (Breusch and Pagan, 1980) for the homogeneity test among industries in the random effect model. The test statistic is

$$LM=\frac{nT}{2(T-1)}\left[\frac{T^2\bar{e}'\bar{e}}{e'e}\right]^2 \sim X^2(1) \qquad (12)$$

and we have also rejected the hypothesis ($X^2(1)=2428>X_{0.95}(1)=3.84$).

When deciding whether the fixed effect model or the random effect model is more appropriate for our purposes, we can examine several viewpoints. The fixed effect model has the disadvantage of losing the degrees of freedom because it introduces dummy variables. However, in addition to efficiency issue, we have to consider the specification problem. The random effect model has to make a further assumption that there is no correlation between regressors and errors. Otherwise, there can be inconsistency in estimates. We can apply the Hausman Test (Hausman, 1978) to decide which model is more valid. The Hausman statistic

[16] The coefficients of industrial dummies are -8.13,-8.54,-9.30,-9.05,-9.28,-9.30,-9.04,-8.64,-9.20,-9.25,-9.05,-9.39,-9.13,-9.20,-9.63,-9.35,-9.13,-9.38,-9.27,-9.20,-9.14,-8.85,-8.48,-8.22,-8.56,-8.50,-8.02,-8.30,-7.85,-8.58,-7.88 and -8.08 from the first industry to the 32nd industry. All are statistically significant at 1% level.

[17] The constant term is -8.93, which is statistically significant at 1% level.

is

$$W = (\hat{\beta}_{Fixed} - \hat{\beta}_{Random})' \hat{\Psi}^{-1} (\hat{\beta}_{Fixed} - \hat{\beta}_{Random}) \tag{13}$$
$$\text{where } \hat{\Psi} = V[\hat{\beta}_{Fixed} - \hat{\beta}_{Random}]$$

and we cannot reject the hypothesis that there is no correlation between regressors and errors ($X^2(20) = 17.35 < X^2_{0.95} = 31.41$). Therefore, we have come to the conclusion that the random effect model is more appropriate for our purpose, but we have used both models in the following analysis.[6]

2. Separability Test

In calculating the real value-added, many national statistical agencies have used the double deflation method. In the double deflation method, nominal values of gross output and of intermediate input are deflated by gross output price and intermediate input price indices respectively.[7] This method is equivalent to making a strong assumption about the production function. When we use the double deflation method, real value-added production function can be represented as following:

$$Y = Q - (E + M) \tag{14}$$

where Y denotes value-added, Q denotes gross output, E denotes energy input, and M denotes intermediate input, respectively, where all values are real.

Using this formula, we can represent gross output as

$$\begin{aligned} Q &= Y + (E + M) \\ &= Y(K, IT, L) + H(E + M) \end{aligned} \tag{15}$$

where K, IT, L, E and M denote non-IT capital stock, IT capital stock, labor input, energy input, and other intermediate material inputs respectively.

Compared with the general gross output function, $Q = F(K, IT, L, E, M)$, Eq.(15) has put a restriction on the form of the gross output production function. In other words, it assumes the production function which is separable between the two categories of inputs, one being K, IT, and L and the other being E and M. This form of separability is referred to as additively strong separability.[8] By testing the validity of using this form of production function, we want to find which is more correct, the value-added productivity, or the gross output productivity.

Berndt and Christensen (1973) tested the separability for the first time using the flexible quadratic functional form, the translog function. They suggested the weak separability condition; Allen partial elasticities between the factors in the separable group and in the other group should be equal. Denny and Fuss (1977) have criticized that Berndt and Christensen (1973)'s test is a joint test of the separability and the form of function and they suggested the approximation test. It assumed that translog production function is just the second-order

[6] The acceptance of the random effect model does not mean the rejection of the fixed effect model (Baltagi, 2001). Moreover, Hausman and Taylor (1981) suggested the correlation test for parts of the regressors, but we will not go further for our practical purpose.

[7] Sims (1969)

[8] Chambers (1988)

TABLE 3. THE RESULTS OF THE SEPARABILITY TEST

	F-Test	Wald Test
SUR	$F(6,95)=9.8983>F_{0.95}=2.19$	$X^2(6)=46.997>X^2_{0.95}=12.59$
Fixed Effect Model	$F(6,652)=7.4145>F_{0.95}=2.10$	$X^2(6)=44.487>X^2_{0.95}=12.59$
Random Effect Model	$F(6,683)=38.732>F_{0.95}=2.10$	$X^2(6)=232.39>X^2_{0.95}=12.59$

approximation of real production function, rather than the exact production function. The approximation test has excluded the condition of the form of production function. They have also used the translog cost function as a duality of translog production funtion for the separability test. Many other studies[9] have used the translog cost function. The cost function approach has the advantage of reducing the possibility of multicollinearity among inputs which might occur in the production function approach. However, the possibility of multicollinerarity exists not only among inputs but also among input prices. Furthermore, the quality of data in input prices might be inferior to the quality of inputs themselves. Therefore, in our paper, we have used the production function approach.

By extending the proposition 5 in Denny and Fuss (1977), we can defind the following separability condition.

(Proposition)

If $\beta_{14}=\beta_{15}=\beta_{24}=\beta_{25}=\beta_{34}=\beta_{35}=0$ in Eq.(1), then the translog gross output production function can be the separable production function as Eq.(16)

$$\log Q=Y(\log K,\ \log IT,\ \log L)+G(\log E,\ \log M) \tag{16}$$

For the test of the separability, we have used the F-statistic and Wald statistic.[10]

$$F=\frac{1}{J}(Rb-q)'[R\hat{V}R']^{-1}(Rb-q) \doteqdot F(J,\ nT-K)$$

$$W=(Rb-q)'[R\hat{V}R']^{-1}(Rb-q) \doteqdot X^2(J)$$

where $\hat{V}$ denotes the variance of b, J denotes the number of restrictions, K denotes the number of coefficients, n denotes the number of equations in each year, and T denotes the number of years.

As seen in Table 3, we cannot accept the hypothesis of separability in all three models; SUR, the Fixed Effect Model, and the Random Effect Model.

Although it is usually assumed that real value-added function exists and is invariant to intermediate inputs, we can not accept the separability hypothesis like many other studies in the US.[11] From these results, it may be inferred that the productivity analysis based on real value-added might be incorrect and it is more appropriate for the productivity measurement to

[9] Berndt and Wood (1975), Norsworthy and Malmquist (1983), and Yuhn (1991)
[10] Greene (2003)
[11] Berndt and Christensen (1973,1974), Berndt and Wood (1974), Denny and Fuss (1977), and Yuhn (1991)

TABLE 4. IT CAPITAL ELASTICITY OF GROSS OUTPUT IN 1981-1994 AND 1995-2002

	1981-1994	1995-2002	1995-2002 excluding 1997, 1998
Fixed Effect Model	0.1918	−0.6185***	−0.5490***
	(0.1310)	(0.1923)	(0.1970)
Random Effect Model	0.3969***	−0.4072***	−0.3720***
	(0.0589)	(0.0554)	(0.0586)

***: significant at 1% level (standard error in parenthesis)

use gross output as an output measure.

There are two possible reasons for this surprising result, which is common in relevant studies. First, the explanatory variables in the estimation equations are not perfectly exogenous. Since they are determined endogenously at the firm or industry level, they are likely to move together. Second, the test is conducted under the implicit assumption about the functional form of the production function. Although the translog production function is one of the most flexible functional forms, our approach tests translog function hypothesis as well as separability hypothesis at the same time. These two possible reasons will be treated in future studies by alternatively testing cost functions with more flexible function.

III. *The Contribution of IT Capital Stock*

1. The Solow Paradox

Solow (1987) proposed the productivity paradox showing no correlation between the development of the IT industry and productivity in the United States. It indicates that the development of IT industry has made many changes in production process, but any improvement in productivity may not be found. After his proposition, many studies have confirmed the paradox in several countries.

This is also true in Korea as no large contribution of IT capital to gross output in the estimation of production function has been found yet. As seen in Table 2, the coefficients of IT capital (β_2) are 0.0888 in SUR, -0.1770 in the fixed model, and -0.1751 in the random effect model, respectively. This is smaller than the coefficient of non-IT capital (β_1), 0.1113, 0.8594, and 0.6787. Moreover, the values of the panel data model are negative. This is difficult to interpret because this means that gross output decreases as IT capital input increases. As a result, we can conclude that there is no IT-using effect, as it coincides with the Solow paradox.

Even if we divide the periods into two, 1981-1994 and 1995-2002, we cannot obtain the result that IT-capital is efficiently used in the production process. Even if we exclude the Asian crisis periods (1997, 1998), the result has not been changed (Table 4).

2. Differences in the use of IT

As described in Ha and Pyo (2004), the IT capital intensities differ drastically between sectors. Even compared to non-IT capital, the differences are great. Therefore, the IT-using effects may differ with each other. To consider these differences, we divided all of the sectors

TABLE 5. IT CAPITAL ELASTICITY OF GROSS OUTPUT AND THE IT CAPITAL INTENSITY

Sector	IT-capital Intensity	SUR	Fixed Effect Model	Random Effect Model
Manufacturing	Entire	0.0177***	−0.3935***	−0.3405**
		(0.0021)	(0.1058)	(0.0164)
	Low	0.0469***	−0.5358***	−0.4910***
		(0.0008)	(0.1203)	(0.0074)
	High	0.0309***	−0.4399*	−0.3057***
		(0.0019)	(0.2439)	(0.0363)
Service	Entire	0.1364***	0.5319**	0.4383***
		(0.0043)	(0.2585)	(0.0603)
	Low	0.0486***	−1.1401***	−1.1219***
		(0.0031)	(0.4268)	(0.1019)
	High	0.0596***	0.6270*	0.5673***
		(0.0054)	(0.4338)	(0.0346)

*: significant at 10% level (standard error in parenthesis)
**: significant at 5% level
***: significant at 1% level

into high-intensity sectors and low-intensity sectors, and divided them further into manufacturing sectors and service sectors.[12] The average IT-capital intensities in the four categories in the year 2002 were 0.0126 (low-intensity manufacturing sectors), 0.0581 (high-intensity manufacturing sectors), 0.0044 (low-intensity service sectors), and 0.0872 (high-intensity service sectors). The high-intensity service sectors, which contain most of the service sectors, use the IT-capital most intensively.[13] The high-intensity manufacturing sectors, which are composed of the IT-manufacturing sectors and others, use the IT-capital heavily as well. With this division, we estimated the translog gross output production function. The results follow in Table 5.

We have found that the larger the IT-capital intensity, the larger the IT-capital elasticity of gross output. Also, we have found that only a service sector which has large IT-capital intensity has the IT-using effect. This means that because not all of the sectors have the IT effect, we cannot find the IT-using effect by using the data of the entire economy. This fact is further clarified by the correlation between the IT capital elasticities of gross output and the IT capital intensities in each sector. This can be seen in Figure 1.

In order to find the cause of the difference in IT capital use between sectors, we have calculated the Allen Partial Substitution Elasticity between IT capital and non-IT capital. It has a positive value when both capital are substitutes, but a negative value when they are complements. Specifically, if the value is above one, their substitutability is said to be elastic. The formula of the Allen partial elasticity of substitution between i, j inputs is:

$$\varepsilon_{ij}=\frac{\beta_{ij}+S_iS_j}{S_iS_j}$$ [14]

[12] The low-intensity manufacturing sectors are 3,4,5,6,10,11,13,14,16,19,21 and the high-intensity manufacturing sectors are 7,8,9,12,15,17,18,20. The low-intensity service sectors are 22,26,29,32 and the high-intensity service sectors are 23,24,25,27,28,20,31.

[13] Mun and Nadiri (2002) have also found the same tendency in US data.

[14] β_{ij} are calculated by the estimation of the translog cost function through SUR and S_i, S_j are share ratios of i, j inputs, respectively.

FIG. 1. IT CAPITAL ELASTICITY OF GROSS OUTPUT AND THE IT CAPITAL INTENSITY

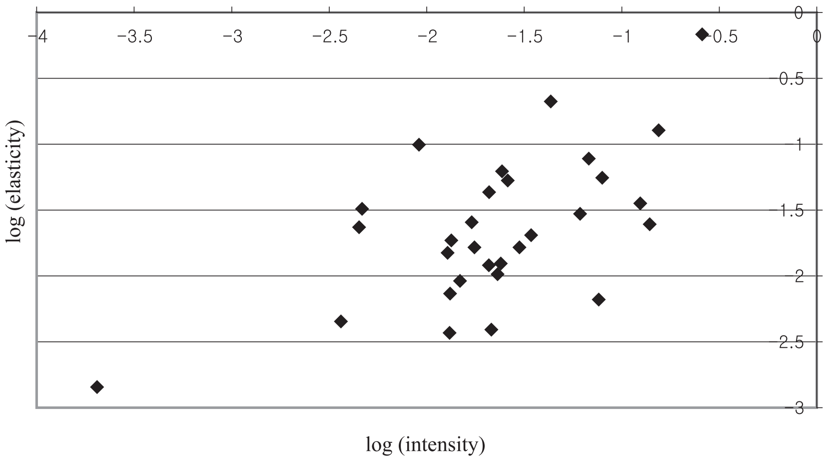

TABLE 6. ALLEN PARTIAL ELASTICITY OF SUBSTITUTION BETWEEN K, IT, AND L

Sector	IT Capital Intensity	$\varepsilon_{K, IT}$	$\varepsilon_{K, L}$	$\varepsilon_{IT, L}$
Entire		6.1231	0.9195	1.6504
Manufacturing	Entire	9.8759	1.8963	7.6968
	Low	6.7663	1.0214	14.1880
	High	−0.4973	2.1907	8.6284
Service	Entire	−2.3559	0.5657	3.4526
	Low	2.7442	0.0285	6.3028
	High	−7.1807	0.6586	7.7547

The elasticity of substitution between non-IT capital and IT-capital is 6.1231, which means that both capital are substitutes for each other. This fact can be the reason of a time lag in introducing IT capital as an input. If the substitutability is large, it takes longer time to use a new type of capital until the old capital deteriorates away.[15]

However, when we divide the entire economy into four categories according to the IT capital intensity as described earlier, this substitutability fades out in the high IT capital intensity sectors. The entire service sector, many sectors of which use IT capital intensively, shows the complementarity (-2.3559) between both capitals. Moreover, high IT-capital intensity manufacturing and service sectors also show complementarity, -0.4973 and -7.1807, respectively.

Therefore, it seems that the sectors which have negative elasticities use IT capital intensively and the ones which have positive elasticities do not use IT capital as heavily. It can be compared with the study of the international differences in IT capital use (Dewan and Kraemer, 2000), which has described the reason as the differences in infrastructure between developing and developed countries.

[15] David (1990)

Second, the elasticity of substitution between labor and IT-capital is greater than the one between labor and non-IT capital in all the categories. It shows that there can be an unemployment problem along with the introduction of IT capital, especially of unskilled workers. As the IT-industries develop, they may hire within themselves, but may also have the displacement of labor effect by the IT-capital. Therefore, the relative sizes of these two effects determine the total effect on labor by using IT capital. In the case of Korea, the effect is negative, that is, using IT capital can reduce the employment. Considering the growth of IT capital use accelerated by the decrease of the price of IT capital, the unemployment can occur in manufacturing sectors, which have greater substitution elasticities between labor and IT capital if the manufacturing sectors begin to use IT capital in full-scale.

IV. *Conclusion*

In this paper, we have tested the existence of real value-added function using the random effect model, which can consider the specific effect of sectors. In other words, we have tested the validity of real value-added as an aggregate index of heterogeneous inputs. This is important in choosing which output measure we should use. The separability assumption has not been accepted. Therefore, we have concluded that gross output is a more appropriate concept than is real value-added.

We have found following results from the estimation of production function. First, the contribution of IT capital to the output is very small or negative in the entire economy. However, different results came out when we estimated them separately according to the IT capital intensity, especially in the service sectors. This means that IT capital has been used effectively in sectors using IT capital intensively. Second, IT capital usage is determined by the ways of production. That can be shown by the substitutability of non-IT capital and IT capital. The high IT capital intensity sectors have the complementarity between both capitals and the low intensity sectors have the substitutability between them. This means that there may be wide IT capital use after already invested non-IT capital deteriorates.

The productivity paradox, that is, there is no improvement in productivity even though the IT technology is widely used, can occur because there is a large difference in the usage of IT capital between sectors. So, if the IT capital is used in more and more sectors, the paradox can be solved. The IT capital-using effect contains the factors which are difficult to measure, other than the effects mentioned above. Actually, IT technology has made changes in the entire economy and is expected to do so in the future. Therefore, if all these factors are included, we can solve the productive paradox more definitely.

References

van Ark B., J. Melka , N. Mulder, M. Timmer, G. Ypma (2002), "ICT Investments and Growth Accounts for the European Union", Final Report on ICT and Growth Accounting for the EG Economics and Finance of the European Commission, Brussels, Groningen Growth and Development Centre.

Baltagi, B. (2001), *Econometrics Analysis of Panel Data*, 2nd Ed., John Wiley & Sons, Ltd., West Sussex, England.

Barten A. (1969), "Maximum Likelihood Estimation of a Complete System of Demand Equations", *European Economic Review 1*, pp.7-79.

Berndt E. (1990), *The Practice of Econometrics: Classic and Contemporary*, Addison-Wesley Publishing Company.

Berndt E. and L. Christensen (1973), "The Translog Function and the Substitution of Equipment, Structures, and Labor in US Manufacturing, 1929-1968", *Journal of Econometrics 1*, pp.81-114.

Berndt E. and L. Christensen (1974), "Testing for the Existence of a Consistent Aggregate Index of Labor Input", *American Economic Review 3*, pp.391-404.

Berndt E. and D. Wood (1975), "Technology, Prices, and the Derived Demand for Energy", *Review of Economics and Statistics 57*, pp.259-268.

Breusch T. and A. Pagan (1980), "The LM Test and its Applications to Model Specification in Econometrics", *Review of Economic Studies 47*, pp.239-254.

Chambers, R. (1988), *Applied Production Analysis: A Dual Approach*, Cambridge University Press.

Colecchia A. and P. Schreyer (2002), "The Contribution of Information and Communication Technologies to Economic Growth in Nine OECD Countries", *OECD Economic Studies 34*, pp.153-171, OECD, Paris.

David, P. (1990), "The Dynamo and the Computer: An Historical Perspective on the Modern Productivity Paradox", *The American Economic Review 80*, pp.355-361.

Denny M. and D. May (1978), "Homotheticity and Real Value-added in Canadian Manufacturing", in Fuss and McFadden eds.,*Production Economics*, pp.53-70, North-Holland Publishing Company.

Denny M. and M. Fuss (1977), "The Use of Approximation Analysis to Test for Separability and the Existence of Consistent Aggregates", *American Economic Review 67*, pp.404-418.

Dewan S. and K. Kraemer (2000), "Information Technology and Productivity: Evidence from Country-Level Data", *Management Science 46*, pp.548-562.

Greene W. (2003), *Econometric Analysis*, 5th ed., Prentice Hall.

Ha Bong Chan and Pyo Hak K. (2004), "The Measurement of IT Contribution by Decomposed Dynamic Input-Output Tables in Korea (1980-2002)", *Seoul Journal of Economics 17,* pp.511-546.

Hausman, J. (1979), "Specification Tests in Econometrics", *Econometrica 46*, pp.1251-1271.

Hausman, J. and Taylor W. (1981), "Panel Data and Unobservable Individual Effects," *Econometrica 49*, No.6, pp.1377-1398.

Mun Sung-Bae and M. Ishaq Nadiri (2002), "Information Technology Externalities: Empirical Evidence From 42 U.S. Industries", *NBER Working Paper 9272*, National Bureau of Economic Research.

Norsworthy, J. and D. Malmquist (1983), "Input Measurement and Productivity Growth in Japanese and U.S. Manufacturing", *The American Economic Review 73*, pp.947-967.

Pyo Hak K. (2003), "Estimates of Capital Stock by Industries and Types of Goods in Korea (1953-2000)", *Journal of Korean Economic Analysis 9*, pp.203-282 (In Korean).

Pyo Hak K., Rhee Keun Hee, and Ha Bong Chan (2003), "Growth Accounting, Productivity Analysis, and Purchasing Power Parity in Korea(1984-2000)", presented at the Fourth Workshop on the International Comparison of Productivity among Asian Countries, November, 2003, Tokyo, Japan.

Pyo Hak K., Rhee Keun Hee, and Ha Bong Chan (2005), "Sources of Industrial Growth and Productivity Estimates in Korea (1984-2002)", *Journal of Korean Economic Analysis 11*, pp.109-172 (In Korean).

Sims, C. (1969), "Theoretical Basis for A Double Deflated Index of Real Value Added", *The Review of Economics and Statistics 51*, pp.470-471.

Solow R. (1987), "We'd Better Watch Out", *New York Times Book Review*, July 12.

Yuhn Ky-Hyang (1991), "Functional Separability and the Existence of Consistent Aggregates in U.S. Manufacturing", *International Economic Review 32*, pp.229-250.

Zellner, A. (1962), "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests of Aggregation Bias", *Journal of the American Statistical Association 57*, pp.500-509.

Appendix. Industrial Classification in Input-output Tables

		1980	1985	1990	1995	2000
1	agriculture and fishing	1-38	1-37	1-34	1-30	1-30
2	mining	39-58	38-51	35-50	31-45	31-45
3	food	59-98	52-91	51-93	46-88	46-86
4	textile, apparels, leather	99-130, 196	92-128, 197, 315	94-124	89-119	87-117
5	wood	131-133, 135-138	129-131, 133-135	125-130	120-125	118-123
6	paper allied	139-148	136-145	132-142	136-134	124-132
7	printing and publishing	149-151	146-148	143-145	135-138	133-136
8	coal and petroleum products	186-194	186-195	177-187	139-149	137-147
9	chemicals	152-185	149-185	146-176	150-173	148-171
10	rubber and plastic	195, 197, 198	196, 198-199	188-193	174-179	182-177
11	stone, clay, glass	199-213	200-215	194-209	180-195	178-193
12	primary metal	214-236	216-237	210-231	196-216	194-214
13	fabricated metal	237-242, 244-247	239-248	232-237, 239-245	217-227	215-225
14	machinery	248-261	249-266	246-264	228-246	226-245
15	computer and peripherals	277	282	265-267	269-270	268-269
16	electrical machinery	262-274, 278	267-278, 283	268-280	247-254, 271-275	246-253, 270-274
17	electric components	279-284	284-288	286-293	255-262	254-261
18	sound, video, communication equipment	285-286, 275-276	289-290, 279-281	281-285	263-268	262-267
19	instruments	300-303	304-307	294-297	276-281	275-280
20	transportation equipment	287-299	291-303	298-311	282-295	281-294
21	furniture and misc. manufacturing	304-312, 243, 134	308-314, 316, 132, 238	312-317, 238, 131	296-305	295-304
22	construction	313-333	324-342	325-341	313-329	312-328
23	electricity, gas, water	334-340	317-323	318-324	306-312	305-311
24	trade	341	343-344	342-343	330-331	329-330
25	hotels and restaurants	342-343	345-346	344-345	332-333	331-332
26	transportation, storage	344-356	347-360	346-358	334-346	333-345
27	communication	357-359	361-363	359-360	347-349	346-349
28	finance, insurance	360-363	364-367	361-365	352-356	352-357
29	real estate	364-366	368-370	366-368	357-359	358-360
30	business services	382-385	371-375	369-375	360-369	361-371
31	social and personal services	368-381, 386-393	378-399	378-402	372-399	350-351, 374-401
32	government	367	376-377	376-377	370-371	372-373