No. **653**

Measuring Distortion in Capital Allocation
- The Case of Heavy and Chemical Industries in Korea -

by

Atsuko Ueda

December 1995

Measuring Distortion in Capital Allocation
- The Case of Heavy and Chemical Industries in Korea -

Atsuko Ueda*

University of Tsukuba
Institute of Socio-Economic Planning
1-1-1 Tennodai, Tsukuba, Ibaraki 305, Japan
(email: ueda@shako.sk.tsukuba.ac.jp)

November, 1995

Abstract

This paper investigates whether or not capital allocation was distorted in favor of the heavy and chemical industries in the manufacturing sector in Korea during 1970-1990. Expected marginal products of capital are compared by estimating production functions of each industry. According to the test results, there was overinvestment in basic metal industries and machinery industries in the 1970s, while there was underinvestment in chemical industries at least in the 1970s. The result suggests that more capital was allocated toward industries whose TFP growth rates were high, and toward producer goods industry than consumer goods industry. Distortion in capital allocation becomes smaller in the 1980s, however.
JEL Code: C1,C5,O16

I thank to Seki Asano, Ian Coxhead, Steven Durlauf, Moto Fukushige, Blake LeBaron, Rodolfo Manuelli, and John Rust for helpfull comments and suggestions. The research is partly supported by the David Granick Area Studies Award.

1. Introduction

Government interventions in Korea has been widely recognized as well as its remarkably high economic performance. Economists studying the Korean economy have argued that selective industrial policy has played an important role in promoting industrialization (e.g., Amsden, 1989; Jones and Sakong, 1980; Wade, 1990; Pack and Westphal, 1986; World Bank, 1992). In particular, it is commonly believed that the government controlled over capital allocation by giving priority to selected industries.

Controls over capital allocation by the government has been explained on the grounds of imperfect financial market. In Korea, firms have depended heavily on credit which has been strictly regulated and controlled by the government. Between 1963-1974, corporate finance in Korea came from internal savings (19.9%), new equity (13.7%), and debt (66.4%) including debt from commercial and special banks (34.9%) that had been publicly owned until the early 1980s, and from foreign loans (19.0%) which required government approval and guarantee (Jones and Sakong, 1980). Liberalization of financial market that began in the 1980s is yet in process in Korea.

In spite of rich circumstantial evidences, however, little effort has been made to evaluate the impact of selective intervention on capital allocation quantitatively. Westphal and Kim (1977) contribute to estimating incentive rates in Korea by industry type in terms of international trade. Based on this work, Westphal (1990) argues that export incentives were given almost uniformly across all industries, but that target industries were strongly promoted by controls over the allocation of investment finance. However, the empirical study is mainly limited to the year 1968, and, as Westphal (1990) himself noted, neither includes government's direct controls over capital allocation nor investigates the response of capital allocation to incentives.

This paper investigates whether or not capital allocation has been distorted to promote the heavy and chemical industries during 1970-1990, because the Heavy and Chemical Industries (HCI) Program launched in 1973 (when light industries are yet the main source of export) is one of the most famous selective industrial policies. Borrowing heavily from abroad including the World Bank, the government push heavy and chemical industries. To promote steel industry, for example, the government founded POSCO (Pohang Iron and Steel Corporation) as a public enterprise, with getting technical support from Japan. In the early 1980s, heavy industries surpassed light industries in export value; POSCO is now one of the lowest-cost steel makers in the world (World Bank, 1992), Hyundai is successfully exporting automobiles, and Korean made electrical machinery is flooding in the world market. If the government controlled over capital allocation to promote heavy and chemical industries beyond simply correcting market failure, then capital allocation should be distorted in favor of these industries.

The test result found that there was preferential capital allocation toward basic metal industries and machinery industries in the 1970s, but that there was underinvestment in chemical industries at least in the 1970s and possibly in the 1980s. The finding of the test result indicates that more capital was allocated toward basic metals and machinery industries whose TFP (total factor productivity) growth rates were the highest in the manufacturing sector, and less toward chemical industries whose TFP growth was the lowest. This result is unchanged when tax incentive in favor of basic metal industries are considered. The detail level analysis suggests that more capital was allocated toward producer goods industry than consumer goods industry in heavy and chemical industries. Distortion in capital allocation becomes smaller in the 1980s, however.

The plan of the rest of this paper is as follows. Section 2 develops an empirical model and a test method. Sections 3 reports the test result of capital allocation by industry at a moderately aggregate level, and Section 4 further investigates effects of taxation, and capital allocation behavior at a more detailed industry level. Section 5 gives concluding remarks.

2. Methodology

2.1. The Model and Assumptions

Suppose that a representative firm in sector i produces output Y_t^i with capital input K_t^i and labor input L_t^i at time t. The production technology is

$$Y_t^i = A_t^i \cdot \theta_t^i \cdot F(K_t^i, L_t^i; \underline{\beta}^i) \tag{2.1}$$

where A_t^i is the total factor productivity, θ_t^i is a stochastic shock on production, $F(K_t^i, L_t^i; \underline{\beta}^i)$ is a CRS (constant-returns-to-scale) function, and $\underline{\beta}^i$ is a set of parameters.

Without distortion of capital allocation, investment should be made so as to equate expected marginal products of capital (MPK) across industries. Therefore,

$$E_t[MPK^i_{t+1}] = E_t[MPK^j_{t+1}] \tag{2.2}$$

for all industries i and j $(i \neq j)$ where

$$MPK^i_{t+1} = \frac{\partial Y^i_{t+1}}{\partial K^i_{t+1}}$$

Before developing a test method, I impose a few assumptions for the expectation scheme. First, assume that a stochastic process $\{\theta_t\}$ follows either

(i) $\ln\theta^i_t \equiv \epsilon^i_t \sim$ i.i.d. N(0,σ^2_i) and people do not know ε^i_{t+1} at time t (i.i.d. assumption)

or

(ii) $\ln\theta^i_{t+1} = \rho^i \ln\theta^i_t + \eta^i_{t+1}$, $(0 < \rho^i < 1)$, $\eta^i_t \sim$ i.i.d. N(0,ω^2_i), and η^i_{t+1} is not known at time t (AR(1) assumption) in case that autocorrelation is observed in the sequence of $\{\ln\theta_t\}$.

Secondly, one period ahead of TFP:A_{t+1} is assumed to be known. (Superscript i is omitted for simplicity unless otherwise required.) This is not too unrealistic assumption considering the industrialization experience in Korea, since productivity growth may be well predicted by planned new infrastructure and/or newly imported technology which is already available in advanced countries. Now, TFP growth rates are calculated by

$$TFPG = \frac{dY}{Y} - (1-w)\frac{dK}{K} - w\frac{dL}{L} \tag{2.3}$$

where w is the ratio of wages to value added. Thus TFP can be calculated given initial TFP: $A_1 = 1.0$. As an alternative to relax the above assumption, growth rate of TFP: r may be assumed to be constant over time to smooth out the productivity change, i.e.,

$$A_{t+1} = e^r A_t = e^{r \cdot t}$$

Finally, labor input L_{t+1} is assumed to be known at time t in order to focus on investment behavior.

2.2. Test Method

To test the null hypothesis (2.2) that expected MPK is equated among industries, the production technology (2.1) is estimated at first. Then, estimates of parameters are used to test the hypothesis.

2.2.1. Estimate production functions

Assuming A_{t+1} is known at time t, estimation of production technology is straightforward. Using a sequence $\{Y_t/A_t, K_t, L_t\}$ with calculated TFP, take the logarithm of the production technology

$$\ln(Y_t/A_t) = \ln F(K_t, L_t; \underline{\beta}) + \epsilon_t \tag{2.4}$$

where ϵ_t follows either i.i.d. or an AR(1) process. Alternatively, assuming a constant TFP growth rate, the production technology is

$$\ln Y_t = r \cdot t + \ln F(K_t, L_t; \underline{\beta}) + \epsilon_t \tag{2.5}$$

The CRS function $F(K, L; \underline{\beta})$ is parameterized as the Cobb-Douglas production function, and alternatively, the Translog production function[1]. In addition to the Cobb-Douglas from, an alternative form is tested because the first derivative of capital could be varied by a choice of parametric form. The Cobb-Douglas form in the logarithm is parameterized as

$$\ln(F(K, L; \underline{\beta})/L) = \beta_1 + \beta_2 \ln(K/L) \tag{2.6}$$

and the Translog form is

$$\ln(F(K, L; \underline{\beta})/L) = \beta_1 + \beta_2 \ln(K/L) + \beta_3(\ln K \ln L - \frac{1}{2}(\ln K)^2 - \frac{1}{2}(\ln L)^2) \tag{2.7}$$

with CRS restriction. Because stochastic shocks may be correlated across industries (i.e., $\mathrm{E}[\epsilon_t^i \epsilon_t^j] \neq 0$ or $\mathrm{E}[\eta_t^i \eta_t^j] \neq 0$), SUR (seemingly unrelated regression) estimation is applied. EGLS estimation follows Judge et al. (1985), Chapter 12.

---

[1] Since the Cobb-Douglas function fixes the elasticity of substitution at unity, a flexible form such as the CES function is more preferable. However, nonlinear estimation of the CES function often resulted in convergence failure using the Korean data. The Translog form that is estimated by linear regression in the logarithm is employed as an alternative.

2.2.2. Test the hypothesis

The i.i.d. case Expected MPK is

$$E_t[\ MPK_{t+1}\ ] = E_t[\ \theta_{t+1}]A_{t+1}F_K(K_{t+1}, L_{t+1}; \underline{\beta}) \tag{2.8}$$

where F_K is the partial derivative of F(K,L) with respect to K. With the i.i.d. assumption, (2.8) is

$$\mu_{t+1} \equiv E[e^{\epsilon}]A_{t+1}F_K(K_{t+1}, L_{t+1}; \underline{\beta}) \tag{2.9}$$

where $E[e^{\epsilon}] = \frac{1}{2}\sigma^2$. The hypothesis to be tested is, in the logarithm,

$$\ln \mu^i_{t+1} - \ln \mu^j_{t+1} = 0 \tag{2.10}$$

Now

$$\ln \hat{\mu}^i_{t+1} - \ln \hat{\mu}^j_{t+1} = H_{t+1}(\widehat{\underline{\beta}}^i) - H_{t+1}(\widehat{\underline{\beta}}^j) + \frac{1}{2}(\hat{\sigma}^2_i - \hat{\sigma}^2_j) \tag{2.11}$$

where $H_{t+1}(\underline{\beta}) = \ln F_K(K_{t+1}, L_{t+1}; \underline{\beta}) + \ln A_{t+1}$. Asymptotic variance of (2.11) is

$$V \equiv D\widehat{\Sigma}^{ij}_{\beta}D' + \frac{2}{M(T-l)}(\hat{\sigma}^2_i - \hat{\sigma}^2_j)^2 \tag{2.12}$$

by the Delta method, where D is a $(1 \times 2l)$ vector

$$\begin{aligned} D &= \begin{bmatrix} D_i \\ -D_j \end{bmatrix} \\ D_i &= \frac{\partial H_{t+1}(\underline{\beta}^i)}{\partial \underline{\beta}^i}\Big|_{\underline{\beta}^i = \hat{\underline{\beta}}^i} \end{aligned}$$

$\widehat{\Sigma}^{ij}_{\beta}$ is the covariance matrix of $\underline{\beta}^i$ and $\underline{\beta}^i$ from SUR estimation, M is the number of equations in SUR estimation, T is the sample number, and l is the number of parameters in each equation. Hence, an asymptotic confidence interval of expected MPK is derived by

$$\exp[\ \ln \hat{\mu}^i_{t+1} - \ln \hat{\mu}^j_{t+1} \pm c_{\alpha}\sqrt{V}\ ]$$

where c_{α} is a critical value.

An addition of r (TFP growth rate) is straightforward. A replacement of $\ln A_{t+1}$ by rt in $H_{t+1}(\underline{\beta})$ gives an estimate of $\ln \mu_{t+1}$ and an addition of r to $\underline{\beta}$ gives asymptotic variance V.

The AR(1) case Assume $\ln\theta_t = \rho\ln\theta_{t-1} + \eta_t,\ \eta_t \sim i.i.d.N(0, \omega^2)$. Then, $E_t[MPK_{t+1}]$ is

$$\mu_{t+1} \equiv E[e^{\eta}]\theta_t^{\rho} A_{t+1} F_K(K_{t+1}, L_{t+1}; \underline{\beta}) \tag{2.13}$$

and

$$\ln\hat{\mu}_{t+1}^i - \ln\hat{\mu}_{t+1}^j = H_{t+1}(\underline{\widehat{\beta}^i}, \widehat{\rho}^i) - H_{t+1}(\underline{\widehat{\beta}^j}, \widehat{\rho}^j) + \frac{1}{2}(\widehat{\omega}_i{}^2 - \widehat{\omega}_j{}^2) \tag{2.14}$$

where $H_{t+1}(\underline{\beta}, \rho) = \ln F_K(K_{t+1}, L_{t+1}; \underline{\beta}) + \rho\{\ln(Y_t/A_t) - \ln F(K_t, L_t; \underline{\beta})\} + \ln A_{t+1}$. Asymptotic variance is

$$V = D\widehat{\Sigma}_{\beta,\rho}^{ij} D' + \frac{2}{M(T-l)}(\hat{\omega}_i^2 - \hat{\omega}_j^2)^2 \tag{2.15}$$

where D is a $(1 \times 2l)$ vector

$$\begin{aligned} D &= \begin{bmatrix} D_i \\ -D_j \end{bmatrix} \\ D_i &= \begin{bmatrix} \frac{\partial H_{t+1}(\underline{\beta}^i, \rho^i)}{\partial \underline{\beta}^i}\Big|_{\underline{\beta}^i = \underline{\hat{\beta}}^i, \rho^i = \hat{\rho}^i} \\ \frac{\partial H_{t+1}(\underline{\beta}^i, \rho^i)}{\partial \rho^i}\Big|_{\underline{\beta}^i = \underline{\hat{\beta}}^i, \rho^i = \hat{\rho}^i} \end{bmatrix} \end{aligned}$$

The rest follows the i.i.d. case. Also, TFP may be smoothed out by using a constant growth rate r.

2.3. Data

The data used in the estimation are annual data of the manufacturing sector at the 2-digit level by 9 industries during the period 1970-1990, and at the 3-digit level by 28 industries during the period 1968-1989 for the detail level analysis. Estimated real gross capital stock is obtained from Pyo (1992) (K_t in 1970 is the capital stock at the end of 1969, for example). Value added and indirect tax at the 2-digit level are obtained from the Bank of Korea, *National Accounts 1990* for 1970-88 and *Economic Statistics Yearbook, various years* for 1989-90. Value added at the 3-digit level, labor, and compensation to employee (w to calculate TFP) are obtained from manufacturing surveys (Economic Planning Board, *Report on Industrial Census, various years, Report on Mining and Manufacturing Census, various years;* Korea Statistical Association, *Report on Mining and Manufacturing Survey, various years).* These manufacturing surveys are limited to establishments

Table 2.1: Annual Average Growth Rates by Industry

(%)

	Value Added		Capital Stock		TFP	
	1970-79	1980-90	1970-79	1980-90	1970-79	1980-90
Manufacturing	15.3	12.3	17.6	12.8	.0	1.9
Chemicals	13.6	12.0	14.4	15.0	-0.3	1.0
Basic Metals	37.6	12.8	28.2	10.4	7.6	3.6
Machinery	28.4	17.4	24.9	15.8	6.0	4.2

with 5 or more persons engaged, but are considered the best available source as proxies of value added at the detailed level and labor input.

From 1970 to 1990, basic metal industries expanded its share in value added from 1.4% to 7.8%, and from 15.9% to 36.2% for machinery industries, while chemical industries shrink its share from 18.2% to 17.8%. Table 2.1 compares annual average growth rates of value added, capital stock, and total factor productivity (TFP) during 1970-1979 and 1980-1990 (the period 1979-80 is excluded because of a big drop in production). Basic metal industries and machinery industries show high performance in TFP growth; these industries also report the highest growth rates of capital accumulation of the 9 industries. Comparing basic metals and machinery, all of value added, capital stock, and TFP in basic metals grew more rapidly than machinery in the 1970s, and vice versa in the 1980s. By contrast, chemical industries report the lowest TFP growth of the 9 industries, and lower growth rates than average in value added.

2.4. Monte Carlo Experiments

To estimate the first derivative of an original function $F(K, L; \underline{\beta})$, the test applies the Delta method based on asymptotic theory. However, the number of observations in the available data is quite limited. Therefore, before presenting the test result, I provide Monte Carlo experiments to check if the developed method is applicable to analyze the problem with small samples.

Assuming a "true" parameter set $\underline{\beta}$, $\underline{\hat{\beta}}$ is estimated by generating a sequence {Y,K,L} where $\ln Y = \ln F(K, L; \underline{\beta}) + \epsilon$ with randomly generated ϵ which follows either i.i.d. or AR(1). K and L are randomly drawn from the uniform distribution, and a combination (K, L) is created as a sorted

Table 2.2: Monte Carlo Experiments on Different Sample Number

	rejection %		
	Cobb-Douglas (i.i.d.)		
	n = 20	n = 30	n = 50
lower 2.5%	2.470	2.400	2.732
upper 2.5%	2.600	2.017	1.912

Table 2.3: Monte Carlo Experiments on Different Parameters

	rejection %			
	Cobb-Douglas (i.i.d.)			
β_2	0.5	0.3	0.7	0.5
σ	0.01	0.01	0.01	0.04
lower 2.5%	2.470	2.395	2.465	2.560
upper 2.5%	2.600	2.350	2.425	2.110

sequence (that is, the smallest K is matched with the smallest L). Then an asymptotic confidence interval is checked to see whether or not it includes true expected MPK at every point t. This test is repeated by 1,000 times. Therefore, confidence intervals are tested 20,000 times with the i.i.d. assumption with the sample number 20, for example. Parameters for the Cobb-Douglas form (2.6): $\{\beta_1, \beta_2, \sigma\}$ are $\{0, 0.5, 0.01\}$, and for the Translog form (2.7): $\{\beta_1, \beta_2, \beta_3, \sigma\}$ are $\{0, 0.5, 0.05, 0.01\}$ and $\rho = 0.8$ in the AR(1) case in experiments, unless otherwise mentioned.

Table 2.2 reports the result of Monte Carlo experiments on different sample number: $n = 20$, 30, and 50. Each experiment expects 2.5% rejection both at the lower and upper levels. Every case seems to construct a 95% confidence interval pretty well; the $n = 20$ case does not necessarily report a bad result comparing to the $n = 50$ case. Note that rejection rates varied 2-3% for 2.5% depending on the number of experiment over the range of 500-3000.

Table 2.3 reports the result of Monte Carlo experiments on different parameters with the sample number equalling 20. The experiments indicate that test result is robust in changing parameters of the production technology.

Finally, Table 2.4 reports the result of Monte Carlo experiments on different assumptions. Each

Table 2.4: Monte Carlo Experiments on Production Function

rejection %

True Model		Model used in the test							
		Cobb-Douglas				Translog			
		i.i.d.		AR(1)		i.i.d.		AR(1)	
		5%	1%	5%	1%	5%	1%	5%	1%
C-D,i.i.d.	lower	2.470	0.275	4.126	1.195	2.335	0.560	4.119	1.048
	upper	2.600	0.335	4.095	1.221	2.445	0.345	3.865	1.048
C-D, AR(1)	lower	12.668	6.589	5.489	2.684	12.553	7.000	7.498	4.029
	upper	13.053	6.821	5.321	2.521	11.005	5.174	5.833	2.256
TL, i.i.d.	lower	29.920	25.210	20.858	14.953	2.325	0.560	4.129	1.055
	upper	34.840	29.880	25.037	18.526	2.445	0.360	3.885	1.055
TL, AR(1)	lower	29.137	25.042	20.616	14.663	12.626	7.074	7.498	4.087
	upper	34.063	28.521	22.247	16.032	11.063	5.205	5.907	2.288
CES(-1.0),i.i.d.	lower	39.205	36.620	35.784	31.784	8.430	4.849	5.842	2.131
	upper	44.690	41.490	38.616	33.700	6.269	2.925	5.402	2.171
CES(-0.2),i.i.d.	lower	29.855	25.150	20.826	14.921	2.355	0.630	4.140	1.034
	upper	34.825	29.840	25.037	18.516	2.440	0.440	3.890	1.060
CES(0.01),i.i.d.	lower	5.140	1.620	4.784	1.589	2.345	0.560	4.119	1.048
	upper	3.120	0.680	3.942	1.289	2.445	0.345	3.865	1.048
CES(0.2),i.i.d.	lower	34.230	29.545	24.074	18.942	2.320	0.545	4.101	1.067
	upper	29.730	24.595	19.605	13.526	2.380	0.380	3.784	1.036
CES(-0.2),AR(1)	lower	29.089	25.011	20.574	14.616	12.626	7.058	7.418	4.066
	upper	34.032	28.468	22.247	16.005	11.116	5.226	5.902	2.246

row indicates the true data generating process (DGP), and each column indicates assumptions used in the test.

The developed test method shows good performance when the Cobb-Douglas function represents the true technology with i.i.d. stochastic shocks, by using either the Cobb-Douglas function or the Translog function with correctly assuming that stochastic shocks are i.i.d., and when the Translog form represents true technology with i.i.d. shocks by correctly assuming the Translog form with i.i.d. stochastic shocks in the test. However, when the Translog form represents the true technology, tests using the Cobb-Douglas form reject more than 40% of true values.

A caution should be given when stochastic shocks have autocorrelation. Even with correct specification, the test rejects true values more frequently than desired levels both in the Cobb-Douglas case and the Translog case. At the 1% level, 5-6% may be rejected in the AR(1) case.

Finally, to check the robustness of using the Cobb-Douglas form and the Translog form, tests are done when the CES function

$$Y = (aK^{\gamma} + bL^{\gamma})^{1/\gamma}$$

represents true technology with $\{a, b\} = \{0.5, 0.5\}$ and a value of γ (< 1.0) indicated in parenthesis in the table. Unless the CES function is very close to the Cobb-Douglas form ($\gamma = 0.01$ in the table), test results using the Cobb-Douglas function quickly deteriorates. By contrast, tests using the Translog form seem to yield better results in testing the CES-type DGP with moderately wider range of γ.

Overall, the MPK test is useful to test expected MPK with a sample of 20, although the test may reject true values more frequently in the AR(1) case than desired level. Also, caution must be made when the Cobb-Douglas technology does not represent the true technology.

3. Results

The hypothesis to be tested is that expected MPK of each industry is equated to expected MPK of the manufacturing sector (henceforth "manufacturing"). Expected MPK should be compared between all i and j industries ($i \neq j$, $i,j = 1,\ldots,9$), but I conventionally employ the above method, because expected MPK of each industry must be equated to that of "manufacturing" if expected MPK is equated to each other. Because LM (Lagrange Multiplier) test proposed by Breusch and Pagan (1980) strongly rejects the hypothesis that a covariance matrix of residuals is diagonal, chemicals, basic metals, machinery and manufacturing are estimated by SUR; therefore, the number of equation in SUR: M equals 4 at the 2-digit level.

Table 3.1 reports estimation result of the production technology leaving out calculated TFP. While R^2 is quite high, the Durbin-Watson statistic by linear regression is low enough to doubt autocorrelation[2]. With the AR(1) assumption, the Durbin-Watson statistic seems to be in a reasonable range assuming either the Cobb-Douglas function or the Translog function. Puzzling is that the production technology of basic metal industries seems to be almost linear in capital stock; also, other estimates of the coefficient on capital (β_2) seem also considerably high.

---

[2] The Jarque-Bera Normality test does not reject normality at the 5% level in all cases.

Table 3.1: Estimation of Production Function with calculated TFP

standard error in ( )

	Chemicals	Basic Metals	Machinery	Manufacturing
Cobb-Douglas, i.i.d.				
R^2	0.985			
D-W	0.490	0.513	0.514	0.460
β_1	0.158	-2.547	-0.070	0.881
	(0.058)	(0.128)	(0.070)	(0.078)
β_2	0.866	1.028	0.702	0.732
	(0.014)	(0.031)	(0.015)	(0.013)
Cobb-Douglas, AR(1)				
D-W	1.483	1.596	1.605	1.701
β_1	0.160	-2.439	-0.078	0.746
	(0.091)	(0.205)	(0.112)	(0.128)
β_2	0.863	0.998	0.699	0.754
	(0.021)	(0.051)	(0.024)	(0.021)
ρ	0.774	0.758	0.732	0.844
	(0.152)	(0.155)	(0.143)	(0.127)
Translog, i.i.d.				
R^2	0.990			
D-W	0.605	0.800	0.526	0.564
β_1	-1.344	-3.511	-0.526	-0.561
	(0.477)	(0.467)	(0.410)	(0.632)
β_2	1.600	1.590	0.911	1.224
	(0.230)	(0.263)	(0.182)	(0.221)
β_3	0.177	0.155	0.046	0.083
	(0.055)	(0.071)	(0.039)	(0.035)
Translog, AR(1)				
D-W	1.087	1.549	1.694	1.502
β_1	-2.990	-2.607	-1.051	-0.275
	(0.542)	(0.416)	(0.401)	(0.601)
β_2	2.333	1.072	1.139	1.106
	(0.265)	(0.242)	(0.185)	(0.200)
β_3	0.339	0.015	0.096	0.060
	(0.064)	(0.068)	(0.041)	(0.033)
ρ	0.822	0.740	0.778	0.806
	(0.099)	(0.161)	(0.150)	(0.136)

Table 3.2: Estimation of Production Function with smoothed TFP growth

standard error in ( )

	Chemicals	Basic Metals	Machinery	Manufacturing
r	-0.007	0.045	0.044	0.001
Cobb-Douglas,i.i.d.				
R^2	0.887			
D-W	0.573	1.485	0.669	0.610
β_1	0.248	-1.944	0.037	1.229
	(0.273)	(0.209)	(0.160)	(0.208)
β_2	0.824	0.916	0.676	0.662
	(0.064)	(0.052)	(0.034)	(0.034)
Cobb-Douglas,AR(1)				
D-W	1.481	1.896	1.911	1.650
β_1	0.019	-2.076	0.028	1.018
	(0.399)	(0.205)	(0.219)	(0.267)
β_2	0.876	0.947	0.678	0.698
	(0.094)	(0.051)	(0.046)	(0.043)
ρ	0.731	0.194	0.647	0.741
	(0.155)	(0.220)	(0.169)	(0.160)
Translog,AR(1)				
D-W	1.550	2.050	1.879	1.751
β_1	4.601	-4.021	-0.335	5.038
	(2.661)	(0.629)	(0.807)	(1.566)
β_2	-1.353	2.077	0.830	-0.651
	(1.291)	(0.351)	(0.365)	(0.522)
β_3	-0.531	0.309	0.032	-0.223
	(0.308)	(0.095)	(0.080)	(0.086)
ρ	0.688	-0.068	0.647	0.647
	(0.168)	(0.230)	(0.173)	(0.171)

By smoothing TFP with a constant growth rate, SUR estimations are done by fixing r at the annual average TFP growth rate, because $\hat{r}$ estimated at once in SUR are unreliably higher value than expected. This conventional method may still be useful to relax the strong assumption to use calculated TFP as described before. Instead of relaxing the strong assumption, however, this model postulates that people do not realize the change of TFP growth rates in 20 years as indicated in Table 2.1. Also, Table 3.2 omits the estimation result of the Translog form with the i.i.d. assumption because of unreliable estimates in which part of MPK of manufacturing is negative.

The test results are reported by either "HH" (the hypothesis that expected MPK is equated is rejected at the 1% level, and expected MPK is higher than manufacturing),"H" (at the 5% level), "LL" (the hypothesis is rejected at the 1% level and lower than manufacturing), "L" (at the 5% level) or "-" (the hypothesis is not rejected). In other words, "HH" and "H" indicate underinvestment comparing to the average of the manufacturing sector, and "LL" and "L" indicate overinvestment.

Table 3.3 reports the test result using calculated TFP. Chemicals report underinvestment throughout the period between 1970-1990 assuming the Cobb-Douglas form, and the Translog form with the i.i.d. assumption. Assuming the Translog production function with AR(1), the result is weaker; yet underinvestment is reported throughout the 1970s.

By contrast, basic metals report overinvestment throughout the 1970s with any assumption. Machinery reports overinvestment up to 1978 in the strongest case, but only in 1972 and 1973 assuming the Translog with AR(1) at the 1% level, which is almost equivalent to the 5% level by the Monte Carlo experiment.

Table 3.4 reports the test result by smoothing TFP growth over time. The result looks similar to the previous one with calculated TFP, but weaker in telling overinvestment or underinvestment.

Figures 3.1 and 3.2 illustrate the change of estimates of expected MPK over time. Using calculated TFP, Figure 3.1 shows similar movement of expected MPK with any combination of functions and stochastic shocks. While chemicals keep higher levels throughout the period, basic metals and machinery tend to keep lower levels. However, expected MPK seems to be converging

Table 3.3: Test Result with calculated TFP

	Chemicals				Basic Metals				Machinery			
	C-D		TL		C-D		TL		C-D		TL	
year	iid	AR	iid	AR	iid	AR	iid	AR	iid	AR	iid	AR
70	HH		HH		LL		LL		LL		LL	
71	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	L
72	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	LL
73	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	LL
74	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	-
75	HH	HH	HH	HH	LL	LL	LL	LL	LL	L	L	-
76	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	L
77	HH	HH	HH	HH	LL	LL	LL	LL	LL	L	L	-
78	HH	HH	HH	HH	LL	LL	LL	LL	LL	-	-	-
79	HH	HH	HH	HH	LL	L	LL	LL	-	-	-	-
80	HH	HH	HH	H	L	-	-	-	-	-	-	-
81	HH	HH	HH	HH	-	-	-	-	-	-	-	-
82	HH	H	HH	H	-	-	-	-	-	-	-	-
83	HH	HH	HH	-	-	-	-	-	-	-	-	-
84	HH	HH	HH	-	-	-	-	-	-	-	-	-
85	HH	HH	H	-	-	-	-	-	-	-	-	-
86	HH	HH	HH	-	-	-	-	-	-	-	-	-
87	HH	HH	H	-	-	-	-	-	-	-	-	-
88	HH	HH	H	-	-	-	-	-	-	-	-	-
89	HH	HH	H	-	-	-	-	-	-	-	-	-
90	HH	HH	H	-	-	-	-	-	-	-	-	-

C-D: Cobb-Douglas, TL: Translog, AR:AR(1)

Table 3.4: Test Result with smoothed TFP growth

	Chemicals			Basic Metals			Machinery		
	CD		TL	CD		TL	CD		TL
year	iid	AR	AR	iid	AR	AR	iid	AR	AR
70	HH			LL			LL		
71	HH	HH	-	LL	LL	-	LL	LL	-
72	HH	H	-	LL	LL	-	LL	LL	-
73	HH	H	-	LL	LL	-	LL	LL	-
74	HH	H	-	LL	L	-	LL	LL	-
75	HH	H	-	LL	-	-	LL	L	-
76	HH	-	-	LL	LL	-	LL	L	-
77	HH	H	-	LL	LL	-	L	-	-
78	HH	H	-	L	L	-	-	-	-
79	HH	H	-	-	L	L	-	-	-
80	HH	-	H	-	-	-	-	-	-
81	HH	H	HH	-	-	-	-	-	-
82	HH	-	-	-	-	-	-	-	-
83	HH	-	-	-	-	-	-	-	-
84	HH	-	-	-	-	-	-	-	-
85	H	-	-	-	-	-	-	-	-
86	H	-	-	-	-	-	-	-	-
87	H	H	H	-	-	-	-	-	-
88	H	H	H	-	-	-	-	-	-
89	H	H	H	-	-	-	-	-	-
90	H	H	H	-	-	-	-	-	-

CD:Cobb-Douglas, TL:Translog, AR:AR(1)

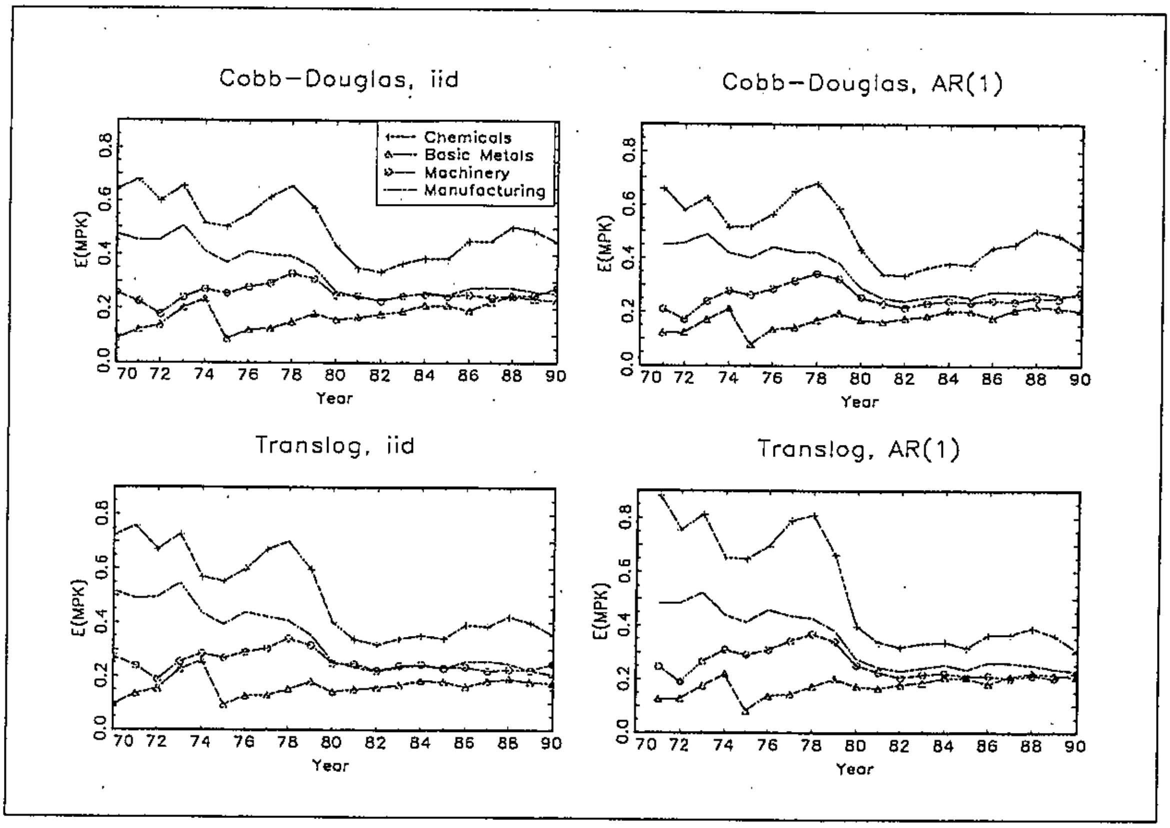


Figure 3.1: Expected MPK (with calculated TFP)

over time; in particular, machinery almost keeps the same level as manufacturing in the 1980s. By smoothing TFP growth, Figure 3.2 illustrates different movement of expected MPK; especially, the Translog case with AR(1) does not show convergence over time. However, both figures similarly illustrate higher expected MPK of chemicals, lower expected MPK of basic metals, and a little lower expected MPK of machinery than manufacturing.

The test result on basic metals and machinery (particularly on basic metals) is consistent with the view that the heavy and chemical industries received preferential capital allocation in the 1970s, while the result for chemicals does not support this view. The test result is rather consistent with the view that capital is more allocated toward potential industries in the sense of technological advancement, because basic metals and machinery recorded the highest TFP growth rates of the manufacturing sector, while chemicals recorded the lowest growth.

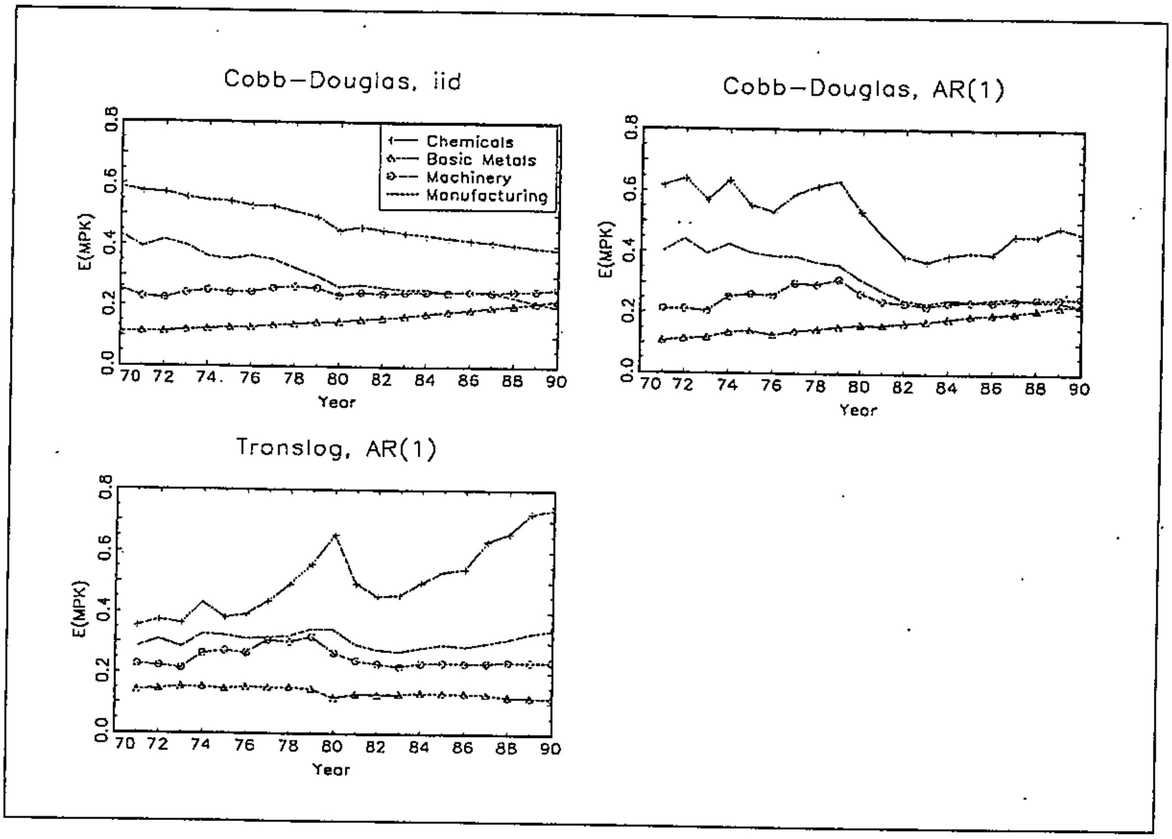


Figure 3.2: Expected MPK (with smoothed TFP growth)

Table 4.1: Average Tax Rate of the Manufacturing, 1970-1990

Chemicals	Basic Metals	Machinery	Manufacturing
18.5%	3.4%	14.7%	18.6%

4. Further Investigations[3]

4.1. Taxation

It is not easy, or even impossible, to identify the cause of distortions in capital allocation. There could be various kinds of incentive policies in addition to direct controls over capital allocation to cause distortion. Moreover, such policies are very likely to be implemented at the same time to promote targeted industries. It is possible, however, to eliminate effects of taxation and subsidy incentives differentiated by industry from the test. In order to focus on the control over capital, the test is performed by using after tax expected MPK.

I assume that people know the tax rate for next year. This is not an unrealistic assumption because tax rates have been quite stable during 1970-1990. Even if a tax rate changes, the change may be anticipated in advance of the investment decision.

Table 4.1 compares average (indirect) net tax rates (tax minus subsidy) to the values added during 1970-1990. The net tax rate of basic metals is the lowest (3.4%) of the 9 industries, while net tax rates of machinery and chemicals were the second and third highest (food including tobacco raises the average tax rate of manufacturing). Obviously, basic metals benefit from low tax rates while machinery and chemicals do not.

Tables 4.2 reports the test result of tax adjusted case. The test result is mostly the same as the previous result. Basic metals seem to enjoy preferential capital allocation at least up to the early 1980s, and so does machinery until 1977, beyond tax incentive. Chemicals suffer from underinvestment as reported in the previous tests. From this result, tax incentive alone does not seem to suffice to explain capital allocation distortion.

---

[3] In this section, reported results use calculated TFP.

Table 4.2: Test Result with Taxation

	Chemicals				Basic Metals				Machinery			
	CD		TL		CD		TL		CD		TL	
	iid	AR	iid	AR	iid	AR	iid	AR	iid	AR	iid	AR
70	HH		HH		LL		LL		LL		LL	
71	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	L
72	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	LL
73	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	LL
74	HH	HH	HH	HH	LL	LL	L	LL	LL	L	L	-
75	HH	HH	HH	HH	LL	LL	LL	LL	LL	L	L	-
76	HH	HH	HH	HH	LL	LL	LL	LL	LL	L	L	L
77	HH	HH	HH	HH	LL	LL	LL	LL	LL	-	L	-
78	HH	HH	HH	HH	LL	LL	LL	LL	-	-	-	-
79	HH	HH	HH	HH	LL	L	LL	LL	-	-	-	-
80	HH	HH	HH	H	L	-	-	-	-	-	-	-
81	HH	HH	HH	HH	-	-	-	-	-	-	-	-
82	HH	HH	HH	H	-	-	-	-	-	-	-	-
83	HH	HH	HH	-	-	-	-	-	-	-	-	-
84	HH	HH	H	-	-	-	-	-	-	-	-	-
85	HH	HH	HH	-	-	-	-	-	-	-	-	-
86	HH	HH	H	-	-	-	-	-	-	-	-	-
87	HH	HH	H	-	-	-	-	-	-	-	-	-
88	HH	HH	H	-	-	-	-	-	-	-	-	-
89	HH	HH	H	-	-	-	-	-	-	-	-	-
90	HH	HH	-	-	-	-	-	-	-	-	-	-

CD: Cobb-Douglas, TL: Translog, A:AR(1)

Table 4.3: Test Result at the detail level

	Industrial Chemicals				Chemical Products				Iron and Steel				Non-ferrous Metals			
	C-D		TL		C-D		TL		C-D		TL		C-D		TL	
	i	A	i	A	i	A	i	A	i	A	i	A	i	A	i	A
68	-		-		HH		HH		LL		LL		-		-	
69	-	-	-	-	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	LL
70	HH	HH	HH	-	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	LL
71	-	-	-	-	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	LL
72	-	-	-	-	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	LL
73	-	-	-	-	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	LL
74	-	LL	-	-	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	LL
75	LL	LL	L	LL	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	LL
76	LL	LL	LL	LL	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	LL
77	-	-	-	-	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	LL
78	H	H	HH	H	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	LL
79	-	-	-	-	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	LL
80	LL	L	-	-	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	LL
81	LL	LL	LL	LL	HH	HH	HH	HH	LL	LL	LL	LL	LL	LL	LL	LL
82	LL	LL	LL	LL	HH	HH	HH	HH	LL	LL	LL	-	LL	LL	LL	LL
83	LL	LL	LL	L	HH	HH	HH	HH	LL	LL	LL	L	LL	LL	LL	LL
84	LL	LL	LL	LL	HH	HH	HH	HH	LL	LL	LL	L	LL	LL	LL	LL
85	LL	LL	LL	L	HH	HH	HH	HH	LL	LL	L	-	LL	LL	LL	LL
86	LL	LL	LL	LL	HH	HH	HH	HH	LL	LL	LL	L	LL	LL	LL	LL
87	LL	LL	LL	LL	HH	HH	HH	HH	LL	LL	LL	L	LL	LL	LL	L
88	LL	LL	LL	LL	HH	HH	HH	HH	LL	LL	LL	L	LL	LL	LL	LL
89	LL	LL	LL	L	HH	HH	HH	HH	LL	LL	L	-	LL	LL	LL	L

C-D:Cobb-Douglas, TL:Translog, i: i.i.d. case, A: AR(1) case

4.2. Test Results at the Detail Level

The test has been performed at the moderately aggregate level (2-digit level) by 9 industries so far. However, more specific industries could be picked up as target industries such as "steel" industry among "basic metal" industries. Therefore, the test is performed at the 3-digit level: industrial chemicals, and chemical products in chemical industries, iron and steel, and non-ferrous metals in basic metal industries, and fabricated metal products, general machinery (including computer), electrical machinery, and transport equipment in machinery industries. Therefore, the number of equation in SUR :M equals 9.

Table 4.4: Test Result at the detail level (continued)

	Fabricated Metal Products				General Machinery				Electrical Machinery				Transport Equipment			
	C-D		TL		C-D		TL		C-D		TL		C-D		TL	
	i	A	i	A	i	A	i	A	i	A	i	A	i	A	i	A
68	HH		HH		HH		HH		HH		HH		LL		LL	
69	-	L	-	-	HH	HH	H	-	HH	HH	HH	HH	LL	LL	LL	LL
70	LL	LL	L	L	-	-	-	L	HH	-	HH	-	LL	LL	LL	LL
71	LL	LL	LL	LL	-	-	L	LL	H	-	H	-	LL	LL	LL	LL
72	LL	LL	LL	LL	-	-	L	LL	-	LL	-	LL	LL	LL	LL	LL
73	LL	LL	LL	LL	-	-	-	LL	HH	HH	HH	H	LL	LL	LL	LL
74	LL	LL	-	LL	LL	LL	LL	LL	HH	HH	HH	HH	LL	L	L	LL
75	-	-	-	-	LL	LL	LL	LL	HH	HH	HH	HH	LL	L	LL	LL
76	-	-	HH	H	LL	LL	LL	LL	HH	HH	HH	HH	LL	LL	LL	LL
77	-	HH	HH	HH	LL	LL	LL	LL	HH	HH	HH	HH	LL	L	LL	LL
78	HH	HH	-	HH	LL	LL	LL	LL	HH	HH	HH	HH	LL	LL	LL	LL
79	-	H	-	HH	LL	LL	LL	LL	HH	HH	HH	HH	LL	L	LL	L
80	-	H	H	HH	LL	LL	LL	LL	HH	HH	-	HH	LL	-	L	-
81	H	HH	HH	HH	LL	LL	LL	LL	H	HH	-	HH	LL	-	-	-
82	HH	HH	H	HH	LL	LL	LL	LL	-	-	-	HH	-	-	-	-
83	H	HH	H	HH	LL	LL	LL	LL	HH	HH	-	HH	-	-	-	-
84	HH	HH	-	HH	LL	LL	LL	LL	HH	HH	H	HH	L	-	-	-
85	-	HH	-	HH	LL	LL	LL	-	HH	HH	-	HH	-	-	-	-
86	-	HH	-	HH	LL	LL	LL	-	HH	HH	HH	HH	-	-	-	-
87	-	-	-	-	LL	LL	L	-	HH	HH	HH	HH	-	-	-	H
88	-	-	-	-	LL	LL	LL	-	HH	HH	HH	HH	-	-	-	H
89	-	-	-	-	LL	LL	L	-	HH	HH	HH	HH	-	-	-	H

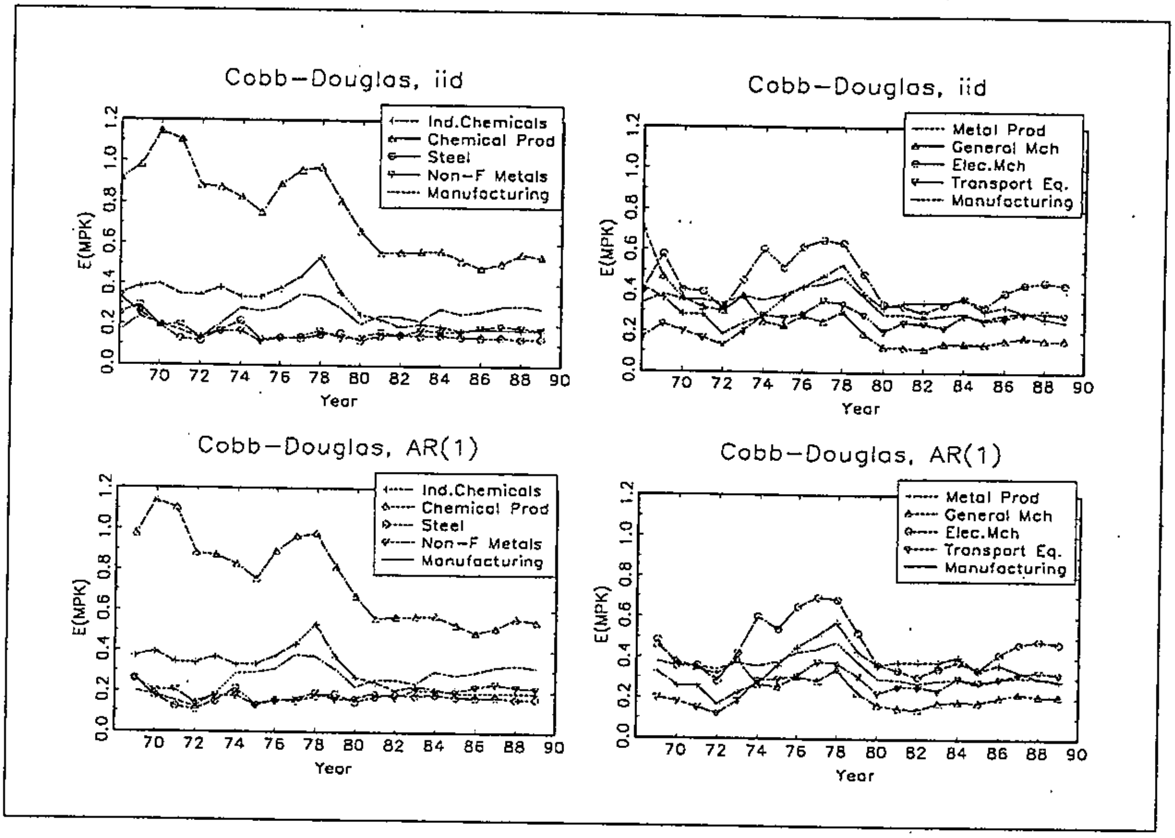
C-D:Cobb-Douglas, TL:Translog, i: i.i.d. case, A: AR(1) case

Tables 4.3 and 4.4 report the test result, and Figures 4.1 and 4.2 illustrate the change of expected MPK over time by industry. Again, note that the Durbin-Watson statistic indicates autocorrelation of residuals for most industries.

The test results for chemicals are divided. Industrial chemicals report overinvestment in 1975-76 and in the 1980s, while chemical products such as medicine report underinvestment throughout the period. As for basic metals, both iron and steel industry and non-ferrous metals industry report overinvestment throughout the period, except for iron and steel in the 80s and non-ferrous metals in the late 80s using the Translog function with AR(1).

The test results for machinery are also divided. As for fabricated metal products, there was overinvestment in the early 1970s, and underinvestment from the late 1970s to the mid 1980s. It is interesting that this drastic change happened in 1974 right after the HCI project began. As for general machinery, there was underinvestment at least from 1974 to 1984. Electrical machinery seems to suffer from underinvestment throughout the period except 1972. Transport equipment seems to be overinvested up to the early 1980s. Among transport equipment, shipbuilding expanded its production earlier (in 1960s and 1970s) and did automobile later (in the late 1970s and 1980s). Therefore, shipbuilding possibly benefited from preferential capital allocation more than automobiles.

In general, the test result suggests that consumer goods such as chemical products and electrical machinery suffered from underinvestment, while producer goods such as industrial chemicals, iron and steel, non-ferrous metals, and general machinery enjoyed preferential capital allocation. However, the disparity among industry seems to become smaller in the 1980s.


Cobb−Douglas, iid

Cobb−Douglas, iid

Cobb−Douglas, AR(1)

Cobb−Douglas, AR(1)

Figure 4.1: Expected MPK at the Detail Level

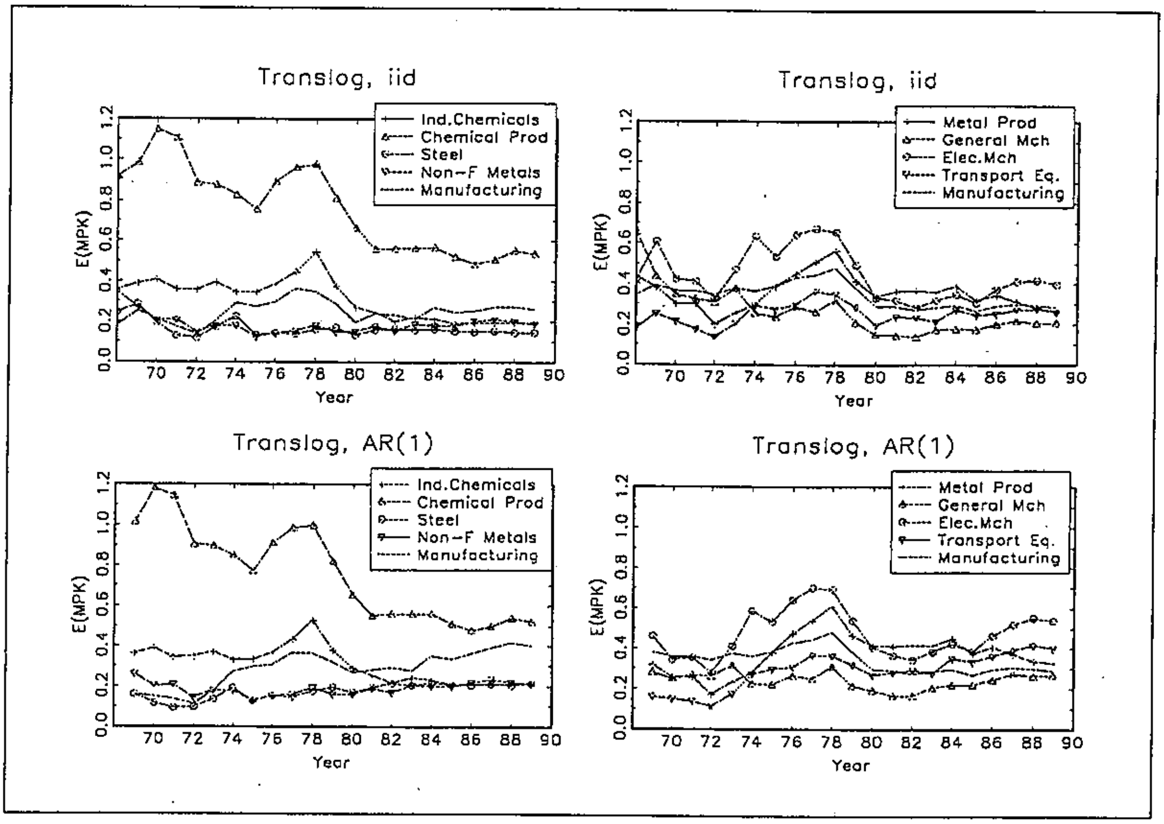


Figure 4.2: Expected MPK at the Detail Level (Continued)

5. Concluding Remarks

This paper has investigated whether or not capital allocation was distorted in favor of the heavy and chemical industries in Korea. The test result suggests that there was overinvestment in basic metal industries and machinery industries in the early 1970s, while there was underinvestment in chemical industries throughout 1970s and possibly in the 1980s. This result was unchanged with considering tax incentive. The result is interesting in the sense that more capital was allocated toward basic metal and machinery industries whose TFP growth rates were the first and second highest but less was allocated to chemical industries whose TFP growth recorded the lowest. Another interesting result at the detail level is that more capital seems to be allocated toward producer goods than consumer goods.

Distortion in capital allocation may not be observed under competitive financial market without government interventions in theory. Therefore, the test result is in favor of the view that the Korean government made distortional capital allocation, particularly in the 1970s. However, the distortion in capital allocation seems to become smaller in the 1980s.

Distortion in capital allocation may not be necessarily mean inefficient resource allocation. One rationalization may be attributed to intra- and inter-industry externalities. It is easy to guess that steel and iron industry requires huge initial investments. Also, producer goods industry may have spillover effects toward other industries more than consumer goods industry. Another claim may be made on the "next year" myopic assumption. In order to overcome painful "learning" period, continuous investment may be required in spite of low returns until becoming competitive in the world market. The Korean government might consider technical advancement over a longer term than yearly base; in other words, they do not expect to equate expected MPK for next year, but may prospect 5 or 10 years after, having implemented 5-year Economic Plan from 1962 that still continues today.

References

[1] Amsden, Alice H. (1989), *Asia's Next Giants: South Korea and Late Industrialization*, New York: Oxford University Press

[2] Benhabib, Jess and Boyan Jovanovic (1991), "Externalities and Growth Accounting", *American Economic Review* 81(1), 82-113

[3] Breusch, T.S. and Pagan, A.R. (1980), "The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics", *Review of Economic Studies* 47, 239-253

[4] Chen, Edward (1979), *Hyper-growth in Asian Economies*, New York:Holmes

[5] Dollar, David and Kenneth Sokoloff (1990), "Patterns of Productivity Growth in South Korean Manufacturing Industries, 1963-1979", *Journal of Development Economics* 33, 309-327

[6] Jones, Leroy P., and Il Sakong (1980), *Government, Business, and Entrepreneurship in Economic Development: The Korean Case*, Cambridge Mass.: Harvard University press

[7] Judge, George G. et al. (1985), *The Theory and Practice of Econometrics*, New York:John Wiley & Sons

[8] Kwon, Jene K. (1986), "Capital Utilization, Economies of Scale and Technical Change in the Growth of Total Factor Productivity", *Journal of Development Economics* 24, 75-89

[9] Mason, E.S. et al. (1980), *The Economic and Social Modernization of the Republic of Korea*, Cambridge Mass: Harvard University Press

[10] Nishimizu, Mieko and Sherman Robinson (1984), "Trade Policies and Productivity Change in Semi-industrialized Countries", *Journal of Development Economics* 16, 177-206

[11] Pack, Howard and Larry E. Westphal (1986), "Industrial Strategy and Technological Change: Theory versus Reality", *Journal of Development Economics* 22, 87-128

[12] Pyo, Hak K. (1992), "A Synthetic Estimate of the National Wealth of Korea, 1953-1990", KDI Working Paper, No.9212

[13] Pyo, Hak K. (1988), "Estimates of Capital Stock and Capital/Output Coefficients by Industries: Korea (1953-1986)", *International Economic Journal* 3(2), 79-121

[14] Ueda, Atsuko (1994), "Capital Allocation and Economic Growth in Korea", unpublished Ph.D. Thesis, University of Wisconsin-Madison

[15] Wade, Robert (1990), *Governing the Market: Economic Theory and the Role of Government in East Asian Industrialization*, Princeton: Princeton University Press

[16] Westphal, Larry E. (1990), "Industrial Policy in an Export- Propelled Economy: Lessons from South Korea's Experience", *Journal of Economic Perspectives*, 14(3), 41-59

[17] Westphal, Larry E. and Kwang Suk Kim (1977), *Industrial Policy and Development in Korea*, World Bank Staff Working Paper no.263

[18] World Bank (1993), *The East Asian Miracle: Economic Growth and Public Policy*, Washington D.C.:World Bank

[19] World Bank, Operations Evaluation Department (1992), *World Bank Support for Industrialization in Korea, India, and Indonesia*, Washington D.C.:World Bank