Measuring of Firm Specific Productivities: Evidence from Japanese Plant Level Panel Data

Ichimura, H [1], Y. Konishi [2] and Y. Nishiyama[3]

[1] Graduate School of Public Policy, University of Tokyo
[2] Institute of Economic Research, Hitotsubashi University, Tokyo
[3] Institute of Economic Research, Kyoto University, Kyoto
Email: konishi@ier.hit-u.ac.jp

Keywords: *segment level data, identification problem, observable and unobservable productivity shock*

EXTENDED ABSTRACT

In Japan, after bursting babble economy since the middle of 1990's, the growth rate has not been increasing obviously, and it is said the productivity keeps declining. This period is sometime called "the lost decade". Recently, a number of researchers and the government try to get an answer what did occur in the period, and find an effective policy for raising industrial productivity and growth rate of GDP. Recently, we can use micro level data, for example, the plants and segments data as well as firms' data. It allows empirical researches to make more precise statistical analysis.

In estimation of production function of firms, there are problems of endogeneity and self selection due to firm specific productivity shocks and entry/exit decisions. To the best of our knowledge, empirical works have not paid much attention to the limitations of these problems. Then, methodologically, measurement of productivity is an interesting and challenging problem. There are some methods proposed to handle the problems such as Olley and Pakes (1996) and Levinsohn and Petrin (1999, 2003). Here, endogeneity means input levels may not be independent of the "disturbances". The reason is that it is likely each firm determines the input levels depending on the firm-specific productivity, which is observable only for the firm, not econometricians, and thus the "disturbance" in the estimated equation involves the (unobserved) firm specific productivity shock, which should be highly correlated with the input levels, and other ordinary shocks. In the papers referred above, they consider that the endogeneity occurs only in the capital level, not in the labour input. It is a practical matter if this assumption is adequate or not, but if it is incorrect, we will get inconsistent estimates.

In this paper, we have developed two kinds of semiparametric instrumental variable estimators, one extending the Robinson's (1988) semiparametric estimator and the other using series expansion of unknown nonparametric function(s). We suppose both capital and labour inputs are correlated with the productivity. We adopt the lag variables of labour and capital as their instruments instead of investment or intermediate inputs unlike Olley and Pakes or Levinsohn and Petrin. Moreover, our econometric model automatically adapts to the effect of exit decision made by each firm. We apply it to plant/segment level panel data of financial report of Japanese firms listed in Tokyo Stock Exchange market. We found different technology of capital and labour among these industries by our estimator and our estimator works better in the empirical study in terms of sign and magnitude of technological parameters of inputs than Levisohn and Petrin (2003)'s estimator.

Moreover, using the estimation results, we decompose the so-called total factor productivity (TFP) or Solow residual into the firm specific productivity and other exogenous shocks based on the assumption that the exogenous shocks are uncorrelated with the inputs. Interestingly, we found that the firm specific productivity has not changed much in these five years. The fluctuation of TFP for each firm comes mostly from that of exogenous shocks, which we may think, the demand shock or other macroeconomic shocks. It is sometimes said that the productivity of Japanese economy has declined since the burst of babble economy, it may not be due to the productivity falls of Japanese firms, but due to a simple macroeconomic demand problem. Since we have investigated only some restricted number of industries, we need to extend it to other industries as well. Also, we can see the productivity changes only 2000~2005, it is not sufficient to make a strong statement. We will also need to extend it to cover 1980's and 1990's as well using some other dataset.

1. INTRODUCTION

In Japan, after bursting babble economy since the middle of 1990's, the growth rate has not been increasing obviously, and it is said the productivity keeps declining. This period is sometime called "the lost decade". Recently, a number of researchers and the government try to get an answer what did occur in the period, and find an effective policy for raising industrial productivity and growth rate of GDP. Recently, we can use micro level data, for example, the plants and segments data as well as firms' data. It allows empirical researches to make more precise statistical analysis. Fukao and Kwon (2006) make the plant level data set in their project and use them to examine of productivity and they found the reasons of declining of productivities in last lost decade.

In the productivity analysis, the most common measure of productivity is Total Factor Productivity TFP, hereafter. Beginning with a pioneering work by Solow (1957), economists regard the constant term of Cobb-Douglas production function as the TFP. Production technology of a firm or an economy is characterized by its production function (or cost function alternatively).

We briefly describe the production function. Cobb and Douglas (1928) proposes a production function with the following the form,

$$Y_{it} = AK_{it}^{\beta_k} L_{it}^{\beta_l} \tag{1}$$

where *Y*, *K*, *L* indicate the output level, capital and labour inputs respectively and A, β_k , β_l are parameters determining the production technology. We transform the Cobb-Douglas production function into a log-linear form.

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + u_{it} \tag{2}$$

Equation (1) or equivalently (2) is called the Cobb-Douglas production function. Christensen, Jorgenson and Lau (1973) consider an extension of the Cobb-Douglas production function to the following more general and flexible functional form that including the polynomials of independent variables, that is called the Translog production function. These two functional forms are used widely in theoretical and empirical Economic research, and estimation of production function has been one of the main issues in empirical economics and econometrics. Especially, a lot of previous empirical works estimate the production function by least square method and treat the regression residuals as TFPs.

Though the regression residual is commonly used as an estimate of TFP, we should point out that the existence of an econometric problem an endogeneity problem. Endogeneity means here that after each firm observe their TFP (technology or productivity), they decide the levels of factor inputs. Then l_{it} and k_{it} and error terms must be correlated, which causes a bias in the OLS estimators. Obviously, the problem comes from that each firm can observe its own productivity but econometricians cannot.

There are some methods proposed to handle the problems such as Olley and Pakes (1996) and Levinsohn and Petrin (1999, 2003), hereafter we call O &P and L&P methods. They split out the error term into two parts as follows. ω_{it} represents the firm specific productivity or technological shock and η_{it} denotes the ordinary error term.

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \eta_{it} \tag{3}$$

They consider a correlation between ω_{it} and k_{it} explicitly, and it contributes to find an influence of the each firm productivity shock to their output growth. To the best of our knowledge, there are not many researches that apply these methods to Japanese plant level dataset. Fukao *et al.* (2007) is one of the important previous works, where they apply L & P method to estimate the production function of Japanese plant level. Their main interest is in Japanese wage function however, they use L & P estimation method to check the validity of the parameter of labor productivity supplementary.

In this paper, we apply L & P method to Japanese segments data of firms which belong to variety of industries, not only manufacturing industry but also service, commerce, whole sale trade, a real estate and car trucking industries. Because the endogeneity problem does not seem to be completely solved by O& P and L & P methods, we propose an alternative IV estimator. Applying our method to the same segment data set, and we also observe the firm specific productivities.

The following section shows a review of some papers that solve the endogeneity and the sample selection problems of the productivity analysis. Section 3 shows our alternative IV estimator to examine the firm specific productivity. While Section 4 gives results of the OLS, L & P and our method, we examine the firm specific productivity and decompose the productivity shock and the error term using the estimation results, in Section 5. Concluding remarks and future research are in Section 6.

2. REVIEW OF THE PREVIOUS WORKS

A number of previous researches are provided about measuring the TFP and macro productivity about economic growth. Here we ensure readers understand the meaning of terms used when discussing alternative methods.

Now we have a production function equation in equation (3). Suppose ω_{it} represents each firm's technology / productivity shocks that they are observable only for the firm, and each firm decides levels of factor inputs after observing the actual ω_{it} . Under this assumption, factor inputs and the productivity shock are correlated and it becomes a cause of the endogeneity problem in the estimation of equation (3).

Olley and Pakes (1996) and Levinsohn and Petrin (1999, 2003) show a solution to this problem using the firm's investment decisions as a proxy of ω_{it} in (3). We can obtain accumulated K by standard perpetual inventories method as below, where K is the capital stock, I is the investment and δ is depreciation ratio.

$$K_{it+1} = (1-\delta) K_{it} + I_t \tag{4}$$

Pakes (1996) proves that optimizing firms have investment functions that are strictly increasing in the unobservable productivity shock. We can write investment function as $i_t = i_t(\omega_t, k_t)$. The monotonicity allows investment function to be inverted to get $\omega_t = \omega_t(i_t, k_t)$. Including ω_{it} in the model, it gives a relation with k_{it} explicitly, and they could solve an endogeneity problem between k_{it} and ω_{it} . Inserting $\omega_t = \omega_t(i_t, k_t)$ in equation (3), we can write the model as a partially linear model, and obtain consistent semiparametric estimates of β_l and ϕ by Robinson (1988) as follows. Write

$$\begin{aligned} y_t &= \beta_0 + \beta_l l_t + \beta_k k_t + \omega_t(i_t, k_t) + \eta_t \\ &= \beta_l l_t + \phi_t(i_t, k_t) + \eta_t \end{aligned}, \tag{5}$$

and subtract $E(y_t | i_t, k_t) = \beta_l E(l_t | i_t, k_t) + \phi_t(i_t, k_t)$ from equation (5). Then we obtain this equation,

$$y_t - E(y_t \mid i_t, k_t) = \beta_l \{l_t - E(l_t \mid i_t, k_t)\} + \eta_t . \tag{6}$$

Replacing the conditional expectations by nonparametric estimates as below, we can stimate equation (7) by least square method to obtain the consistent estimator of β_l .

$$y_t - \hat{E}(y_t \mid i_t, k_t) = \beta_l \{l_t - \hat{E}(l_t \mid i_t, k_t)\} + \eta_t \tag{7}$$

In the second step, we identify β_k of the model. Assume ω_{it} follows a first order markov process, $\xi_t = \omega_t - E(\omega_t | \omega_{t-1})$ is uncorrelated with k_t , and put

$$\begin{aligned} \phi_t(i_t, k_t) &= \beta_0 + \beta_k k_t + \omega_t(i_t, k_t) \\ &= \beta_0 + \beta_k k_t + E(\omega_t \mid \omega_{t-1}) + \xi_t \end{aligned} . \tag{8}$$

Inserting equation (8) into (5), we have

$$\begin{aligned} y_t &= \beta_0 + \beta_l l_t + \beta_k k_t + \omega_t + \eta_t \\ &= \beta_0 + \beta_l l_t + \beta_k k_t + E(\omega_t \mid \omega_{t-1}) + \xi_t + \eta_t \end{aligned} \tag{9}$$

where $\xi_t + \omega_t$ and k_t , l_t are uncorrelated. In the third step, we estimate β_0 and β_k , given β_0 and β_k , we can implement nonparametric estimation for $E(\omega_t | \omega_{t-1})$, and obtain $\hat{E}(\omega_t | \omega_{t-1})$, inserting $\hat{\beta}_l$ and $\hat{E}(\omega_t | \omega_{t-1})$ into (9) and we can estimate

to get estimators of β_0 and β_k using non-linear least square or generalized method of moments. Levinsohn and Petrin (2003) show that the intermediate inputs can also be used to solve the endogeneity problem.

3. AN ALTERNATIVE ESTIAMTOR -IKN ESTIMATOR-

Olley and Pakes (1996) and Levinsohn and Petrin (1999, 2003) show how to use investment and intermediate inputs to control for correlation between capital inputs level and unobservable firm specific productivity shock. And they can identify the constant term and the parameters of inputs and surely they are consistent estimators.

However, the endogeneity problem of inputs level and unobservable firm specific productivity does not seem to be completely solved by these methods. They only consider the correlation between capital input level k_{it} and unobservable firm specific productivity shock ω_{it} . Because they adopt a estimation method by Robinson (1987), if l_{it} is also determined by firms depending ω_{it} like k_{it} , we can see $E(l_t | i_t, k_t) = E(l_t | \omega_t) = l_t$ and their procedure of getting $\hat{\beta}_l$ collapses. And if there was no the econometric technical problem as above, the assumption does not look reasonable in actual decision making of firms.

Thus we propose an alternative IV estimator and we names it Ichimura-Konishi Nishiyama estimator, hereafter we call it IKN estimator. We suppose that the firm specific productivity influences labor input level as well as capital's one. We adopt the lag variables of labor and capital as their instruments instead of investment or intermediate goods like Olley and Pakes or Levinsohn and Petrin. Moreover, our model also includes the effect of entry-exit firm decision to confirm their productivity. We can rewrite equation (3) as

$$\begin{aligned} y_{it} &= \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it} \qquad (10) \\ &= \beta_0 + \beta_l l_{it} + \beta_k k_{it} + E\left(\omega_{it} \middle| k_{it-1}, l_{it-1}\right) + \omega_{it} - E\left(\omega_{it} \middle| k_{it-1}, l_{it-1}\right) + \varepsilon_{it} \\ &= \beta_0 + \beta_l l_{it} + \beta_k k_{it} + g\left(k_{it-1}, l_{it-1}\right) + \xi_{it} + \varepsilon_{it} \end{aligned}$$

where,

$$g\left(k_{it-1}, l_{it-1}\right) \equiv E\left(\omega_{it} \middle| k_{it-1}, l_{it-1}\right), \xi_{it} \equiv \omega_{it} - E\left(\omega_{it} \middle| k_{it-1}, l_{it-1}\right).$$

From this equation, we could know immediately $E(\xi_{it} | k_{it-1}, l_{it-1}) = 0$, $E(\varepsilon_{it} | k_{it-1}, l_{it-1}) = 0$, $E(k_{it} k_{it-1}) \neq 0$ and $E(l_{it} l_{it-1}) \neq 0$, then $f_k(k_{it-1})$ and $f_l(l_{it-1})$ for any functional forms of f_k and f_l are usable as instrumental variables for k_{it}, l_{it}. And also we can use a relationship of $E(\xi_{it} | k_{it-2}, l_{it-2}) = E[E(\xi_{it} | k_{it-1}, l_{it-1}) | k_{t-2}, l_{t-2}] = 0$, it means $f_k(k^s{}_{it-2})$ and $f_l(l^s{}_{it-2})$ are also usable as instrumental variables for k_{it}, l_{it}. Because k_{it}, l_{it} are endogenous variables, we apply instrumental variable method to estimate of our model. To implement estimation of equation (10), we adopt polynomial functions of $k_{it-1}, l_{it-1}, k_{it-2}, l_{it-2}$ as instrumental variables and we can approximate $g(k_{it-1}, l_{it-1})$ by trigonometric, splines and any other smoothed functions.

We describe IKN estimator's advantages and disadvantages briefly. We could allow for the correlation between ω_{it} and l_{it} as well as ω_{it} and k_{it}. We don't need to use investment as a proxy variable of ω_{it}, because usually it is hard to obtain segment level's investment data as Levinsohn and Petrin (2003) pointed it out. The demerit is that we use $k_{it-1}, l_{it-1}, k_{it-2}, l_{it-2}$ as instrument variables so that number of observation effectively used decreases.

4. ESTIMATION

We estimate the Cobb-Douglas production function (eq.2 & 4) by 3 methods which are OLS, L & P method and IKN method. Our data set is panel data of the Japanese segment level that covers the all kinds of industries and the period from 2000 to 2005.

4.1. Data

Our data set is from Nikkei NEEDS which is financial report, and our targets are listed companies that belong to the first section market at Tokyo Exchange Market. It is periods from 2000 to 2005 and segment level panel data. We should describe about a segment shortly. A segment belongs to a firm, it is sometime the smallest production unit, equal to the plant or constructed some sectors of the firm. Usually, each firm produces a large variety of goods; it is difficult to identify which technology is used to produce a good in firm-level analysis. Therefore, we sort the data and make groups by kinds of products and combine the segments if they produce same products by Japan Standard Industry Classification: JSIC 3 or 4-digits level in order to measure homogeneity technology in the group. We focus on 10 of the varieties industries in Table.1. We use their value added as their output variables that is dependent variable. They are composed by subtracting the cost of raw materials and sales administrative expense from the total amount of the sales. Independent variables are Capital (K) and Labour (L) are adopted fixed assets and work forces. For L&P estimation, an investment (I) variable is capital Expenditure.

4.2. Estimation results

We found different technology of capital and labour among these industries by IKN and obtained some reasonable results without medical products. OLS estimator results also look reasonable, but the estimators don't have consistency and tend to upper wards biases. In almost L & P results, we can not see the significance of the parameters of L. It suggests that O & P and L & P style's estimation can not identify $\hat{\beta}_l$ well. Contrastingly, our assumption of endogeneity problems seems to be valid. Moreover, some OLS and IKN estimator results are very similar. Though we discuss about them in Section 5, the phenomena imply the firm specific productivities are not existent or their fluctuating are sharply.

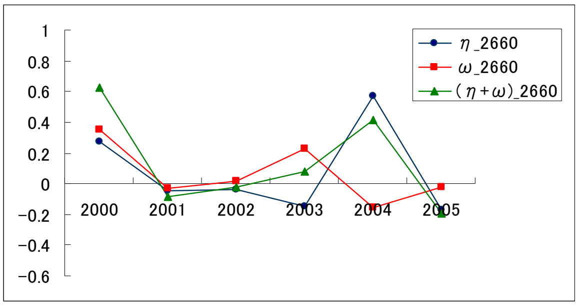
5. MEASURING THE FIRM SPECIFIC PRODUCTIVITY

After bursting babble economy since the middle of 1990's, we had an economic stagnation for a while, and it is said that the bottom was 2001. Since then, we can see a very slightly economic recovery. Measuring the TFPs in the 2000-2005 periods, we might see the influences of the business fluctuations to the firm level productivities. Here, using the estimation results, we could decompose $\hat{\omega}_t + \hat{\eta}_t$ that is the firm specific productivity (pure TFP) and the error term, and we show results in Figure 1.We focus on observing the results of (B), (F) and (G). In previous productivity analysis, we usually discuss about the productivity by $\hat{\omega}_t + \hat{\eta}_t$. In these 3 results, $\hat{\omega}_t + \hat{\eta}_t$ seem to have upper wards trend, so we might conclude "the productivity increases in the period", but pure TFP $\hat{\omega}$ does not change actually. We should say the technological productivities keep stable in the period in the industries. We said the phenomena in previous section, (G)'s estimation results are very similar both of OLS and IKN. It means the correlation between 2 inputs and ω_{it} is not existent or quite small. In that situation, we can not find the productivity changes of, $\hat{\omega}$ of (G) stays around "0" and don't change the level. We should note that there could be the industries which don't have correlation between inputs level and the firm-specific productivities.

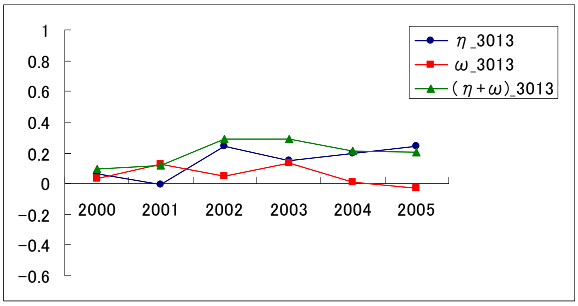
Table 1. Estimation Results of OLS, L &P and IKN. * and ** present 10% and 5% significant level.

Drugs & Medicines (JSIC 1760)			
	OLS	L & P	IKN
lnK	0.927**	0.638**	0.819**
lnL	0.148	0.118	0.215
Obs.	351	349	179
Special Industry Machinery (JSIC 2660)			
	OLS	L & P	IKN
lnK	0.690**	1.145**	0.711**
lnL	0.310**	0.282	0.300**
Obs.	237	230	91
Motor Vehicles-Parts & Accessories (JSIC 3010)			
	OLS	L & P	IKN
lnK	0.684**	0.857**	0.767**
lnL	0.305**	0.205	0.237**
Obs.	510	501	267
Computer Programming Services (JSIC 3910)			
	OLS	L & P	IKN
lnK	0.547**	0.923**	0.608**
lnL	0.271**	0.291	0.344**
Obs.	514	487	226
Data Processing & Information Services (JSIC 3920)			
	OLS	L & P	IKN
lnK	0.606**	0.698**	0.631**
lnL	0.255**	0.312**	0.250**
Obs.	352	329	135
Common Motor Tracking (JSIC 4410)			
	OLS	L & P	IKN
lnK	0.683**	0.350**	0.676**
lnL	0.226**	0.292*	0.240**
Obs.	353	350	182
General Machinery & Equipment; Wholesale Trade (5310)			
	OLS	L & P	IKN
lnK	0.830**	1.267**	0.587**
lnL	0.227**	0.285	0.631**
Obs.	158	146	65
Electrical Machinery-Equipment & Supplies; Wholesale Trade (JSIC5330)			
	OLS	L & P	IKN
lnK	0.523**	0.694**	0.659**
lnL	0.322**	0.057	0.241**
Obs.	216	187	99
Department Stores & General Supermarkets (JSIC 5510)			
	OLS	L & P	IKN
lnK	0.546**	0.654*	0.526**
lnL	0.351**	0.304	0.365**
Obs.	246	187	135
Sales Agents of Buildings & Houses &Land (JSIC 6810)			
	OLS	L & P	IKN
lnK	0.695**	0.943**	0.726**
lnL	0.204**	0.156	0.192**
Obs.	822	677	340
Real Estate Lessors-Except House & Room Lessors(6910)			
	OLS	L & P	IKN
lnK	0.708**	0.462**	0.709**
lnL	0.105**	0.034	0.092**
Obs.	1188	1039	561

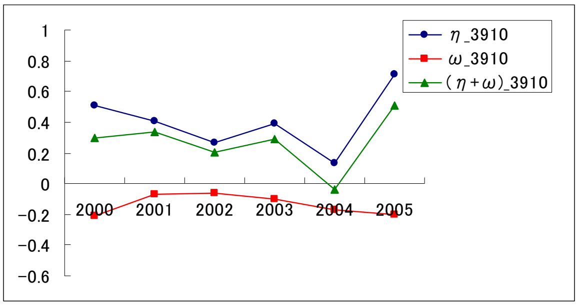
(A) Special Industry Machinery (JSIC: 2660-2668)



(B)Motor vehicles parts and accessories (JSIC: 3013)



(C) Computer Programming and other Software Services (JSIC: 3910-3912)



(D)Common Motor Tracking (JSIC: 4410-4412)

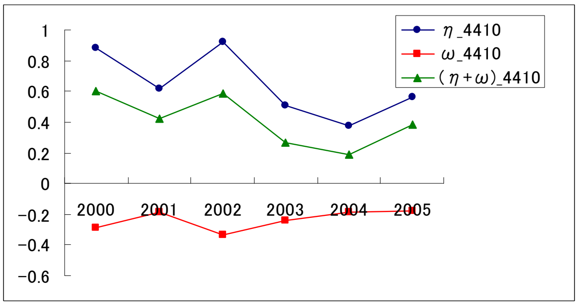
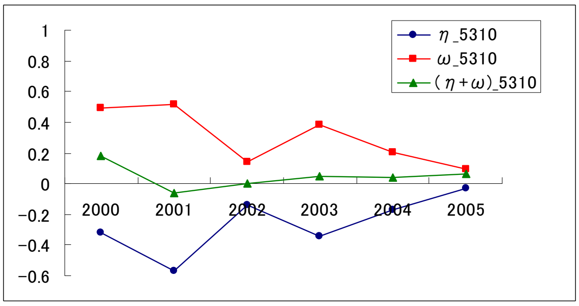
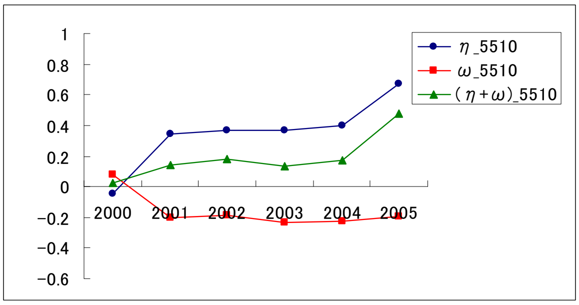


Figure 1. Decomposition of productivity shocks and other shocks.

(E) General Machinery & Equipment (Wholesale Trade) (JSIC: 5310-5314)



(F) Department Stores & General Merchandise Supermarkets (JSIC: 5510-5511)



(G) Sales Agents of Buildings & Houses & Land Subdividers & Developers (JSIC: 6810-6812)

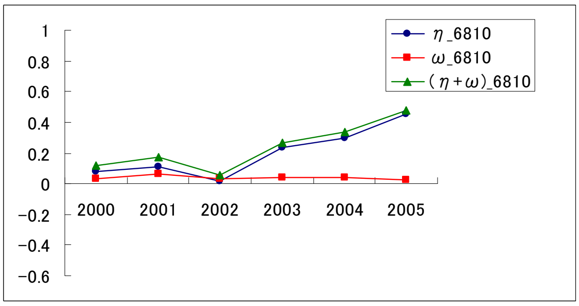


Figure 1. Decomposition of productivity shocks and other shocks.

6. CONCLUSION AND FUTURE RESEARCH

The alternative estimator IKN presented in this paper provides a new measure for the segment level productivity. We found different technology of capital and labour among these industries by IKN. We also applied L&P estimation procedure to Japanese data of some financial reports. We proposed an alternative estimation method to O&P and L&P for production function under a stochastic firm- and time- specific technology which causes a nuisance endogeneity. This procedure allows that labour depends on the technology level unlike O&P or L&P, and exit decisions are endogenous automatically under certain conditions. We applied this method and obtained some reasonable results for machinery and equipments, car parts, trucking, department stores, estate agents and so on. We will apply this method to other industries. We measure firm- & time specific production skills in a similar manner as TFP. Using the above measure, we could decompose he firm specific productivity (pure TFP) and the error term.

Konishi and Nishiyama (2002) pointed out that Cobb-Douglas and Trans log production function are not adequate functions for measuring the productivity based on firm specific analysis, and they show the necessity to check the functional form statistically by Hong and White (1995) nonparametric functional form test. In this paper, we adopt the Cobb-Douglas production function basically, so we will construct the Hausman and Hong and White type test for our estimator. Moreover, we will compares the properties of these alternative estimators theoretically and numerically. Finally, using the measuring the productivities results, we will aggregate them into industry level as in L & P in order to observe the change of productivities in recent years.

7. REFFERENCES

Christensen, L. R., D. W. Jorgenson and L. J. Lau (1973), Transcendental logarithmic production frontiers, *Review of Economics and statistics*, 55, 28-45.

Cobb, C. W. and P. H. Douglas (1928), A theory of production, *American Economic Review*, 18, Supplement, 139-165.

Fukao, K. and H.U. Kwon (2006), Why did Japan's TFP growth slow down in the lost Decade? An empirical analysis based on firm-level data of manufacturing firms, *The Japanese Economic Review*, 57 (2), 195-227.

Fukao, K., R. Kambayashi, D. Kawaguchi, H.U. Kwon, Young Gak Kim and I, Yokoyama (2007), Deferred compensation: Evidence from employer-employee matched data from Japan, mimeo.

Hong, Y., and H. White. (1995), Consistent specification testing via nonparametric series regression. *Econometrica*, 63, 1133-1159.

Konishi, Y. and Y. Nishiyama (2002), Nonparametric Test for Translog Specification of Production Function in Japanese Manufacturing Industry, in A.E. Rizzoli and A.J. Jakeman (eds.), *Integrated Assessment and Decision Support, Proceedings of the 1st Biennial Meeting of the International Environmental Modelling and Software Society*, 2002, 2(4), 597-602.

Levinsohn, J. and A. Petrin (1999) , When industries become more productive, Do firms? : investigating productivity dynamics, *NBER working paper series*; working paper 6893; Cambridge: National Bureau of Economic Research.

Levinsohn, J and A. Petrin (2003), Estimating production functions using inputs to control for unobservables, *Review of Economic Studies*, 70 Issue 2 , 317-411.

Olley, G., S. and A. Pakes (1996), The dynamics of productivity in the telecommunications equipment Industry, *Econometrica*, 64, 1263-1297.

Pakes, A (1996), Dynamic structural models problems and prospects: mixed continuous discrete control and market interaction, In Sims, C. (Ed.), *Advances in Econometrics*, Sixth World Congress, II, 171-259.

Robinson, P. M. (1988), Root-n consistent semiparametric regression, Econometrica, 55(4), 931-954.

Solow, R. M. (1957), Technical change and aggregate production function, *Review of Economics and Statistics*, 39, 312-320.