Economics Bulletin

Volume 30, Issue 4

Lumpy capital adjustment and technical efficiency

Keiichi Shima
Hirosaki University

Abstract

This paper investigates the impact of lumpy capital adjustment on productivity at the firm level using data on Japanese manufacturing industries. We estimate stochastic production frontiers, taking firm heterogeneity into account. We find that investment spikes are negatively related to technical efficiency. Furtermore, we find a negative relationship between machinery capital age and measured efficiency.

I would like to thank an anonymous referee and the editor, John P. Conley, for their useful comments.
Citation: Keiichi Shima, (2010) "Lumpy capital adjustment and technical efficiency", *Economics Bulletin*, Vol. 30 no.4 pp. 2817-2824.
Submitted: Sep 20 2010. **Published:** October 28, 2010.

1 Introduction

In recent years, a number of empirical studies have attempted to establish the relationship between technology, investment and productivity. Power (1998) examined the link between investment and productivity and found virtually no evidence of a positive correlation between productivity and high levels of investment using pooled regressions at the U.S. plant level. Huggett and Ospina (2001) investigated the effect of technology adoption on productivity growth. They calculated total factor productivity (TFP) growth at the plant level using Colombian data. They regressed TFP growth on current and past values of technology adoption measures. They found evidence that productivity growth falls when a plant undertakes a large equipment purchase and that the effect of the large investment on productivity growth continues to be negative for subsequent years. Sakellaris (2004) also used the U.S. plants data and obtained similar results. These findings indicate that lumpy investment episodes result in the costly adoption of new technology embodied in new capital.

These authors employ a two-stage approach to assess the impact of investment spikes on productivity or productivity growth. In the first stage, they construct productivity variables such as labor productivity, TFP or TFP growth. In the second stage, they regress productivity variables on current and past investment spike dummies. In contrast, our alternative approach is based on estimating a stochastic frontier production function. Our methodology incorporates the technical efficiency effects induced by large investment episodes that embody new technology and involve costly adoption.

2 Linking Productivity and Investment Spike

We obtain firm-level TFP measures by estimating a log-linear Cobb-Douglass production function for each industry. Individual firms are indexed i, and industries are indexed by j, for each year t in the sample:

$$\ln y_{it} = \ln a_{jt} + \alpha_j \ln k_{it} + \beta_j \ln l_{it} + \gamma_j \ln m_{it} + \epsilon_{it} \tag{1}$$

where y_{it} is gross output. Since coefficients on the log capital k_{it}, labor l_{it} and material inputs m_{it} can vary by industry, this specification allows for different factor intensities in different industries. An additional specification is

$$\ln a_{jt} = \sum_t fy_t + \sum_j ind_j \tag{2}$$

where fy_t is a year dummy and ind_j is an industry dummy. Industries are classified at the two-digit SIC level.

Consider the stochastic frontier production function for firm data. We postulate that the error term in equation (1) is composed of two different types of disturbances:

$$\epsilon_{it} = u_{it} + v_{it} \tag{3}$$

where u_{it} is a non-negative random variable associated with technical efficiency of production, and v_{it} is assumed to be i.i.d. with $N(0, \sigma_v^2)$. The term u_{it} is assumed to be distributed independently of v_{it}. Following Battese and Coelli (1993), the technical efficiency effect in the stochastic frontier model is specified by

$$u_{it} = z_{it}\delta + w_{it} \tag{4}$$

where z_{it} is a vector of explanatory variables associated with firm specific technical efficiency, δ is the corresponding vector of parameters, and w_{it} is a random error. The term w_{it} is assumed to follow a $N(0, \sigma^2)$ distribution truncated from below at $-z_{it}\delta$, which is consistent with u_{it} being a non-negative truncation of $N(z_{it}\delta, \sigma^2)$.

In this paper, $z_{it}\delta$ is assumed to be defined by

$$z_{it}\delta = \delta_{age,j}age_{it} + \sum_{\tau=0}^{4} \delta_{spk,\tau}spike_{it-\tau} + \delta_{trd,j}t \tag{5}$$

where age_{it} is machinery age for individual firms, $spike_{it}$ is an investment spike dummy and thus $spike_{it-\tau}$ is a dummy based on the length of time since the last investment spike, τ. A time trend is also included in the explanatory variables. Since coefficients for the machinery age and time trend variables can vary by industry, this specification allows for industry differences.

The parameters of the stochastic production frontier and the model for the technical efficiency effect are estimated simultaneously using the maximum likelihood method. Following the suggested parameterization by Battese and Coelli (1993), we let $\sigma_s^2 \equiv \sigma^2 + \sigma_v^2$ and $\lambda \equiv \sigma^2/\sigma_s^2$. From the distributional assumptions on u_{it} and v_{it}, the log likelihood function can be written as

$$\begin{aligned}
\ln L = & -\frac{nT}{2}\log 2\pi - nT\ln\sigma_s - \frac{1}{2\sigma_s^2}\sum_{i=1}^{n}\sum_{t=1}^{T}(\epsilon_{it} - z_{it}\delta) \\
& + \sum_{i=1}^{n}\sum_{t=1}^{T}\ln\Phi\left((\lambda\epsilon_{it} + (1-\lambda)z_{it}\delta)/\sqrt{\lambda(1-\lambda)\sigma_s^2}\right) \\
& - \sum_{i=1}^{n}\sum_{t=1}^{T}\ln\Phi\left(z_{it}\delta/\sqrt{\lambda\sigma_s^2}\right)
\end{aligned} \tag{6}$$

where $\Phi(\cdot)$ is a distribution function of a standard normal variable.

3 Data

We use annual firm-level data from the Development Bank of Japan's Corporate Finance Databank. The data consist of financial statements for publicly traded firms listed on either the first or second sections of the Tokyo, Osaka or Nagoya stock exchanges. We construct a panel dataset of the Japanese manufacturing firms in eleven industries covering the period 1980-2004. Industries at the two-digit level are as follows: *Chemicals, Petroleum and Coral, Rubber, Stone Clay and Glass, Iron and Steel, Nonferrous Metals, Fabricated Metals, Nonelectrical Machinery, Electrical Machinery, Transportation Equipment,* and *Precision Instruments.* The resulting sample contains 623 firms.

We calculate output as firm sales (total value of shipments) plus changes in inventories of finished goods and work in process. m_{it} is material expense for intermediate goods, which includes inputs from contracted work. l_{it} is total employment, and k_{it} is real capital stock. Real capital stock is calculated separately for buildings, structures, machinery, equipment, and vehicles using the perpetual inventory method and then aggregated. We calculate investment as the change in book value of capital stock plus depreciation expense reported by the firm. The output, material inputs, and investment are at constant prices. To reduce the impact of potential accounting manipulations of book values of capital stock, we use the earliest available book value of capital as the initial value in the DBJ dataset. This starting date occurs before 1971. Depreciation rates for each type of capital stock are taken from Hayashi and Inoue (1991).

In accordance with the literature, we define investment spikes only for machinery. Machinery capital accounts for the largest share of total investment and is often assumed to embody technological progress. Power (1998) defines a lumpy investment episode at the plant level as occurring if the gross investment rate exceeds 0.2. This threshold is intended to eliminate routine maintenance expenditures. We use firm level data. A firm consists of several plants. Each plant produces different products in the firm's range. Investment timing varies across plants. In order to detect an unusual amount of investment at the firm aggregation level, we use a large deviation from the normal investment.

To identify lumpy investment episodes at the firm level, we construct a standardized measure of the investment-to-capital ratio. Following Caballero, Engel and Haltiwanger (1995), we subtract from the original observations the corresponding firm-level mean and divide this difference by the corresponding firm-level standard deviation. We classify an observation as a spike if the standardized investment-to-capital ratio exceeds 1.5. In experiments not shown in this paper, essentially the same results were obtained using 1.75 and 2.0 thresholds.

Machinery age is measured as follows. Under the declining balance depreciating rule, the book value of machinery and its acquisition value satisfies

$$b_t = (1 - d_t)^n \, q_t$$

where b_t is the book value of capital, q_t is the acquisition book value, and d_t is the accounting constant depreciation rate in year t. In this equation, n is assumed to be the machinery age. The accounting depreciation rate is defined by $d_t = g_t / (b_t + g_t)$, where g_t is depreciation expense. Taking the log of both sides of the equation above yields the

Table I: Estimation results

	Coeffcient		Standard error	Coeffcient		Standard error
	Machinery age: $\delta_{age,j}$			Time trend: $\delta_{trd,j}$		
Chemicals	-.104	***	(.012)	.025	***	(.005)
Petroleum and Coral	-.040		(.055)	.075	**	(.038)
Rubber	-.241	***	(.049)	.013		(.035)
Stone Cray and Glass	-.031	*	(.016)	-.013		(.010)
Iron and Steel	-.331	***	(.037)	.004		(.025)
Nonfferous Metals	-.002		(.012)	-.072	***	(.012)
Fabricated Metals	-.064	***	(.019)	-.034	***	(.012)
Nonelectrical Machinery	-.144	***	(.012)	.019	***	(.005)
Electrical Machinery	-.111	***	(.009)	.069	***	(.004)
Transportation Equipment	-.403	***	(.032)	.056	***	(.014)
Precision Instruments	-.537	***	(.070)	.106	***	(.032)
	Investment spike: $\delta_{spk,\tau}$					
$Spike_t$	-.318	***	(.063)			
$Spike_{t-1}$	-.393	***	(.065)			
$Spike_{t-2}$	-.369	***	(.067)			
$Spike_{t-3}$	-.326	***	(.063)			
$Spike_{t-4}$	-.310	***	(.064)			
Variance parameters:						
σ_s	.645	***	(.013)			
λ	.979	***	(.001)			
Number of observations	12646					
Log likelihood	169.28					

Significance: *** at 1%, ** at 5%, and * at 10% level, respectively.

machinery age measure

$$age_{it} = \frac{\ln q_{it} - \ln b_{it}}{\ln (b_{it} + g_{it}) - \ln b_{it}}$$

4 Empirical Results

Our results are presented in Table I. We use machinery age, investment spikes and a time trend as determinants of technical efficiency. The estimated coefficients of the technical efficiency model are highly significant. Coefficients on machinery age are negative across all industries, indicating that older machines are less efficient than younger ones (coefficients are significant in all industries except two). The positive coefficients on the time trend suggest that production efficiency of manufacturing firms tends to increase throughout the sample period. This may imply the existence of technology spillover effects. The exception to this observation is the metals industries, which seem to have an opposite tendency regarding the time trend.

The negative estimates for all investment spike dummies indicate that large investment episodes reduce TFP levels but have persistence effects even after the timing of the spike. This tendency implies that the adjustment cost of large investment is substantial and that it is not a one-time loss. Drops in production are likely to be persistent after the large investment episodes.

Vintage capital models assume that technical progress is embodied in new capital. Firms invest to reap benefits of technical progress embodied in new capital. As in the models of Nelson (1964), Hulten (1992) and Wolff (1996), productivity of a firm should be associated with its vintage or age distribution of capital stock. Under embodied technical change, investment spikes should raise productivity.

Several empirical findings indicate a negative relationship between capital age and productivity. Previous studies, such as Baily, Hulten and Campbell (1992) and Bahk and Gort (1993), have found a negative correlation between capital age and productivity at the plant level. Hulten (1992) using U.S. manufacturing sector data and Wolff (1996) using six OECD countries data document that the average age of capital stock negatively affects output growth. On the other hand, productivity may not improve immediately after the adoption of new capital. Jensen, McGuckin and Stiroh (2001) finds that new entrant plants display productivity levels below the industry averages. Sakellaris (2001) and Huggett and Ospina (2004) also show that productivity growth falls after investment spikes. The negative relationship between investment spikes and productivity predicts that firms face sunk costs. However, vintage capital models can not explain the persistent reduction in TFP shown in Table 1.

From a different perspective, models of learning by doing also link technology and productivity. In Jovanovic and Nyarko (1996) and Klenow (1998), productivity increases as firms learn about the given technology. Once the productivity gains on the given technology are exhausted, firms can switch to a better technology. But a switch of technologies temporarily reduces expertise because technical knowledge is highly specific to particular production processes. The model of Klenow (1998) clearly states that productivity initially falls when firms adopt new technologies, but gradually rises as the firms acquire experience with the new technologies. Jensen, McGuckin and Stiroh (2001) empirically show that surviving plants improve their relative standing in the productivity distribution as they age. Power (1998) finds that productivity tends to monotonically increase with plant age. The positive correlation between technical efficiency and the time trend and the reduction in technical efficiency accompanying investment spikes in table 1 are both consistent with predictions of learning models as well as the empirical findings described above.

5 Conclusion

This paper has considered technical efficiency induced by large investment episodes. We estimate the technical efficiency effects in a stochastic frontier production function. With firm-level data from the Japanese manufacturing sector, we find a persistent relationship between investment spikes and production efficiency drops thereafter. After controlling for a time trend, aging capital stock has a negative impact on production efficiency, although the magnitudes differ by industry.

These findings are summarized as follows. First, reductions of machinery age at firms significantly increase their productivity. The empirical results of this paper provide support for the hypothesis that machinery age is a significant source of technical efficiency. The replacement of old with new machines exhibits a strong relationship with technical efficiency. Second, drops in production after large investments and productivity growth over time are both consistent with firm/plant dynamics models by Jovanovic and Nyarko (1996) and Klenow (1998).

References

Battese, G.E. and T.J. Coelli (1993) "A stochastic frontier production function incorporating a model for technical inefficiency effects" Working Paper No.69, Department of Econometrics, University of New England.

Bahk, B.H. and M. Gort (1993) "Decomposing learning by doing in new plants" *Journal of Political Economy* **101**, 561-583.

Baily, M.N., C. Hulten and D. Campbell (1992) "Productivity dynamics in manufacturing plants" *Brookings Papers on Economic Activity*, 187-267.

Caballero, R.J., E.M.R.A. Engel and J.C. Haltiwanger (1995) "Plant level adjustment and aggregate investment dynamics" *Brookings Papers on Economic Activity* **2**, 1-39.

Hayashi, F. and T. Inoue (1991) "The relation between firm growth and Q with multiple capital goods: theory and evidence from panel data on Japanese firms" *Econometrica* **59**, 731-753.

Huggett, M. and S. Ospina (2001) "Does productivity fall after the adoption of new technology?" *Journal of Monetary Economics* **48**, 173-195.

Hulten, C.R. (1992) "Growth accounting when technical change is embodied in capital" *American Economic Review* **82**, 964-980.

Jensen, B.J., R.H. McGuckin and K.J. Stiroh (2001) "The impact of vintage and survival on productivity: evidence from cohorts of U.S. manufacturing plants" *Review of Economics and Statistics* **83**, 323-332.

Jovanovic, B. and Y. Nyarko (1996) "Learning by doing and the choice of technology" *Econometrica* **64**, 1299-1310.

Klenow, P.J. (1998) "Learning curves and the cyclical behavior of manufacturing industries" *Review of Economic Dynamics* **1**, 531-550.

Nelson, R.R. (1964) "Aggregate production functions and medium-range growth projections" *American Economic Review* **54**, 575-606.

Power, L. (1998) "The missing link: technology, investment and productivity" *Review of Economics and Statistics* **80**, 300-313.

Sakellaris, P. (2004) "Patterns of Plant Investment" *Journal of Monetary Economics* **48**, 173-195.

Wolff, E.N. (1996) "The productivity slowdown: the culprit at last? Follow-up on Hulten and Wolff" *American Economic Review* **86**, 1239-1252.