Productivity Growth and Patterns of Efficiency Changes in Korean Economy: Stochastic Frontier Approach with Industry-Panel Data

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This paper applies the group-specific stochastic frontier production model to the Korean 32-industry level panel data set for the period of 1984-1997. The methodology allows for not only estimating temporal variation in total factor productivity, but also identifying the contribution of technical efficiency separately from technical progress. The empirical results of this study show that productivity growth of Korean economy was driven mainly by technical efficiency improvement in the 1980s, but by technical progress in the 1990s. At the industry level, the petroleum products industry was the most efficient in the 1980s, but its efficiency rank fell to 5 in 1997. On the other hand, the communication industry improved its technical efficiency dramatically; its technical efficiency growth rate was ranked at 14 in 1985, but at 1 since 1993.

Keywords: Total factor productivity, Technical efficiency, Technical progress, Stochastic frontier production model, Panel data

JEL Classification: D24, C23, O47

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I. Introduction

The rapid and sustained economic growth of Korea up to 1998 when it encountered a severe financial crisis recording -6.9 percent GDP growth rate has drawn extensive research on sources of its economic growth. Most of these studies have applied the "Solow" growth equation to account for economic growth and total factor productivity (*TFP*) growth (Dollar and Sokoloff 1990; Young 1995; Pyo, Kong, Kwon, and Kim 1992; Park and Kwon 1995; Yuhn and Kwon 2000). In this growth accounting approach, technical progress (*TP*) is considered to be the unique source of *TFP* growth since it assumes implicitly that all economic units are technically efficient.

However, the Solow approach cannot identify technical efficiency separately from technical progress and thereby contributing little to the debate on what was the real cause of the 1997-1998 Financial Crisis in Korea. International Monetary Fund (2003) has defined the capital account crises of Korea and Brazil as "twin crises" implying a simultaneous development of balance of payments crisis and domestic credit crunch. The domestic credit crunch and the resulting excess demand for overseas short-term borrowing is the consequence of cumulative inefficiency in its industrial sectors as discussed in Pyo (2000, 2004). Therefore, we need to identify sources of inefficiency separately from those of technical progress.

The purpose of the present paper is to identify sources of economic growth in Korea by using 32-industry panel data for the period of 1984-1997. The same data set for the period of 1984-2002 has been used recently in Pyo and Ha (2007) to test the separability of real value added from gross output production function and to test the Solow paradox by adopting both fixed-effect and random-effect translog production model. In order to identify the contribution of technical efficiency separately from technical progress, we have adopted a stochastic frontier model in the *TFP* analysis of the Korean economy following Kim and Han (2001), Mahadevan and Kim (2003), Sun and Kalirajan (2005), and Kim and Lee (2006). This approach allows for the decomposition of *TFP* into technical progress and changes in technical efficiency (*TE*). That is, variation in technical efficiency can be attributed to productivity growth.

Kim and Han (2001) applied the Battese and Coelli (1992, BC) stochastic frontier model in their analysis of Korean manufacturing industries. However, the BC model imposes on a strong assumption of identical temporal variation in technical efficiency across different economic units. Therefore, unit A which is more efficient in earlier period than unit B, is restricted to be estimated more efficient in later period, too and then the efficiency ranks of all units should remain constant throughout sample period. This assumption may be unreasonable especially in panel data sample with long time-series observations since it is possible for efficiency ranks to fluctuate in the long run. Mahadevan and Kim (2003) and Sun and Kalirajan (2005) applied the random coefficient frontier model which relaxes the specific distribution assumption of technical inefficiency imposed on in the previous literature. Kim and Lee (2006) applied the Lee (2006a) stochastic frontier model in their analysis of East Asian economic growth. The Lee model relaxes the assumption of identical temporal pattern partially by adding group-specific parameters representing temporal variations of technical efficiency. More specifically, this “group-specific” model allows economic units from different groups to have different temporal patterns, while restricting economic units from the same group to the same pattern. This is a reasonable way to add flexibility to the previous stochastic frontier models if prior information about grouping is available.

This paper intends to follow the line of the group-specific stochastic frontier approach, but in a modified way. Lee (2006a) is not a legitimate model when we use panel data with long time series, since its “asymptotic” applies as N (number of cross section observation) goes to infinity and a number of parameter increases as time series observation grow. However, Lee (2006b) also develops a group-specific stochastic frontier model which is applicable for panel data with long time series by implementing parametric specifications on temporal pattern of technical efficiency. This model is legitimate for our sample panel data of 32 industries covering the period of 1984-1997. Specifically, we can compare temporal changes in productivity between industries of 1-digit classification as well as between more segregated industries with this model.

Another contribution to the literature is our industry level sample data. Among previous analyses, Yuhn and Kwon (2000) and Kim and Lee (2006) used aggregate data, Kim and Han (2001) and Mahadevan and Kim (2003) used firm level data. Recently Sun and Kalirajan (2005) applied the 3-digit industry level data of manufacturing industries for the productivity analysis of the Korean economy which were obtained from the *UNIDO Industrial Statistical Yearbook*. We also use industry-level data from the database of Pyo, Rhee, and Ha (2006). Unlike Sun and Kalirajan (2005), our data set covers the whole Korean economy including agriculture, mining and service as well as manufacturing. In addition, our labor data are differentiated from others used in the aforementioned empirical studies. Either number of workers or working hours was used as a labor input in the previous studies, but our labor data were constructed by taking account of quality factors (gender, age, and education) as well as quantity factor (working hours).

In the following Section II, we describe our adopted stochastic frontier model for the decomposition of *TFP*. Then Section III presents the results of an empirical analysis including econometric results with the summary description of database in Appendix. Finally, we summarize our conclusions in Section IV.

II. The Group-Specific Stochastic Frontier Model and Decomposition of *TFP*

A deterministic frontier production function is defined by

$$y_{it}=f(x_{it},\ t;\ \beta)\exp(-u_{it}), \tag{1}$$

where y_{it} is the output for firm $i(i=1,\cdots,N)$ in the period $t(t=1,\cdots,T)$; $f(\bullet)$ is the production frontier; x is an input vector; t is a time trend as a proxy for technical change; and u_{it} is the nonnegative technical inefficiency term for firm i in period t. Kumbhakar and Lovell (2000) derived the output growth function from the Equation (1) as follows;

$$\dot{y}=\frac{f(x,\ t)}{dt}-\frac{du}{dt}=TP+\sum_j \varepsilon_j \dot{x}_j-\frac{du}{dt} \tag{2}$$

where ε_j is the output elasticity of input j and a dot over a variable implies its rate of change. Therefore, the output growth is not only affected by technical progress (TP) and changes in input use, but also by the change in technical efficiency. This underlines the advantage of stochastic frontier models in the productivity analysis. A traditional Divisia index of productivity change is defined as the

TABLE 1

INDUSTRY CODE

Industry id.	Sectors	Classisfication in IO Table (1995/1998)
1	Agriculture	1-30
2	Coal Mining	31-32
3	Metal and Non-metal	35-45
4	Food	46-88
5	Textile	89-104, 111-113
6	Apparels	105-108, 118
7	Lumber and Wood	120-125
8	Furniture	296-298
9	Paper Allied	126-134
10	Printing, Publishing Allied	135-138
11	Chemicals	150-173
12	Petroleum Products	139-149
13	Leather	109-110, 114-117, 119
14	Stone, Clay, Glass	180-195
15	Primary Metal	196-198, 209-213
16	Fabricated Machinery	199-208, 214-227
17	Machinery	228-246
18	Electrical Machinery	247-275
19	Motor	282-288
20	Transportation Equip.	289-295
21	Instrument	276-281
22	Rubber and Misc. Plastic	174-179
23	Misc. Manufacturing	299-305
24	Construction	313-329
25	Electric Utility	306-309
26	Gas and Water Utility	310-312
27	Communication	347-349
28	Transportation	334-346
29	Trade	330-333
30	Other Private Service	350-351, 360-369, 372-399
31	Public Service	370-371
32	Finance	352-359

difference between the rate changes of output and an input quantity index as

$$T\dot{F}P=\dot{y}-\sum_{j}s_{j}\dot{x}_{j} \tag{3}$$

where $s_j=w_jx_j/E$, E is total expenditure and w is input price. By substituting (2) into (3), $T\dot{F}P$ is defined as

$$\dot{TFP} = TP - \frac{du}{dt} + (RTS - 1)\sum_j \frac{\varepsilon_j}{RTS}\dot{x}_j \tag{4}$$

where *RTS* is returns to scale. The Equation (4) implies the *TFP* growth is decomposed into technical progress, changes in technical efficiency and scale effects.

The stochastic frontier production model in the panel data setting is defined by

$$\ln y_{it} = \alpha_t + \ln x_{it}\beta + v_{it} - u_{it} = \ln x_{it}\beta + \alpha_{it} + v_{it}, \tag{5}$$

where x_{it} is $1\times k$ vector of inputs, β is a $k\times 1$ vector of coefficients, and v_{it} is an *i.i.d.* $N(0, \sigma^2)$. The time-varying parameter α_t is the frontier intercept term at time t (no overall intercept is included in β). Accordingly, $\alpha_{it} = \alpha_t - u_{it}$ represents firm i's efficiency level at time t. Note that $u_{it} \geq 0$, so $\alpha_{it} \leq \alpha_t$. This is a standard setup.

When α_{it} (or equivalently, u_{it}) are considered as "fixed effects," the number of parameters ($NT+K$) exceeds the number of observations. Therefore, different time-varying models have emerged as different choices for these forms for the same purpose of reducing the number of parameters. BC, Kumbhakar (1990), and Lee and Schmidt (1993) were the first generation of the time-varying models which proposed a flexible alternative that assumed a common temporal pattern in technical inefficiency across different firms as follows:

$$\ln y_{it} = \ln x_{it}\beta + \theta_t\alpha_i + v_{it}, \quad i = 1, \cdots, N, \quad t = 1, \cdots, T, \tag{6}$$

where α_i and θ_t represent an individual firm's efficiency and temporal variation in efficiency, respectively. The difference between the aforementioned models emerges from the assumption of θ_t. Lee and Schmidt treated θ_t as a parameter to be estimated while Kumbhakar and BC considered θ_t as a parametric function. Specifically, Kumbhakar (1990) considered the case of $\theta_t(\eta) = [1+\exp(\eta_1 t + \eta_2 t^2)]^{-1}$, and BC considered $\theta_t(\eta) = \exp(-\eta(t-T))$. The number of parameters depends on the length of time series observation in the Lee and Schmidt model, but it is fixed in the latter two models. Therefore, Lee and Schmidt could not apply their model to panel data with long time series.

Recently, Lee (2006b) proposed a group-specific model by relaxing the identical temporal pattern assumption imposed on the model of Equation (6) and imposing parametric specification on a group-specific temporal pattern of efficiency, as follows:

$$\ln y_{it} = \ln x_{it}\beta + \theta_t(\eta_g)\alpha_i + v_{it} \qquad g = 1, 2, \cdots, G \quad \text{and} \quad i \in \text{Group } g, \tag{7}$$

where Group g has G_g firms so that $N = \sum_{g=1}^{G} G_g$ and $\theta_t(\eta_g) = \exp(-\eta_g(t-T))$.

This model requires *a priori* information to compose firms into groups. However, the pre-assigned grouping can be tested using $\eta_g = \eta_h$ for $g \neq h$, for example, to see whether Groups g and h have an identical temporal pattern of technical inefficiency. Furthermore, in addition to testing the identical temporal pattern assumption of BC by applying the hypothesis of $\eta_1 = \eta_2 =, \cdots, = \eta_G$, the time invariance hypothesis of any specific group, $\eta_g = 0$, can also be tested.

Lee (2006b) showed the fixed effects treatment and then consistency does not hinge on the assumption that the inputs are uncorrelated to efficiency. It also does not depend on the distribution of the technical inefficiency because of being fixed, and it simply proceeds conditionally from whatever the realizations may be. The objective function and the first-order conditions of the concentrated least squares (CLS) estimator were derived as follows

$$SSE = \sum_{i=1}^{N} (Y_i - X_i\beta)' M_g (Y_i - X_i\beta) \tag{8}$$

$$\frac{\partial SSE}{\partial \beta} = -2 \sum_{i=1}^{N} X_i' M_g (Y_i - X_i\beta) = 0\,, \quad i \in \text{Group } g \text{ and } g = 1,\ 2, \cdots, G \tag{9}$$

$$\frac{\partial SSE}{\partial \eta_g} = -\frac{2}{\theta(\eta_g)'\theta(\eta_g)} \left[\textstyle\sum_{i \in G_g} e_i'\theta(\eta_g)e_i - \sum_{i \in G_g} e_i' P_g e_i \theta(\eta_g)\right] \frac{d\theta(\eta_g)}{d\eta_g} = 0 \tag{10}$$

where, $Y_i = \ln y_i$, $X_i = \ln x_i$, $M_g = I_T - P_G$, $P_g = \theta(\eta_g)[\theta(\eta_g)'\theta(\eta_g)]^{-1}\theta(\eta_g)'$ and $e_i = Y_i - X_i\beta$.

From Equation (9), we derive the solution $\hat{\beta}$, which is a function of $\hat{\eta}_g$ as

$$\hat{\beta} = (\sum_i X_i' \hat{M}_g X_i)^{-1} (\sum_i X_i' \hat{M}_g Y_i). \tag{11}$$

Therefore, the numerical minimization can be accomplished as follows: (i) with any consistent initial value of $\hat{\beta}$, minimize the objective function (8) with respect to only $\hat{\eta}_g$; (ii) substitute the value of $\hat{\eta}_g$ from (i) to the solution of Equation (11). Then, iterate the two steps until they converge.

Lee (2006b) also provided with the test statistic of the generalized likelihood ratio (*LR*) test as follows:

$$LR = \frac{SSE_R - SSE_U}{\hat{\sigma}^2}, \tag{12}$$

where SSE_U can be SSE of Equation (8), and where SSE_R is the same as SSE, but estimated and calculated under the restriction that $\eta_1 = \eta_2 = \cdots = \eta_G$ or parts of η_g ($\forall g = 1, \cdots, G$) are equal to each other, for example, $\eta_g = \eta_h$ or $\eta_g = \eta_h = \eta_f$.

III. Data and Empirical Results

The dataset used to compare growth and *TFP* among Korean industries was derived from Pyo, Rhee, and Ha (2006) over the period 1984-1997 (see the appendix for the details of the data derivation). Table 2-1 represents the average annual growth rates of gross output and four factor inputs (capital, labor, energy, and material) for the sample industries. The percentage output growth rate was highest in motor industry (18.49%), followed by communication (18.11%) and gas and water utility (18.08%) industries. The capital stock grew the fastest in transportation equipment (20.50%), which was followed by gas and water utility (18.76%) and construction (17.02%). Motor industry also experienced the fastest growth in labor (10.96%) and material (19.11%) inputs while gas and water utility (21.33%) did in energy.

Of the 1-digit industry classification considered in Table 2-2, service industry grew the fastest at 10.34%, followed by manufacturing industry (8.71%). On the other hand, agriculture and mining merely grew only at 1.68% and 0.11%, respectively. The growth rate of the capital stock was the fastest in service (12.37%), but agriculture also showed fast capital growth rate of 9.84%. Labor growth rates are relatively low in all industries and energy and material grew fast, led by service industry.

For empirical analysis, a translog stochastic frontier production

TABLE 2-1
SAMPLE DATA DESCRIPTION (1984-1997)

Industry Code	Output	Capital	Labor	Energy	Material
1	1.68	9.84	-2.33	3.58	3.98
2	-7.21	-1.26	-22.82	-8.04	-3.97
3	7.43	-1.26	0.16	6.22	9.91
4	3.99	7.98	1.86	2.83	3.79
5	4.49	3.64	-1.91	3.77	4.31
6	2.75	3.46	-1.59	1.96	2.61
7	3.04	7.01	-3.11	2.38	2.85
8	7.95	16.71	3.79	4.15	8.15
9	8.84	13.91	-2.81	6.28	8.31
10	9.05	10.74	3.21	6.30	9.75
11	11.10	12.65	-2.24	9.00	10.84
12	3.73	15.87	-9.27	2.20	11.91
13	3.77	0.70	-4.85	0.45	4.16
14	10.74	5.58	2.32	9.26	10.92
15	10.45	8.35	-0.64	12.19	9.88
16	9.94	13.22	4.30	6.77	10.00
17	12.88	9.87	5.50	7.23	12.68
18	16.36	11.49	2.42	9.80	14.75
19	18.49	12.04	10.96	10.63	19.11
20	8.99	20.50	-1.91	-0.54	10.12
21	13.16	11.63	2.24	9.12	12.77
22	12.64	13.78	-3.30	9.36	12.52
23	1.90	6.97	-1.19	1.47	1.78
24	8.93	17.02	5.53	7.78	11.44
25	8.88	7.80	3.52	4.28	10.69
26	18.08	18.76	10.30	21.33	15.21
27	18.11	10.56	2.42	9.01	12.90
28	7.02	6.19	3.75	3.97	10.89
29	7.52	14.73	3.74	4.44	8.36
30	9.86	14.61	5.56	9.44	14.67
31	3.80	11.91	3.48	2.84	6.63
32	10.91	9.79	6.64	14.11	13.73

TABLE 2-2
SAMPLE DATA DESCRIPTION (1984-1997): 1-DIGIT

Industry	Output	Capital	Labor	Energy	Material
Agriculture	1.68	9.84	-2.33	3.58	3.98
Mining	0.11	-1.26	-11.33	-0.91	2.97
Manufacturing	8.71	10.31	0.19	5.73	9.06
Service	10.34	12.37	4.99	8.58	11.61

TABLE 3
TEST RESULTS OF HYPOTHESES INVOLVING GROUPING

Hypothesis	LR statistic	*df*	*p*-value
1. $\eta_1=\eta_2=\eta_3=\eta_4=\eta_5=\eta_6$ (BC Model)	127.737	5	0.000
2. $\eta_5=\eta_6$ (Construction = Service)	4.781	1	0.029
3. $\eta_3=\eta_4$ (Light Manu. = Heavy Manu.)	2.787	1	0.095
4. $\eta_1=\eta_2$ (Agriculture = Mining)	0.005	1	0.944
5. $\eta_4=\eta_5$ (Heavy Manu. = Construction)	0.152	1	0.696
6. $\eta_1=\eta_2$ and $\eta_3=\eta_4$ (Agriculture = Mining and Light Manu. = Heavy Manu.)	2.791	2	0.248
7. $\eta_1=\eta_2$ and $\eta_3=\eta_4=\eta_5$ (Agriculture = Mining, and Light Manu. = Heavy Manu. = Construction)	2.809	3	0.422

function is assumed to specify the technology in industries, as follows:

$$\ln y_{it}=\alpha_t+\sum_j \delta_j \ln x_{jit}+\sum_j \sum_l \beta_{jl} \ln x_{lit} \ln x_{jit}+v_{it}-\theta_t(\eta_g)u_i \qquad (13)$$

$$j,\ l=K, L, E, M, t$$

where y is the output, and K, L, E, M, and t are labor, capital stock, energy, material, and time trend respectively. From Equation (13), technical change and elasticity of input can be derived as

$$TP_{it}=\partial \ln y_{it}/\partial tr=\delta_t+2\beta_t t+\sum_{j\neq t} \beta_{jt} \ln x_{jt} \qquad (14)$$

$$\varepsilon_j=\partial \ln y/\partial \ln x_j=\delta_j+2\beta_{jj} \ln x_j+\sum_{k\neq j} \beta_{jk} \ln x_k \qquad (15)$$

The next step that we considered was how to categorize 32 Korean industries into a number of groups. In this empirical exercise, we made six different groups at first as (agriculture, mining, light manufacturing, heavy manufacturing, construction, and other service) and tested several hypotheses by which to reduce the number of groups, in order to finalize the grouping.

Table 3 presents the test results of various null hypotheses. The null hypotheses were tested using the aforementioned generalized likelihood ratio tests. The first null hypothesis was that there was an identical temporal pattern of technical inefficiency across all industries (H_0: $\eta_1 = \eta_2 = \cdots = \eta_6$), which was rejected at the 1% significance level. If the null hypothesis were true, the estimation model would be that of BC. The results suggested that at least one of six groups had a different temporal pattern of technical inefficiency as compared to the other groups. The second null hypothesis (H_0: $\eta_5 = \eta_6$) was that construction and other service industries had identical temporal variations in technical efficiency. Its LR statistic is 4.781 and then the hypothesis is rejected at 5% significance level.

However, the hypotheses (H_0: $\eta_3 = \eta_4$ and H_0: $\eta_1 = \eta_2$) test results showed that agriculture and mining industries as well as light and heavy manufacturing had identical temporal changes in efficiency, respectively. In addition, the hypothesis of H_0: $\eta_4 = \eta_5$ was set to test whether construction industry has a similar pattern to heavy manufacturing industries and its p-value is 0.696 implying the hypothesis can not be rejected. From the sixth and seventh hypotheses, we concluded our final grouping as three; Group 1 (agriculture and mining), Group 2 (manufacturing and construction) and Group 3 (service).

The parameter estimates for the production frontiers are presented in Table 4-1. The estimates of the BC model are also shown for comparison. The parameter estimates are significantly different between the two models and the t-values are generally larger in this group-specific model with the BC specification (G-BC) than in the BC model. The η in the BC model indicates the average temporal pattern of technical efficiency over all industries. According to its t-value, it is not statistically significant at 5%. However, The G-BC model provides with three different parameters relevant to the temporal pattern and the η_1 representing that of Group 1 (agriculture and mining) is not significantly different from zero, but the estimates of η_2 and η_3 have large enough t-values to show their statistical significance. The average of the three estimates is approximately close to zero and this implies that even though overall average of TE is time-invariant, segregated industries could have different directions of efficiency movements.

In addition, Table 4-2 presents the test results of various null hypotheses involving parameters of the translog production function. The first null hypothesis of the Cobb-Douglas function is rejected at the 1% significance level for this sample. Thus, the Cobb-Douglas production function is not a legitimate specification for the Korean

TABLE 4-1
COEFFICIENT ESTIMATES OF THE STOCHASTIC FRONTIER PRODUCTION FUNCTION

BC Model				G-BC Model			
Variables	Estimates	Variables	Estimates	Variables	Estimates	Variables	Estimates
$(\ln K)$	0.023 (0.10)	$(\ln K)(\ln M)$	0.025 (1.25)	$(\ln K)$	0.330 (1.88)	$(\ln K)(\ln M)$	-0.021 (-1.28)
$(\ln L)$	0.074 (3.78)	$(\ln K)t$	0.004 (1.57)	$(\ln L)$	0.755 (6.42)	$(\ln K)t$	-0.008 (-3.89)
$(\ln E)$	1.059 (7.08)	$(\ln L)(\ln E)$	-0.001 (-0.04)	$(\ln E)$	1.358 (14.62)	$(\ln L)(\ln E)$	0.011 (1.27)
$(\ln M)$	-0.367 (-1.43)	$(\ln L)(\ln M)$	-0.049 (-2.18)	$(\ln M)$	-0.638 (-5.19)	$(\ln L)(\ln M)$	-0.102 (-5.99)
t	0.087 (1.88)	$(\ln L)t$	0.001 (0.30)	t	0.208 (7.59)	$(\ln L)t$	0.014 (4.96)
$(\ln K)^2$	-0.020 (-1.86)	$(\ln E)(\ln M)$	-0.112 (-12.49)	$(\ln K)^2$	0.003 (0.40)	$(\ln E)(\ln M)$	-0.110 (-16.24)
$(\ln L)^2$	0.002 (0.15)	$(\ln E)t$	0.002 (1.62)	$(\ln L)^2$	0.048 (4.75)	$(\ln E)t$	0.010 (7.55)
$(\ln E)^2$	0.035 (6.03)	$(\ln M)t$	-0.009 (-2.74)	$(\ln E)^2$	0.012 (2.02)	$(\ln M)t$	-0.028 (-8.16)
$(\ln M)^2$	0.091 (7.59)	η	-0.002 (-0.42)	$(\ln M)^2$	0.128 (13.65)	η_1	0.003 (0.24)
t^2	-0.000 (-0.22)			t^2	0.003 (8.40)	η_2	-0.088 (-13.80)
$(\ln K)(\ln L)$	-0.003 (-0.15)			$(\ln K)(\ln L)$	0.004 (0.23)	η_3	0.071 (7.13)
$(\ln K)(\ln E)$	-0.010 (-0.98)			$(\ln K)(\ln E)$	0.003 (0.34)		
Objective Junction		2.477		Objective Junction		1.763	

Note: t-statistics are in parentheses.

economy, given the assumption of the translog production. The second hypothesis in Table 4-2, that there is no technical change, is also rejected at the 1% significance level for the sample. The third hypothesis is the neutrality of technical progress. Technical progress is neural if all β_{jt}s $(j=K, L, E, M)$ are equal to zero. This hypothesis is rejected at the 1% significance level.

To consider the measurement of technical efficiency, the separation of $\hat{u}_{it}$ from $\hat{\alpha}_{it}$ follows the same method used by Lee (2006b):

TABLE 4-2
TEST RESULTS OF HYPOTHESES INVOLVING COEFFICIENTS OF PRODUCTION FUNCTION

Hypothesis	F-statistic	$df1$, $df2$	p-value
1. $\beta_{LL}=\beta_{KK}=\ldots=\beta_{EM}$	60.713	15, 333	0.000
2. $\delta_t=\beta_{tt}=\beta_{tL}=\beta_{tK}=\beta_{tE}=\beta_{tM}=0$	30.721	6, 333	0.000
3. $\beta_{tL}=\beta_{tK}=\beta_{tE}=\beta_{tM}=0$	35.193	4, 333	0.000

$$\hat{\alpha}_t=\max_i \theta_t(\hat{\eta}_g)\hat{\alpha}_i, \tag{16}$$

where $\hat{\alpha}_t=[\theta(\hat{\eta}_g)'\theta(\hat{\eta}_g)]^{-1}\theta(\hat{\eta}_g)'e_i(\hat{\beta})$ and the inefficiency term u_{it} is then estimated as

$$\hat{u}_{it}=\hat{\alpha}_t-\theta_t(\hat{\eta}_g)\hat{\alpha}_i, \quad \forall i \in \text{Group } g. \tag{17}$$

Because the dependent variable is expressed in natural log form, the technical efficiency scores are calculated from Equation (18) as follows:

$$\hat{TE}_{it}=\exp(-\hat{u}_{it})=\exp[-(\hat{\alpha}_t-\theta_t(\hat{\eta}_g)\hat{\alpha}_i)]. \tag{18}$$

Here, technical efficiency is a relative concept and the average efficiency index is related to the variance of α_i: The higher the variance, the smaller the average efficiency.

This relative efficiency concept should be taken into account in application studies. In productivity studies of countries, the efficiency measure of, for example, Korean economy could be high when the sample data includes only Asian countries, but its measure could be very low if the sample is extended to include more developed Western countries because of nature of the relative measure. Therefore, temporal flow of efficiency measure and its ranking is more meaningful for the analysis than absolute measure of efficiency.

Figure 1 shows the yearly average of *TE* change, *TP* and *TFP* growth. *TE* change and *TP* moved in opposite directions having downward-sloping and upward-sloping curves, respectively while the *TFP* growth of Korean economy shows more or less constant curves during the sample period of 1984-1997. That is, the catch-up effects of efficiency improvement was a major factor of productivity growth

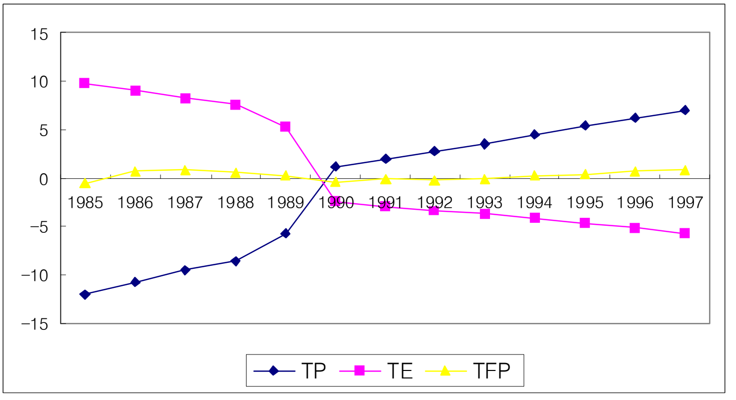


FIGURE 1

TEMPORAL VARIATIONS IN AVERAGE *TFP* GROWTH RATE

in the 1980s, but the innovation effects of technical progress was attributed to productivity growth in the 1990s. There are arguments on technology adoption that after firms adopt a new technology, not all the firms in the old technology move to the new technology efficiently whereas the general notion is that firms with high-technology reach the best practice of technology better than firms with low-technology. Our empirical result in Figure 1 implies this argument positively since it can be understood as new technology has been adopted or invented continuously in the 1990s, technical efficiency has been hardly maintained to the level with old technology. Considering the relative nature of estimated efficiency, the decline of *TE* may also imply increasing variation in efficiency among industries. That is, the efficiency gap between the most efficient industry and all other industries has been widened on average over time. Kim and Lee (2006) found technical progress attributes to productivity growth of more developed Western countries while efficiency improvement attributes to that of less developed East Asian countries. Our empirical findings are consistent with their results in the sense that Korean economy was driven by the catch-up effects when less developed in the 1980s, but by the innovation effects when more developed in the 1990s.

Figure 2 focuses on the fluctuation of *TE*. All three groups of industries showed improvement in *TE* in the 1980s and decline in *TE* in the 1990s. But there are differences among three groups; Group 3

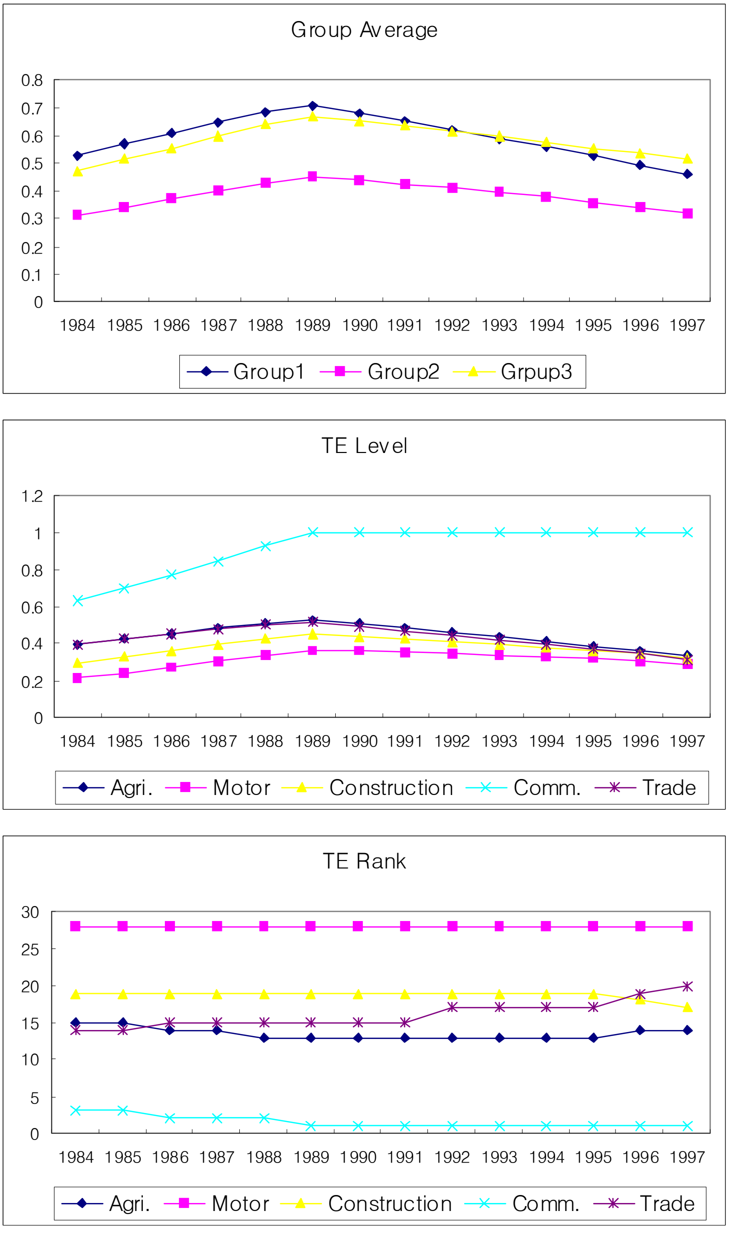


FIGURE 2
TEMPORAL VARIATIONS IN TECHNICAL EFFICIENCY OF
GROUP AND SELECTED INDUSTRY

TABLE 5
TECHNICAL EFFICIENCY RANK OF INDUSTRY

Industry Code	84-86	87-89	90-92	93-95	96-97
1	15	13	13	13	14
2	5	6	6	6	7
3	2	3	3	3	3
4	32	32	32	32	32
5	29	29	29	29	29
6	24	24	24	24	24
7	17	17	17	15	13
8	6	7	9	9	9
9	23	23	23	23	23
10	8	9	10	10	10
11	25	25	25	25	25
12	1	1	2	4	5
13	18	18	18	18	16
14	22	22	22	22	22
15	31	31	31	31	31
16	27	27	27	27	27
17	26	26	26	26	26
18	30	30	30	30	30
19	28	28	28	28	28
20	20	20	20	20	20
21	11	11	11	11	11
22	21	21	21	21	21
23	16	16	16	14	12
24	19	19	19	19	18
25	9	8	7	7	6
26	12	12	12	12	15
27	3	2	1	1	1
28	13	14	14	16	17
29	14	15	15	17	19
30	7	5	5	5	4
31	10	10	8	8	8
32	4	4	4	2	2

of service industries was less efficient than in earlier sample period, but its *TE* level passed that of Group 1 in 1993. The last two graphs in Figure 2 show the *TE* movement of the selected industries. The communication industries improved rapidly its *TE* in the 1980s and have stayed on top with respect to *TE* since 1989. The motor industry has been the least efficient among the selected industries throughout the sample period. However, the efficiency gap between

TABLE 6

SOURCES OF ECONOMIC GROWTH (%): GROUP COMPARISON

	Period	$\dot{y}$	$\dot{TE}$	$\dot{TP}$	Scale	$\dot{TFP}$
Group 1	85-89	3.86	5.86	-6.16	1.19	0.90
	90-97	-1.38	-5.42	7.71	-0.63	1.65
	85-97	0.63	-1.08	2.37	0.07	1.36
Group 2	85-89	11.78	8.71	-10.23	2.15	0.63
	90-97	6.81	-3.82	3.05	0.36	-0.41
	85-97	8.72	1.00	-2.06	1.05	-0.01
Group 3	85-89	9.88	6.72	-8.04	0.76	-0.56
	90-97	10.92	-4.01	5.40	-0.37	1.02
	85-97	10.52	0.12	0.23	0.06	0.41

Note: Group 1: Agriculture and Mining, Group 2: Manufacturing and Construction, Group 3: Service

motor and other industries has been narrowed in the late 1990s. From the *TE* rank graph, the most noticeable fact is that the efficiency rank of the trade industry fell down from 14 in 1984 to 20 in 1997.

Table 5 also presents the most and the least efficient industries in each period and their efficiency levels changed over time. Industry 12 (petroleum products) turned out to be the most efficient in the 1980s, but its efficiency rank fell to 5 in 1996-97. On the other hand, Industry 27 (communication) continued to improve its efficiency rank and to be the most efficient industry since 1990. Industry 4 (Food) had been the least efficient industry in all periods and this result is consistent with the previous empirical results of Mahadevan and Kim (2003) and Sun and Kalirajan (2005) which analyzed the productivity changes in Korean manufacturing. Gains in technical efficiency was estimated to be negative in the period 1980-1994 by Mahadevan and Kim (2003) and relatively sluggish improvement in technical efficiency during 1970-1997 was reported by Sun and Kalirajan (2005).

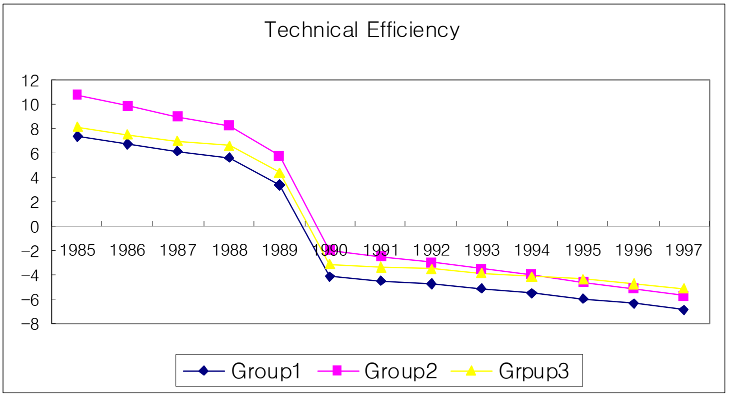
Turning attention to the *TFP* decomposition and source of economic growth, Table 6 reveals the decomposition of output growth by comparing the group average productivity measures. Group 2 and 3, manufacturing and service industries, achieved outstanding performance with regard to output growth. In particular, average annual output growth of Group 2 (manufacturing and construction) was 11.78% in the late 1980s and 6.81% in the period of 1990-97.

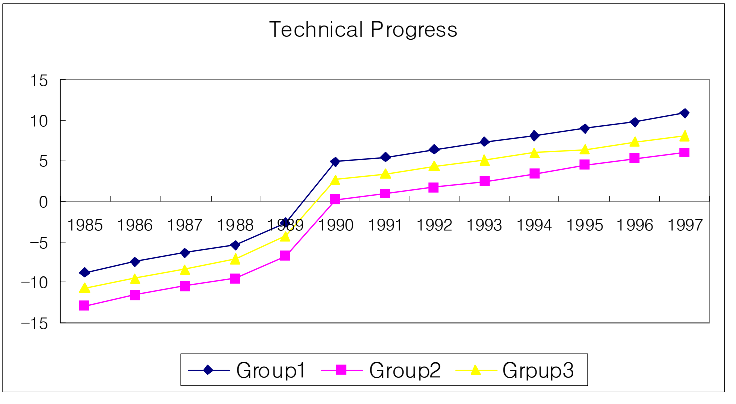
Moreover, the average output growth of Group 3 (service) showed the highest among the three groups. It was 9.88% in the former period and 10.92 in the latter period and Group 3 was the only group to achieve higher output growth in the 1990s than in the 1980s. On the other hand, Group 1 (agriculture and mining) showed negative output growth in the 1990s.

TE changes of the three groups revealed similar temporal patterns. It was a major source of economic growth in the 1985-89, but it became negative in the 1990s. *TP* improved dramatically and became a major source of economic growth in the 1990s. The scale effects had similar temporal pattern to *TE*. It was positive in the 1980s, but turned to be negative in the 1990s. This temporal trend implies the degree of returns to scale of the Korean economy changed from increasing returns to decreasing returns over time. According to the measures of *TFP* growth, Group 1 and 3 achieved productivity gain over time, while Group 2 experienced decline in productivity. Considering positive *TFP* growth in the 1990s, negative output growth of Group 1 was caused by decline in input use.

Overall, the output growth of Korean industries was attributed to the extensive use of labor, capital, energy and material inputs. This empirical result is different from Kim and Lee (2006) which found *TE* improvement was one of main sources of Korean economic growth. However, our sample data include only Korean industries whereas Kim and Lee (2006) used Penn World Data including Western countries. Therefore, we may conjecture that the wide efficiency gap between the most efficient country and Korea had been narrowed rapidly as Korean economy reached world's best practice of technology closely and then a positive *TE* changes are measured in the analysis of Kim and Lee. On the other hand, our analysis compares the gap between the most efficient industry and other industries. If the gap had been widened by *TE* improvement of the most efficient industry, then other industries are measured to have a decline in *TE* even though their efficiency improved when compared the same industries in other countries.

Yearly movements in component changes in output are illustrated in Figure 3 for the three groups of industries. Group 2 was on the upper frontier of $\dot{TE}$ until 1996 when Group 3 showed higher growth rate of *TE*. The wide gap that had existed in $\dot{TE}$ between Group 1 and other groups narrowed consistently, as the latter groups kept gaining $\dot{TE}$ throughout the sampling period. Group 1 also led *TP*





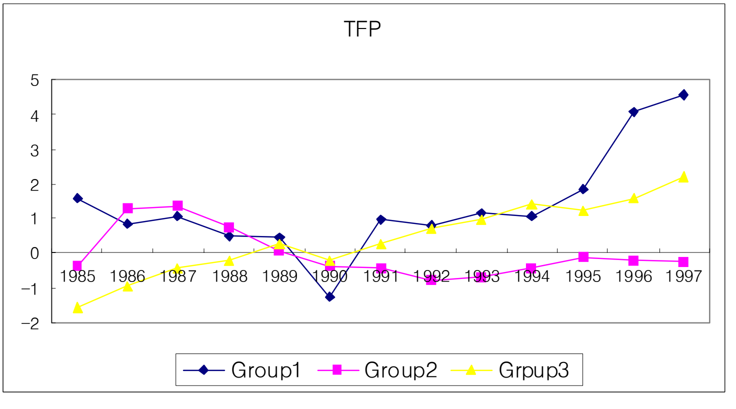


FIGURE 3

TEMPORAL VARIATIONS IN *TFP* GROWTH RATE: GROUP COMPARISON throughout the sample period, but all three groups showed similar temporal pattern and the gaps among the three groups were more or less constant. *TFP* movement showed some heterogeneity among groups. The *TFP* growth of Group 3 had shown a stable upward trend while Group 1 experienced a negative trend in the 1980s, but a positive trend in the 1990s. Especially, *TFP* of Group 1 improved rapidly after 1996.

Figure 4 also displays temporal movements in component changes in output of selected industries. The communication experienced high *TE* growth rates in the 1980s and zero growth rate since it became the most efficient industry from 1990. A zero growth rate of the most efficient industry is obtained by nature of relative efficiency. Generally, the Korean communication is known as a fast growing industry. If its *TE* also continues to improve rapidly in the 1990s, the relative measure of *TE* (difference between the most efficient industry and others) may measure decline in *TE* of other industries even though their absolute *TE* improves. The trade industry was on the lower frontier of $\dot{TE}$ throughout the periods considered. The gap that had existed in *TE* between the communication industry and other industries widened consistently since 1990. The communication industry led *TP* until 1995, when the trade industry took the leading role by a narrow margin. The motor industry led $\dot{TFP}$ in the early period, but it declined throughout the period considered. The communication industry was on the upper frontier of $\dot{TFP}$ since 1987 and its high $\dot{TFP}$ in the 1990s distinguished itself from other industries.

Taking account of relative measure of *TE*, rank of productivity growth may present valuable information. Figure 5 displays temporal variation of productivity growth rank. This figure presents differences between the selected industries more apparently. *TE* improvement rate was the fastest in the motor industry before 1990 and the communication industry took the leading role since then and it achieved the first rank from 1993. Even though the motor industry experienced a slight decline in *TE* growth rate rank, it still remained relatively high rank between 5 and 8 throughout the sample period. The construction, agriculture and trade industries remained their ranks of *TE* growth rate more or less constant during the sample period. The communication industry achieved its *TP* rank at 4-6 until 1994, while the trade industry maintained its *TP* rank constant throughout the sample period at 5-8. On the other hand, the

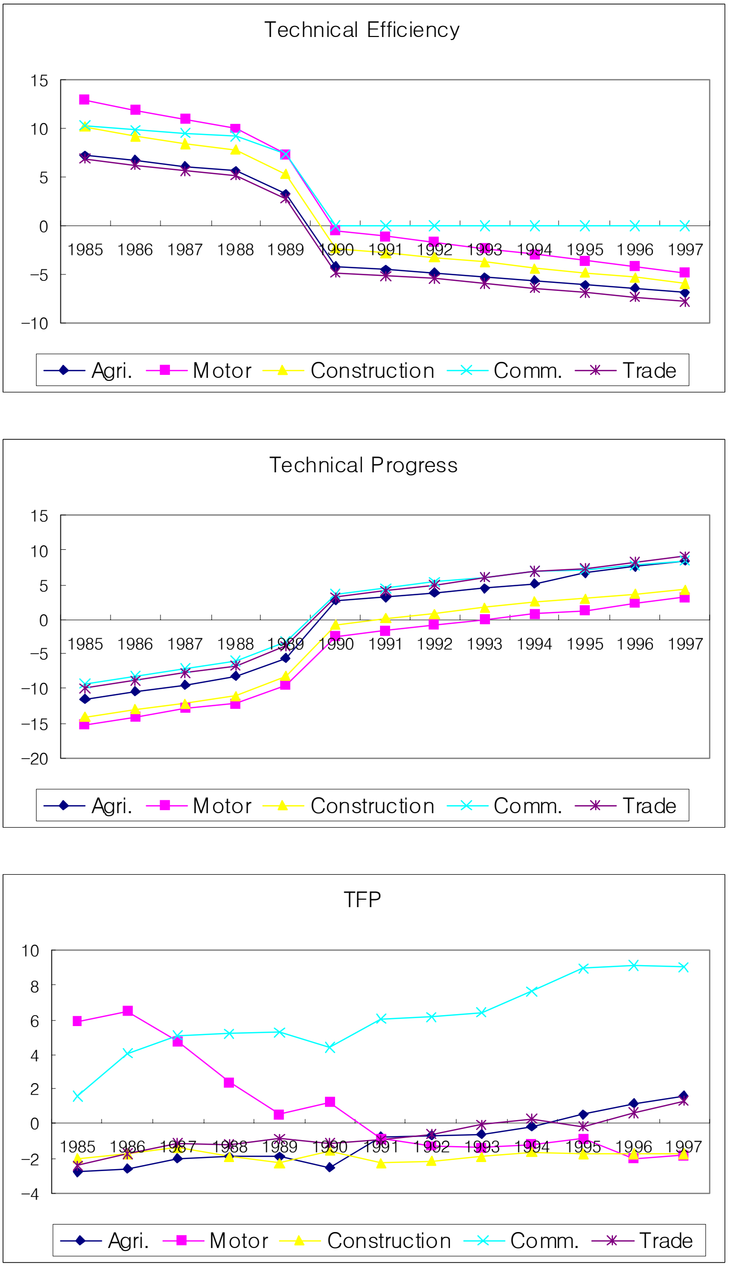


FIGURE 4

TEMPORAL VARIATIONS IN *TFP* GROWTH RATE: SELECTED INDUSTRIES

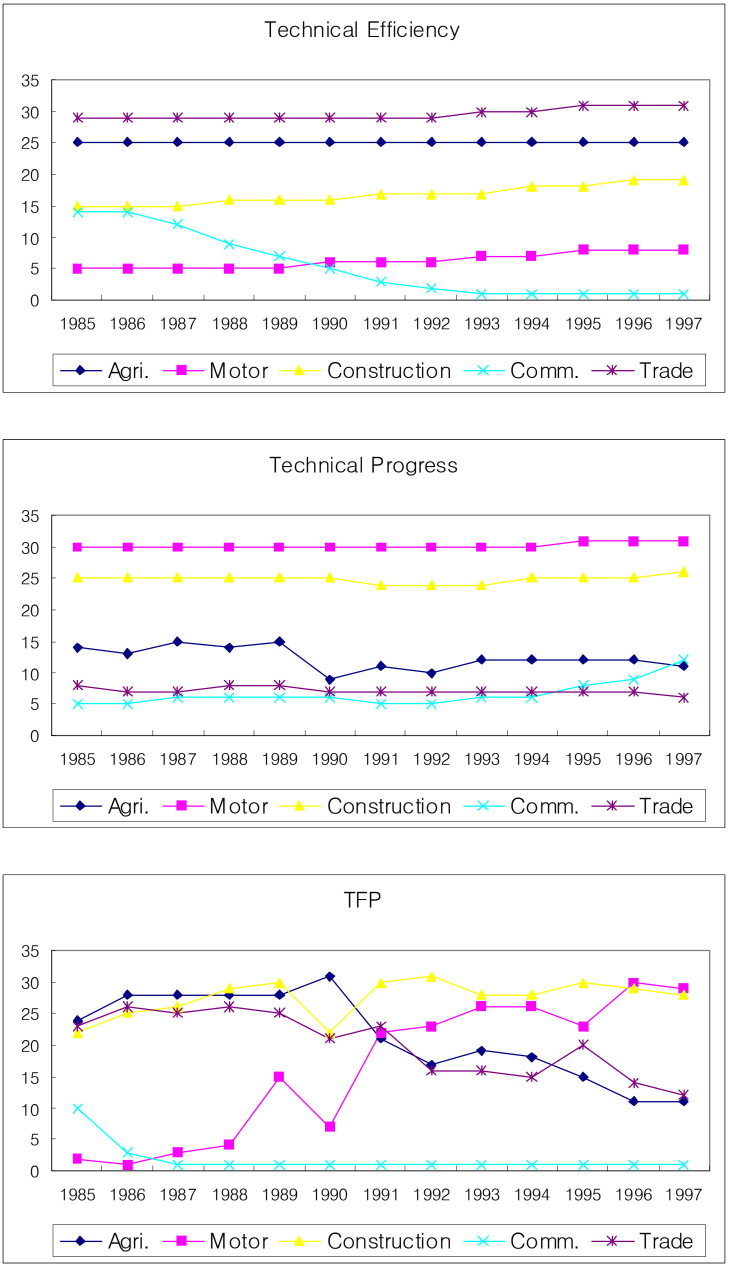


FIGURE 5

TEMPORAL VARIATIONS IN *TFP* GROWTH RANK: SELECTED INDUSTRIES construction and motor industries remained stable and low ranks at 25 and 30, respectively. The ranks of *TFP* growth rate imply that the motor industry was one of the fast growing industries in the 1980s and turned to be one of the worst in the 1990s with respect to *TFP*. On the other hand, the agriculture and trade industries improved their ranks of *TFP* growth rate in the 1990s.

IV. Conclusion

The empirical results of this study show that productivity growth of Korean economy was driven mainly by *TE* improvement in the 1980s, but by technical progress in the 1990s. Considering the nature of relative efficiency measure, the decline of *TE* measure in the 1990s may be caused by the fast *TE* growing in the most efficient industry (communication). If the *TE* gap between communication and other industries had been widened over time because of fast growing of communication, our *TE* measures of other industries could be estimated as declining even if other industries improved their *TE* level over time.

According to group average measure and hypothesis, the three groups of industries had different temporal pattern of *TE* so that the efficiency rank of each industry fluctuated during the sample period. Group 1 (agriculture and mining) and 3 (service) achieved productivity gain during the sample period while Group 2 (manufacturing and construction) experienced decline in productivity. The *TFP* growth of Group 3 had shown a stable upward trend while Group 1 experienced a negative trend in the 1980s, but a positive trend in the 1990s. However, all three groups had similar trend that high growth rates appeared in *TE* in the 1980s and in technical progress in the 1990s.

In the industry level, the petroleum products industry was the most efficient in the 1980s, but its efficiency rank fell to 5 in 1997. On the other hand, the communication industry improved its *TE* dramatically; its *TE* growth rate was ranked at 14 in 1985, but at 1 since 1993. The food industry had been the least efficient in all periods. In addition, the rank of *TFP* growth rate imply that the motor industry was one of the fast growing industries in the 1980s, but turned to be one of the worst in the 1990s, while the agriculture and trade industries improved their Ranks of *TFP* growth rate in the 1990s.

The empirical results of this study show that changes in technical efficiency had a significant effect on productivity growth. This study provides additional insight into the analysis of *TFP* growth in Korean economy by applying a stochastic frontier model.

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Appendix: 32-Sector Database for Korea (1984-2002)

A full description of 32-sector database for Korea during the period of 1984-2002 is available in Pyo, Rhee, and Ha (2006). In what follows, we summarize the method of constructing the industry panel data.

A. Gross Output Data from National Accounts and Input-Output Table

National accounts by the Bank of Korea (1999, 2004) reports annual series (1970-2002) of gross output, intermediate consumption, GDP, indirect taxes, consumption of fixed capital, domestic factor income, compensation of employees, and operating surplus of 21 industries including 9 manufacturing industries and 3 sub-sectors of government services in current prices following 1993 UN System of National Accounts.

The Bank of Korea has also published Input-Output Tables since 1960. Its most recent 2000 Input-Output Table is the 19*th* Table. The detailed description of Input-Output Tables during 1970-2000 is summarized in Table 1. The Table for 1995 has 402, 168, 77, and 28 industrial sectors in basic, small, medium, and large classifications, respectively. Therefore, the estimation of time series Input-Output Tables following those methods described in Kuroda (2001) would be required if we have to estimate *KLEM* model with more than 21 industrial classifications since Input-Output Tables are available only in selected years. We have attached the reclassification of I-O Tables in Table 2 and 3.

For the present study, we have generated gross output and value-added by 32 industries through RAS method. The generated annual data of both gross output and value-added have been adjusted to match against National Income Accounts which do not contain both indirect tax and subsidy. Since RAS method is sensitive to the benchmark year's value of the I-O coefficients, we have used the I-O Table in the closest year as benchmark value.

We have used V-Table to generate commodity prices by 32 sectors and then used the generated commodity prices to estimate output prices by 32 sectors.

B. Measurement of Capital Stocks and Capital Input Service

The success of late industrialization by newly industrializing economies could not have been made possible if both the rapid accumulation of capital and its changing distribution among sectors were not realized in their development process. However, it is difficult to identify these factors empirically because the time series data of capital stocks in fast-developing economies by both types of assets and by industries are not readily available. The lack of investment data for a sufficiently long period of time to apply the perpetual inventory estimation method was the main cause of the problem. However, the National Statistical Office of the Republic of Korea has conducted nation-wide national wealth survey four times since 1968. Korea is one of a few countries which have conducted economy-wide national wealth surveys at a regular interval. Since the first *National Wealth Survey* (*NWS*) was conducted in 1968, the subsequent surveys were made in every ten years in 1977, 1987, and 1997, respectively. Since such regular surveys with nation-wide coverage are very rare in both developed and developing countries, an analysis on the dynamic profile of national wealth seems warranted to examine how national wealth in a fast growing economy is accumulated and distributed among different sectors.

The estimation of national wealth by types of assets and by industries was made by Pyo (1998) and updated in Pyo (2003) by modified perpetual inventory method and polynomial benchmark-year estimation method using four benchmark-year estimates. The latter study modifies and extends the earlier one in two respects. First, the result of 1997 *NWS* has been released in 1999 so that we can make use of additional benchmark-year estimates. Second re-basing the estimates of capital stocks from 1990 prices to 1995 prices seems inevitable because Bank of Korea has re-based their national accounts accordingly.

When we applied the polynomial benchmark year equation to estimate the proportional retirement rates for the sub-periods of

1977-87 and 1987-97, most of estimates became negative including the average economy-wide retirement rates (-3.0% for 1977-87 and -3.1% for 1987-97) except other Construction (0.6%) and Transport Equipment (3.4%) in 1977-87 and Nonresidential Building (0.9%) in 1987-97. Therefore, following Pyo (1998), we have applied the polynomial benchmark year estimation method to estimating depreciation by types of assets only. Thus we have generated net stocks by types of assets first for the period of 1968-97 and then, distributed them over different sectors of industries by using interpolated industrial weights between the respective benchmark years.

We have decided to estimate net capital stock first and then to estimate gross capital stock by using interpolated net-gross conversion ratios for the following two reasons. The basic reason is due to the fact that the margin of prediction error from the polynomial benchmark year equation turns out to be larger with gross capital stock than with net capital stock as had been observed in Pyo (1992).

Since the database of Pyo (2003) covers 10 broad categories of industrial sector together with 28 sub-sectors of Manufacturing, it can be reclassified and reconciled with 32-sector classification for the ICPA project. Assuming that the flow of capital service is proportional to capital stock, we used the average capital stock of two years as the capital service.[1]

In order to make quality adjustments to the capital input data, we have taken the following steps:

(1) Following Kuroda (2001), we define the capital service of asset i in industry j as

$$K^{ij}(t)=b^{ij}(t)\bar{A}^{j}(t) \qquad i=1,\cdots,n; \quad j=1,\cdots,m$$

$$b^{ij}(t)\cdot\frac{1}{2}[A^{j}(t)+A^{j}(t-1)] \tag{A.1}$$

where $b^{ij}(t)$ denote the proportion of the *i-th* asset type on the *j-th* sector's total capital service input $\bar{A}^{j}(t)$ which is the average of

[1] We could not use the formula of Kuroda and Nomura (1999) because investment data in National Income Accounts are classified either by asset type or by industry but not by both.

unweighted sum over all assets during the *t-th* and $(t-1)th$ period.

(2) The growth rate of capital service input is defined as

$$\ln K^j(t) - \ln K^j(t-1) = [\ln \bar{A}^j(t) - \ln \bar{A}^j(t-1)] + \sum_l \bar{v}_i^j [\ln b^{ij}(t) - \ln b^{ij}(t-1)]$$
$$j = 1,\ 2, \cdots, J \qquad \text{(A.2)}$$

where $\bar{v}_i^j$ is the average share of an individual component in the value of property compensation. The first term on the right side is the change of the quantity of capital service and the second term is the change of the quality of the capital service.

The growth rate of the quality of capital was very small in comparison to the growth rate of the quantity of capital. There was no substantial change in the structure of capital in Korea during 1984-2002.

Following Jorgenson, Gollop, and Fraumeni (1987) and Timmer (2000), the aggregate index of capital services over the different types of assets in j-sector ($K_i(t)$) can be assumed as a translog function of the services of individual assets ($\bar{A}_i^j(t)$) as follows:

$$\ln K^j(t) - \ln K^j(t-1) = \sum_i \bar{v}_i^j [\ln \bar{A}_i^j(t) - \ln \bar{A}_i^j(t-1)] \qquad \text{(A.3)}$$

where weights are given by the average shares of each type of capital in the value of property compensation:

$$\bar{v}_i^j = \frac{1}{2}[v_i^j(t) + v_i^j(t-1)] \qquad \text{(A.4)}$$

where $v_i^j(t) = p_i^j(t) K_i^j(t) / \sum_i p_i^j(t) K_i^j(t)$ and $P_i(t)$ is the rental price of capital services from asset type i.

In order to apply the above aggregation formula, it is necessary to impute the rental prices of capital services. In the absence of taxation, Hall and Jorgenson (1967), Jorgenson, Gollop, and Fraumeni (1987) and Jorgenson and Yun (1991) have derived the following formula for imputing the rental price of capital services from asset type i:

$$P_i(t) = \{r(t) + \delta_i - \Pi_i(t)\} q_i(t-1) \qquad \text{(A.5)}$$

where $r(t)$ is the rate of return, $q_i(t)$ is the acquisition price of investment good i with $\Pi_i(t)=[q_i(t)-q_i(t-1)]/q_i(t-1)$ which is the rate of inflation in the price of investment good i. The nominal rate of return after tax is usually assumed to be the same for all assets in an industry so that $r(t)$ does not have subscript i.

The acquisition prices of each asset in different industries are not usually available and, therefore, investment deflators are frequently used as substitutes for the acquisition prices. But investment deflators in *National Accounts* are available either by types of assets or by industries not by both. Estimates of depreciation rates in Pyo (2003) are also available either by types of assets or by industries not by both.

Faced with lack of data and consistent estimates for the variables to impute rental price of capital in each industry, we have adopted the following approach.

In order to get capital input prices different for both each asset i and each industry j, we have slightly changed Eq. (A.5) to Eq. (A.5)′, which is the formula of the capital input price for both each asset i and each industry j:

$$P_j^i(t)=\{r_j(t)+\delta_i-\Pi_i(t)\}q_i(t-1) \tag{A.5$'$}$$

In Eq. (A.5)′ we have assumed that the price of investment asset $i(q_i)$, the rate of depreciation of asset $i(\delta_i)$, and the inflation rate of investment asset $i(\Pi_i)$ are identical across all industries. But we have assumed that the rate of return can be different in each industry.

The application of the Eq. (A.5)′ requires data on the rate of return by industry $j(r_j)$, the acquisition price of investment asset $i(q_i)$, and the rate of depreciation of asset $i(\delta_i)$. Because we do not have data for the nominal rate of return for each industry but for the nominal value of capital services summed over all types of assets in jth industry, we estimated the rate of return for each industry, $r_j(t)$, by using the equality between the nominal capital income in jth industry (CI_j) and nominal value of capital services summed over all types of assets in jth industry ($\sum_i P_i^j(t)\cdot K_i^j(t)$). From this equality we estimated the rate of return for each industry, $r_j(t)$ as follows:

$$\begin{aligned} CI_j(t) &= \sum_i P_i^j(t)\cdot K_i^j(t) \\ &= \sum_i \{r_j(t)+\delta_i-\Pi_i(t)\}q_i(t-1)K_i^j(t) \end{aligned}$$

$$r_j(t)=\frac{CI_j(t)-\sum_i\{\delta_i-\Pi_i(t)\}q_i(t-1)K_i^j(t)}{\sum_i q_i(t-1)K_i^j(t)} \qquad \text{(A.6)}$$

Using these nominal rates of return of each industry ($r_j(t)$), we were able to calculate the rental price of capital services of each asset and industry by adding the depreciation rate and subtracting the inflation rate of capital, and multiplying the result to the price of capital.

C. Measurement of Labor Input

In order to measure labor input for *KLEM* model, we have to obtain both quantity data of labor input such as employment by industries and hours worked and quality factors such as sex, education and age. Both availability and reliability of labor statistics in Korea have improved since 1980. But the measurement of labor input by industries cannot be readily made because the statistics of employment by industries are not detailed enough to cover 32 sectors.

Following the characteristics of labor input described in Kuroda (2001), the sources of labor statistics are presented in Table 4. *Economically Active Population Yearbook* by National Statistical Office reports the number of employment, unemployment, not-economically-active population and economically active population by 10 categories of age group (15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, and 60 over). Employment by industries is available in 9 broad categories of industries: (1) Agriculture, Forestry, and Fishing, (2) Mining, (3) Manufacturing, (4) Construction, (5) Wholesale, Retail, Restaurants, and Hotel, (6) Electricity and Gas, (7) Transportation, Storage, and Communication, (8) Finance, Insurance, Real Estate, and Business Service, and (9) Other Services. More detailed classifications of employment will have to rely on Employment Table, which is published as a supporting table to Input-Output Table. But it is available only every five year when main Input-Output Tables are published. *Mining and Manufacturing Census* (Survey) by National Statistical Office also report employment statistics but it is limited to mining and manufacturing only. Unemployed persons by gender and educational attainment are also available from the same source.

Report on Monthly Labor Survey by Ministry of Labor publishes monthly earnings and working days of regular employees by 12 broad categories of industries. *Survey Report on Wage Structure* by the same ministry reports wages by 6 categories of occupational classification in old series (1980-1992) and now reports 9 new categories in new series (1993-1999): (1) Senior Officials and Managers, (2) Professionals, (3) Technicians, (4) Clerks, (5) Service and Sales Workers, (6) Skilled Agriculture and Fishery Workers, (7) Craftsmen and Assembler, (8) Plant and Machine Operator, and (9) Other Laborer. Nominal and real wage index are also available from *Report on Monthly Labor Survey* by Ministry of Labor.

For the present study, we have obtained the raw data file of *Survey Report on Wage Structure* from the Ministry of Labor and *Economically Active Population Survey* from National Statistical Office for the period of 1984-2002. The data are classified by two types of gender (Male and Female), three types of age (16-34, 35-54, and 55 above), and three types of education (middle school and under, high school, and college and/or above) and, therefore, there is a total of 18 categories of labor.

Since the raw-data file of the *Survey Report on Wage Structure* contains more detailed industrial classification than that of the *Economically Active Population Survey*, we calculated the quantity of labor from the *Economically Active Population Survey* and the quality of labor from the *Survey Report on Wage Structure*. This enables us to include self-employed labor as well as to use more detailed data. However, since the *Survey Report on Wage Structure* does not include the Agriculture and Government sectors, we had to use the average value of the entire economy for the quality measure of these two sectors.

In order to make quality adjustments to the employment data, we have taken the follow steps:

(1) Defining P_{Ll}^{j} as wage rate for j-sector and l-type category of labor, the share of labor income by l-type category of labor in j-sector can be expressed as;

$$v_{Ll}^{j} = \frac{p_{Ll}^{j} L_{l}^{j}}{\Sigma p_{Ll}^{j} L_{l}^{j}} \tag{A.7}$$

The average weight of j-sector and l-type labor income during the period of $(t-1)$ and t can be generated as;

$$\bar{v}_{Ll}^{j} = \frac{1}{2}\left[v_{Ll}^{j}(t) + v_{Ll}^{j}(t-1)\right] \tag{A.8}$$

(2) In order to make a quality adjustment to labor input data, we have further decomposed labor input of j-sector and l-type as follows:

$$L_l^j(t) = d_l^j(t)\, M^j(t)\, H^j(t) \tag{A.9}$$

where d_l^j denotes relative weight of working hours of l-type in j-sector. In other words, $L_l^j(t)$ measures labor input of l-type labor in j-sector. M^j and H^j denote the employment and average working hours of j-sector respectively.

(3) Finally, the growth rate of j-sector labor input has been computed as follows:

$$\begin{aligned}\ln L^j(t) - \ln L^j(t-1) &= [\ln M^j(t) - \ln M^j(t-1)] + [\ln H^j(t) - \ln H^j(t-1)] \\ &\quad + \sum_l \bar{v}_{Ll}^{j}[\ln d^j(t) - \ln d^j(t-1)] \qquad j = 1,\ 2, \cdots,\ 32\end{aligned} \tag{A.10}$$

where the first bracket on the right hand side measures change in employment, the second bracket measures change in average working hours, and the third bracket measures the change in quality of labor through change in weighted working hours.

The average growth rate of the quality of labor is 1.33% and it explains about 42% of the growth rate of labor. It is a relatively high proportion in comparison to the proportion of the quality of capital.

D. Measurement of Energy Input and Material Input

In order to separate energy input from intermediate input, we have decomposed intermediate inputs into two input categories following ICPA criterion. For this purpose, we have used I-O Tables and identified 5 sectors (sector 2, 4, 14, 28, and 29) as energy input sector and the remaining 28 sectors as material input sector.

E. Deflators for Gross Output and Inputs

The 21-sector gross output data by Bank of Korea's national accounts are available only in current prices. For the period after 1985, we have used V-Table in both constant and current prices to generate implicit gross output deflators by sector. For the period before 1985, we have used Linked I-O Table in constant prices to generate implicit gross output deflators by sector for 1985 and interpolated the data for 1984. For the deflators of energy input and material input, we have used the same sources of data; V-Table for the period after 1985 and Linked I-O Table before 1985. The basic characteristics of *KLEM* database in Korea (1984-2002) in 1995 prices is presented in Table 5. During the period of 1984-2002, Korea's gross output has grown at the average annual rate of 7.95 percent. Four inputs have grown at the rate of 9.36% (*K*), 3.15% (*L*), 5.28% (*E*), and 8.47% (*M*), respectively.

F. Input Shares

Regarding shares of inputs, we have used Compensation of Employees in Gross Domestic Product and Factor Income by Kind of Economic Activity in national accounts and Operating Surplus to generate relative share of labor input and capital input respectively in total value-added and then adjusted them into shares in total gross output. We have divided the amount of energy input and material input by gross output to generate shares of energy input and material input respectively.

In the following Appendix Table, we present average growth rates of gross output and four inputs in 1995 constant prices. The gross output of whole industries has grown at an average annual rate of 8.04 percent while capital (*K*), labor (*L*), energy (*E*), and material input (*M*) have grown at the rate of 9.36 percent, 3.15 percent, 6.68 percent, and 8.65 percent respectively during the period. The average estimated shares of four inputs were 0.20 (v_K), 0.20 (v_L), 0.08 (v_E) and 0.52 (v_M), respectively. We have estimated total factor productivity based on both gross output growth accounting and value added growth accounting.

APPENDIX TABLE

KLEM DATA IN KOREA (1984-2002)

(1995 Prices)

Year	Gross Output (bill. Won)	*K* (bill. Won)	*L* (100,000hour)	*E* (bill. Won)	*M* (bill. Won)
1984	320640	273246	41711	28576	145281
1985	339199	301366	43116	24885	158202
1986	384485	331320	43556	29246	179567
1987	439153	366098	47350	34362	207712
1988	486723	408891	48921	38819	230433
1989	514333	460284	49911	42292	244819
1990	569375	523683	50585	27729	296468
1991	622993	599730	51736	31184	324144
1992	657020	677878	52080	33933	343405
1993	696338	755237	52971	37269	362548
1994	754081	838348	54336	41352	392516
1995	829403	930893	56097	48772	430735
1996	905645	1031360	57127	54132	474389
1997	978101	1130389	57246	57184	514881
1998	918702	1208037	52486	70490	457315
1999	1034499	1270100	53264	77940	525203
2000	1162277	1339583	55659	86816	600586
2001	1241612	1427315	56627	90451	628288
2002	1363415	1530471	58221	95153	689711
growth (%)	8.04	9.36	3.15	6.68	8.65

Notes: 1) Capital (*K*) and labor (*L*) are the values without quality.
2) The growth rates are the average growth rates.
3) The growth rates of capital and labor include both growth rates of quantity and quality.

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