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ICHIMURA Hidehiko
RIETI

KONISHI Yoko
RIETI

NISHIYAMA Yoshihiko
RIETI

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An Econometric Analysis of Firm Specific Productivities: Evidence from Japanese plant level data*

H. Ichimura
(Graduate School of Economics, Graduate School of Public Policy, University of Tokyo)
Y. Konishi
(Fellow, RIETI; Japan JSPS Postdoctoral Fellowships for Research Abroad; Yale University)
Y. Nishiyama†
(Kyoto Institute of Economic Research, Kyoto University)

Abstract

In estimating the production function of firms, problems of endogeneity and self selection exist as a result of firm-specific productivity shocks and entry/exit decisions. Several methods have been proposed to handle these problems, such as those by Olley and Pakes (1996) and Levinsohn and Petrin (1999, 2003). However, the endogeneity of labor input does not seem to be completely solved by these methods. We therefore propose an alternative semiparametric IV estimator. We suppose that firm-specific productivity influences labor input as well as capital input. We adopt the lagged variables of inputs as their instruments instead of investment inputs, unlike Olley and Pakes. Moreover, our econometric model should automatically adapt to the effect of the exit decision of each firm. We applied the model to Japanese plant-level panel data from 1982 to 2004 on the Census of Manufactures provided by the Ministry of Economy, Trade and Industry. We found that our estimator works well in an empirical study in terms of sign and magnitude of the technological parameters. Using the estimation residuals, we decomposed the TFP into firm-specific productivity and other exogenous shocks. We also aggregated the productivity shocks to industry-level productivities to determine the transition. We examined whether negative technological shocks were the main cause of poor economic performance in Japan during the "lost decade", and found that productivity did not decline in most Japanese industries since the 1980s. This implies that the recession might have been caused by demand-side factors rather than supply-side issues.

Keywords: Productivity; Endogeneity; TFP Decomposition; Demand Shock
JEL classification: C14, D24, L23, L60

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† Email: nishiyama@kier.kyoto-u.ac.jp

1 Introduction

Since the burst of the bubble economy in the early 1990s, the growth rate of the Japanese economy has obviously not been increasing, and it is said that the productivity continues to decline. This period is sometimes called the "lost decade". A number of researchers investigated what occurred during the period. The government also attempts to answer the question in the quest for an effective policy to increase GDP growth. One possible reason for the low or negative growth rate is the low level of industry productivity. Although we can take a macroeconomic approach for such an analysis, recent microeconometric developments allow us to investigate the problem using micro-data such as plant and segment-level data. Such an analysis will yield a more precise statistical result at various levels of aggregation.

The most commonly used measure of productivity is the total factor productivity (hereafter TFP). Production technology of a firm or an economy is characterized by its production function. Cobb and Douglas (1928) proposed a production function with the following form:

$$Y_{it} = AL_{it}^{\beta_l}K_{it}^{\beta_k} \tag{1}$$

where Y_{it}, L_{it}, K_{it} indicate the output level, labor and capital inputs, respectively of firm (or any production unit such as a plant) i at time t. β_l, β_k and A, are parameters that determine the production technology. In the case of Cobb-Douglas production technology, TFP is defined by $\log A$, and it has been empirically measured by its estimate since the pioneering work by Solow (1957). Taking the logarithm of (1) and adding a disturbance term u_{it}, we transform the Cobb-Douglas production function into a log-linear form,

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

where $l_{it} = \log L_{it}$, $k_{it} = \log K_{it}$,$\beta_0 = \log A$. Christensen, Jorgenson and Lau (1973) considered an extension of the Cobb-Douglas production function to the following more general and flexible functional form that is a polynomial of independent variables:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{lk} l_{it} k_{it} + \beta_{kk} k_{it}^2 + u_{it}. \tag{3}$$

This is called the Translog production function. These two functional forms are widely used in theoretical and empirical economic research, and in the context of productivity analysis.

Numerous previous empirical works estimated the production function of the above forms (2) and/or (3) by using the ordinary least squares (OLS) method and treated $\hat{\beta}_0 + \hat{u}_{it}$ as an estimate of TFP, where $\hat{\beta}_0$ and $\hat{u}_{it}$ are estimate of β_0 and the regression residual. In this context, however, as discussed in Marschak and Andrews (1944) and many other subsequent papers, there can exist an econometric problem of endogeneity in OLS estimation. Firms may determine the factor input levels depending on their productivities, namely $\beta_0 + u_{it}$ if they can observe their own idiosyncratic shocks u_{it} before making the decision. Then l_{it} and k_{it} must be correlated with the error term, which creates a bias in the OLS estimators.

Several methods have been proposed to handle this endogeneity problem such as Olley and Pakes (1996) and Levinsohn and Petrin (1999, 2003), abbreviated as O&P and L&P respectively. They split the error term u_{it} into two components as follows:

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

ω_{it} represents firm-specific productivity or technological shock, which firms can, but econometricians cannot, observe before their input decision. Thus, it is possibly correlated with the factor inputs. η_{it} denotes the ordinary error term uncorrelated with the explanatory variables. They explicitly considered a correlation between ω_{it} and k_{it}, assuming exogeneity in l_{it}, and propose estimation methods solving the endogeneity problem.

The purpose of this paper is three-fold. First, we propose an alternative estimation method to O&P, L&P and their variants. Our alternative is a semiparametric instrumental variable estimator that is relatively easier to compute and allows for endogeneity in both capital and labor inputs, unlike O&P and L&P. Exogeneity of l_{it} is an empirical issue and it may or may not be an adequate assumption. For example, l_{it} is more likely to be exogenous in such industries in which a labor union has significant bargaining power and managers cannot easily change the labor input. On the other hand, l_{it} may be endogenous in industries employing many part-time workers or seasonal workers. In principle, exogeneity in l_{it} should lead to a bias in OLS, O&P, and L&P estimates, and we examine its direction theoretically. Second, we propose two methods to decompose the residuals into ω_{it} and η_{it}. This is important for the following reason. When TFP, the sum of β_0, ω_t, and η_t, of a country is declining, the government claims that "the productivity is low" and wants to increase it through economic policy. However, the necessary policy to be taken by the government must differ based on which of ω_{it} and η_{it} is the main cause of the poor economic performance. In the present setting, ω_{it} represents the technological (the supply side) shocks and η_{it} includes other shocks, such as demand shocks. If the former is the main cause, the government should give firms incentive to invest in R&D to improve supply-side performance. If the latter, say demand shock, is the cause, the government should implement a suitable macroeconomic policy to increase demand. In standard TFP measurements, we typically obtain only, $\omega_{it} + \eta_{it}$, but this is not sufficient to determine the most appropriate and/or efficient policy. The government must know ω_{it} and η_{it} separately for such a purpose. Third, we applied the proposed method to estimate production functions of a variety of industries in Japan using plant level data from 1982 to 2004, and decompose the TFP into ω_{it} and η_{it}. Then we determined whether the productivity, or more precisely technology, of Japanese firms declined during the so-called "lost decade" period of 1992-2002.

In the empirical study, the proposed estimation procedure provides reasonable estimates of β_l and β_k, and we found that the estimates mostly supported the bias direction of OLS and L&P depending on the industry. In some industries, we found no bias in L&P where we supposed that there was no endogeneity in l_{it}. We computed the productivity shock ω_{it} for each plant and year, and constructed industry-level productivity shocks. In general, we found no negative productivity shocks though it is said that productivity decreased or was very low during the "lost decade".

The following section reviews some of the previous research that solved the endogeneity problem in productivity analysis. Section 3 proposes an alternative IV estimator to O&P and L&P. Section 4 shows estimation results of the OLS, L&P, and the proposed method, and discusses about the bias resulting from endogeneity in l_{it}. We explain how to decompose the TFP into productivity shock and the error term, and apply the methods to the present Japanese data in Section 5. We also show supporting evidence that our estimation and decomposition performs reasonably well. Concluding remarks and future research are in Section 6.

2 A Brief Review of the Literature

A number of previous studies estimated production functions from a variety of motivations. Here we want to estimate it to compute micro-level productivity. The above model provides a possible econometric model in the case where firms determine their factor inputs after observing their technological shocks. This econometric model is widely used in empirical research after O&P and L&P, and its variants have been developed recently. We quickly review the literature in this field.

Several methods proposed to handle this endogeneity problem include O&P and L&P. They split out the error term u_{it} into two components as follows:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \eta_{it}. \tag{4}$$

ω_{it} represents firm-specific productivity or technological shock, which firms can, but econometricians cannot, observe before their input decision. Thus, it is possibly correlated with the factor inputs. ω_{it} is assumed to be a first-order Markov process and η_{it} denotes the ordinary error term uncorrelated with the explanatory variables. They explicitly consider a correlation between ω_{it} and k_{it}, assuming exogeneity in l_{it}, and propose estimation methods to solve the endogeneity problem.

O&P propose a solution to this problem using the investment decision of each firm as a proxy to ω_{it} in (4). This is motivated by Pakes (1996) which proves that optimizing firms have investment functions that are strictly increasing in the unobservable productivity shock ω_{it}. L&P use materials m_{it} to proxy ω_{it} instead of investment, because of many zero-investment observations. As pointed out by L&P (2003, p. 321), the investment function may have kinks that can cause a bias. We explain the method proposed by O&P and L&P in the context of the latter paper under a slightly simplified setting. The monotonicity of the input demand function with respect to ω_{it} allows the inversion:

$$\omega_{it} = \omega(m_{it}, k_{it}). \tag{5}$$

They assume $E(\omega_{it}) = 0$ and $E(\eta_{it}|k_{it}, l_{it}) = 0$. The former is for the identifiability of β_0 and the latter means that η_{it} is the standard disturbance term. Inserting (5) into equation (4), we can write the model as a partially linear form:

$$\begin{aligned} y_{it} &= \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega(m_{it}, k_{it}) + \eta_{it} \\ &= \beta_l l_{it} + \phi(m_{it}, k_{it}) + \eta_{it}, \end{aligned} \tag{6}$$

where $\phi(m_{it}, k_{it}) = \beta_0 + \beta_k k_{it} + \omega(m_{it}, k_{it})$ is an unknown function of m_{it}, k_{it}. Then we can apply Robinson (1988) to obtain consistent semiparametric estimates of β_l and $\phi(\cdot, \cdot)$ as follows. As a result of $E(\eta_{it}|m_{it}, k_{it}) = 0$, we have, from (6),

$$E(y_{it}|m_{it}, k_{it}) = \beta_l E(l_{it}|m_{it}, k_{it}) + \phi(m_{it}, k_{it}). \tag{7}$$

Subtracting (7) from (6), we obtain,

$$y_{it} - E(y_{it}|m_{it}, k_{it}) = \beta_l \{l_{it} - E(l_{it}|m_{it}, k_{it})\} + \eta_{it}. \tag{8}$$

Replacing the conditional expectations by nonparametric estimates, we apply the least squares method to estimate β_l. To estimate $\phi(\cdot, \cdot)$, we regress $y_{it} - \hat{\beta}_l l_{it}$ on (m_{it}, k_{it}) nonparametrically.

In the second step, β_0, β_k are identified and estimated. Letting $\xi_{it} = \omega_{it} - E(\omega_{it}|\omega_{i,t-1})$, write

$$\begin{aligned} \phi(m_{it}, k_{it}) &= \beta_0 + \beta_k k_{it} + \omega(m_{it}, k_{it}) \\ &= \beta_0 + \beta_k k_{it} + E(\omega_{it}|\omega_{i,t-1}) + \xi_{it}. \end{aligned} \tag{9}$$

Inserting equation (9) into (6), we have

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + E(\omega_{it}|\omega_{i,t-1}) + \xi_{it} + \eta_{it}, \tag{10}$$

where $\xi_{it} + \eta_{it}$ is uncorrelated with k_{it}, l_{it}. Given some fixed values of β_0 and β_k, we can "estimate" ω_{it} by

$$\hat{\omega}_{it} = y_{it} - \beta_0 - \hat{\beta}_l l_{it} - \beta_k k_{it}.$$

It is possible to construct an estimate for $E(\omega_{it}|\omega_{i,t-1})$ by regressing $\hat{\omega}_{it}$ on $\hat{\omega}_{i,t-1}$ nonparametrically, which is denoted as $\hat{E}_{(\beta_0,\beta_k)}(\omega_{it}|\omega_{i,t-1})$. The subscript (β_0, β_k) indicates that the estimated conditional expectation depends on the prefixed values of (β_0, β_k). Inserting $\hat{\beta}_l$ from the first step and this estimate into (10) , we have

$$y_{it} \approx \beta_0 + \hat{\beta}_l l_{it} + \beta_k k_{it} + \hat{E}_{(\beta_0,\beta_k)}(\omega_{it}|\omega_{i,t-1}) + \xi_{it} + \eta_{it}.$$

Then we can estimate (β_0, β_k) using a non-linear least squares method or the generalized method of moments.

Ackerberg, Caves and Frazer (2006) (hereafter, ACF) proposed an alternative estimation method that allows firm's dynamic decision of labor. Using intermediate inputs m_{it}, we can write (11) analogously to (5) as follows:

$$\omega_{it} = \omega(m_{it}, k_{it}, l_{it}). \tag{11}$$

Inserting this into (4) and dropping the constant term, we obtain

$$\begin{aligned} y_{it} &= \beta_l l_{it} + \beta_k k_{it} + \omega(m_{it}, k_{it}, l_{it}) + \eta_{it} \\ &= \Phi(\omega_{it}, k_{it}, l_{it}) + \eta_{it}. \end{aligned}$$

$\Phi(\omega, k, l)$ is obiviously identifiable and estimable. Assuming that ω_{it} is a first order Markov process, we have

$$\begin{aligned} \omega_{it} &= E(\omega_{it}|\omega_{i,t-1}) + \xi_{it} \\ &= g(\omega_{i,t-1}) + \xi_{it}. \end{aligned}$$

For this disturbance ξ_{it}, we have a moment condition $E(\xi_{it}|k_{it}, l_{i,t-1}) = 0$. Given values for (β_k, β_l) and using an estimate for Φ, we can construct

$$\hat{\omega}_{(\beta_k,\beta_l)}(m_{it}, k_{it}, l_{it}) = \hat{\Phi}(\omega_{it}, k_{it}, l_{it}) - \beta_l l_{it} - \beta_k k_{it}.$$

They regressed $\hat{\omega}_{(\beta_k,\beta_l)}(m_{it}, k_{it}, l_{it})$ on $\hat{\omega}_{(\beta_k,\beta_l)}(m_{i,t-1}, k_{i,t-1}, l_{i,t-1})$ and obtained the regression residual $\hat{\xi}_{(\beta_k,\beta_l)}(m_{it}, k_{it}, l_{it})$. Finally, the above moment conditions are used to estimate (β_k, β_l).

To the best of our knowledge, not many studies applied these methods to a Japanese plant-level dataset. Fukao and Kwon (2006) used plant-level data of Japan to examine productivity during the "lost decate". Fukao et al. (2007) applied the L&P method to estimate the plant-level production function of Japanese firms. However, their main interest was not in the TFP, but in the wage function and labor productivity. Kim (2008) measured TFP based on a similar econometric model taking into account endogeneity, where ω_{it} is determined at least in part by R&D.

Doraszelski and Jaumandeu (2007) studied the relation between R&D and ω_{it} using data from Spanish manufacturing companies. They took the approach by ACF explicitly modeling ω_{it} such that it depends on R&D. Kim (2008) used the same method to examine Japanese data. Fox and Smeets (2007) explored solutions to the "too much" dispersion of measured TFP in the cross-sectional direction by considering labor quality and adopting the O&P method. Gandhi, Navarro and Rivers (2009) introduced the idea of using the share equations to identify firm-specific productivity. The key advantages of their method are first, to avoid the endogeneity of inputs and second, to adopt additional heterogeneities among firms in their estimation to improve the accuracy of measuring firm-level productivity. Blundell and Bond (2000) proposed a solution to the finite sample bias problem given weak instruments in implementing the first-differenced GMM estimation, and applied a system GMM to estimate the Cobb-Douglas production function. They found a higher and strongly significant capital coefficient in the U.S. data.

Many other papers are related to this problem. See the references in these articles. We also refer to Ackerberg, Benkard, Berry and Pakes (2007) and Syverson (2010) for a brief survey of this field.

3 An Alternative Estimator

We propose an estimator for (4) with the above stated endogeneity. O&P and L&P show how to use investments and intermediate inputs to control for the correlation between k_{it} and ω_{it}. They identified the parameters in an ingenious way and proposed estimators. However, the endogeneity problem of input levels does not seem to be solved completely by these methods because they only take into account the correlation of productivity shock ω_{it} with capital input level k_{it}, not with labor input l_{it}. If l_{it} is also determined by firms depending on ω_{it} like k_{it}, we have $E(l_{it}|m_{it}, k_{it}) = E(l_{it}|\omega_{it}) = l_{it}$. Then β_l is not obviously identified in view of (8), and the first-step estimation procedure for β_l collapses.

As long as the assumption related to exogenous labor input is correct, either O&P or L&P will provide consistent estimates of the parameters. One may not, however, agree with the assumption as an actual decision that firms make. It is, we believe, an empirical issue, that should not be simply assumed without empirical investigations. We propose an alternative semiparametric IV estimator that allows for the endogeneity in both inputs. We adopt the lagged input variables as the instruments and rewrite equation (10) as

$$\begin{aligned} y_{it} &= \beta_0 + \beta_l l_{it} + \beta_k k_{it} + E(\omega_{it}|l_{i,t-1}, k_{i,t-1}) + \xi_{it} + \eta_{it} \\ &= \beta_0 + \beta_l l_{it} + \beta_k k_{it} + g(l_{i,t-1}, k_{i,t-1}) + \xi_{it} + \eta_{it}, \end{aligned} \tag{12}$$

where $g(l_{i,t-1}, k_{i,t-1}) = E(\omega_{it}|l_{i,t-1}, k_{i,t-1})$ and $\xi_{it} = \omega_{it} - E(\omega_{it}|l_{i,t-1}, k_{i,t-1})$. From this equation, we immediately know the following moment conditions:

$$E(\xi_{it}|l_{i,t-1},k_{i,t-1})=0,$$

$$E(\eta_{it}|l_{i,t-1},k_{i,t-1})=0.$$

Although we want to consider the above two moment conditions separately, we can only use

$$E(\xi_{it}+\eta_{it}|l_{i,t-1},k_{i,t-1})=0, \tag{13}$$

for the estimation of parameters since ξ_{it} and η_{it} are not separable. Using that ω_{it} is a first order Markov process, we also have the following moment condition:

$$E(\xi_{it}+\eta_{it}|l_{i,t-2},k_{i,t-2})=0. \tag{14}$$

If $g(\cdot,\cdot)$ is known, the above conditions would identify the parameters and we can easily estimate them. Since it is unknown, we approximate it by a linear combination of series functions. Letting $\phi_p(u)$, $p=0,1,2,\cdots$ be a set of basis functions over a suitable L^2 space, we can appoximate any function in the space as

$$g(l_{i,t-1},k_{i,t-1})\approx\sum_{p=0}^{J_n}\sum_{q=0}^{J_n}c_{pq}\phi_p(l_{i,t-1})\phi_q(k_{i,t-1}), \tag{15}$$

for some $J_n\to\infty$ as $n\to\infty$ more slowly than n. Plugging (15) into (12), we obtain the final form,

$$y_{it}=\beta_0+\beta_l l_{it}+\beta_k k_{it}+\sum_{p=0}^{J_n}\sum_{q=0}^{J_n}c_{pq}\phi_p(l_{i,t-1})\phi_q(k_{i,t-1})+\xi_{it}+\eta_{it}. \tag{16}$$

We can estimate $\beta_0,\beta_l,\beta_k,c_{pq}$ by a GMM method using the moment conditions (13) and (14). Any basis functions can be used in theory for $\phi_p(\cdot)$, but if we use standard polynomials, we easily face the multicollinearity problem; therefore, we can include polynomials up to, say, only the third order.

We briefly describe the advantages and disadvantages of this estimator. We allow for the correlation between ω_{it} and k_{it} as well as ω_{it} and l_{it}. O&P use investment as a proxy variable for ω_{it} but it is not necessary here. There are two problems with using investments as Levinsohn and Petrin (2003) pointed out. First, investment data are hardly available, especially at the plant or segment level. Second, the investment function may not be smooth, which can create an estimation bias. A disadvantage is that we use $l_{i,t-1},k_{i,t-1},l_{i,t-2},k_{i,t-2}$ as instrumental variables so that the number of observation effectively used decreases. We also point out the possibility of high correlation between k_{it} and $k_{i,t-1}$, and/or betweenl_{it} and $l_{i,t-1}$, which make the estimate unstable. When we have access to suitable exogenous or predetermined variables for period $t-1$, we can use them similarly to L&P. Indeed, we do so in the following sections; namely, we use the following moment condition in place of (14):

$$E(\xi_{it} + \eta_{it} | e_{i,t-1}, m_{i,t-1}) = 0,$$

where $e_{i,t-1}$ and $m_{i,t-1}$ are electricity usage and materials respectively.

4 An Empirical Study for Japanese Plant Level Data

Using plant level Japanese micro panel data, we estimate the Cobb-Douglas production function by three methods, OLS, L&P, and the new method proposed in the previous section, called INK hereafter. Although it is possible to apply suitable panel estimation methods, we do not take this approach because of the possibility of changes in technological parameters β_k, β_l over time. We use the data as a series of cross sectional observations partly because we have rather large sample sizes in many manufacturing industries for each year.

In terms of estimation, we are interested in the following points. First, we would like to examine whether the technological parameters β_k and β_l changed over time. It is said that, in Japan, labor productivity has been increasing over time in recent years, but capital productivity has been decreasing. We can confirm this by estimating parameters year by year and comparing the estimates over time. Second, we would like to check whether any endogeneity, as considered in the model, exists. If no endogeneity exists, all three estimators must provide similar results. If only the capital input is endogenous, as assumed by L&P, L&P and INK must provide similar results. If all inputs have endogeneity, the three methods must give different estimates.

4.1 Estimation Model

We employ the same type of model as (4);

$$y_{it} = \beta_{0t} + \beta_{lt} l_{it} + \beta_{kt} k_{it} + \omega_{it} + \eta_{it}, \tag{17}$$

where y_{it}, l_{it}, k_{it} are log-value added, log-labor input and log-capital input of plant i at time t. ω_{it} and η_{it} indicate productivity shock and exogenous idiosyncratic disturbance, respectively. This is the same specification as (4) in the previous sections, but different in that the parameters can be time dependent. We use the observations of materials m_{it} and electricity usage e_{it} as the instruments in addition to $k_{i,t-1}, l_{i,t-1}$. Because $k_{i,t-1}$ and $k_{i,t-2}$ are highly correlated in our data, including both $k_{i,t-1}$ and $k_{i,t-2}$ simultaneously as instruments is inadequate. We proxy ω_{it} by $e_{i,t-1}$, $m_{i,t-1}$ for reasons discussed later. Letting $\{\phi_p(x)\}_{p=0}^{\infty}$ be a complete basis of an L_2 space, we use the following estimation model:

$$y_{it} = \beta_{0t} + \beta_{kt}k_{it} + \beta_{lt}l_{it} + \omega_{it} + \eta_{it}, \;\; i = 1, \cdots, n, \;\; t = 1, \cdots, T,$$

$$\omega_{it} = g(e_{i,t-1}, m_{i,t-1}) + \xi_{it} = \sum_{p=0}^{J_n}\sum_{q=0}^{J_n} c_{pq}\phi_p(e_{i,t-1})\phi_p(m_{i,t-1}) + \xi_{it},$$

with the moment conditions,

$$E(\xi_{it} + \epsilon_{it}|e_{i,t-1}, m_{i,t-1}, l_{i,t-1}, k_{i,t-1}) = 0,$$

where $g(e_{i,t-1}, m_{i,t-1}) = E(\omega_{it}|e_{i,t-1}, m_{i,t-1})$ and J_n is a user-determined constant satisfying $J_n \to \infty$ and $J_n/n \to 0$ as $n \to \infty$. In our empirical analysis, we employ the trigonometric series by transforming the energy input by $2\pi(e_{i,t-1}/\max_i e_{i,t-1}) - \pi$ for each year and similarly for the materials.

4.2 Bias Evaluations Resulting from Endogeneity: OLS and L&P

Before showing the empirical results, we studied the possible bias of OLS and L&P estimators for (17). Bias exists when either or the both of the explanatory variables are endogenous. We evaluated the bias direction under endogeneity. Let $s_{xy} = n^{-1}\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})$, and write the OLS estimator as

$$\begin{pmatrix} \tilde{\beta}_l \\ \tilde{\beta}_k \end{pmatrix} = \begin{pmatrix} \beta_l \\ \beta_k \end{pmatrix} + \frac{1}{s_{kk}s_{ll} - s_{kl}^2}\begin{pmatrix} s_{kk}s_{lu} - s_{lk}s_{ku} \\ s_{ll}s_{ku} - s_{lk}s_{lu} \end{pmatrix},$$

where $u = \omega + \eta$. We have $s_{kk}s_{ll} - s_{kl}^2 > 0$ unless k and l are completely correlated. If k is endogenous, $s_{ku} > 0$, and if l is endogenous, $s_{lu} > 0$. We first consider the bias of $\tilde{\beta}_l$. Putting $\rho_{xy} = s_{xy}/\sqrt{s_{xx}s_{yy}}$, we write

$$\tilde{\beta}_l - \beta_l = \frac{s_{kk}s_{lu} - s_{lk}s_{ku}}{s_{kk}s_{ll} - s_{kl}^2} = \frac{s_{kk}\sqrt{s_{ll}s_{uu}}}{s_{kk}s_{ll} - s_{kl}^2}(\rho_{lu} - \rho_{lk}\rho_{ku}).$$

The sign of the bias is the same as that of $\rho_{lu} - \rho_{lk}\rho_{ku}$ because $s_{kk}\sqrt{s_{ll}s_{uu}}/(s_{kk}s_{ll} - s_{kl}^2) > 0$. We observe $0 < \rho_{lk} < 1$ in our dataset; thus, $E(\tilde{\beta}_l) - \beta_l < 0$ when only K_{it} is endogenous. If both K_{it} and L_{it} are "equally endogenous" (meaning $\rho_{lu} \approx \rho_{ku}$), or L_{it} is "more endogenous" than K_{it} (meaning $\rho_{lu} > \rho_{ku}$), $E(\tilde{\beta}_l) - \beta_l > 0$ tends to hold. Similarly, writing

$$\tilde{\beta}_k - \beta_k = \frac{s_{ll}s_{ku} - s_{lk}s_{lu}}{s_{kk}s_{ll} - s_{kl}^2} = \frac{s_{ll}\sqrt{s_{kk}s_{uu}}}{s_{kk}s_{ll} - s_{kl}^2}(\rho_{ku} - \rho_{lk}\rho_{lu}),$$

we see that $E(\tilde{\beta}_k) - \beta_k > 0$ when only K_{it} is endogenous, both K_{it} and L_{it} are "equally endogenous", or K_{it} is "more endogenous" than L_{it}.

L&P should be asymptotically unbiased when only K_{it} is endogenous. However, if both K_{it} and L_{it} are endogenous, β_l tends to have a positive bias in view of its identification

Table 1: Bias Direction

Endogeneity	Parameter	OLS	L&P	INK
Only K	β_k	$+$	0	0
	β_l	$-$	0	0
Both K&L	β_k	$+(*)$	$+/0/-$	0
	β_l	$+(*)$	$+$	0

(*) When $\rho_{lu} \approx \rho_{ku} (> 0)$.

strategy (L&P(2003), eq.(4)):

$$y_{it} - E(y_{it}|k_{it}) = \beta_l\{l_{it} - E(l_{it}|k_{it})\} + \xi_{it} + \eta_{it}.$$

L&P assumes that labor input is not endogenous, or l_{it} and η_{it} are uncorrelated. This motivates them to use a least squares method following Robinson (1988). If, however, labor input is also endogenous, l_{it} and η_{it} should have a positive correlation. Then the L&P estimate of β_l should have a positive bias in view of the above equation. We do not know the sign of the bias for β_k by L&P. INK should be asymptotically unbiased even when both K_{it} and L_{it} are endogenous. Table 1 summarizes the results.

4.3 Data

We use "Census of Manufactures" provided by *the Ministry of Economy, Trade and Industry* in the empirical study. Our target is establishments (plants) with 30 or more employees. This includes about 1.33 millions establishments for 23 years from 1982 to 2004. The plants are classified by Japanese Standard Industrial Code (hereafter JSIC). Plants producing two or more kinds of products are classified by the product with the largest shipment value from the plant. We use the six largest industries and two major high-tech industries by two-digit JSIC. Table 2 shows the number of plants and the mean of value added in each of the eight industries: food (9), general machinery (26), metal products (25), apparel (12), electrical machinery (27), transportation equipment (30) and information & communication electronics equipment (28) and electronic parts & devices (29). L&P picked up the eight largest industries in the Chilean data: food, metal, textile, wood product, other chemicals, bevarages, printing and publishing, and apparel. The food industry is the largest in these two countries and the apparel industry is also large, but the others are not common. Japan has more weight on the heavy manufacturing industries. Figure 1 shows the number of plants in the food and apparel industries. The food industry is considered stable against economic fluctuations, while the apparel industry may be relatively sensitive. After the burst of the economic bubble in 1991, the number of apparal plants continued to decrease.

We define the dependent variable, value-added, and covariates, capital and labor inputs,

Table 2: Number of Plants and the Mean of Value Added (Million Yen)

	JSIC: 9		JSIC: 12		JSIC: 25		JSIC: 26	
Year	Plants	Value Added	Plants	Value Added	Plants	Value Added	Plants	Value Added
1981	5961	713.8	3802	211.9	4043	664.2	5268	1240.9
1985	6275	830.2	5001	251.4	4109	840.8	5712	1449.9
1990	6954	954.7	5380	300.7	4617	1099.9	6079	1839.5
1995	7311	1094.9	4539	329.3	4594	1198.9	5735	1792.5
2000	7309	1105.1	2760	337.1	4206	1112.9	5617	1781.1
2004	7067	1101.0	1789	327.7	3908	1051.2	5263	1841.1
	JSIC: 27		JSIC: 28		JSIC: 29		JSIC: 30	
Year	Plants	Value Added	Plants	Value Added	Plants	Value Added	Plants	Value Added
1981	3051	1165.8	1793	1385.4	1925	1062.1	3088	2647.9
1985	3786	1446.3	1674	1632.4	2753	1474.6	3260	3356.3
1990	4361	1733.8	1352	2457.9	2663	2117.7	3315	4110.2
1995	4146	1933.1	1565	3459.3	2733	2674.0	3283	4169.3
2000	3622	2037.4	1380	3812.3	2559	3527.8	3145	4033.1
2004	3012	2098.6	978	3565.9	2172	3802.3	3282	4519.2

JSIC 9: Food, 12: Apparel, 25: Metal, 26: General Machinery, 27: Electrical Macinery, 28: Information & Communication Electronics Equipment, 29: Electronic Parts & Devices, 30: Transportation Equipment

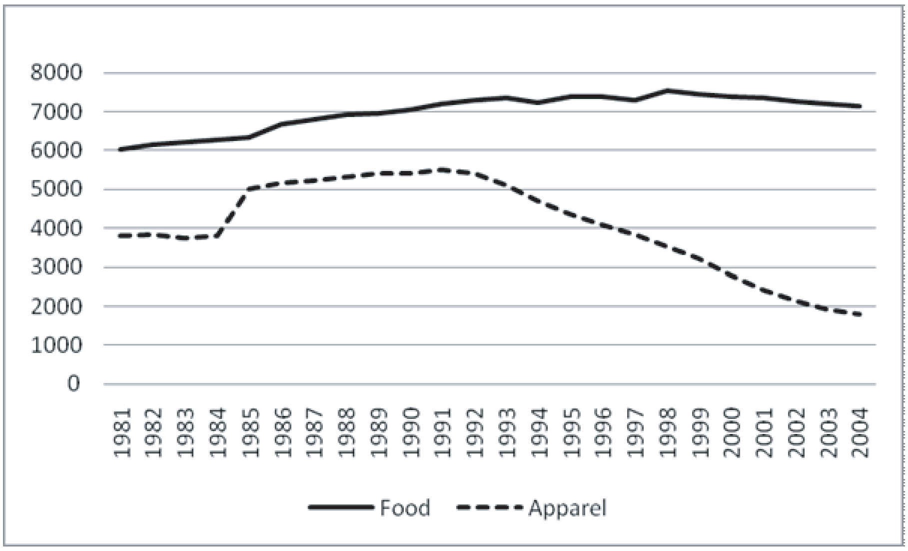

Figure 1: Number of the Plants: Food and Apparel Industry

in our empirical work as follows. To obtain the value-added (VA) of production activities in year t, we use the following variables:

- VA = (total shipment) - (cost of materials, fuels and electricity) - (starting inventory of finished and half-finished products) + (final inventory of finished and half-finished products)

The value of tangible fixed assets (K) includes buildings and structures, machinery and equipment with a durable life of one year or longer. We use the number of regular workers as labor input (L):

- K = (Starting tangible fixed asset) + (acquired tangible fixed asset during the year)− (depreciation)

- L = (# of full time workers) + (# of part-time workers) + (# of workers dispatched from other companies).

In choosing the proxy for ω_{it}, we have four informative intermediate inputs such as electricity, fuels, materials and water. L&P uses three intermediate inputs (fuels, materials and electricity) as proxy variables. We note that present dataset contains no plant-level investment observations. The Chilean data of L&P include investment observations, but also include over 50% of zero observations in each industry. They prefer materials and/or electricity to fuels as the proxy given the larger percentage of "non-zero" observations in the industries chosen. Table 3 shows the percentage of zero observations of in the four intermediate inputs for the eight industries in our dataset. We found that more than 90% of the plants reported non-zero observations for all four inputs in each of the eight industries.

L&P provided further guidance in selecting proxy variables. First, intermediate inputs used as a proxy should be reliably and stably supplied, and then they should be highly correlated with ω. L&P point out that electricity supply was unreliable in Chile during the period, and that a delivery problem for fuels might exist. In the present Japanese data, such supply problems in energy seem not to exist. Second, they mention a measurement problem related to the intermediate inputs. We would like to measure the exact amount of inputs used for production in a year. Firms usually record only the input purchased, not the amount used, in a year. L&P expects that electricity, for example, can be a good proxy because it cannot be stored. The amount of fuels and materials should have measurement errors because of the possible input inventory. L&P has the observations on consumed amounts of electricity, but only new purchases of fuels and materials.

Our dataset contains the consumption-based data on electricity, fuels, materials and water in each year, all of which satisfy the above two requirements, in addition to having a good non-zero observation rate. We eventually chose electricity and materials as proxy variables and IV variables in our estimation. We dropped the fuels and water because the former included more non-zero observations than the other candidates and the latter had a relatively large correlation with electricity and materials.

Table 3: The Percentage of Zero Observations

Industry (JSIC)	Electricity	Fuels	Materials	Water
Food (9)	0.69 %	2.40 %	0.89 %	0.17 %
Apparel (12)	0.39 %	6.14 %	4.74 %	0.63 %
Metal (25)	1.21 %	6.34 %	1.66 %	0.32 %
General Machinery (26)	0.81 %	7.45 %	1.00 %	0.34 %
Electrical Machinery (27)	0.96 %	9.13 %	5.06 %	0.45 %
Information & Communication Electronics Equipment (28)	0.87 %	8.24 %	7.32 %	0.51 %
Electronic Parts & Devices (29)	0.97 %	9.53 %	6.91 %	0.51 %
Transportation Equipment (30)	2.16 %	5.87 %	3.52 %	0.54 %

4.4 Estimation Results

We are mainly concerned with the following two points in parameter estimation. First, we would like to examine whether the technological parameters β_k and β_l have been changing over time. It is said that, in Japan, labor productivity has been increasing lately over time but capital productivity has been decreasing. Indeed, the relative shares of labor and capital are approximately (0.65,0.35) in 1980 but (0.75, 0.25) in 2008 according to the Japanese SNA report. Second, we would like to check whether endogeneity exists based on the bias examination in the previous section. If there is no endogeneity at all, all three estimators must provide similar results. If only capital input has endogeneity as supposed by O&P and L&P, the L&P and INK estimator must be close. If all inputs have endogeneity, the three methods must give different estimates. Our purpose is not to statistically test whether endogeneity exists, but rather to gain an impression about it.

Figure 2 presents the estimation results for eight industries. We use the solid line and the solid line with circles for OLS results, the dotted line and the dotted line with circles for L&P results, and the dashed line and the dashed line with circles for INK results. Lines with circles are the estimates for β_l and lines without circles are for β_k. β_l are always larger than β_k for all industries, and this does not depend on the estimation method. Moreover, all three estimates of β_k are less than 0.4 and β_l are over 0.6 for all industries. Although we expected that β_l increases and β_k decreases lately given macro economic indices, our results indicate that both β_k and β_l have been stable for all industries. We may conclude that labor-intensive industries have recently increased their share in the entire economy.

We would also like to examine the existence of input endogeneity. In Figure 2, we observe that OLS provides greater coefficient estimates than L&P and INK in all industries. Also, $\hat{\beta}_{l\_LP}$ is greater than $\hat{\beta}_{l\_INK}$ in the food, electrical machinery, metal and general machinery industries, while $\hat{\beta}_{k\_LP}$ is about the same as or slightly smaller than $\hat{\beta}_{k\_INK}$. This is consistent with the case in Table 1 when both k_{it} and l_{it} are endogenous. Thus, we conjecture that because of endogeneity problems in both inputs, the OLS has an upward bias for both β_k, β_l while L&P for β_l has upward bias in at least some industries. The apparel industry is an exception, where $(\hat{\beta}_{l\_LP}, \hat{\beta}_{k\_LP})$ are almost the same as $(\hat{\beta}_{l\_INK}, \hat{\beta}_{k\_INK})$. This suggests that only capital input has endogeneity in this industry, as supposed by L&P. From these findings, we may conclude that there exists endogeneity both in k and l in some industries investigated here.

5 Measuring Firm-Specific Productivity

In the standard TFP analysis where ω_{it} does not appear, or there is no endogeneity, we simply run an OLS regression and compute the residual, and then regard this as productivity. Similarly, in view of (4), it is natural to compute the residual,

$$\widehat{\omega_{it} + \eta_{it}} = y_{it} - \hat{\beta}_0 - \hat{\beta}_l l_{it} - \hat{\beta}_l k_{it} \tag{18}$$

to obtain the productivity shock, where $\hat{\beta}_0, \hat{\beta}_l, \hat{\beta}_k$ are INK estimates. Noting that $E(\eta_{it}|k_{it}, l_{it}) = 0$, we might be able to regard $\widehat{\omega_{it} + \eta_{it}}$ as an estimate of technological shock. However, this residual should in fact include not only technological shocks but also other shocks such as demand shock. Therefore we should be careful in regarding $\widehat{\omega_{it} + \eta_{it}}$ as an estimate of productivity shock ω_{it}. As discussed in the introduction, small ω_{it} and small η_{it} can lead to completely different policy implications. Furthermore, statistically, if $Var(\eta_{it})$ is large, (18) may not be an accurate estimate of ω_{it}. Thus, in our view it must be important to extract ω_{it} out of $\widehat{\omega_{it} + \eta_{it}}$.

It also seems reasonable to estimate ω_{it} by

$$\hat{g}(l_{i,t-1}, k_{i,t-1}) = \sum_{p=0}^{J_n} \sum_{q=0}^{J_n} \hat{c}_{pq} \phi_p(l_{i,t-1}) \phi_q(k_{i,t-1})$$

in view of (12) and (15). However, we do not believe this is satisfactory because, obviously, k_{it} and l_{it} (or other inputs at time t) must possess more information on ω_{it} than variables at $t-1$. Writing $\omega_{it} = g(k_{i,t-1}, l_{i,t-1}) + \xi_{it}$, $g(k_{i,t-1}, l_{i,t-1})$ includes information only at time $t-1$ and that of time t should be squeezed into ξ_{it}. In this sense, ξ_{it} must include information on ω_{it}. It is also possible to measure ω_{it} from the profit maximization behavior of each firm. In the following section, we describe how to identify or extract ω_{it} at least in part, and decompose the residual (18) into the two components $\hat{\omega}_{it}$ and $\hat{\eta}_{it}$.

5.1 ω_{it} Identification Methods

We can think of two ways to predict ω_{it}. One is statistical and the other is based on the economic theory of profit maximization.

The key feature for identification of the first way is the properties $E(\eta_{it}|l_{it}, k_{it}) = 0$, but $E(\omega_{it}|l_{it}, k_{it}) \neq 0$. We first consider the ideal case where ω_{it} is measurable with respect

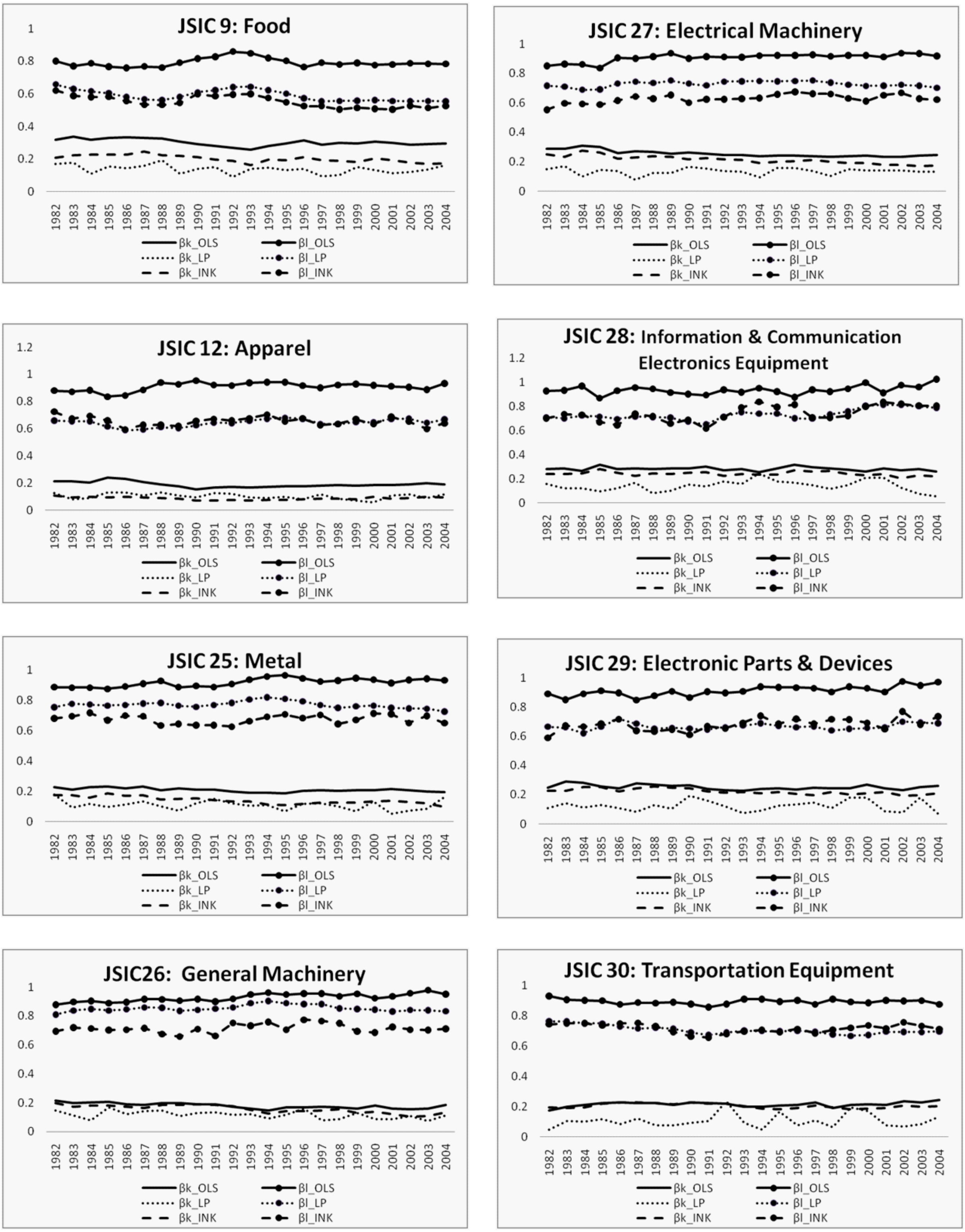

Figure 2: Estimation Results (OLS, LP and INK)

to the $\sigma-$algebra generated by (l_{it}, k_{it}). In this case, we have

$$\begin{aligned} E(\omega_{it} + \eta_{it}|l_{it}, k_{it}) &= E(\omega_{it}|l_{it}, k_{it}) + E(\eta_{it}|l_{it}, k_{it}) \\ &= \omega_{it} + 0 = \omega_{it}. \end{aligned} \tag{19}$$

If firms cannot fully adjust the inputs to the change in ω_{it}, it may not be measurable with respect to the $\sigma-$algebra generated by (l_{it}, k_{it}). Then, we have

$$E(\omega_{it} + \eta_{it}|l_{it}, k_{it}) = E(\omega_{it}|l_{it}, k_{it}) \tag{20}$$

unlike (19). However, as long as firms try to select the inputs optimally given their ω_{it}, it is likely that $\omega_{it} \approx E(\omega_{it}|l_{it}, k_{it})$. Therefore, we can believe that (19) still holds approximately. This provides us with a moment condition for identification of ω_{it}. Indeed, we can statistically justify the approximation in the sense that

$$E(\omega_{it} + \eta_{it}|l_{it}, k_{it}) = argmin_{h(\cdot,\cdot)} E[\{\omega_{it} - h(l_{it}, k_{it})\}^2|l_{it}, k_{it}],$$

namely, it is the minimum conditional mean squared error unbiased predictor of ω_{it} given (l_{it}, k_{it}). Therefore, it is an optimal predictor of ω_{it} given (l_{it}, k_{it}) in any case. This is a regression based approach to obtain ω_{it}, and we hereafter write it ω_{it_reg}. We remark that we can replace l_{it}, k_{it} by any other inputs $x_{it} = (l_{it}, k_{it}, e_{it}, m_{it}, \cdots)$, which are highly correlated with ω_{it}. In particular, inputs that firms can adjust flexibly are suitable.

The second approach uses the first-order condition of profit maximization by firms. Let $Y_{it} = f(L_{it}, K_{it}) = e^{\omega_{it}} A L_{it}^{\beta_l} K_{it}^{\beta_k}$ be the production function measured by the value-added, which each firm faces. It does not include the idiosyncratic error η_{it} because firms cannot observe it; thus, firms maximize their profit with respect to this production function without ϵ_{it}. Let $f_L(L_{it}, K_{it}) = \partial f(L_{it}, K_{it})/\partial L_{it}$, and w_t be the price of labor input. The first order condition of profit maximization with respect to L_{it} is

$$f_L(L_{it}, K_{it}) = \mathrm{w}_t \tag{21}$$

and given the Cobb-Douglas specification,we have

$$f_L(L_{it}, K_{it}) = e^{\omega_{it}} A \beta_l L_{it}^{\beta_l - 1} K_{it}^{\beta_k}. \tag{22}$$

Note that we do not need the price of te products because $f(L, K)$ is measured by the value-added. Combining (21) and (22), and multiplying by L_{it}, we have

$$e^{\omega_{it}} A \beta_l L_{it}^{\beta_l} K_{it}^{\beta_k} = \mathrm{w}_t L_{it}.$$

Then using $Y_{it} = AL_{it}^{\beta_l} K_{it}^{\beta_k}$,

$$\omega_{it} = log(\frac{\mathrm{w}_t L_{it}}{A\beta_l Y_{it}}). \tag{23}$$

Given the observations of total labor cost ($\mathrm{w}_t L_{it}$), value-added Y_{it}, and estimates of β_l, A, we can compute ω_{it} and hereafter write it as ω_{it_foc}.

In theory, both (20) and (23) should provide reasonable estimates, but it is not easy to say which of the two methods is better. We suppose ω_{it_reg} is more robust, as it does not assume profit maximization, but ω_{it_foc} must provide good estimates for highly competitive industries. (19), (20) are reliable if the firm can fully adjust the inputs depending on ω_{it}, namely, the inputs are flexibly adjusted.

5.2 Estimation of ω_{it} and its Aggregation

We can estimate ω_{it} in two ways based on the two identification approaches of ω_{it} described in section 5.1. In any case, we first estimate model (16) for an industry using the method described in Section 4, where we obtain the parameter estimates $\hat{A}$, $\hat{\beta}_k$, $\hat{\beta}_l$, $\hat{c}_{pq}$ for each industry.

Following the first identification, we first obtain the residual (18), then estimate ω_{it_reg} by regressing $\widehat{\omega_{it} + \eta_{it}}$ on $x_{it} = (k_{it}, l_{it}, e_{it}, m_{it}, \cdots)$, which is a vector of inputs at time t, to obtain

$$\hat{\omega}_{it\_reg} = \hat{E}(\widehat{\omega_{it} + \eta_{it}} | x_{it}). \tag{24}$$

We can simply run an OLS regression to construct (24), but if linearity is not a suitable assumption, we can apply a nonparametric kernel regression estimation,

$$\hat{\omega}_{it\_reg} = \frac{\sum_{j=1}^{n} \frac{1}{h} H(\frac{x_{jt} - x_{it}}{h}) \widehat{\omega_{jt} + \eta_{jt}}}{\sum_{j=1}^{n} \frac{1}{h} H(\frac{x_{jt} - x_{it}}{h})}, \tag{25}$$

where $H(\cdot)$ is a positive multivariate kernel function that integrates to unity, and h is a positive bandwidth. We can also apply any other nonparametric regression methods such as series estimation. We later use k_{it}, l_{it}, their quadratic terms and quantity of water to predict the productivity ω_{it_reg} in the empirical analysis.

(24) must provide a satisfactory estimate, but we can further attempt to exclude explicitly demand shocks, which should not be included in ω_{it}. We add the following regressor which can be regarded as a proxy for demand shocks. The inventory ratio to shipment is defined as

$$\begin{aligned} ISR_{it} = \frac{final\ inventory_{it}}{shipment_{it}} &= \frac{p_t \times Quant.\ of\ final\ inventory_{it}}{p_t \times Quant.\ of\ shipment_{it}} \\ &= \frac{Quant.\ of\ final\ inventory_{it}}{Quant.\ of\ shipment_{it}} \end{aligned}$$

$$= c_i + unexpected\, demand\ shock_{it},$$

where p_t is the price of the product, and c_i denotes the firm-specific planned inventory ratio independent of t, or each firm's fixed risk management for inventory. Then, $ISR_{it} - c_i$ represents unexpected demand shock. We use the first difference of demand shock $\Delta ISR_{it} = ISR_{it} - ISR_{it-1}$ to remove c_i. To implement the decomposition of ω_{it_reg} and η_{it}, we include inputs and a demand shock proxy in the regression. Specifically, letting z_{it} be the amount of water use, we run a regression

$$\widehat{\omega_{it} + \eta_{it}} = \alpha_0 + \alpha_{l1} l_{it} + \alpha_{l2} l_{it}^2 + \alpha_{k1} k_{it} + \alpha_{k2} k_{it}^2 + \alpha_z z_{it} + \alpha_d \Delta ISR_{it} + u_{it}$$

and compute

$$\hat{\omega}_{it\_reg} = \hat{\alpha}_0 + \hat{\alpha}_{l1} l_{it} + \hat{\alpha}_{l2} l_{it}^2 + \hat{\alpha}_{k1} k_{it} + \hat{\alpha}_{k2} k_{it}^2 + \hat{\alpha}_z z_{it}.$$

Note that we exclude the demand effect ΔISR_{it} as it should not be included. This provides an estimate of technological shock for plant i at time t.

Following the second approach of identification (23), we can simply construct

$$\hat{\omega}_{it\_foc} = \log\left(\frac{\mathrm{w}_t L_{it}}{\hat{A}\hat{\beta}_l Y_{it}}\right). \tag{26}$$

As done in L&P(1999), we can further construct industry-level productivities $\hat{\omega}_t$, by aggregating $\hat{\omega}_{it}$, as

$$\hat{\omega}_t = \sum_{i=1}^{n} s_{it} \hat{\omega}_{it},$$

where s_{it} represents the product share of plant i at time t. We can compute such $\hat{\omega}_t$ for each industry and time t, and can further aggregate $\hat{\omega}$'s of different industries to a macro level using analogous weights. L&P (1999) also aggregate individual productivities to industry-level productivities to examine the source of the productivity transition. Changes in the level of $\hat{\omega}_t$ from one year to another are decomposed into four sources; new entries, exits, share changes and individual productivity changes (see L&P (1999)). This tells us why the productivity of a certain industry rises or falls. In our analysis, we aggregate each plant using a two-digit code.

Figure 3 shows the growth rate from 1983 to 2004 of aggregated $\hat{\omega}_{t\_reg}$ and $\hat{\omega}_{t\_foc}$, with a solid line and a dotted line, respectively, for a variety of industries. We first remark that the levels of $\hat{\omega}_{t\_reg}$ and $\hat{\omega}_{t\_foc}$ are always positive throughout the period, although we suppress them. We briefly describe the Japanese economy during this period, which was mostly stable from 1982 to 1985. The economy bubbled from 1986 to 1991, and the period from 1992 to 2002 is called the "lost decade." It is believed that the economy upturned around 2003; however, we maintained a low GDP growth rate since then. During the bubble economy, GDP grew over 6%, while after the bubble burst the average growth rate was about 1.3 % and was negative in some years.

We evaluate the bubble economy and the "lost decade" periods in terms of the growth rate of $\hat{\omega}_t$ from 1982, because growth rates were moderate and stable around this period and near the 3.3% average from 1955 to the present. In addition, we can obtain similar results even if we change the base year of 1982 to another year during 1980-1983. $\hat{\omega}_{t\_reg}$ have been increasing in food, general machinery and electrical machinery. Apparel, metal and transportation equipment industries jumped up in the 1980's and after 1990 maintained a higher level than in 1982. On the contrary, during the bubble period, we observe higher growth rates than in 1982 in information & communication electronsic equipment, but the level of $\hat{\omega}_{t\_reg}$ decreased after the bubble economy. $\hat{\omega}_{t\_reg}$ of electronic parts & devices was observed to be lower than that of 1982 in most years. We found that five industries maintained the same or higher level of $\hat{\omega}_{t\_reg}$ than in the starting year of 1982.

We should point out that $\hat{\omega}_{t\_foc}$ are volatile compared with $\hat{\omega}_{it\_reg}$ for eight industries. In a regression-based method, we used additional information on demand shocks to make $\hat{\omega}_{it\_reg}$ independent of demand. Therefore, it should be less affected by demand shocks than $\hat{\omega}_{it\_foc}$. $\hat{\omega}_{t\_reg}$ and $\hat{\omega}_{t\_foc}$ moved quite similarly in information & communication electronics equipment. Seven other industries seemed to have large gaps in the magnitude of the growth rates between two methods. However, they had similar fluctuation patterns since 1990 even though the levels differ.

We cannot say which of $\hat{\omega}_{t\_reg}$ and $\hat{\omega}_{t\_foc}$ is superior, but we shall take the former rather than the latter for the following reasons. First, we can incorporate additional information such as all t period inputs for production and demand effects into the regression. Second, the regression-based method does not impose a profit maximization restriction and, thus, is considered more robust. Third, $\hat{\omega}_{t\_reg}$ appears more stable than $\hat{\omega}_{t\_foc}$ in our data, which might be related to the previous two reasons. We used the regression-based results $\hat{\omega}_{it\_reg}$ as the productivity measurement in the following.

Figure 4 compares the average growth rates of the productivity measured by the standard TFP (residuals of OLS) and $\hat{\omega}_{t\_reg}$ during the bubble economy and the lost decade for each of the eight industries. During the bubble economy, we observed that both TFP and $\hat{\omega}_{t\_reg}$ had positive average growth rates for all eight industries. In the lost decade, however, we observed that the growth rate of TFP was negative in five industries, which was smaller than the growth rate of $\hat{\omega}_{t\_reg}$. We suppose that the standard TFP is heavily affected by demand shocks and it is not an adequate measure of productivity.

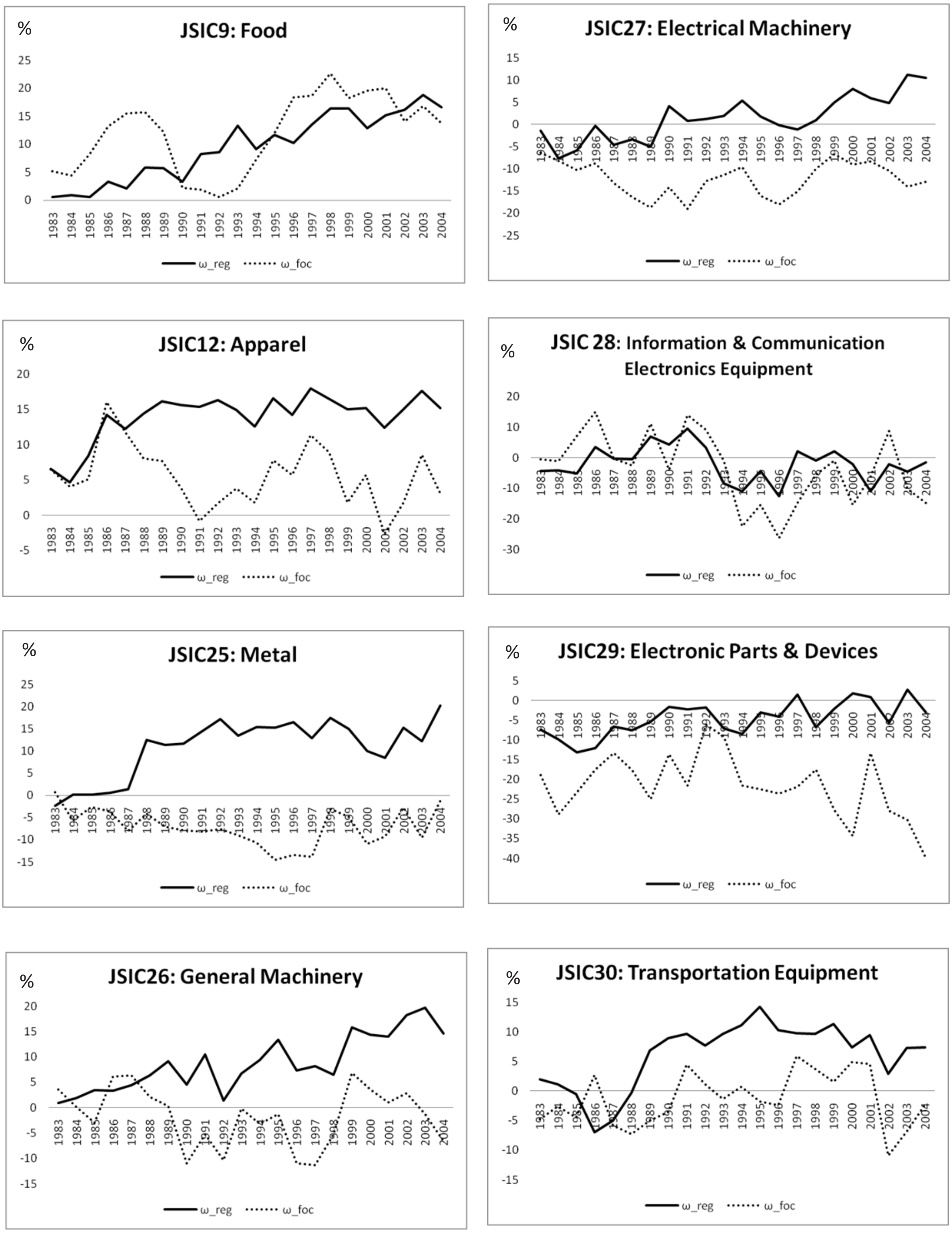

Figure 3: the Growth Rates of $\hat{\omega}_{t\_reg}$ and $\hat{\omega}_{t\_foc}$ (1983-2004)

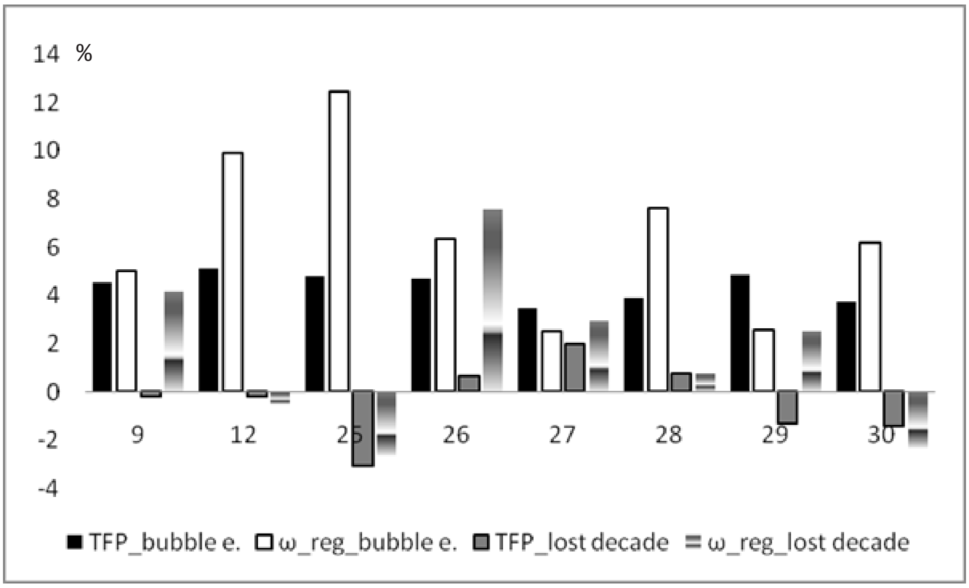

Figure 4: Average growth rate of productivity of TFP (OLS residuals) and $\hat{\omega}_{t\_reg}$, x axis presents JSIC.

5.3 Supporting Evidence from Semi-macro Indices

In the regression based method, we obtain $\hat{\omega}_{it\_reg}$ and then $\hat{\eta}_{it} = \widehat{\omega_{it} + \eta_{it}} - \hat{\omega}_{it\_reg}$. $\hat{\eta}_{it}$ can be aggregated for each industry in the same manner as the construction of $\hat{\omega}_{t\_reg}$:

$$\hat{\eta}_t = \sum_{i=1}^{n} s_{it}\hat{\eta}_{it},$$

where s_{it} are the product shares of plant i at time t. $\widehat{\omega_{it} + \eta_{it}}$ must include demand shocks, and we attempted to make $\hat{\omega}_{it\_reg}$ to exclude the demand effect. Then, demand shocks must be squeezed into $\hat{\eta}_{it}$. We examine whether or not this is true using semi-macro indices. We picked up two indices that represent demand shocks for each industry: "Business Indicator" (hereafter BI) and "Index of inventory turnover" (hereafter IIT) from the Indices of Industrial Production by *METI*, and computed the correlation coefficients between each index and $\hat{\eta}_t$.

We aggregated $\hat{\eta}_{it}$ to four-digits JSIC code. BI is an index of the economic mood of each industry and IIT measures the gap between demand and expected demand. The expected correlation with $\hat{\eta}_t$ is positive for BI and negative for IIT. The results are shown in Table 4 for the four industries in which BI and IIT are available. JSIC codes 2721, 2732, 2912, and 2913 indicate kitchenware, electric lighting fixtures, semiconductor devices and integrated circuits, respectively. We found negative correlations for all four industries with IIT, as expected, while three industries showed positive correlation with BI. Thus the signs mostly coincide with our expectations, and we suppose that $\hat{\eta}_t$ includes demand shocks. We also did the same calculation under a higher level of aggregation to using two-digits JSIC codes, and the result was not as clear as with the four-digit JISIC code aggregation, meaning that only about half the industries possessed correlation signs as expected. This may be because high level aggregation mixes heterogeneous agents, resulting in vague correlation.

Table 4: Correlation between $\hat{\eta_t}$ and demand index 4 digits

JSIC(4 digits)	Business Indicator	Index of Inventory turnover
2721	-0.422	-0.755
2732	0.300	-0.684
2912	0.576	-0.415
2913	0.499	-0.588

Table 5: Correlation between $\omega_t\hat{\_}_{reg}$ and Production Capacity Index (4 digits)

JSIC	Production Capacity Index
2721	0.856
2732	0.787
2912	0.805
2913	0.291

We would also like to determine whether $\hat{\omega}_{it}$ is positively correlated with a semi-macro index of industry-level productivity. One such possible index is the "Production capacity index" (PCI) from the same survey of BI and IIT. This index indicates the production capacity of each industry. We computed the correlation coefficient of PCI and $\hat{\omega}_t$, expecting it to be positive. We tabulated the results in Table 5, which shows a positive correlation for all four industries, as expected.

6 Conclusions and Future Research

We proposed an alternative production technology estimation method to O&P and L&P under stochastic firm- and time- specific technology shocks that cause a nuisance endogeneity. Our procedure allows both capital and labor inputs to depend on technology level, unlike O&P or L&P. Exit decisions by firms should also be automatically adapted under certain conditions. We also proposed two measures for plant-level productivities. One uses regression of the residual (TFP) on the input levels, and the other uses the first order condition of profit maximization by firms. We applied OLS, L&P and the new estimation procedures (INK) to Japanese micro datasets, and estimated production functions and productivities of various industries from 1982 to 2004. We compared the estimates to determine whether or not the endogeneity as considered exists. We also examine whether capital and labor coefficients changed over time at the micro level. Based on the estimates, we computed industry-level productivities to investigate whether productivity shocks in fact declined during the "lost decade" as is often claimed.

The Japanese government and some economists claim that Japan should increase the productivity in view of recent poor macroeconomic performance. This statement is, presumably, based on the measurement of $\omega_{it} + \eta_{it}$ in our framework. Supposing that $\omega_{it} + \eta_{it}$ is low, the policy implication should be very different between when ω_{it} is low and when η_{it} is low. From the present analysis, however, ω_{it}, the technology shocks, have not been declining throughout time. We conjecture that the recession during the "lost decade" in Japan was caused mostly by η_{it} shocks, and not productivity shocks, such as demand fluctuations. Therefore, we believe that the government should pay more attention to the demand side than the supply side, namely productivity, although, of course, increasing productivity should be good for the economy in any case.

We attempted to mitigate the endogeneity problem in the production function regression, but we cannot say that this has been completely solved. We, including O&P, L&P and others, treat ω_{it} as the productivity shock that firms can observe but that econometricians cannot. In fact, ω_{it} is essentially any shock that causes endogeneity by definition, which is observable to firms and affect their input behavior. Then, this can include demand shocks observed by firms, and we cannot definitely say that the estimates of ω_{it} are productivity shocks. Moreover, we did not use the operation ratio of capital and actual working hours, which may affect the parameter estimates, and thus ω_{it}. We need to more carefully handle these problem. One possibility is to use the "Current Survey of Production", which provides us with the information on how much of a product can be produced by plant, or plant capacity. Using this and the realized amount of products, we may be able to identify the demand shock observed or predicted by the firm. This can be used to remove observed demand shock effects included in the present estimates of $\hat{\omega}_{it}$. The research toward this direction is currently under way.

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