RIETI Discussion Paper Series 13-E-003

Decomposition of Supply and Demand Shocks in the Production Function using the Current Survey of Production

KONISHI Yoko
RIETI

NISHIYAMA Yoshihiko
Kyoto University

RIETI
Research Institute of Economy, Trade & Industry, IAA

The Research Institute of Economy, Trade and Industry
http://www.rieti.go.jp/en/

RIETI Discussion Paper Series 13-E-003
January 2013

Decomposition of Supply and Demand Shocks in the Production Function using the Current Survey of Production

KONISHI Yoko
Research Institute of Economy, Trade and Industry
NISHIYAMA Yoshihiko
Kyoto Institute of Economic Research, Kyoto University

Abstract

The purpose of this paper is to decompose total factor productivity (TFP)-type quantity into supply/productivity, demand, and other shocks. We propose a method of decomposing these three kinds of shocks in the production function using the gap between the actual amount of production and the production capacity of each plant. We construct a model to describe the capacity and realized production under Cobb-Douglas technology and attempt to compute the demand and supply/productivity shocks separately using the Current Survey of Production by METI. This dataset provides product-based data for production, sales, inventory, labor, and the production capacity of each plant at the present input levels. The main idea is that production capacity does not, or cannot, change against a short-term change in demand, but realized production should reflect such demand shocks observed by firms. We found no negative productivity shocks but found severe demand shocks during the financial crisis of 2007-2008 in our empirical results .

Keywords: Productivity, Production capacity, Supply shock, Demand shock, Plant-level data
JEL classification: C14, D24

The authors appreciate that various supports from the RIETI and are also grateful for helpful comments and suggestions by Professor Kyoji Fukao (Hitotsubashi University, RIETI-PD), Vice President Masayuki Morikawa (RIETI), President and CRO Masahisa Fujita (RIETI) and seminar participants at RIETI. This research was partially supported by the Ministry of Education, Culture, Sports, Science and Technology (MEXT), Grant-in-Aid for Scientic Research (No. 22330067 and 22730183).

1 Introduction

When the economic performance of an industry is poor, it is often said that the firms should raise their productivity. The main reason may indeed be bad productivity, but it could also be decreased demand perhaps due to recession. While it may be true that raising productivity will help the industry or firms regardless of the underlying cause, policy implications will be different. If decreased demand is the cause, the government should run a policy stimulating demand, but if reduced productivity is the cause, subsidies or tax benefits for R&D may be a suitable policy. In this sense, determining the main driving force of the poor performance of an industry/firms is important.

Total factor productivity (TFP) is the most commonly used productivity measure in the literature, especially in macroeconomics. However, it is often computed as a residual from production function estimation. It is virtually impossible to decompose it into demand and supply factors. There has been some research attempting such decomposition, for example, Levinsohn and Petrin (1999, 2003) and Ichimura, Konishi, and Nishiyama (2011). This paper is one such attempt. We use plants' production capacity and realized production data available in the Current Survey of Production (CSP) dataset.

The production technology of a firm or an economy is characterized by its production function. A common specification is the Cobb-Douglas production function:

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

where Y_{it}, L_{it}, and K_{it} indicate the output level, labor input, and capital input, respectively, of firm (or any production unit, such as a plant) i at time t. β_l, β_k, and A, are unknown constants. Obviously, firms with a large A can produce more, and thus, they are said to possess high productivity. TFP for a Cobb-Douglas technology is defined by $\log A$, and it has been empirically measured by its estimate since the pioneering work of Solow (1957). Taking the logarithm of (1) and adding a disturbance term u_{it}, we obtain the log-linear form of the

Cobb-Douglas production function:

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

where $l_{it} = \log L_{it}$, $k_{it} = \log K_{it}$, and $\beta_0 = \log A$. Christensen, Jorgenson, and Lau (1973) generalized it to the following more flexible functional form, called the translog production function:

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

These two functional forms are widely used in theoretical and empirical economic research, and in the context of productivity analysis.

Production functions given by (2) or (3) are often estimated by the ordinary least squares (OLS) method regarding $\hat{\beta}_0 + \hat{u}_{it}$ is regarded as an estimate of TFP, where $\hat{\beta}_0$ and $\hat{u}_{it}$ are the estimate of β_0 and the regression residual, respectively. However, as discussed in Marschak and Andrews (1944) and many other subsequent papers, there can exist an endogeneity problem caused by the correlation between disturbance u_{it} and the regressors. The source of the correlation is that a firm may determine its factor input levels depending on its productivity, namely $\beta_0 + u_{it}$, if this can be observed before making the decision.

Several methods have been proposed to handle this endogeneity problem, such as Olley and Pakes (1996), Levinsohn and Petrin (1999, 2003), and Ichimura, Konishi, and Nishiyama (2011). These methods construct a model splitting error term u_{it} into two components as follows:

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

Here, ω_{it} is considered as the firm-specific productivity or technological shock, which firms can, but econometricians cannot, observe. Thus, it is possibly correlated with factor inputs. ϵ_{it} denotes the ordinary error term independent of the system. The above methods assumed a correlation between ω_{it} and l_{it} considering k_{it} to be exogenous, and proposed consistent estimators.

The purpose of this paper is, as stated, to decompose TFP-type quantity into demand, supply, and other shocks. For this purpose, we use the estimation method in Ichimura, Konishi, and Nishiyama (2011), which we henceforth refer to as the IKN estimation method, and OLS estimates for parameter estimation. The parameters to be estimated are the constant, capital, and labor coefficients, and the rate of operation for capital. We apply this method to two industries, die-cast and machinery. In the empirical study, the proposed estimation procedure provides reasonable estimates of β_l and β_k. In the die-cast industry, we found from the Hausman test that there is no bias in OLS, implying that there is no endogeneity. We computed the productivity shock and demand shock for each plant and year, and constructed industry-level counterparts. In general, we found no negative productivity shocks but severe demand shocks during the Lehman shock period.

The following section reviews some of the previous research that solved the endogeneity problem in productivity analysis. The idea of TFP decomposition is also presented. Section 3 describes the data. Section 4 shows the estimation results. The concluding remarks and future research are in Section 5.

2 Decomposition of demand and supply shocks

We discuss how we can decompose demand and supply shocks when the data of production capacity and realized production are available. Production capacity is the possible production level given the present input amounts, and thus is affected by the supply shock, but not by the (short-term) demand shock. This is the key idea for identification of supply shock. On the other hand, realized production level must depend on all shocks (the supply shock, demand shock and other idiosyncratic shocks), the difference between the two production levels reflects the demand shock and the other idiosyncratic shocks. Firms will reduce labor/capital inputs (if possible), when they observe a negative demand shock. As it is perhaps impossible to change labor/capital in short term, this shock will be adjusted by reducing the rate of operation. Thus it should reflect the demand shock. This will provide us the demand shock and the remainder will be the idiosyncratic shock.

2.1 Model of production capacity and realized production

We start with simple models of production capacity and realized production under a Cobb-Douglas technology. Suppose that a plant of a certain product has a Cobb-Douglas production function:

$$Y_{it} = A_{it} K_{it}^{\beta_k} L_{it}^{\beta_l}.$$

Remember that given product price p and inputs price (r, w) (for capital and labor, respectively), the optimal inputs from profit maximization are

$$K_{it}^{*} = \left[\frac{r}{p A_{it} \beta_k} \left(\frac{r \beta_l}{w \beta_k} \right)^{\beta_l} \right]^{\frac{1}{\beta_k + \beta_l - 1}}, \tag{4}$$

$$L_{it}^{*} = \left[\frac{w}{p A_{it} \beta_l} \left(\frac{w \beta_k}{r \beta_l} \right)^{\beta_k} \right]^{\frac{1}{\beta_k + \beta_l - 1}}. \tag{5}$$

Given production level Y and input prices (r, w), the optimal inputs from cost minimization are

$$K_{it}^{+} = \left[\frac{Y}{A_{it}} \left(\frac{w \beta_k}{r \beta_l} \right)^{\beta_l} \right]^{\frac{1}{\beta_k + \beta_l}}, \tag{6}$$

$$L_{it}^{+} = \left[\frac{Y}{A_{it}} \left(\frac{r \beta_l}{w \beta_k} \right)^{\beta_k} \right]^{\frac{1}{\beta_k + \beta_l}}. \tag{7}$$

Log-production capacity $\bar{y}_{it}$ is determined using technology and present log-inputs $\bar{k}_{it}$, $\bar{l}_{it}$ as follows:

$$\bar{y}_{it} = \alpha + \beta_k \bar{k}_{it} + \beta_l \bar{l}_{it} + \omega_{it}. \tag{8}$$

Here, we suppose that $A_{it} = \exp(\alpha + \omega_{it})$, and ω_{it} indicates the productivity shock as in Olley and Pakes (1995), Levinsohn and Petrin (1999, 2003), and Ichimura, Konishi, and Nishiyama (2011). These papers estimate the production function parameters taking into account the possibility of endogeneity from productivity shock ω_{it}. If firms can observe ω_{it} and optimize the capital and labor input levels simultaneously, $\bar{k}_{it}$ and $\bar{l}_{it}$ should be correlated with ω_{it}, and thus, the OLS estimates of (8) should be biased. This is, however, an empirical issue and observing that the operation rate of labor and capital is not 100% in many cases, it may be more natural to consider that firms cannot adjust labor and capital inputs simultaneously at least in part. (Note that inputs such as materials and energy must be simultaneously adjusted and thus the rate of operation should always be 100%.) An extreme situation is the no-adjustment case when ω_{it} is independent of $\bar{k}_{it}$, $\bar{l}_{it}$, or firms cannot adjust the labor and capital input levels at all after observing ω_{it}. A more likely situation is that they adjust the levels only in part, which yields present level $\bar{k}_{it}$, $\bar{l}_{it}$. Practically, some parts of labor or capital are relatively easy to change, but others are not.

Next, we consider how much firms produce in fact, given this production capacity. Firms decide their production amounts (say, monthly) looking at the inventory and the economic situation or demand. If the economy is in a recession and producing the maximum amount $\bar{y}_{it}$ is considered inadequate, they will produce only $y_{it} < \bar{y}_{it}$ without using all the present inputs. Suppose they use only $100\Delta_{it}\% \in (0, 100)$ of labor input and $100\Delta_{it}^{\nu}\%$ of capital input; namely, $(\Delta_{it}^{\nu} K_{it}, \Delta_{it} L_{it})$. Here, ν is introduced to allow for different rates of operation for capital and labor. It may be natural to assume that the rates of operation are the same for both labor and capital because the optimal rate of inputs is constant under a Cobb-Douglas technology in view of the first-order condition

$$\frac{\beta_k}{\beta_l} = \frac{rK}{wL},$$

where r and w are the factor prices of capital and labor. If this assumption is indeed correct, $\nu = 1$ holds. In this analysis, we estimate ν as well, and test if $\nu = 1$ or not. We note that δ_{it} could be positive when the economy is good.

Then, the realized production level would be

$$\begin{aligned} y_{it} &= \alpha + \beta_k(\nu \log \Delta_{it} + \bar{k}_{it}) + \beta_l(\log \Delta_{it} + \bar{l}_{it}) + \omega_{it} + \epsilon_{it} && (9) \\ &= \alpha + (\nu\beta_k + \beta_l)\delta_{it} + \beta_k \bar{k}_{it} + \beta_l \bar{l}_{it} + \omega_{it} + \epsilon_{it}, && (10) \end{aligned}$$

where $\delta_{it} = \log \Delta_{it}$ and ϵ_{it} are idiosyncratic errors independent of the inputs and ω_{it}. Given observations $(\bar{y}_{it}, y_{it}, \delta_{it}, \bar{k}_{it}, \bar{l}_{it})$, we can estimate both equations (8) and (9).

We can view the above model in a different way. Suppose that firm i originally planned to produce up to capacity $\bar{y}_{it}$, but observes a demand decline and decides to reduce log-production by ξ_{it}. It would then act as a cost minimizer to determine input levels by minimizing the cost given the fixed log-production level of $\bar{y}_{it} - \xi_{it}$. Then, from (6), log-inputs should be reduced simply by $\frac{\xi_{it}}{\beta_k + \beta_l}$, and thus, the inputs will change to

$$\bar{k}_{it} - \frac{\xi_{it}}{\beta_k + \beta_l}, \bar{l}_{it} - \frac{\xi_{it}}{\beta_k + \beta_l}.$$

Imposing the theoretical restriction of $\nu = 1$, and comparing them with (9), we have

$$\delta_{it} = -\frac{\xi_{it}}{\beta_k + \beta_l}.$$

Then, y_{it} in (9) indeed is reduced by ξ_{it}. This gives us the relationship between demand shock ξ_{it} and rate of operation δ_{it}.

2.2 IKN estimator

We briefly review the semiparametric IV estimator by Ichimura, Konishi, and Nishiyama (2011) under endogeneity caused by productivity shocks. We adopt the lag variables of labor and capital as instruments for the endogenous inputs. Ichimura, Konishi, and Nishiyama (2011) assume that only the realized production data exist. Further, they do not explicitly consider the operation rate.

Their estimated model is

$$y_{it} = \alpha + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \epsilon_{it},$$

where y_{it}, k_{it}, l_{it} are log production, log labor input, and log capital, respectively. ω_{it} is a technological shock observable for the firm, and ϵ_{it} is an idiosyncratic shock.

$$\begin{aligned} y_{it} &= \alpha + \beta_l l_{it} + \beta_k k_{it} + E(\omega_{it}|k_{i,t-1}, l_{i,t-1}) + \xi_{it} + \epsilon_{it} \\ &= \alpha + \beta_l l_{it} + \beta_k k_{it} + g(k_{i,t-1}, l_{i,t-1}) + \xi_{it} + \epsilon_{it}, \end{aligned} \tag{11}$$

where $g(k_{i,t-1}, l_{i,t-1}) = E(\omega_{it}|k_{i,t-1}, l_{i,t-1})$ and $\xi_{it} = \omega_{it} - E(\omega_{it}|k_{i,t-1}, l_{i,t-1})$. Then, we have the following moment condition:

$$E(\xi_{it} + \epsilon_{it}|k_{i,t-1}, l_{i,t-1}) = 0 \tag{12}$$

for the estimation of parameters. Under the Markovness assumption of ω_{it}, we also have the following moment condition:

$$E(\xi_{it} + \epsilon_{it}|k_{i,t-2}, l_{i,t-2}) = 0. \tag{13}$$

Since $g(\cdot, \cdot)$ is unknown, they propose to approximate it by a linear combination of series functions. Letting $\phi_p(u)$, $p = 1, 2, 3, \cdots$ be basis functions of a suitable L^2 space, Ichimura, Konishi, and Nishiyama (2011) write

$$g(k_{i,t-1}, l_{i,t-1}) \approx \sum_{p=0}^{J_n} \sum_{q=0}^{J_n} c_{pq} \phi_p(k_{i,t-1}) \phi_q(l_{i,t-1}) \tag{14}$$

for some $J_n \to \infty$ as $n \to \infty$ more slowly than n. Substituting (14) into (11), they obtain the final form of the equation as

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \sum_{p=0}^{J_n} \sum_{q=0}^{J_n} c_{pq} \phi_p(k_{i,t-1}) \phi_q(l_{i,t-1}) + \xi_{it} + \eta_{it}. \tag{15}$$

With this expression, obviously, only $\alpha + c_{00}$ is identified. Letting c_{00} be absorbed in α, unknown parameters $\alpha, \beta_k, \beta_l, c_{pq}$ are estimated by the GMM method using moment conditions (12) and (13).

Ichimura, Konishi, and Nishiyama (2011) encounter a difficulty in decomposing ω_{it} and ϵ_{it}. They make use of the fact that ω_{it} is correlated with the inputs to obtain the estimate of ω_{it}, but this captures only some part of ω_{it}. In this paper, we also employ this to estimate the model. However, we use an additional dataset of CSP that provides us with production capacity and the operational rate of labor input. We exploit this information to better decompose ω_{it} and ϵ_{it}.

2.3 Identification and estimation of demand, supply, and idiosyncratic shocks

In view of the above model (8), it is possible to estimate production function parameters α, β_k, β_l by IKN estimators, using the lagged inputs as instruments. Note that we need not include idiosyncratic errors in this model because the dependent variable is production capacity. We may need to use the IKN, and not the OLS, estimates because present input levels $\bar{k}_{it}, \bar{l}_{it}$ should be determined given technological shock ω_{it}. These are thus likely to be correlated with ω_{it}. This causes the endogeneity bias discussed in the literature. See, for example, Olley and Pakes (1995), Levinsohn and Petrin (1999, 2003), Ichimura, Konishi, and Nishiyama (2011), and the references therein. However, as discussed in the previous section, the existence of such an endogeneity is an empirical issue in reality, and thus, we test if $\bar{k}_{it}, \bar{l}_{it}$ are indeed endogenous in terms of ω_{it}. We can easily test this using the Hausman test which compares the IKN and OLS estimates.

In the production function estimation, it may be common to include inputs other than capital and labor, such as materials and energy consumption. When the dependent variable is sales, and not the amount of production, expenditure on such inputs should be considered. However, if the dependent variable is production quantity, then the inputs that determine capacity are not flexible. In this paper, we only use the production amount, and hence, we do not need to include such inputs, especially when these additional inputs are easily adjustable.

Given the estimates of α, β_k, β_l, it is convenient, unlike in IKN, in that we can estimate ω_{it} directly by

$$\hat{\omega}_{it} = \bar{y}_{it} - \hat{\alpha} - \hat{\beta}_k \bar{k}_{it} - \hat{\beta}_l \bar{l}_{it}$$

because (8) does not include the idiosyncratic error. IKN attempts to extract ω_{it} from the residual using a second-step regression on $\bar{k}_{it}, \bar{l}_{it}$ and other macroeconomic variables.

We use (9) in the next step to identify and estimate the idiosyncratic shock. Subtracting (9) from (8), we have

$$y_{it} - \bar{y}_{it} = (\nu\beta_k + \beta_l)\delta_{it} + \epsilon_{it}.$$

We have the estimates of β_k, β_l and the data on δ_{it}, the operation rate of labor input. Then, we can estimate ν simply using OLS without constant because ϵ_{it} is the idiosyncratic error from the regression:

$$y_{it} - \bar{y}_{it} - \hat{\beta}_l \delta_{it} = \nu(\hat{\beta}_k \delta_{it}) + \epsilon_{it}. \tag{16}$$

We can also estimate the two equations simultaneously by GMM, which should increase the efficiency of estimation. In the following empirical section, we only report the results of the two stage estimation for simplicity suppressing the simultaneous estimation. In testing $\nu = 1$, we use the t value, but we cannot use the standard normal table to construct the critical values. This is because regressor $\hat{\beta}_k \delta_{it}$ includes estimate $\hat{\beta}_k$, and the standard error of $\hat{\nu}$ is affected by its variance. The asymptotic variance is shown in the Appendix. Given these estimates, we can estimate ϵ_{it} by the residual:

$$\hat{\epsilon}_{it} = y_{it} - \bar{y}_{it} - \hat{\beta}_l \delta_{it} - \hat{\nu}\hat{\beta}_k \delta_{it}.$$

Therefore, we can compute all the shocks from this model using the parameter estimates.

Finally, given all these estimates, we can compute the demand shock as

$$\hat{\xi}_{it} = (\hat{\nu}\hat{\beta}_k + \hat{\beta}_l)\delta_{it}$$

or

$$\hat{\xi}_{it} = (\hat{\beta}_k + \hat{\beta}_l)\delta_{it}$$

under the $\nu = 1$ constraint.

3 Data

We use the CSP data collected by METI. The objective of CSP is to understand the monthly trends in the manufacturing and mining industries in Japan, and to make direct inferences for Japanese industrial policies. The survey targets establishments or firms that produce manufacturing or mineral goods. CSP comprises of four parts: product; raw material, fuel, and electricity; labor; and production capacity. The first part includes the monthly production, shipment, sales, and inventory for each product produced by the establishment/firm. The second part covers the monthly consumption and inventory for each raw material, and the monthly fuel and electricity consumption. The third part comprises the number of workers at the end of each month. The fourth part—production capacity—is the most noteworthy aspect of CSP. Production capacity is a key feature of this paper, and is defined as the possible production level given the present input amounts. According to CSP, production capacity is the maximum amount of production when the plant can use their standard amount of production facilities and labor. Production facilities, we call $\overline{k}_{it}$, are existence machines and equipment without the stopping facilities. Labor ($\bar{l}_{it}$) are standard number of employees that engage in the facilities of each plant. We can know the gap between the actual amount of production and the production capacity using CSP; this enables us to decompose the supply and demand shocks in the production function.

In our empirical application, we estimate (8) and (9), with the dependent variables being log-production capacity $\bar{y}_{it}$ and realized production y_{it}. We obtain both variables from CSP. The explanatory variables are present log-inputs $\bar{k}_{it}$, $\bar{l}_{it}$: while we obtain $\bar{l}_{it}$ from CSP, $\bar{k}_{it}$ is unavailable in CSP. Further, we sometimes use the lag of raw material and/or electricity consumption as instrumental variables in IKN estimation. Although CSP collects these items, the data are available for only a few industries. Thus, we need to find $\bar{k}_{it}$ and intermediate goods from other items. The Census of Manufacturing (CM) conducted by METI is the most adequate survey for our purpose. CM is an annual survey and covers all establishments that produce manufacturing goods. It includes inputs and intermediate goods. We link CSP's establishments to CM's via a common code and name-based aggregation: the matching rate is about 88%. While CM provides data for each establishment, CSP reports product-based data. As such, we adjust CM's $\bar{k}_{it}$ and intermediate goods to product-based data using the product-establishment ratio: the ratio of the number of workers who produce the goods to the total number of workers in the establishments. Moreover, we examine yearly $\bar{y}_{it}$, y_{it} and $\bar{l}_{it}$ for use with CM data. In order to identify demand shock ξ_{it}, we need to input labor operation ratio $\delta_{it} = \log \Delta_{it}$ in (9), which is the ratio of the number of workers present at the end of a month to the total number of workers employed in that month.

The CSP dataset includes 111 industries, and we focus on industries with variable production capacity. In all, we cover 72 industries, after considering production capacity and labor for industries with a large enough sample size and with similar listed goods. In this study, we apply our method to the metal cutting machine tools industry (# 2110) and the die-cast industry (# 2560) for the period from 2005 to 2009.

4 Empirical application

The purpose of this paper is, as stated, to decompose the TFP-type quantity into demand, supply, and other shocks. For this purpose, we use the IKN and OLS estimation methods for (8) using CSP and CM data:

$$\overline{y}_{it} = \alpha + \beta_k \bar{k}_{it} + \beta_l \bar{l}_{it} + \omega_{it}.$$

The parameters to be estimated are constant α, and the capital and labor coefficients β_k and β_l, respectively. We also obtain productivity shock ω_{it} as the estimation residual. Table 1 shows the OLS estimation results for the metal cutting machine tools industry and the die-cast industry, with the data pooled from 2005 to 2009 for each establishment. For our pooled dataset, we compute the standard error considering autocorrelation for the t-test statistics. To consider the time trend or changes in economy and/or technology, we add the year dummy in (8). Both industries have significantly positive estimators for β_l and β_k, and β_l is larger than β_k. In the OLS estimation, we assume that the firms do not adjust the input levels while observing their productivity; however, if firms can observe ω_{it} and optimize the capital and labor input levels simultaneously, $\bar{k}_{it}$ and $\bar{l}_{it}$ should be correlated with ω_{it}, and thus, the OLS estimates of (8) should be biased. To solve this problem, we also estimate (8) using the IKN estimates. In Table 2, the estimators of β_k and β_l are significantly positive and $\beta_k + \beta_l$ are less than one in both industries. In this sense, we can obtain reasonable estimates of β_l and β_k. As compared to the OLS results, $\hat{\beta}_k$ are smaller for both industries. While for the metal cutting machine tools industry, $\hat{\beta}_l$ under OLS is almost double that under IKN, for the die-cast industry, $\hat{\beta}_l$ is almost the same under both. There exist blank cells for which variables are omitted in the estimation due to multicollinearity.

We can summarize briefly that the IKN and OLS estimation results are different for the metal cutting machine tools industry and similar for the die-cast industry.

<Insert Tables 1 and 2 here>

To verify this intuition, we use the Hausman test which compares the IKN and OLS estimates. The results of the Hausman test are given in Table 3; these results yield that we should use IKN estimates for the metal cutting machine tools industry and OLS estimates for the die-cast industry. Further, for the die-cast industry, we found that the Hausman test yields no bias under OLS estimates, which implies that there is no endogeneity among productivity and inputs.

<Insert Table 3 here>

Using the IKN estimates for the metal cutting machine tools industry and OLS estimates for the die-cast industry in (9), we implement the OLS estimation for the equation as follows:

$$y_{it} - \bar{y}_{it} - \hat{\beta}_l \delta_{it} = \nu_t(\hat{\beta}_k \delta_{it}) + \epsilon_{it}.$$

Table 4 shows the estimation results of ν, the difference in the operation rates of $\bar{k}_{it}$ and $\bar{l}_{it}$ for each year. We show the derivation of the asymptotic variance of $\hat{\nu}$ in the Appendix. However, all estimators of ν seem to be far from the theoretical assumption $\nu = 1$, and hence, we test $\nu = 1$ using the asymptotic variance of $\hat{\nu}$. Consequently, $\nu = 1$ is not rejected in each estimation. Table 5 provides us the descriptive statistics for the operation rate of $\bar{l}_{it}$ with actual CSP data. The average is about 0.95 and it is less than one. This indicates that establishments cannot adjust the labor input level in short term. We need to know the operation rate of $\bar{k}_{it}$ for computing $\Delta_{it}^{\hat{\nu}_{jt}}$, where Δ_{it} is the operation rate of $\bar{l}_{it}$ and $\hat{\nu}_{jt}$ is the estimator of j industry's ν at year t. For example, if we adopt $\nu = 1$ for the metal cutting machine tools industry in 2006, the operation rates for both inputs are 0.980. In contrast, if we adopt different operation rates for $\bar{k}_{it}$ and $\bar{l}_{it}$, the average of $\Delta_{it} = 0.980$, and then $\Delta_{it}^{\hat{\nu}_{jt}} = 0.914$. Given these estimations, we get the parameters and operation rates of the two inputs, productivity ω_{it}, and idiosyncratic shock ε_{it}.

<Insert Tables 4 and 5 here>

Finally, we use all the above estimation results and compute the demand shock as

$$\hat{\xi}_{it} = (\hat{\nu}\hat{\beta}_k + \hat{\beta}_l)\delta_{it}$$

or

$$\hat{\xi}_{it} = (\hat{\beta}_k + \hat{\beta}_l)\delta_{it}$$

under the $\nu = 1$ constraint.

Figures 1 and 2 show omega ($\hat{\omega}_{it}$), demand shock ($\hat{\xi}_{it}$), and TFP ($\hat{\omega}_{it}+\hat{\xi}_{it}+\varepsilon_{it}$ for each plant and year, with industry-level counterparts being aggregated using the weighted average. In both industries, we do not observe a negative level of productivity even though we have a very severe economy shock in the Lehman crisis. At the same time, ordinal TFP decreases rapidly after the big shock. Further, we could not find a positive demand shock in this period.

<Insert Figures 1 and 2 here>

5 Concluding remarks

We attempt to estimate the production functions for some particular products and decompose the so-called TFP or the estimation residual into ξ_{it}, ω_{it}, and ϵ_{it} (namely demand, supply, and idiosyncratic shocks, respectively). After the pioneering work of Marschak and Andrews (1944), this direction of research has been pursued by many researchers including Olley and Pakes (1996) and Levinsohn and Petrin (1999, 2003). Our approach is novel in that we use the data of both production capacity and realized production. Because of this, we believe that our decomposition should be more accurate than the others. For example, the above two works treat TFP as an estimate of ω_{it}. Ichimura, Konishi, and Nishiyama (2011) regress TFP on the present input levels trying to extract ω_{it}, which is one way of decomposition, but this can only yield ω_{it} that can be explained by the inputs.

We applied our procedure to the metal cutting machinery and die-cast industries. We found that the decomposition seems to work rather well showing that productivity did not fall during the period of Lehman shock but the demand shock was large.

6 Appendix

We show the asymptotic variance of the second step estimator of ν in (16). Suppose that $E(\epsilon_i|x_i) = 0$, $E(\epsilon_i^2|x_i) = \sigma_\epsilon^2$, and

$$y_i = \nu\beta x_i + \epsilon_i.$$

We want to estimate ν by OLS using a first step estimate of β, which is independent of ϵ_i. Namely, the model to be estimated is

$$y_i = \nu\hat{\beta} x_i + \hat{\epsilon}_i.$$

We assume that ϵ_i and $\hat{\beta}$ are independent. The estimator can be written as

$$\begin{aligned}
\hat{\nu} &= (\sum \hat{\beta}^2 x_i^2)^{-1} \sum \hat{\beta} x_i y_i \\
&= (\sum \hat{\beta}^2 x_i^2)^{-1} \sum \hat{\beta} x_i (\nu\beta x_i + \epsilon_i) \\
&= \nu\hat{\beta}^{-1}\beta + \hat{\beta}^{-1}(\sum x_i^2)^{-1} \sum x_i \epsilon_i,
\end{aligned}$$

and thus, we have

$$\sqrt{n}(\hat{\nu} - \nu) = \nu\hat{\beta}^{-1}\sqrt{n}(\beta - \hat{\beta}) + \hat{\beta}^{-1}(\frac{1}{n}\sum x_i^2)^{-1}\frac{1}{\sqrt{n}}\sum x_i\epsilon_i.$$

Therefore, noting that ϵ_i and $\hat{\beta}$ are independent, we get

$$Asy.Var(\sqrt{n}(\hat{\nu} - \nu)|X) = \nu^2\beta^{-2}AsyVar(\hat{\beta}) + \beta^{-2}\sigma_\epsilon^2(\frac{1}{n}\sum x_i^2)^{-1}.$$

This can be estimated by

$$Asy.\hat{V}ar(\sqrt{n}(\hat{\nu} - \nu)) = \hat{\nu}^2\hat{\beta}^{-2}As\hat{y}Var(\hat{\beta}) + \hat{\beta}^{-2}\hat{\sigma}_\epsilon^2(\frac{1}{n}\sum x_i^2)^{-1},$$

where $\hat{\sigma}_\epsilon^2 = \frac{1}{n}\sum(y_i - \hat{\nu}\hat{\beta}x_i)^2$.

$\hat{\beta}^{-2}\hat{\sigma}_\epsilon^2(\frac{1}{n}\sum x_i^2)^{-1} = \hat{\sigma}_\epsilon^2\{\frac{1}{n}\sum(\hat{\beta}x_i)^2\}^{-1}$ is the standard estimate of the asymptotic variance of $\hat{\nu}$ considering $\hat{\beta}$ as if it were not an estimator, or the standard software output of the variance of $\hat{\nu}$ when we regress y_i on $\hat{\beta}x_i$.

References

[1] Ackerberg, D., K. Caves, and G. Frazer (2006), Structural Identification of Production Functions, MPRA Paper, University Library of Munich, Unpublished.

[2] Ackerberg, D., C. L. Benkard, S. Berry, and A. Pakes (2008), Econometric tools for analyzing market outcomes, In Heckman J. and Leamer E. (Eds.), Handbook of Econometrics, 6A, 4171-4276, Elsevier.

[3] Blundell, R. and S. R. Bond (2000), GMM estimation with persistent panel data: an application to production function, Econometric Reviews, 19, 321-340.

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

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

[6] Doraszelski, U. and J. Jaumandreu (2007), R&D and Productivity: Estimating Production Function when Productivity is Endogenous, MPRA Paper 1246, University Library of Munich.

[7] Fox, J. and V. Smeets (2007), Do Input Quality and Structural Productivity Estimates Drive Measured Differences in Firm Productivity, Working Paper 07-2, Department of Economics, Aarhus University.

[8] 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, 195-227.

[9] Fukao, K., R. Kambayashi, D. Kawaguchi, H. U. Kwon, Y. G. Kim, and I. Yokoyama (2007), Deferred compensation: evidence from employer-employee matched data from Japan, Mimeo.

[10] Gandhi, A., S. Navarro, and D. Rivers (2009), Identifying Production Functions using Restrictions from Economic Theory, University of Wisconsin-Madison.

[11] Ichimura, H., Y. Konishi, and Y. Nishiyama (2011), An Econometric Analysis of Firm Specific Productivities: Evidence from Japanese Plant Level Data, Discussion Paper DP11-E-002, RIETI.

[12] Kim, Y.G. (2008), Estimating Production Functions with R&D Investment and Endogeneity, Hi-Stat Discussion Paper 229, Institute of Economic Research.

[13] Levinsohn, J. and A. Petrin (1999), When industries become more productive, do firms?: investigating productivity dynamics, NBER Working Paper 6893, Cambridge: National Bureau of Economic Research.

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

[15] Marschak, J. and W. H. Andrews (1944), Random simultaneous equations and the theory of production, Econometrica, 12, 143-205.

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

[17] 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, The Econometric Society.

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

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

[20] Syverson, C. (2010), What determines productivity?, Journal of Economic Literature, Forthcoming.

Table 1: Estimation results of OLS

Industry	2110	2560
covariates	$\hat{\beta}$ /[t-value]	$\hat{\beta}$/[t-value]
lnk	0.2481	0.1933
	[4.59]***	[2.93]***
lnl	0.5037	0.5978
	[6.63]***	[6.23]***
yeard2	-0.0694	-0.1661
	[-0.48]	[-2.08]**
yeard3	-0.0983	-0.1175
	[-0.68]	[-1.47]
yeard4	-0.0265	-0.1076
	[-0.18]	[-1.34]
Constant	0.5534	1.0529
	[1.10]	[3.96]***
Adj-R	0.4189	0.6822
Obs	524	583

*p $<$ 0.1, **p $<$ 0.05, ***p $<$ 0.01

Table 2: Estimation results of IKN

Industry	2110	2560
covariates	$\hat{\beta}$ /[t-value]	$\hat{\beta}$/[t-value]
lnk	0.1755	0.1580
	[3.79]***	[4.93]***
lnl	0.1856	0.6102
	[2.65]**	[14.38]***
sk1	48.4725	190.4169
	[2.06]**	[0.55]
sk2	30.4242	
	[2.08]**	
sk3	5.5824	-1.9724
	[1.64]	[-0.54]
sl1	-59.5650	
	[-1.85]*	
sl2	-10.6332	1037.6505

	[-2.69]***	[1.29]
sl3	-0.2555	648.6740
	[-0.69]	[1.07]
ck1	57.1532	-112.5223
	[2.04]**	[-0.15]
ck2	4.0173	-42.2204
	[0.64]	[-0.08]
ck3	-3.2482	-2.6126
	[-1.85]*	[-0.36]
cl1	30.5588	
	[2.13]**	
cl2	-1.0882	
	[-0.27]	
cl3	-0.2346	-101.3206
	[-0.78]	[-0.30]
sskl11	-65.4644	
	[-1.87]*	
sskl12	-8.1035	35.0015
	[-2.47]**	[0.11]
sskl21	-26.6985	-26.7841
	[-1.87]*	[-0.09]
sckl11	32.0891	
	[1.75]*	
sckl12	0.4909	-166.7044
	[0.16]	[-0.49]
sckl21	16.1274	-7.0317
	[2.52]**	[-0.29]
cckl11	29.4337	
	[2.56]**	
cckl12	-1.6272	118.4183

	[-0.47]	[0.15]
cckl21	-0.6360	-31.8980
	[-0.16]	[-0.06]
cskl11	-52.1345	
	[-1.72]*	
cskl12	-9.5817	41.5889
	[-3.14]***	[0.12]
cskl21	2.8464	20.2088
	[0.55]	[0.22]
yeard3	-0.0333	0.0184
	[-0.27]	[0.24]
yeard4	-0.0380	0.0550
	[-0.31]	[0.71]
yeard5	0.0259	0.1696
	[0.21]	[2.18]**
Constant	53.3320	-86.7034
	[2.23]**	[-0.25]
Adj-R	0.5906	0.7179
Obs	509	568

*p $<$ 0.1, **p $<$ 0.05, ***p $<$ 0.01

Table 3: Hausman test results, IKN vs. OLS

Industry	**2110**	**2560**
χ^2 value	311.44	2.79
p-value	[0.00]***	[0.25]

***p $<$ 0.01

Table 4: Estimation of ν, 2110

Year	2006	2007	2008	2009
ν	4.466	7.740	7.922	18.881
t-value	[0.12]	[0.30]	[0.26]	[0.67]
Adj-R	0.0179	0.0985	0.0500	0.3365
Obs	143	145	144	130

The t-test is $H_0 : \nu = 1$, $H_1 : \nu \neq 1$. The calculation of the asymptotic variance of $\hat{\nu}$ is presented in the Appendix.

Table 5: Estimation of ν, 2560

Year	2006	2007	2008	2009
ν	4.2149	-1.8856	3.6049	5.7785
t-value	[0.16]	[-0.08]	[0.13]	[0.22]
Adj-R	0.0343	-0.0033	0.0250	0.0601
Obs	171	168	170	165

The t-test is $H_0 : \nu = 1$, $H_1 : \nu \neq 1$. The calculation of the asymptotic variance of $\hat{\nu}$ is presented in the Appendix.

Table 6: Summary statistics of the labor operation rate

Year	Industry	Mean	Std. Dev.	5%	95%	Obs.
2005		0.978	0.133	0.814	1.132	150
2006		0.980	0.165	0.835	1.154	150
2007	2110	0.980	0.173	0.792	1.135	151
2008		0.983	0.162	0.839	1.140	149
2009		0.870	0.214	0.531	1.047	139
2005		0.964	0.112	0.801	1.067	175
2006		0.963	0.139	0.800	1.080	172
2007	2560	0.980	0.090	0.865	1.103	168
2008		0.962	0.114	0.864	1.064	170
2009		0.906	0.119	0.696	1.046	165

Figure 1: Product 2110

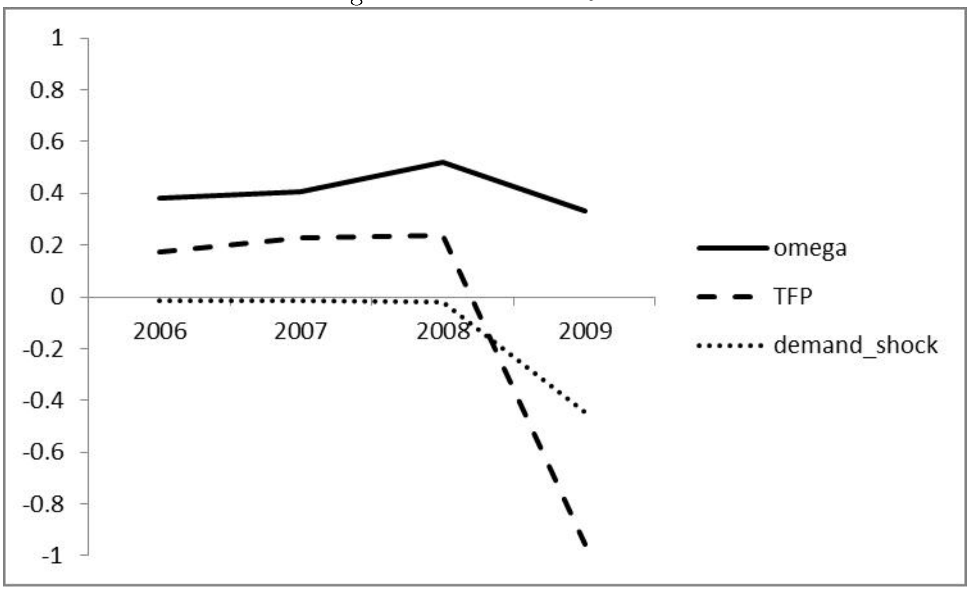

Figure 2: Product 2560