DBJ Discussion Paper Series, No.1304

Misallocation of Capital During Japan's Long Two Decades

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June 2013

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Abstract:

We show that misallocation of resource across firms is the key in explaining the slow Total Factor Productivity growth rate in Japan since the late 1990's. The degree of resource misallocation is summarized by the variation of Total Factor Revenue Productivity across firms. Using the accounting data for Japanese manufacturing firms, we quantify the effect of allocation inefficiency in Japan and show that misallocation is highly cyclical and useful in explaining the fluctuation of aggregate Total Factor Productivity. The resource misallocation in Japan is driven mainly by capital misallocation due to lagged response of firms' investments to idiosyncratic unexpected productivity shock.

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1 Introduction

Lower Total Factor Productivity (TFP) growth is the leading cause of the sluggish GDP growth in Japan after the era of bubble economy. Fukao, Miyagawa, Pyo and Rhee (2011) show that the TFP growth in Japan is lower by 1% after the late 1990's compared with the preceding period. There can be multiple causes for the lower TFP growth rate such as slower technological progress and rapidly aging population in Japan. In this paper, we examine the impact of resource misallocation across firms as an alternative explanation for lower aggregate TFP growth rate in this period.

We quantify the effect of allocation inefficiency on aggregate TFP using the model of monopolistic competition of Dixit and Stiglitz (1987) with allocation friction. Each firm in an industry produces differentiated products. Within an industry, the production function is identical except for the productivity parameter. Each firm, however, faces different level of frictions which effectively raise the cost of inputs for the firm. Given the productivity level and frictions, a firm sets its own price as a monopolist. Without frictions, the profit maximization implies that the marginal revenue productivity of capital and labor should be equalized across firms in an industry. If firm-specific frictions exist, however, then the marginal revenue productivities can differ among firms. The two measures of marginal revenue productivities can be summarized by the firm's total factor revenue productivity (TFPR). We show that the aggregate TFP is a function of the deviation of the firm's individual TFPR from the industry average.

The variation of firm-level TFPR is the useful summary of the allocation efficiency of the economy. We use firm-level accounting data for manufacturing firms in Japan to measure the variation of TFPR each year since 1989. We find that the (cross-sectional) variation of TFPR is highly cyclical and quantitatively important in explaining the GDP growth rate in Japan since the late 1990's. Our findings show that the shock to average productivity is only a part of the TFP growth rate and the deviation of individual productivity from the average is a significant source of the aggregate fluctuation.

We then examine the source of the frictions which drive a wedge in TFPR across firms in an industry. We find that an increase in uncertainty about idiosyncratic productivity shocks is the major source of the frictions in Japan. As it takes time/resources to adjust the level of inputs, an unexpected idiosyncratic shock leads to variation of TFPR across firms. If a firm is hit by a positive (physical) productivity shock, then it does not increase inputs immediately but rather with some time lags. Due to sluggish adjustments of inputs, the variation of TFPR becomes larger as the magnitude of uncertainty (or the size of the shock) becomes larger.

We further investigate the alternative explanation for rising TFPR variation in Japan and find that the learning-by-doing hypothesis can also help explain the part of the variation in TFPR while other potential explanations are not consistent with the data.

Our research relates to the multiple strands of literature on productivity. The preceding research closest to ours is Hsieh and Klenow (2009). Hsieh and Klenow (2009) show that a significant difference in TFP between the U.S. and developing countries can be explained by the difference in allocation efficiency. They conclude that government regulation and public ownership of the firms in China and India are the leading cause for the resource misallocation in these countries. We also use firm's first order condition to identify frictions using the data on Japan manufacturing firms. Our conclusion, however, differs as we find that resource misallocation in Japan is cyclical and unlikely to be explained by government intervention. Instead, we find that lending by policy finance institution in Japan actually helps reduce allocation inefficiency.

Hosono and Takizawa (2012) use plant-level data in Japan to examine to what extent the variation of TFPR is due to financial frictions. To this end, they construct a structural model of a firm with a borrowing constraint. Hosono and Takizawa (2012) fit the model to their data and find that the borrowing constraint can explain about a half of the capital distortion.

Our paper differs from Hosono and Takizawa (2012) in three ways. First, we focus on the time-series variation in allocation efficiency in Japan. Given that the friction is measured as an error of the model, the level of the gain from efficient allocation is subject to model misspecification. Comparing the US and Japan and computing the efficiency gain in the hypothetical case where Japan achieves the US efficiency is one way to avoid taking the model literally as truth. We, on the other hand, focus on the time-series variation of resource misallocation. Thus, unless one believes that model misspecification varies significantly over time, our evaluation of the change in efficiency gain over time is robust to potential model misspecifications.

Second, we use firm-level data to measure productivity and frictions. There are advantages and disadvantages in using firm level data as opposed to plant-level data such as Hosono and Takizawa (2012). If the local licensing or regional-level regulation is the key source of the friction that a producer faces, then one should use plant-level data to measure such friction. On the other hand, if firm-wide frictions such as borrowing constraints or countrywide regulation which affect an entire firm as a legal entity as opposed to each plant, the use of firm-level data is preferred.

Third, we differ from Hosono and Takizawa (2012) in that our approach is less structural than theirs. We investigate the cause of the variation in revenue productivity not by fitting a structural model but by associating the productivity with other observables using the data. In this sense, our work is complementary to Hosono and Takizawa (2012).

Our research also relates to Restuccia and Rogerson (2008) as they also suggest that resource misallocation can have an important effect on aggregate TFP. Our measure of misallocation depends on TFPR, whose importance is highlighted by Foster, Haltiwanger and Syverson (2008).

The rest of the paper is organized as follows. We present the model of monopolistic competition with firm heterogeneity in an industry in Section 2. We show that the aggregate TFP depends on the deviation of firm TFPR from the industry average. We then describe data in Section 3 and present the estimates of misallocation of resources across Japanese firms in Section 4. The source of TFPR variation is analyzed in the following two sections and the role of the government is examined in Section 7. Section 8 concludes.

2 Model

We model firms which operate within a framework of monopolistic competition of Dixit and Stiglitz (1977). For the specific setup and the details about frictions, we follow the model of Hsieh and Klenow (2009). There are industries $s = 1, \ldots, S$ which produce industry-level aggregate output Y_s. Each industry is populated by M_s firms and each firm produces one type of output Y_{si}. Each firm's output is combined to produce Y_s with the production function

$$Y_S = \left(\sum_{i=1}^{M_S} Y_{Si}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

where σ denotes the elasticity of substitution among inputs. Y_s is in turn used to produce the economy-wide aggregate output Y.

Given industry output, a cost minimization problem yields the demand function

$$Y_{Si} = Y_S \left(\frac{P_S}{P_{Si}}\right)^{\sigma}$$

with the price index

$$P_S = [\sum P_{Si}^{1-\sigma}]^{\frac{1}{1-\sigma}}$$

Given the demand function, each firm maximizes profits by choosing optimal level of labor and capital. Each firm has a production function:

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}$$

A firm has its own level of productivity but the input share parameter α_s is the same within the industry. When choosing between labor and capital, we assume there is a firm-specific wedge $1 + \tau_{K_{si}}$ which adds extra funding cost for firm i. We also assume that there is friction in the output parameterized by $\tau_{Y_{si}}$ which prevents a firm from producing at the optimal level possibly due to licensing and government regulation.

Their profit maximization problem solves

$$\max(1 - \tau_{Y_{si}}) P_{si} Y_{si} - w L_{Si} - (1 + \tau_{K_{Si}}) R K_{Si}$$

The first order conditions yield the restriction on the marginal revenue product of labor and capital for the firm:

$$MRPL_{Si} \equiv \frac{\sigma-1}{\sigma}(1-\alpha_s)\frac{P_{Si}Y_{Si}}{L_{Si}} = \frac{w}{1-\tau_{Y_{Si}}} \tag{1}$$

$$MRPK_{Si} \equiv \frac{\sigma-1}{\sigma}\alpha_S\frac{P_{Si}Y_{Si}}{K_{Si}} = R\frac{1+\tau_{K_{Si}}}{1-\tau_{Y_{Si}}} \tag{2}$$

Equations (1) and (2) show that $MRPL_{si}$ should be equalized across firms if there is no friction $\tau_{Y_{si}}$. Similarly, $MRPK_{si}$ should be equalized across firms if the frictions $\tau_{Y_{si}}$ and $\tau_{K_{si}}$ are both zero.

The profit maximization for the monopolistic firm yields the usual price mark-up rule of

$$P_{Si} = \frac{\sigma}{\sigma-1}\left[\frac{w}{1-\alpha_S}\right]^{1-\alpha_S}\left[\frac{R}{\alpha_S}\right]^{\alpha_S}\frac{\left(1+\tau_{K_{Si}}\right)^{\alpha_S}}{\left(1-\tau_{Y_{Si}}\right)A_{Si}}$$

The optimal output is

$$\begin{aligned} Y_{Si} &= Y_S P_S^{\sigma} P_{Si}^{-\sigma} \\ &= Y_S P_S^{\sigma}\left(\frac{\sigma-1}{\sigma}\right)^{\sigma}\left[\frac{1-\alpha_S}{w}\right]^{\sigma(1-\alpha_S)}\left[\frac{\alpha_S}{R}\right]^{\sigma\alpha_S}\left(\frac{\left(1-\tau_{Y_{Si}}\right)A_{Si}}{\left(1+\tau_{K_{Si}}\right)^{\alpha_S}}\right)^{\sigma} \end{aligned}$$

The final output is produced using the production function

$$Y = \prod Y_S^{\theta_S}$$

The cost minimization yields

$$P_S = \frac{\theta_S Y}{Y_S}$$

Again, the labor demand for firm i is

$$L_{Si} = \frac{1-\alpha_S}{w}Y_{Si}\lambda_{Si} = \frac{1-\alpha_S}{w}\frac{(\sigma-1)}{\sigma}\left(1-\tau_{Y_{Si}}\right)Y_{Si}P_{Si}$$

We assume that the aggregate supply of capital and labor is fixed at K and L. Equating the aggregate supply and demand of labor, the sector labor demand can be written as

$$\mathrm{L_S} = L\frac{(1-\alpha_S)\theta_S/\overline{MRPL_S}}{\sum(1-\alpha_{S'})\theta_{S'}/\overline{MRPL_{S'}}}$$

where the average MRPL is

$$\overline{\mathrm{MRPL_S}} = \frac{\mathrm{w}}{\sum\left(1-\tau_{Y_{si}}\right)\frac{P_{Si}Y_{Si}}{P_S Y_S}}$$

Similarly, by aggregating capital demand and equating it to the aggregate supply of capital K, we have

$$\mathrm{K_S} = K\frac{\alpha_S\theta_S/\overline{MRPK_S}}{\sum\alpha_{S'}\theta_{S'}/\overline{MRPK_{S'}}}$$

where

$$\overline{\mathrm{MRPK_S}} = \frac{R}{\sum\frac{1-\tau_{Y_{Si}}}{1+\tau_{K_{Si}}}\frac{\mathrm{P_{Si}}Y_{Si}}{P_S Y_S}}$$

We can then express the aggregate output Y as a function of $\mathrm{K_s}, L_s$ and industry TFP:

$$\mathrm{Y_s} = TFP_s \cdot K_s^{\alpha_s} L_s^{1-\alpha_s}$$

$$\mathrm{Y} = \prod_{\mathrm{s}=1}^{\mathrm{S}}\left(TFP_s \cdot K_s^{\alpha_s} L_s^{1-\alpha_s}\right)^{\theta_s}$$

Next, we show that industry $\mathrm{TFP_s}$ can be expressed as a function of the total factor revenue productivity (TFPR) variation of each firm within industry. The revenue productivity for the individual firm at the optimum is

$$\mathrm{TFPR_{Si}} \equiv \frac{P_{Si}Y_{Si}}{K_{S_I}^{\alpha_S}L_{Si}^{1-\alpha_S}} = \frac{\sigma}{\sigma-1}\left(\frac{R}{\alpha_S}\right)^{\alpha_S}\left(\frac{w}{1-\alpha_S}\right)^{1-\alpha_S}\frac{\left(1+\tau_{K_{Si}}\right)^{\alpha_S}}{1-\tau_{Y_{Si}}}$$

The point of the equation is to show that the revenue productivity can vary across firms in an industry only due to $\tau_{Y_{si}}$ and $\tau_{K_{si}}$, not due to physical productivity A_{si}. Regardless of the physical productivity, the revenue productivity should be equalized across firms in our setup of monopolistic competition. If a firm has higher physical productivity, it should expand the output such that its revenue productivity falls until it is equal to the revenue productivity of other firms in the same industry.

Also, we can rewrite the definition of $\mathrm{TFPR_{si}}$ as

$$\begin{aligned}\mathrm{TFPR_{si}} &= \frac{P_{Si}Y_{Si}}{\left(\frac{\sigma-1}{\sigma}\alpha_S\frac{P_{Si}Y_{Si}}{MRPK_{Si}}\right)^{\alpha_S}\left(\frac{\sigma-1}{\sigma}(1-\alpha_s)\frac{P_{Si}Y_{Si}}{MRPL_{Si}}\right)^{1-\alpha_S}} \\ &= \frac{\sigma}{\sigma-1}\left(\frac{MRPK_{Si}}{\alpha_S}\right)^{\alpha_S}\left(\frac{MRPL_{Si}}{1-\alpha_S}\right)^{1-\alpha_S}\end{aligned} \tag{3}$$

As $\mathrm{TFPR_{si}}$ is a function of $\mathrm{MRPK_{si}}$ and $\mathrm{MRPL_{si}}$, $\mathrm{TFPR_{si}}$ should be equalized across firms in an industry if a firm can freely adjust the level of both labor and capital. In other words, the variation of $\mathrm{TFPR_{si}}$ is the indicator for frictions which prevent firms from achieving their optimal use of either labor or capital.

We also define the industry average total factor revenue productivity as

$$\overline{\mathrm{TFPR_S}} = \frac{\sigma}{\sigma-1}\left(\frac{\overline{MRPK_S}}{\alpha_S}\right)^{\alpha_S}\left(\frac{\overline{MRPL_S}}{1-\alpha_S}\right)^{1-\alpha_S} \tag{4}$$

Then, the industry TFP can be written as

$$\mathrm{TFP_s} = \left(\sum_{i=1}^{M_s}\left\{A_{si}\frac{\overline{TFPR_s}}{TFPR_{si}}\right\}^{\sigma-1}\right)^{\frac{1}{\sigma-1}}$$

If there are no frictions, then the total revenue productivity must be equalized within industry such that $\mathrm{TFPR_{si}} = \overline{TFPR_s}$ for all i in $\mathrm{M_s}$. Thus, industry TFP with efficient allocation can be written as $\overline{\mathrm{A_s}} = \left(\sum_{i=1}^{M_s} A_{si}^{\sigma-1}\right)^{\frac{1}{\sigma-1}}$. The efficiency gain is defined as the ratio between actual output and the output with efficient allocation.

$$\frac{\mathrm{Y}}{\mathrm{Y_{efficient}}} = \prod_{s=1}^{S}\left[\sum_{i=1}^{M_s}\left\{\frac{A_{si}}{\overline{A_s}}\frac{\overline{TFPR_s}}{TFPR_{si}}\right\}^{\sigma-1}\right]^{\frac{\theta_s}{\sigma-1}} \tag{5}$$

The equation shows that to detect the allocation inefficiency, the key indicator is the *variation* of TFPR from the industry average, not the *level* of TFPR. Suppose that $\tau_{Y_{si}} = \tau_{Y_s} \neq 0$ and $\tau_{K_{si}} = \tau_{K_s} \neq 0$ hold for all i. That is, there is a constant but non-zero friction in industry s. Then $\overline{\mathrm{TFPR}}_s = \mathrm{TFPR}_{si}$ still holds for all i and TFP_s is at its 'efficient' level. If an industry has high level of τ_{Y_s} on average but they do not vary across firms, then industry level labor L_s and capital K_s are low while TFP_s is unaffected. Due to fixed supply of labor and capital, the labor and capital market clearance guarantee that average inefficiency does *not* affect outputs in this framework.

The efficiency gain $Y/Y_{\mathrm{efficient}}$ is less than one if the firm with higher physical productivity tends to have higher revenue productivity. That is, if a firm which should expand their output (high A_{si}) does not do so in reality due to some frictions (high TFPR_{si}), then the economy-wide output is less than the efficient level of output, leading to the efficiency gain.

To gain more insights, we rewrite equation (5) assuming that $\log A_{si} \equiv a_{si}$, $\log 1 - \tau_{Y_{si}} \equiv x_{si}$ and $\log(1 - \tau_{Y_{si}})/(1 + \tau_{K_{si}}) \equiv z_{si}$ are jointly normally distributed. In this case, $\log \mathrm{TFPR}_{si} \equiv t_{si}$ are also jointly normally distributed. Then,

$$
\begin{aligned}
&\log Y - \log Y_{efficient} \\
&\qquad = -\frac{1}{2}\sum_{s=1}^{S} \theta_s \{(\sigma - 1)\mathrm{Var}_s[t_{si}] + \alpha_s \mathrm{Var}_s[z_{si}] + (1 - \alpha_s)\mathrm{Var}_s[x_{si}]\} \\
&\qquad - 2(\sigma - 1)\sum_{s=1}^{S} \theta_s \mathrm{Cov}_s(a_{si}, t_{si})
\end{aligned}
$$

holds. Appendix 1 shows the derivation of the decomposition of efficiency gain under log-normality assumption.

The loss in productivity from the inefficient allocation comes from two sources: The first term is the variance of TFPR which is always negative. The second term is the covariance between physical and revenue productivity. To the extent that two measures of productivities are positively correlated, the covariance term lowers the industry-level TFP.

3 Data

The data we use is the DBJ Financial Database of Listed Firms provided by Development Bank of Japan. The database covers all firms listed in Tokyo and other regional stock exchanges in Japan from 1960 to present. The data provides the financial statements and supplements at annual frequency. The database includes delisted firms; therefore there is no survivorship bias.

As our data is limited to listed firms, we are focusing on the sample with relatively smaller frictions. Listed firms typically have better access to the capital market due to better disclosure and smaller information asymmetry. Thus, firms in our sample should find it relatively easier to adjust their capital level when hit by productivity shocks. Therefore, our estimates of TFPR variation can be considered as a lower bound of the true allocation inefficiency in Japan.

We use non-consolidated financial statements for our analysis. Since we need to classify each manufacturing firm into industries, it is better to use non-consolidated data to narrow the scope of the business of the firm. Also, more data items are available for non-consolidated financial statements than consolidated ones. For example, the detailed breakdown of Cost of Goods Sold is available only for non-consolidated statements.

Value added is computed by the following formula:

Value added = Ordinary Profit + Wage – Interests and Dividends Paid +

Interests and Dividends Received + Tax Paid + Depreciation

where ordinary profit is operating profit plus net interest received.

Wage is computed by adding Labor Cost in the Cost of Goods Sold to Wage in Selling, and General and Administration Expenses. This measure of labor cost may miss the cost of pensions and other employment benefits. To examine the severity of the problem, we compute the labor share for all firms each year and compare the average to the labor share in GDP. We find that they are roughly the same (around 70% in the latter half of the sample) and therefore decide to use Wage as a measure of labor cost.

We remove holding companies from the analysis, as their value-added is not comparable to the firms that run business operation. Specifically, a holding firm records their interests and dividends received as Sales instead of Interest Received. Thus, the interests and dividends received by a holding firm will be included in value added. As holding firms typically have no or very little fixed capital and few employees, their productivity measure tends to be extremely high. The difference in accounting makes it hard to compare holding companies to other operating companies.

To identify holding companies, we set the threshold on the ratio of financial investments to total assets. If the ratio exceeds 95%, we judge that the firm is a holding firm and should be removed from the sample. We also test by removing firms whose name includes 'Holdings'. The two methodology yields essentially the same result and thus we report the result based on the 95% threshold.

To classify manufacturing firms into industries, we use the DBJ industry code which mostly corresponds to the four digit SIC code in the US. To maintain the number of firms in each industry large enough for the analysis, we use the median category of DBJ industry code. The median category classifies the manufacturing firms into 17 sectors. Each median category mostly corresponds to the first 2 digits of the SIC codes. For example, the first sector (Food) corresponds to the US SIC codes between 2000 and 2100 and the second sector (Textile) corresponds to the SIC codes between 2200 and 2400 and so on.

Many Japanese firms have their fiscal year ending in March rather than December. When I calculate the productivity using the data as of (or before) March in year t+1, then I treat it as year t observation.

To estimate industry capital share parameter α_s, we use the capital share of the US manufacturing plants obtained from NBER-CES Manufacturing Industry Database. The database contains all manufacturing industries from 1958 to 2005 at4-digit SIC code level and provides the labor compensation and value added for each industry.

4 Allocation Efficiency in Japan from 1989 to 2009

In this section, we show the estimates of the change in allocation efficiency over the period between 1989 and 2009. We focus on this period since 1989 is the peak of the bubble economy in Japan and the beginning of the Japan's lost two decades.

In order to estimate the efficiency gain $Y/Y_{\mathrm{efficient}}$ from the data, we need to set parameters to back out frictions.

Following Hsieh and Klenow (2009), we set the rental rate of capital to $R = 0.1$. As we focus on the variation of the productivity of capital from the industry average, changing R does not change the estimated efficiency gain.

We set the elasticity of substitution between firms' output to $\sigma = 3$. In general, the efficiency gain is increasing in σ. Although we focus on the *change* in efficiency gain between 1989 and 2009, the change can be exaggerated if the *level* of inefficiency is overestimated. Empirically, estimates of the elasticity of substitution range from 3 to 10 (Broda and Weinstein (2006) and Hendel and Nevo (2006)), thus we make a conservative choice to avoid overestimating the efficiency gain.

We set the capital share for each industry α_s to the level of capital share of the corresponding industry in the U.S. With the most developed financial market and relatively few government regulations, the resource allocation in the U.S. market is considered to be relatively undistorted. Thus, we use the capital share in the U.S. as our benchmark to measure resource misallocation in Japan.

The use of the U.S. capital share is necessary to identify the friction in the data. At the optimum, the capital/labor ratio for each firm depends both on the friction and on the capital share parameter α_s. Thus, we cannot separately identify industry average friction and the capital share without exogenously determine either one of the two.

Following Hsieh and Klenow (2009), we estimate the capital share parameter in the U.S. each year by

$$\alpha_{s,t} = 1 - \frac{3}{2}\frac{Wage_{s,t}}{Value\ Added_{s,t}}$$

We multiply the labor share by 3/2 in order to adjust for the non-wage benefits. This way, the average labor share from the NBER-CES database approximately matches the labor share in National Income and Product Accounts.

The estimated $\alpha_{s,t}$ is highly stable over time in our sample period. Thus, we assume that the capital share after 2006 is the same as that of 2005. As a robustness check, we also compared the difference in the TFPR distribution between 1989 and 2005 (instead of 2009) but the results are qualitatively the same as the case of 2009.

Figure 1 plots the cross-sectional distribution of Total Factor Physical Productivity (TFPQ) $\log A_{si} M_s^{\frac{1}{\sigma-1}} / \overline{A_s}$ in 1989 and 2009. It is evident that the distribution in 2009 has longer left tail, suggesting that the variation in TFPQ becomes larger in 2009.

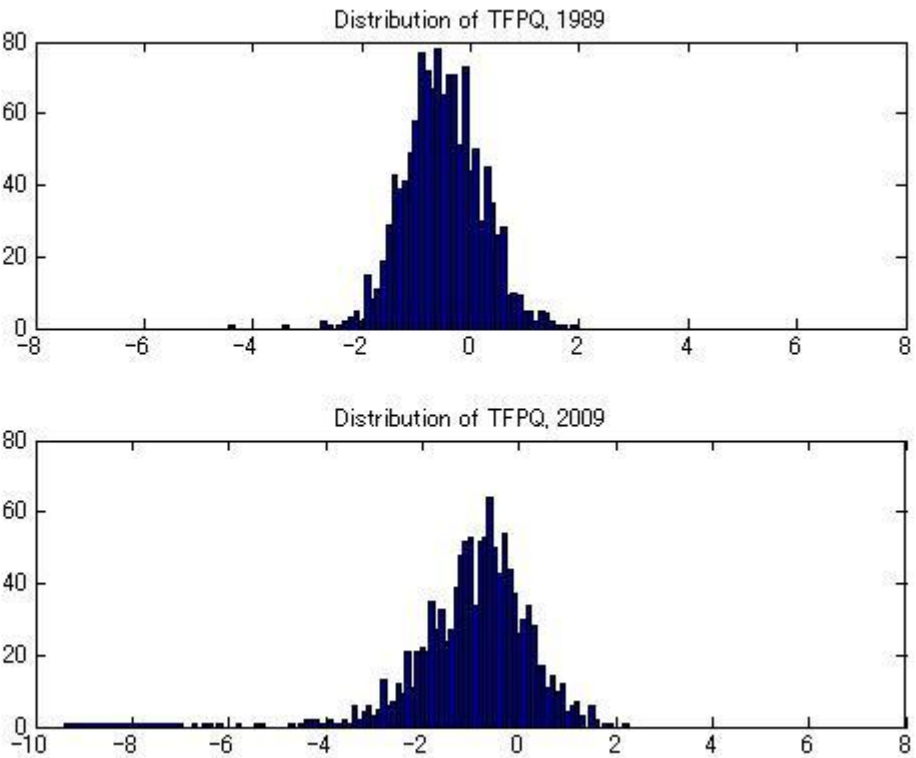

Figure 1: Distribution of Total Physical Productivity

The figure plots the cross-sectional distribution of the deviation of firms' physical productivity from the industry average $\log A_{si} M_s^{\frac{1}{\sigma-1}} / \overline{A_s}$ in 1989 and 2009.

The variation of the TFPQ itself does not imply inefficiency. In our model, it is TFPR which should be equalized across firms. Figure 2 plots the distribution of the log TFPR (relative to the industry average) in 1989 and 2009.

In Figure 2, the TFPR clearly varies more in 2009 than in 1989. Both tails become fatter in 2009. This implies that the allocation efficiency in Japanese manufacturing sector deteriorated during this period.

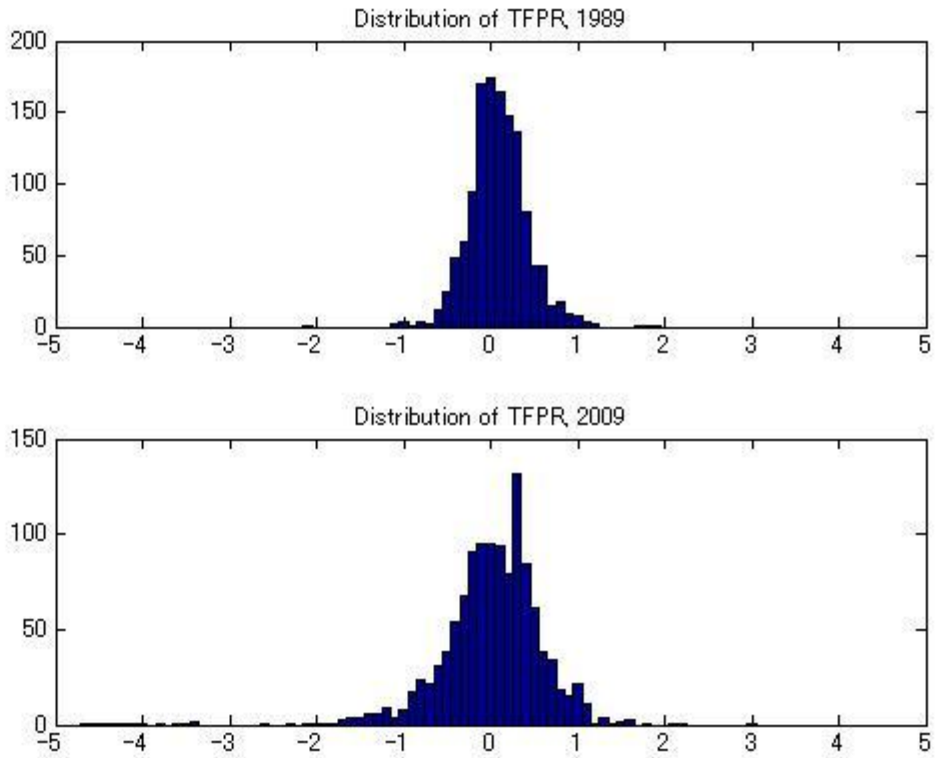

Figure 2: Distribution of Total Revenue Productivity

The figure plots the cross-sectional distribution of the deviation of firms' revenue productivity from the industry average $\log TFPR_{si}/\overline{TFPR_s}$ in 1989 and 2009.

Figure 3 shows the estimated TFP gains from efficient allocation in (5) estimated for each year from 1958 to 2011. As we can see, there is a sharp rise in allocation inefficiency in Japan since the late 1990's. The misallocation of resource peaked in 2008, when the Great Recession began in the U.S.

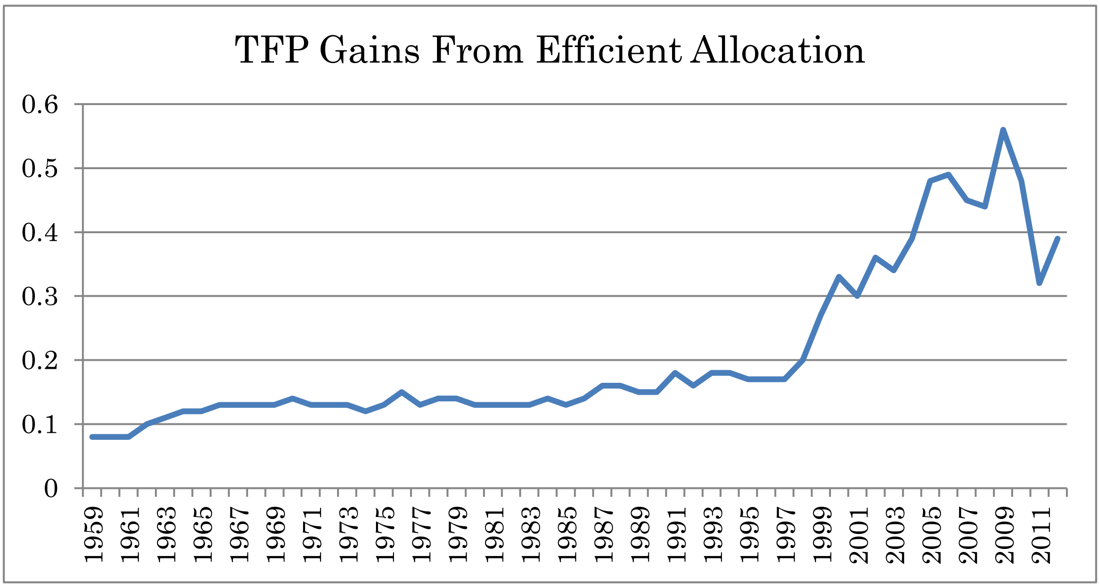

Figure 3: Efficiency Gains in Outputs

Figure plots $\frac{Y_{efficient}}{Y} - 1$, where $Y_{efficient}$ is estimated by equalizing $TFPR_{si}$ at industry average each year. The higher value of the TFP gain indicates there is more inefficiency in resource allocation.

To measure the economic magnitude of the change in allocation inefficiency, we compute the contribution of the change in inefficiency to the GDP growth rate. We do so by multiplying the GDP share of manufacturing industry in Japan to the (negative) log change in the efficiency gain. (Since a rise in efficiency gain means a fall in the observed GDP relative to the efficient level, we use the negative of the change in the efficiency gain.) Figure 4 compares the historical real GDP growth rate in Japan and log change in efficiency gain.

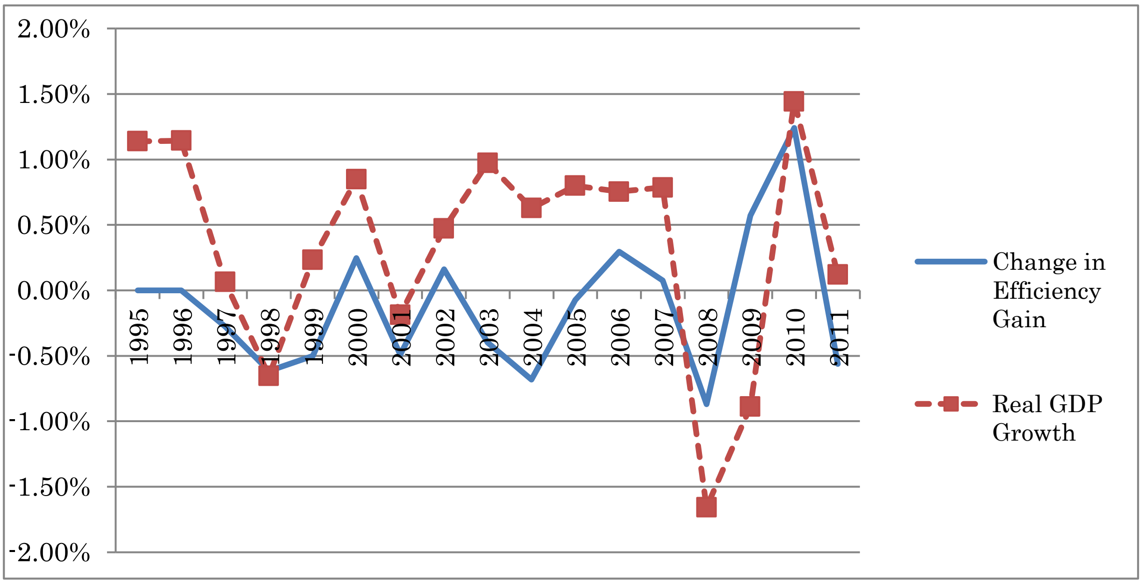

Figure 4: Log Change in Efficiency Gain and Real GDP Growth Rate

Figure plots real GDP growth rate in Japan since 1995 (based on fiscal year ending in March). Change in allocation efficiency is $\log Gain_t/Gain_{t+1}$, where $Gain_t \equiv Y_{efficient,t}/Y_t$ The higher value of the TFP gain indicates there is more inefficiency in resource allocation.

As we can see, the change in the efficiency gain is highly correlated with the real GDP growth in the data. This looks surprising at the first glance since the efficiency gain is computed based on the *deviation* from the industry average TFPR, not the level of TFPR. If the productivity of all firms falls but the deviation from the average does not change, we should see a fall in real GDP growth rate but not in the efficiency gain.

Figure 4 shows that the shock to the efficiency gain is economically significant, when compared with the actual GDP growth rate. In 1998, the real GDP fell by -0.65% per year while the efficiency gain increased by 0.62%. So nearly all of the fall of the GDP in 1998 can be attributed to the rise in allocation inefficiency. Also in 2008, the real GDP fell by 1.66% in a wake of the financial crisis in the US while the efficiency gain rose by 0.87%, explaining more than half of the decrease in the GDP. These figures show that the change in allocation efficiency is an economically significant driver for the value-added in Japan after the 1990s.

Table 1 shows the cross-sectional distribution of the ratio of the TFPR to its industry average as well as the efficiency gain from 1958 to 2011. As we can see, the standard deviation of the TFPR ratio rises from 0.33 in 1989 to 0.61 in 2009. The rise in the standard deivation roughly lines up with the rise in efficiency gain, which increases from 0.15 in 1989 to 0.48 in 2009. If the allocation inefficiency had been constant since 1989 until 2009, the GDP would have been higher by 2.74% in 2009, or 0.27% in terms of annual growth rate. Given the average real GDP growth rate in Japan since 1994 is 0.35%, the magnitude of the loss from the increasing allocation inefficiency in manufacturing sector is considerable.

Table 1: Distribution of TFPR from 1989 to 2009

	# of	Distribution of TFPR				Percentiles					Efficiency
	Obs.	Mean	Std	Skew	Kurt	1%	25%	50%	75%	99%	Gain
1989	1267	0.09	0.33	0.20	6.13	−0.67	−0.12	0.07	0.28	0.98	0.15
1990	1298	0.08	0.37	−0.41	9.95	−0.90	−0.12	0.07	0.29	1.00	0.18
1991	1302	0.09	0.35	−0.02	7.63	−0.75	−0.11	0.08	0.28	1.01	0.16
1992	1318	0.07	0.40	−0.65	7.58	−1.04	−0.15	0.08	0.30	0.98	0.18
1993	1338	0.06	0.45	−1.74	18.23	−1.20	−0.15	0.08	0.30	0.98	0.18
1994	1379	0.05	0.44	−2.01	17.58	−1.36	−0.15	0.09	0.30	0.90	0.17
1995	1404	0.04	0.41	−1.39	13.24	−1.09	−0.16	0.06	0.28	0.96	0.17
1996	1420	0.04	0.35	−0.30	3.99	−0.90	−0.17	0.06	0.27	0.85	0.17
1997	1431	0.04	0.41	−1.03	10.74	−1.10	−0.17	0.06	0.28	0.92	0.20
1998	1441	0.03	0.46	−0.83	11.15	−1.38	−0.18	0.05	0.29	1.03	0.27
1999	1441	0.05	0.45	−0.18	7.67	−1.20	−0.19	0.07	0.31	1.08	0.33
2000	1424	0.02	0.45	−0.25	5.91	−1.22	−0.20	0.04	0.28	1.12	0.30
2001	1399	0.01	0.49	−0.17	7.30	−1.42	−0.23	0.04	0.29	1.21	0.36
2002	1364	−0.01	0.51	−1.24	20.37	−1.29	−0.24	0.01	0.26	1.24	0.34
2003	1334	0.01	0.47	0.37	7.18	−1.24	−0.23	0.02	0.26	1.29	0.39
2004	1310	0.02	0.47	0.26	7.71	−1.18	−0.23	0.02	0.26	1.41	0.48
2005	1298	0.00	0.48	0.18	8.17	−1.31	−0.25	0.01	0.25	1.43	0.49
2006	1278	−0.01	0.51	−0.31	9.88	−1.40	−0.26	−0.01	0.26	1.49	0.45
2007	1249	−0.02	0.50	−0.03	9.25	−1.34	−0.28	−0.02	0.25	1.43	0.44
2008	1218	0.03	0.63	−3.03	45.75	−1.77	−0.26	0.06	0.36	1.43	0.56
2009	1193	0.01	0.61	−1.39	11.24	−1.78	−0.27	0.05	0.35	1.31	0.48

The table tabulates the summary statistics of the distribution of $\log TFPR_{si}/\overline{TFPR_s}$ each year. The efficiency gain is computed by $\frac{\mathrm{Y_{efficient}}}{\mathrm{Y}}-1$, where $\mathrm{Y_{efficient}}$ is estimated by equalizing $\mathrm{TFPR_{si}}$ at industry average each year.

Next, we examine if the allocation inefficiency captured by the variation of the TFPR from the industry average comes from the misallocation of capital or labor. From equations (3) and (4), we obtain

$$\frac{\mathrm{TFPR_{si}}}{\overline{\overline{\mathrm{TFPR_S}}}} = \left(\frac{MRPK_{si}}{\overline{\overline{MRPK_S}}}\right)^{\alpha_S} \left(\frac{MRPL_{si}}{\overline{\overline{MRPL_S}}}\right)^{1-\alpha_S}$$

Taking log and variance of the both sides yield

$$\begin{aligned} \mathrm{Var}\left[\log\left(\frac{\mathrm{TFPR_{si}}}{\overline{\overline{\mathrm{TFPR_S}}}}\right)\right] \\ &= \mathrm{Var}\left[\alpha_s \log\frac{MRPK_{si}}{\overline{\overline{MRPK_S}}}\right] + \mathrm{Var}\left[(1-\mathrm{\alpha_s})\log\frac{MRPL_{si}}{\overline{\overline{MRPL_S}}}\right] \\ &+ 2\mathrm{Cov}\left(\alpha_s \log\frac{MRPK_{si}}{\overline{\overline{MRPK_S}}}, (1-\mathrm{\alpha_s})\log\frac{MRPL_{si}}{\overline{\overline{MRPL_S}}}\right) \end{aligned}$$

This equation shows that we can decompose the variance of the TFPR into the variance of MRPK and the variance of MRPL and their covariance.

Table 2 shows the result of the variance decomposition computed for 1989 and 2009. As we can see, most of the variation of the TFPR comes from the variation in MRPK. Throughout the period from 1958 to 2011, about 70% to 100% of the variance of the TFPR is due to the variance of the MRPK and the small fraction of the variation is accounted for by the variance of MRPL and the covariance between MRPK and MRPL.

Table 2: Variance Decomposition of TFPR

Year	$\sigma^2(TFPR)$	$\sigma^2(MRPK)$		$\sigma^2(MRPL)$		$\mathrm{Cov}(MRPK, MRPL)$	
1989	0.11	0.11	(99.0%)	0.01	(9.0%)	−0.01	(−8.0%)
2009	0.37	0.30	(80.0%)	0.02	(6.0%)	0.05	(13.0%)

The table shows the variance decomposition of TFPR each year. The figures in parenthesis are percentage of variance relative to the variance of TFPR.

Thus, the major source of the allocation inefficiency in Japan between 1989 and 2009 is the misallocation of capital rather than labor.

5 Idiosyncratic Physical Productivity Shocks

The fact that allocative efficiency is highly cyclical in Japan implies that government policy and change in regulations may not be the main driver for the misallocation in Japan. This observation contrasts the conclusion of Hsieh and Klenow (2009) who find that the regulation of the government is the key in explaining the difference in allocation efficiency between the US and developing countries (such as China and India).

In this section, we examine if the variation of TFPR is driven by idiosyncratic physical productivity shocks. If physical productivity A_{si} is stochastic and a firm cannot adjust its input level immediately, then TFPR can vary across firms. If a physical productivity shock is systematic, then the firm should be able to trade state contingent claim so that its input revenue productivity is equalized with other firms state-by-state. On the other hand, if the shock is idiosyncratic, then it cannot be shared by other market participants, leading to deviation of TFPR from the industry average. As we focus on the difference in variation of TFPR between 1989 and 2009, the question is whether there is a rise in uncertainty in an idiosyncratic physical productivity shock.

To measure the magnitude of uncertainty, we first extract idiosyncratic component of physical productivity by supposing $a_{\mathrm{sit}} \equiv \log \mathrm{A}_{\mathrm{sit}}$ has the following structure

$$a_{\mathrm{sit}} = \tilde{a}_{\mathrm{t}} + \epsilon_{\mathrm{sit}}$$

where $\tilde{a}_t$ is a common shock and ϵ_{sit} is a firm-specific shock. We also assume that a firm-specific shock follows AR(1) process

$$\epsilon_{sit} = \rho^{\epsilon}\epsilon_{sit-1} + \eta_{sit}$$

Using the estimates of A_{si} for each year, we fit the model by assuming $\tilde{a}_t = \frac{1}{S}\frac{1}{M_s}\sum_s \sum_{si} a_{sit}$. We run a panel regression of idiosyncratic productivity ϵ_{sit} on its lagged value to extract the residual $\hat{\eta}_{sit}$ with time fixed effects. The residual $\hat{\eta}_{sit}$ is the estimate of the idiosyncratic physical productivity shock and we compute the standard deviation of $\hat{\eta}_{sit}$ each year.

Table 3: Idiosyncratic Productivity and AR(1) Estimates of Shocks

Model Estimates:

ρ^{ϵ}	$\sigma(\hat{\eta}_{sit})$	
0.90	1989	0.23
(0.014)	2009	0.71

The table shows the a panel estimate of $\epsilon_{sit} = \rho^{\epsilon}\epsilon_{sit-1} + \eta_{sit}$ with time fixed effects. The figure in parenthesis is a standard error clustered by time and $\sigma(\hat{\eta}_{sit})$ is the standard deviation of residual computed using the sample in a particular year.

As we can see in Table 3, the uncertainty of idiosyncratic productivity shocks rises significantly from 1989 and 2009. The correlation (over time) between the standard deviation of TFPR and the standard deviation of idiosyncratic physical productivity shock is as high as 0.78. Thus, an unexpected shock to productivity is an important source of the deviation of TFPR. Explaining the variation of TFPR with shocks to physical productivity is not a tautology. We find that uncertainty, rather than a trend, in physical productivity is the main driver of the resource misallocation. Estimating the idiosyncratic shock as a deviation from the industry-specific average rather than overall average produces a very similar result.

One might be concerned about the fact that we use the estimated productivity A_{si} using the same model as we use to extract $TFPR_{si}$. If our assumption about the capital share parameter α_s is wrong then the model specification error might drive both A_{si} and $TFPR_{si}$ in the same direction. To mitigate this concern, we estimate a productivity shock based on the method of Cooper and Haltiwanger (2006). In Cooper and Haltiwanger (2006), the capital share parameter is estimated using instruments such as lagged capital and sales. The detail of the estimation process is in Appendix 2. We find that the uncertainty rises from 1989 and 2009 and that our result is robust to the different way of estimating a physical productivity shock.

The correlation between uncertainty and the variation of TFPR is consistent with two potential explanations. The first explanation is lagged response of firms to unexpected productivity shocks. Since a firm can adjust capital only with some time lags as it takes time to install/discard capital. Thus, when hit by an idiosyncratic productivity shock, a firm responds with lags and adjusts the input level sluggishly, which leads to temporal variation of TFPR. With this lagged response, greater size of an idiosyncratic shock leads to greater variation of TFPR.

The other explanation is hysteresis in firm's investment as in Dixit (1989). Making investment is the same as exercising an option to enter the market. Thus, greater uncertainty increases the value of waiting. If more firms are in an inaction region in 2009 than in 1989 due to rising uncertainty, the variation of TFPR becomes greater in 2009. Unlike the first explanation, Dixit (1989)'s model does not forecast that a firm will respond with lags. If a firm is in an inaction region today and nothing happens next period, then the firm is still unlikely to make any adjustments. Though both sluggish adjustments and real option theory implies the variation of TFPR due to uncertainty, they differ in forecasting firms' future behavior.

To see which of the two explanations better capture the reality, we examine the relationship between TFPR and a firm's future adjustment behavior. If the lagged response of a firm is the driver of the variation of TFPR, then high TFPR should forecast an increase in investment. The typical convex cost function of investment depends not on investment but on its ratio to the capital. Thus, we check if there is any positive relationship between TFPR and future investment/capital ratio.

Table 4: Investment-Capital Ratio and TFPR

k	−3	−2	−1	0	1	2	3
b_1	0.05	0.05	0.08^{**}	0.15^{***}	0.45^{***}	0.41^{***}	0.36^{***}
$b_1(Year)$	0.03	0.03	0.06^{*}	0.13^{***}	0.47^{***}	0.43^{***}	0.37^{***}
$b_1(Industry)$	0.06	0.05	0.09^{*}	0.15^{***}	0.46^{***}	0.43^{***}	0.37^{***}

The table shows the estimated slope coefficient of the regression $\mathrm{TFPR_{it}} = b_0 + b_1(I/K_{it+k}) + \epsilon_{it}$, where $k = -3, -2, -1, 0, 1, 2, 3$. The first row shows the panel regression result with no dummy variables. The second row shows the regression with year dummies while the third row shows the regression with industry dummies. $\mathrm{IK_{it}}$ is winsorized at 1 percentile and 99 percentile to remove outliers. The standard errors are clustered by time first and added 5 lags in time with Newey-West weighting.

Table 4 shows the result of the regression of TFPR at time t onto investment-capital ratio at t+k. We run a panel regression using all the data, with or without year and industry dummies. Regardless of the regression specification, the current deviation of TFPR is highly related to future investment-capital ratio. As capital does not vary too much over time, the variation is driven mainly by investments. Thus, the data is consistent with the interpretation that a firm faces cost of investment and start investing with lags. This sluggish adjustment leads to the variation of marginal revenue product of capital, which explains most of the variation of TFPR.

To summarize our findings thus far, the misallocation of resource in Japanese manufacturing sector increases significantly since 1989. The rising allocation inefficiency of capital explains a sizable portion of Japan's sluggish TFP growth rate after the bubble period. The increase in resource misallocation is driven by rising uncertainty in firm-level physical productivity shock. As the firm responds to a shock with lags, a larger shock leads to greater misallocation of capital. These idiosyncratic physical productivity shocks can be firm-specific technology shocks or shocks to consumers' preference.

6 Other Explanation of the Variation of TFPR

In this section we explore several alternative (but not mutually exclusive) theories other than rising uncertainty that may explain the increased variation in TFPR in Japan over the last two decades. Overall, we do not find convincing alternatives to rising uncertainty in explaining the greater variation of TFPR over time in Japan.

6.1 Increasing Model Error and IPO/delisting probability

The first obvious interpretation of our finding is that the fit of the model becomes worse from 1989 to 2009. The increase in model specification error can cause the variation of the TFPR to grow over time, which may drive our result. If that is the case, what we see in the data may have nothing to do with the increasing allocation inefficiency but the model errors.

Though we cannot completely deny the possibility of model misspecification, we can check the reliability of the estimated TFPR variation by relating it to something which we can observe and interpret.

One test we conduct here is whether there is any relationship between the deviation of TFPR and IPO/delisting probability. If we see higher probability of IPO/delisting conditional on high/low deviation of TFPR, then such deviation of TFPR is less likely an artifact of model misspecification. Also, finding the determinant of IPO/delisting is interesting on its own. For example, finding a factor that is associated with a higher probability of IPO is useful in studying the role of venture capital (e.g. Miyakawa and Takizawa (2012)).

To test the hypothesis whether high/low TFPR is associated with the probability of IPO/delisting, we estimate the following logit model via Maximum Likelihood.

$$\mathrm{Prob}(\mathrm{D}^{\mathrm{IPO}_{\mathrm{it}}} = 1) = \frac{e^{b_0 + b_1 TFPR_{it}}}{1 + e^{b_0 + b_1 TFPR_{it}}}$$

$$\mathrm{Prob}\left(\mathrm{D}^{\mathrm{Delist}_{\mathrm{it}}} = 1\right) = \frac{e^{c_0 + c_1 TFPR_{it}}}{1 + e^{c_0 + c_1 TFPR_{it}}}$$

Table 5: Logit Model Based On TFPR Deviation

D	$\mathrm{b}_1, \mathrm{c}_1$	$\mathrm{t}(\mathrm{b}_1), \mathrm{t}(\mathrm{c}_1)$	$\Delta\mathrm{Prob}(\mathrm{D} = 1)$
Delist	−0.84	−4.22	−0.16
Listed	0.93	9.68	2.18

The table shows the Maximum Likelihood estimates of logit model using the entire panel data. The left-hand variable is dummy variables which take value of one for delisting (or IPO) and zero otherwise. The right hand side variable is the deviation of TFPR from the industry average. The standard errors are clustered by time and t-statistics are computed without assuming the Information Matrix Equality for robustness. $\Delta\mathrm{Prob}(\mathrm{D} = 1)$ is the change in probability of delisting (or IPO) when TFPR changes from the 5 percentile to 95 percentile value.

Table 5 shows the result of the estimated coefficient on TFPR deviation. Higher TFPR is associated with higher probability of IPO and lower probability of delisting. The coefficients are statistically significant at the traditional 5% cutoff level. When we compare the probability of delisting and IPO between a firm with the 95 percentile of TFPR and a firm with the 5 percentile of TFPR, the difference in probability of delisting is -0.16% while the difference in probability of IPO is 2.18%.

Peters (2011) examines how TFPR is associated with firms' entry using firm level data in Indonesia. He runs regression of TFPR on an entry dummy and finds that new entrants have low TFPR rather than high TFPR. Based on this observation, Peters (2011) concludes that credit market frictions are not likely to be the cause of TFPR variation. Our result based on Japanese data shows the contrary: Newly-listed firms are likely to be more financially constrained than already listed firms. Our findings that newly listed firms tend to have high TFPR is consistent with the hypothesis that financial market friction makes it hard for a firm to increase its capital level fast enough.

The fact that the deviation of TFPR is highly associated with IPO and delisting probabilities alleviates the concern that the estimated TFPR deviation is due to increasing model misspecification over time. In the next subsections, we associate the deviation of TFPR to observables to see if we can attribute the friction to other observables in the economy.

6.2 Varying markups with plant size

Our model with the CES aggregation implies that the markup over the marginal cost is the same across all firms. On the other hand, larger firms may have greater power to control the market and to achieve the higher markups. If the variation in firm size becomes greater in 2009 than in 1989, the model misspecification with growing variation in size may be the key driver for our result.

To attribute the TFPR variation to size, we run non-parametric kernel regression of TFPR on log size. We use the Gaussian kernel and the bandwidth is chosen to minimize generalized cross-validation. Appendix 3 shows the details of the kernel regression.

Figure 5 shows that there is no clear relationship between log size (measured by value-added) and TFPR in 1989. On the other hand, TFPR seems to be increasing in log size in 2009. A theory (e.g. Melitz and Ottaviano (2008)) states that there is a stable negative relationship between size and elasticity of demand, but the prediction is not supported by the data in Japan. The fact that the relationship between size and TFPR is not stable suggests that there must be some other mechanism that drives the TFPR variation.

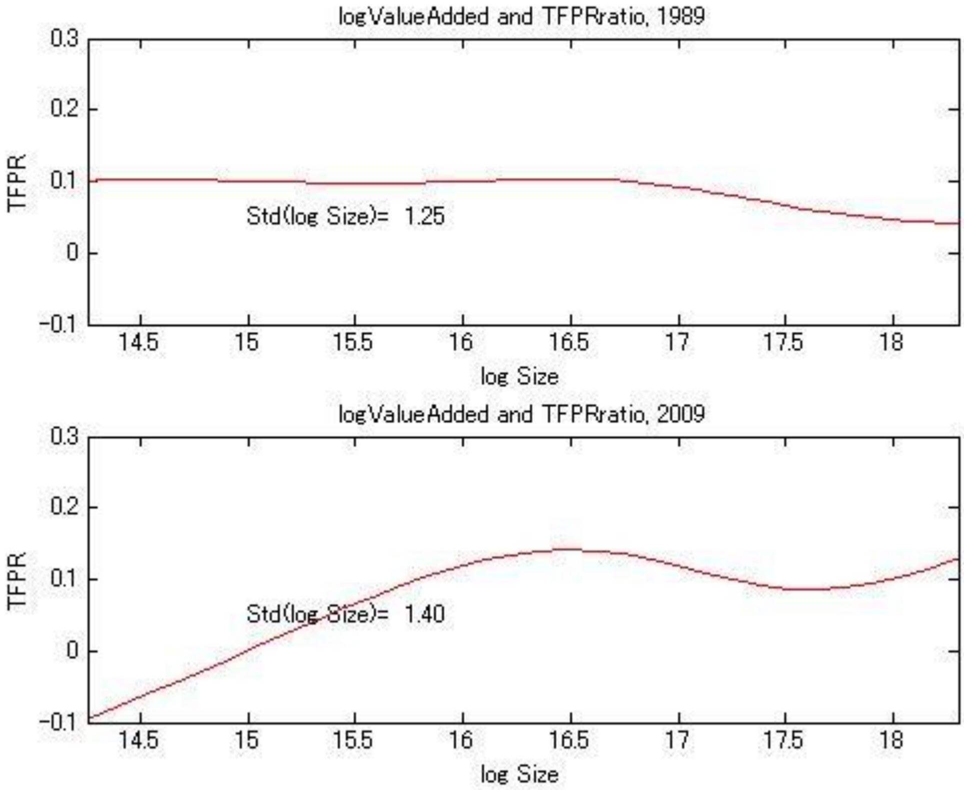

Figure 5: Explaining TFPR with Log Size

Figure plots fitted values of non-parametric kernel regression of the form $\mathrm{TFPR_{si}} = f(\log Size_{si}) + \epsilon_{si}$ where $f(\cdot)$ is estimated using Gaussian kernel. $\mathrm{Std}(\log Size)$ is the cross-sectional standard deviation of $\log Size_{\mathrm{si}}$.

6.3 Adjustment costs

Young firms may have higher TFPR due to higher adjustment costs. That is, a young firm who grows rapidly may face higher constraint to raise capital than an old firm. If there is a stable relationship between age of the firm and TFPR and the variation of age is greater in 2009 than in 1989, then the variation in TFPR can be explained by the variation in age.

Figure 6 shows the result of kernel regression of TFPR onto age of the firm. We measure age of a firm by dividing the accumulated depreciation of their capital by the depreciation per year. For the relationship between TFPR and 'age', we need to measure the physical age of the firms' facilities rather than the age of the firm as a legal entity. Therefore, estimating age using the cumulative depreciation is preferred to using the legal age. The drawback of the approach based on depreciation measure is that the depreciation per year may not be constant over the life of the capital, causing the potential mismeasurement of the vintage of the capital.

As we can see in Figure 6, there seem to be no reliable relationship between the firm's age and TFPR. The relationship is slightly positive in 1989 while it becomes negative in 2009. Thus, it is unlikely that the change in the distribution of the age is the true driver of the increased variation in TFPR.

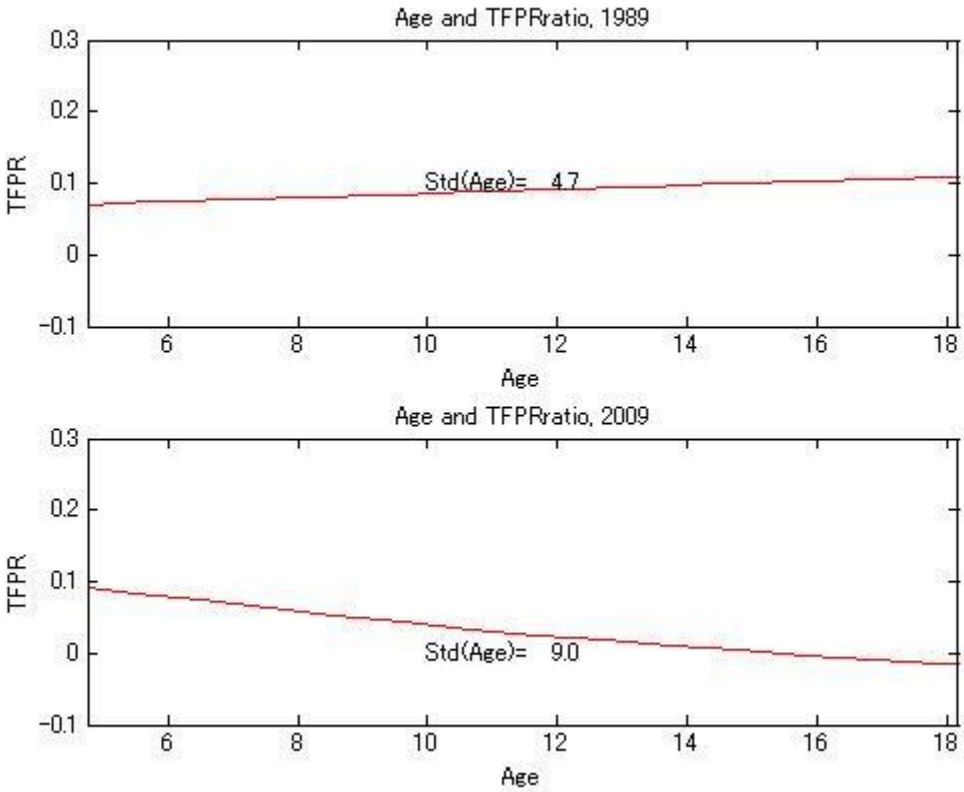

Figure 6: Explaining TFPR with Firm Age

Figure plots fitted values of non-parametric kernel regression of the form $\mathrm{TFPR_{si}} = f(Age_{si}) + \epsilon_{si}$ where $\mathrm{f}(\cdot)$ is estimated using Gaussian kernel. Std(Age) is the cross-sectional standard deviation of Age_{si}.

Age may be a noisy measure of the growth rate of a firm. To directly measure the firm's growth, we compute the input growth rate for each firm over the last one and three years. We measure input by $\mathrm{K}^{\alpha_s} L^{1-\alpha_s}$ and compute the log growth rate for each firm in sample.

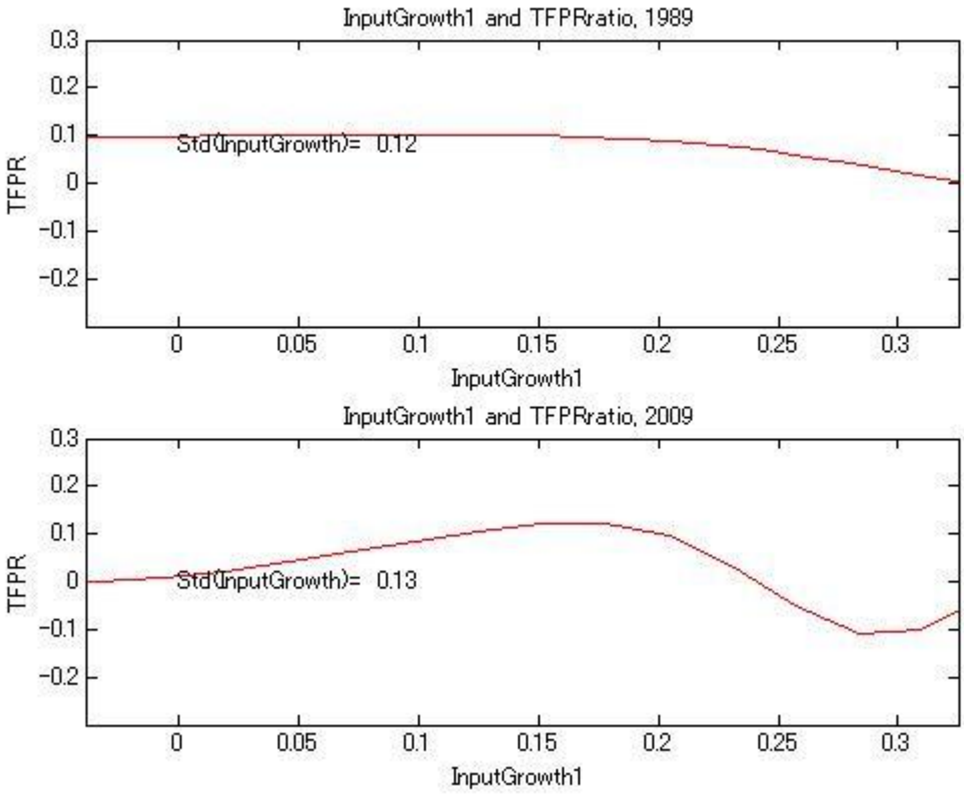

Figure 7: Explaining TFPR with Input Growth Rate

Figure plots fitted values of non-parametric kernel regression of the form $\mathrm{TFPR_{si}} = f(InputGrowth_{si}) + \epsilon_{si}$ where $\mathrm{f}(\cdot)$ is estimated using Gaussian kernel. $\mathrm{InputGrowth_{si}}$ is the log change in $\mathrm{K}_{\mathrm{si}}^{\alpha_s} L_{si}^{1-\alpha_s}$ from the previous year. Std(InputGrowth) is the cross-sectional standard deviation of $InputGrowth_{\mathrm{si}}$.

Figure 7 shows the relationship between input growth rate from time t-1 to t and TFPR at time t. The input growth rate from time t-3 to t shows qualitatively the same result, thus we only show the result with the input growth over the last one year.

As we can see, the relationship between input growth rate and TFPR is not stable over time. In addition, the (cross-sectional) standard deviation of input growth in 2009 is similar to that in 1989. Therefore, the variation in firm growth rate with adjustment cost is not a satisfactory explanation about the increasing variation of TFPR.

The related hypothesis is that young (or small) firms may display greater dispersion of TFPR. If the firms in 2009 are younger or smaller than those in 1989, then it will help explain the greater variation of TFPR in 2009.

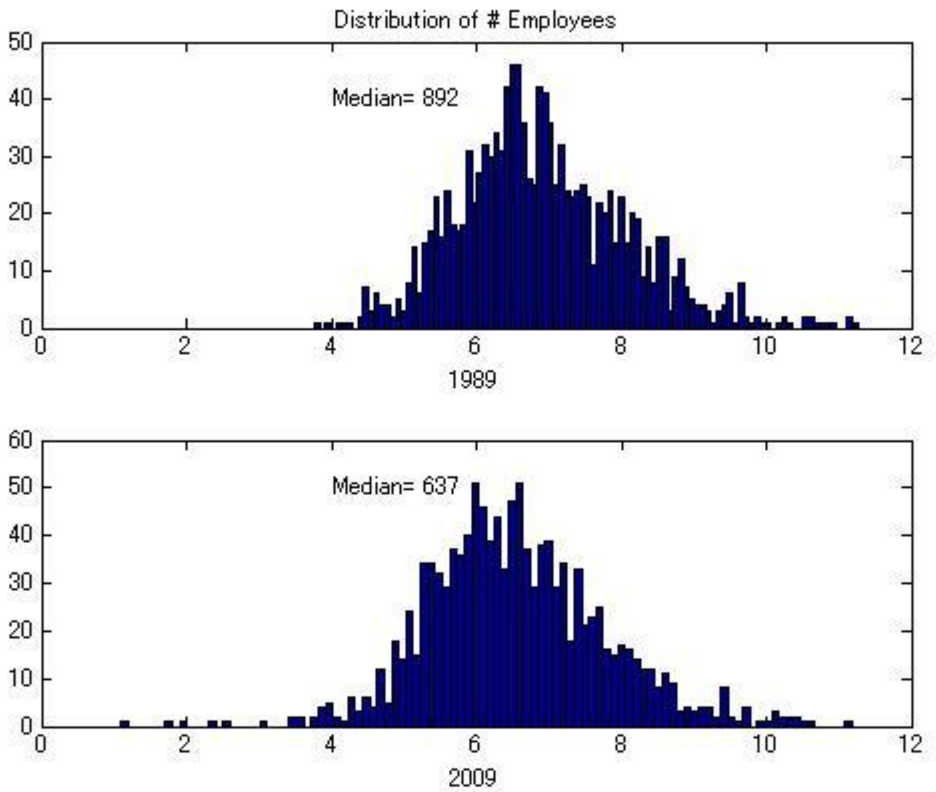

Figure 8: Distribution of (Log) Number of Employees in 1989 and 2009

In this case, we measure the firm size by the number of employees. Figure 8 shows that the median firm is smaller in 2009 than 1989. Thus, if there is a stable relationship between TFPR and the number of employees, then it helps explain the TFPR variation.

Figure 9 shows the kernel regression of TFPR on the number of employees for each firm in sample. The relationship between TFPR and the number of employees is negative in 1989 while it is slightly positive in 2009. Thus, the difference in size measured by the number of employees will not explain the increasing variation of TFPR.

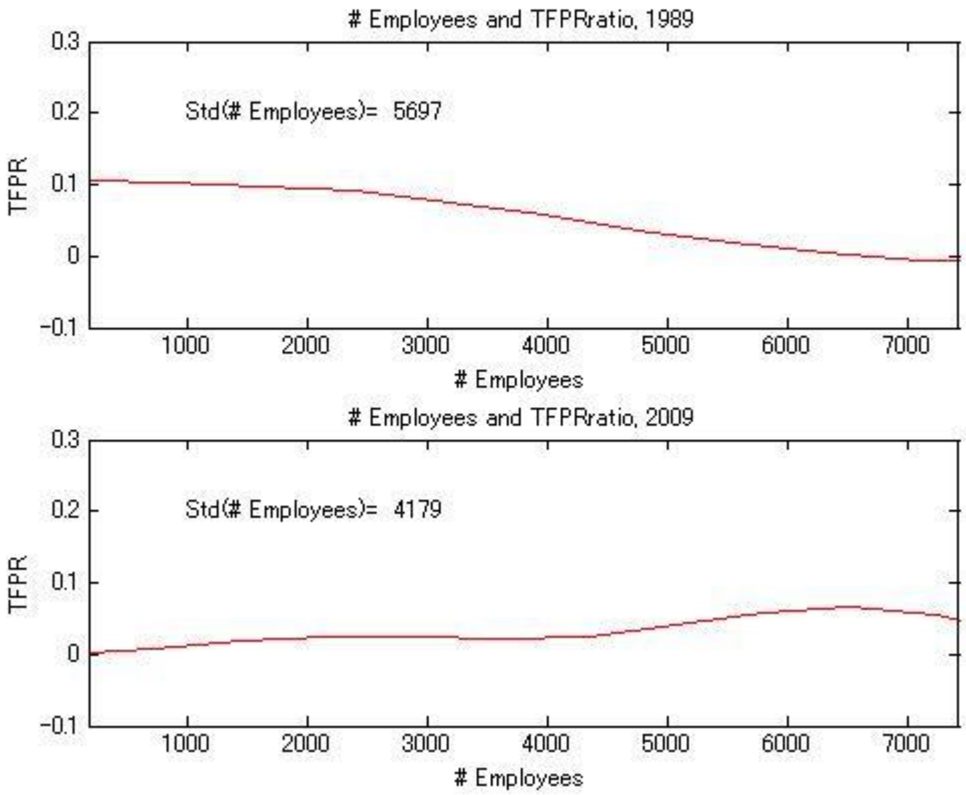

Figure 9: Explaining TFPR with Firm Age

Figure plots fitted values of non-parametric kernel regression of the form $\mathrm{TFPR}_{si} = f(\# \, Employees_{si}) + \epsilon_{si}$ where $f(\cdot)$ is estimated using Gaussian kernel. Std(# Employees) is the cross-sectional standard deviation of the number of employees.

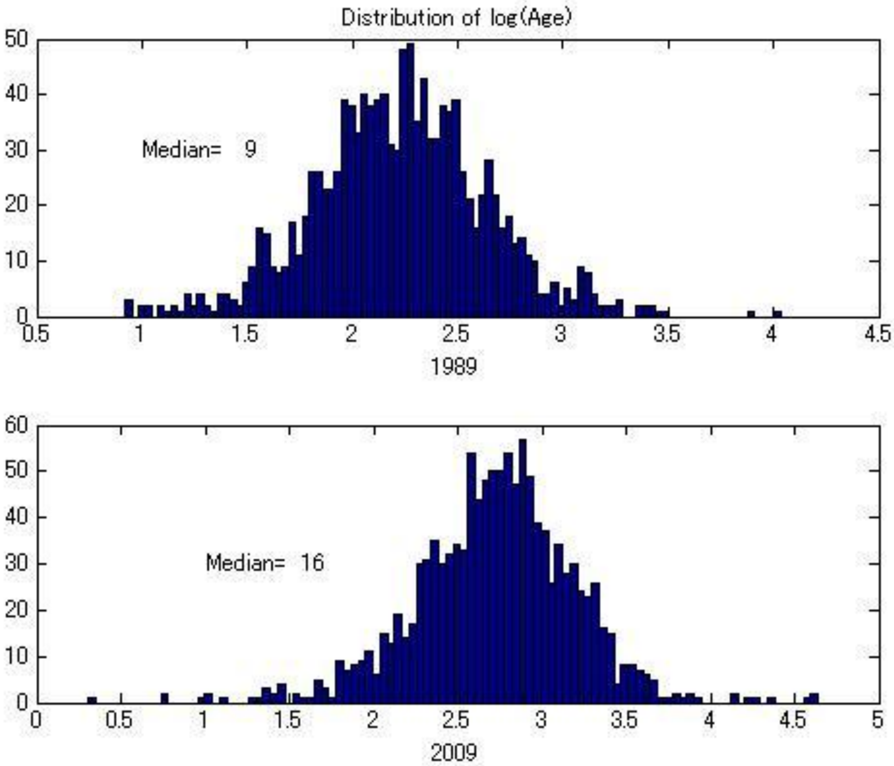

Figure 10: Distribution of Log Age in 1989 and 2009

Figures 10 shows the distribution of log age of the firms. We find that the firms in 2009 are older than those in 1989. Thus, if anything, the variation of TFPR in 2009 might have been even greater if the age of the firms were the same as in 1989.

6.4 Unobserved Investments

Learning by doing hypothesis states that a firm may own 'too much' capital or labor in order to improve future productivity rather than to produce output today. If that is the case, a firm with low TFPR today should experience higher TFPQ growth in the future.

Figure 11 shows the result of kernel regression of TFPR on TFPQ growth rate *next year*. The data seems to support this hypothesis, as there is negative relationship between TFPR today versus TFPQ growth rate in the future. The question is whether it explains the wider variation of TFPR in 2009 as opposed to 1989. The standard deviation of the future TFPQ growth rate increases from 0.27% in 1989 to 0.59% in 2009. While the standard deviation increases by 119% over the period, the slope coefficient of the linear regression of TFPR onto TFPQ growth is -0.25. Thus, the increased variation in the future growth opportunity can explain as much as 0.25*119%=30% increase of the TFPR variation from 1989 to 2009.

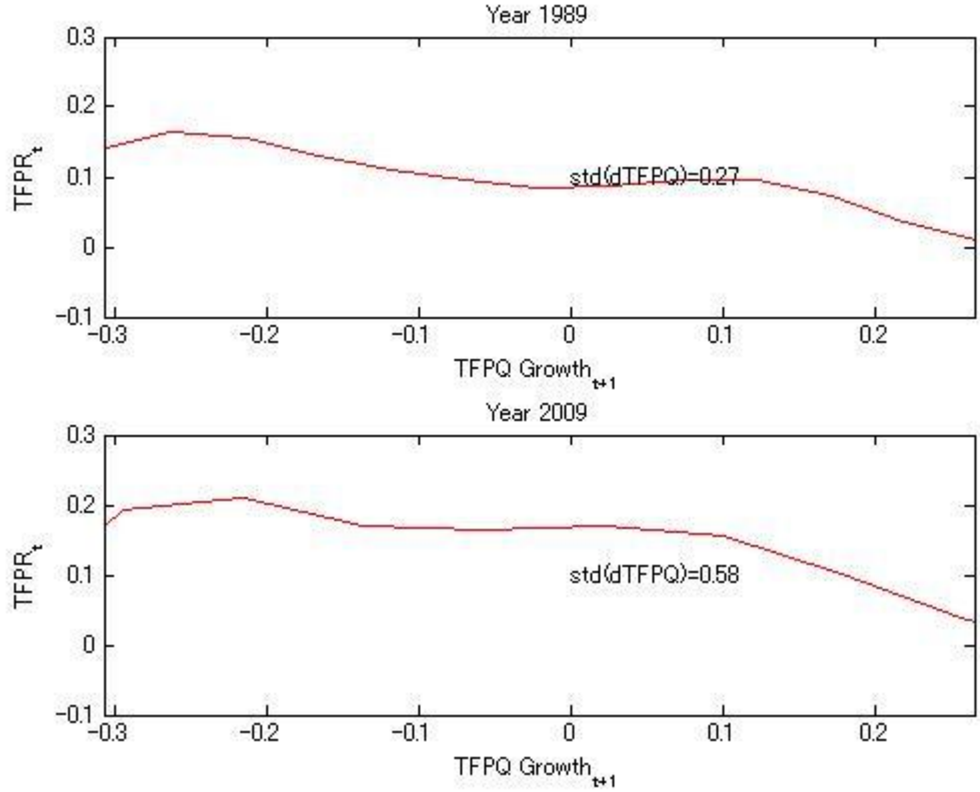

Figure 11: Learning by Doing Effect on TFPR

Figure plots fitted values of non-parametric kernel regression of the form $\mathrm{TFPR}_{\mathrm{si,t}} = f(\Delta A_{si,t+1}) + \epsilon_{si}$ where f(·) is estimated using Gaussian kernel. $\Delta \mathrm{A}_{\mathrm{si,t+1}} \equiv A_{si,t+1} - A_{si,t}$ and Std(dTFPQ) is the cross-sectional standard deviation of $\Delta \mathrm{A}_{\mathrm{si,t+1}}$.

7 Conclusions

In this paper, we show that an increase in allocation inefficiency of capital across firms is one of the major factors in explaining the low TFP growth rate in Japan during the post bubble era. As a firm can adjust its input level only sluggishly, greater uncertainty of the idiosyncratic physical productivity shock to a firm leads to greater misallocation of capital among firms. The remaining question for the future research is what an idiosyncratic productivity shock is and why its volatility increased over the period between 1989 and 2009.

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A1. Derivation of Industry TFP under Log-normality

In this appendix, we simplify the gain from reallocation assuming physical productivity and frictions are log-normally distributed.

$$\frac{\mathrm{Y}}{\mathrm{Y}_{\text{efficient}}} = \prod_{s=1}^{\mathrm{S}} \left[\sum_{i=1}^{M_s} \left\{ \frac{A_{si}}{\overline{A_S}} \frac{\overline{TFPR_S}}{TFPR_{si}} \right\}^{\sigma-1} \right]^{\frac{\theta_S}{\sigma-1}}$$

Taking log and define $\widetilde{\mathrm{TFP}_{\mathrm{S}}} = \log \sum_{i=1}^{M_s} \left\{ \frac{A_{si}}{\overline{A_S}} \frac{\overline{TFPR_S}}{TFPR_{si}} \right\}^{\sigma-1}$. Then

$$\log Y - \log Y_{efficient} = \sum_{s=1}^{S} \frac{\theta_S}{\sigma - 1} \widetilde{TFP_S}$$

Let $\mathrm{a}_{\mathrm{si}} = \log \frac{A_{si} M_S^{\frac{1}{\sigma-1}}}{\overline{A_S}}$ and $\mathrm{t}_{\mathrm{si}} = \log \frac{TFPR_{si}}{\overline{TFPR_S}}$. If we assume that a_{si} and t_{si} are jointly normally distributed, then

$$\begin{aligned} \widetilde{\mathrm{TFP}_{\mathrm{S}}} &= \log \sum_{i=1}^{M_s} \left\{ \frac{A_{si}}{\overline{A_S}} \frac{\overline{TFPR_S}}{TFPR_{si}} \right\}^{\sigma-1} \\ &= \log \frac{1}{M_S} \sum \exp\big((\sigma-1)(a_{si} - t_{si})\big) \\ &= (\sigma-1) E_s[a_{si} - t_{si}] + \frac{1}{2}(\sigma-1)^2 \mathrm{Var}_{\mathrm{s}}[a_{si} - t_{si}] \end{aligned}$$

where $\mathrm{E_s}[\cdot]$ and $\mathrm{Var_s}[\cdot]$ denote the expectation and variance within industry s.
Therefore

$$\log Y - \log Y_{efficient} = \sum_{s=1}^{S} \theta_S E_s[a_{si} - t_{si}] + \frac{1}{2}(\sigma-1) \sum_{s=1}^{S} \theta_S Var_s[a_{si} - t_{si}]$$

By definition, we have $\overline{\mathrm{A_s}} = \left(\sum A_{si}^{\sigma-1}\right)^{\frac{1}{\sigma-1}}$ which can be rewritten as

$$0 = \mathrm{E_s}[a_{si}] + \frac{1}{2}(\sigma-1)\text{Var\_s } [a_{si}]$$

Thus, we have

$$\begin{aligned} \log Y - \log Y_{efficient} &= -\sum_{s=1}^{S} \theta_S E_s[t_{si}] + \frac{1}{2}(\sigma-1) \sum_{s=1}^{S} \theta_S \{Var_s[t_{si}] - 2Cov_s(a_{si}, t_{si})\} \\ &= \log \prod \mathrm{E_s}\left[\left(\frac{\overline{TFPR_S}}{TFPR_{si}} \right)^{\sigma-1} \right]^{\frac{\theta_s}{\sigma-1}} - (\sigma-1) \sum \theta_s \mathrm{Cov_s}(a_{si}, \mathrm{t_{si}}) \end{aligned}$$

What matters is not just a variance of $\mathrm{t_{si}}$ but the covariance between a_{si} and t_{si}.

We can further work on $\mathrm{t_{si}}$ from the definition

$$\log\left(\frac{\mathrm{TFPR_{si}}}{\overline{\mathrm{TFPR_S}}}\right) = \alpha_S \log\frac{MRPK_{si}}{\overline{MRPK_S}} + (1-\alpha_S)\log\frac{MRPL_{si}}{\overline{MRPL_S}}$$
$$= \alpha_s \left\{-\log\frac{1-\tau_{Y_{Si}}}{1+\tau_{K_{Si}}} + \log\sum\frac{1-\tau_{Y_{Si}}}{1+\tau_{K_{Si}}}\frac{\mathrm{P_{Si}}Y_{Si}}{P_S Y_S}\right\}$$
$$+ (1-\alpha_s)\left\{-\log\left(1-\tau_{Y_{si}}\right) + \log\sum\left(1-\tau_{Y_{si}}\right)\frac{P_{Si}Y_{Si}}{P_S Y_S}\right\}$$

Define

$$\mathrm{x_{si}} = \log\left(1-\tau_{Y_{si}}\right)$$
$$\mathrm{y_{si}} = \log\left(\frac{1-\tau_{Y_{Si}}}{1+\tau_{K_{Si}}}\right)$$
$$\omega_{\mathrm{si}} = \log\frac{P_{Si}Y_{Si}}{P_S Y_S}\mathrm{M_s}$$

We can rewrite the weighted average as

$$\sum\frac{1-\tau_{Y_{Si}}}{1+\tau_{K_{Si}}}\frac{\mathrm{P_{Si}}Y_{Si}}{P_S Y_S} = \mathrm{E_s}[\exp(y_{si}+\omega_{si})]$$
$$\sum\left(1-\tau_{Y_{si}}\right)\frac{P_{Si}Y_{Si}}{P_S Y_S} = \mathrm{E_s}[\exp(x_{si}+\omega_{si})]$$

I assume that $\mathrm{x_{si}}, y_{si}, \widetilde{a_{si}} \equiv \log A_{si}$ are jointly normally distributed.
From the cost minimization problem, we have

$$\frac{\mathrm{P_{si}}Y_{si}}{P_s Y_s} = \frac{P_{si}^{1-\sigma}}{\sum P_{si}^{1-\sigma}}$$

Thus

$$\omega_{\mathrm{si}} = \log\frac{P_{si}^{1-\sigma}}{E[P_{si}^{1-\sigma}]}$$

Then we can rewrite $\mathrm{t_{si}}$ as

$$\mathrm{t_{si}} = \alpha_s\{-y_{si} + \log E_s[\exp(y_{si}+\omega_{si})]\} + (1-\alpha_s)\{-x_{si} + \log E_s[\exp(x_{si}+\omega_{si})]\}$$

As we have $\mathrm{E}[\exp(\omega_{si})] = 1$, we can expand the expectation to obtain,

$$\log E_s[\exp(y_{si}+\omega_{si})] = E_s[y_{si}] + \frac{1}{2}Var_s[y_{si}] + Cov_s(y_{si},\omega_{si})$$
$$\log E_s[\exp(x_{si}+\omega_{si})] = E_s[x_{si}] + \frac{1}{2}Var_s[x_{si}] + Cov_s(x_{si},\omega_{si})$$

Now we work on covariance. That is

$$\mathrm{Cov_s}(\mathrm{x_{si}},\omega_{si}) = Cov_s(x_{si},(1-\sigma)p_{si})$$
$$\mathrm{Cov_s}(\mathrm{y_{si}},\omega_{\mathrm{si}}) = \mathrm{Cov_s}(\mathrm{y_{si}},(1-\sigma)\mathrm{p_{si}})$$

where

$$\mathrm{p_{si}} = \log P_{si} = (Const) - \alpha_s y_{si} - (1-\alpha_s)x_{si} - \tilde{a}_{si}$$

Therefore

$$\mathrm{Cov_s}(\mathrm{x_{si}},\omega_{si}) = (1-\sigma)\{-\alpha_s Cov_S(y_{si},x_{si}) - (1-\alpha_s)Var_s(x_{si}) - Cov_S(\tilde{a}_{si},x_{si})\}$$
$$\mathrm{Cov_s}(\mathrm{y_{si}},\omega_{si}) = (1-\sigma)\{-\alpha_s Var_s(y_{si}) - (1-\alpha_s)Cov_S(y_{si},x_{si}) - Cov_S(\tilde{a}_{si},y_{si})\}$$

Using these equations, we have

$$\mathrm{E}[\mathrm{t_{si}}] = \alpha_s\left\{\frac{1}{2}Var[y_{si}] + Cov(y_{si},\omega_{si})\right\} + (1-\alpha_s)\left\{\frac{1}{2}Var[x_{si}] + Cov(x_{si},\omega_{si})\right\}$$

$$= \frac{1}{2}\alpha_s Var(y) + \frac{1}{2}(1-\alpha_s)Var(x)$$

$$+ (1-\sigma)\{-\alpha_s^2 Var(y) - \alpha_s(1-\alpha_s)Cov(x,y) - \alpha_s Cov(\tilde{a},y)$$

$$- \alpha_s(1-\alpha_s)Cov(x,y) - (1-\alpha_s)^2 Var(x) - (1-\alpha_s)Cov(\tilde{a},x)\}$$

$$\mathrm{Var}[\mathrm{t_{si}}] = \alpha_s^2 Var(y) + (1-\alpha_s)^2 Var(x) + 2\alpha_s(1-\alpha_s)Cov(x,y)$$

Now we compute

$$-\mathrm{E}[\mathrm{t_{si}}] + \frac{1}{2}(\sigma-1)Var[t_{si}]$$

$$= -\frac{1}{2}\alpha_s Var(y) - \frac{1}{2}(1-\alpha_s)Var(x)$$

$$+ (\sigma-1)\{-\alpha_s^2 Var(y) - \alpha_s(1-\alpha_s)Cov(x,y) - \alpha_s Cov(\tilde{a},y)$$

$$- \alpha_s(1-\alpha_s)Cov(x,y) - (1-\alpha_s)^2 Var(x) - (1-\alpha_s)Cov(\tilde{a},x)\}$$

$$+ \frac{1}{2}(\sigma-1)\left(\alpha_s^2 Var(y) + (1-\alpha_s)^2 Var(x) + 2\alpha_s(1-\alpha_s)Cov(x,y)\right)$$

$$= -\frac{1}{2}\alpha_s Var(y) - \frac{1}{2}(1-\alpha_s)Var(x)$$

$$- \frac{1}{2}(\sigma-1)\{\alpha_s^2 Var(y) + (1-\alpha_s)^2 Var(x) + 2\alpha_s(1-\alpha_s)Cov(x,y)\}$$

$$- (\sigma-1)\{\alpha_s Cov(\tilde{a},y) + (1-\alpha_s)Cov\,(\tilde{a},x)\}$$

Now we rewrite the three groups of terms:

The second row is

$$\alpha_s^2 Var(y) + (1-\alpha_s)^2 Var(x) + 2\alpha_s(1-\alpha_s)Cov(x,y) = \mathrm{Var}(\alpha_s y_{si} + (1-\alpha_s)x_{si}) = \mathrm{Var_s}(\mathrm{t_{si}})$$

The third row is

$$\alpha_s Cov_s(\tilde{a},y) + (1-\alpha_s)Cov_s\,(\tilde{a},x) = \mathrm{Cov_s}(\tilde{a},\alpha_s y_{si} + (1-\alpha_s)x_{si}) = Cov_s(a_{si},t_{si})$$

The extra covariance terms between $\mathrm{a_{si}}$ and $\mathrm{t_{si}}$ come from the fact that we weight more on bigger firms when computing average. A greater friction (smaller x,y thus bigger t) leads to putting less weight on that firm the average. This weighting scheme makes the average friction higher, and $\mathrm{E}[-\mathrm{t_{si}}]$ smaller. Therefore, we obtain the following expression:

$$\log Y - \log Y_{efficient} = -\sum_{s=1}^{S}\theta_S E_s[t_{si}] + \frac{1}{2}(\sigma-1)\sum_{s=1}^{S}\theta_S\{Var_s[t_{si}] - 2Cov_s(a_{si},t_{si})\}$$

$$= -\frac{1}{2}(\sigma-1)\sum_{s=1}^{S}\theta_s\{\mathrm{Var_s}[\mathrm{t_{si}}] + 4\mathrm{Cov_s}(a_{si},\mathrm{t_{si}})\}$$

$$-\frac{1}{2}\sum_{s=1}\theta_s\left(\alpha_s \mathrm{Var_s}(y_{si}) + (1-\alpha_s)\mathrm{Var_s}(x_{si})\right)$$

We may also impose the identifying assumption for $\mathrm{A_{si}}$ for the data analysis, which is $\mathrm{A_{si}} = \frac{\kappa_S(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}{}^{\alpha_S}L_{si}{}^{1-\alpha_S}}$. Then $\mathrm{Cov_s}(a_{si},t_{si}) = \frac{\sigma}{\sigma-1}Var_s(t_{si})$ holds. In such cases, the efficiency gain is purely a function of the variance of $\mathrm{x_{si}}$ and $\mathrm{y_{si}}$.

A2. Measuring Uncertainty of Idiosyncratic Productivity Shock following Cooper and Haltiwanger (2006)

We decompose the earnings shocks using the methodology of Cooper and Haltiwanger (2006). We estimate the economy-wide capital share parameter instrumenting on the once and twice lagged capital and twice lagged profits. The residuals split between aggregate profitability shocks and the idiosyncratic shocks. We fit AR(1) model to the idiosyncratic shocks to extract innovation to the idiosyncratic profitability shocks.

Table A1: Measuring the Magnitude of Idiosyncratic Profitability Shock

A: Estimated Result		B: Size of Residuals		
θ	ρ^{ϵ}	Year	$\sigma(\epsilon_{it})$	$\sigma(\eta_{it})$
0.855	0.924	1989	0.53	0.18
(0.002)	(0.002)	2009	0.70	0.29

The table shows the result of two-step regressions. First regression is the panel IV estimates of $\log Sales_{it} = \theta \log Capital_{it} + e_{it}$, where the instruments are $\log \mathrm{Capital}_{\mathrm{it}-1}$, $\log Capital_{it-2}$, $\log Sales_{it-2}$. The estimates include time fixed effects. The second step is $\epsilon_{\mathrm{it}} = \rho^{\epsilon}\epsilon_{it-1} + \eta_{it}$ where $\epsilon_{\mathrm{it}} \equiv e_{it} - 1/n \sum_{i=1}^{n} e_{it}$. The figures in parenthesis are standard errors.

Table A1 shows the estimated result. The standard deviation of the shock$\sigma(\eta)$ becomes 61% larger in 2009 than in 1989. During the same period, the standard deviation of the TFPR becomes 85% larger. Thus, a significant portion of the TFPR variation change can be explained by the greater unexpected shocks to firms' profitability. The remaining component of the TFPR variation may be either due to greater cost of investment or more learning-by-doing activities in 2009.

A3. Implementing Kernel Regression

To analyze the source of TFPR variation, I run non-parametric kernel regression of the form

$$\mathrm{TFPR_{si}} = f(z_{si}) + \epsilon_{si}$$

where the function $\mathrm{ff}(\mathrm{z_{si}})$ is estimated non-parametrically using Gaussian kernel.

Specifically, the kernel regression estimator at $\mathrm{z_0}$ is given by

$$\mathrm{f(z_0)} = \frac{\frac{1}{N}\sum_{i=1}^{N} \phi((z_{si} - z_0)/h) TFPR_{si}}{\frac{1}{N}\sum_{i=1}^{N} \phi((z_{si} - z_0)/h)} = \sum_{i=1}^{N} w_{si} TFPR_{si}$$

where $\phi(\cdot)$ is the normal probability density function and h is the bandwidth of the kernel.

The optimal bandwidth is chosen to minimize the cross-validation CV (h),

$$\mathrm{CV(h)} \equiv \sum_{\mathrm{i=1}}^{\mathrm{N}} \left(TFPR_{si} - \hat{f}_{-i}(z_{si})\right)^2 \pi(z_{si})$$

where

$$\hat{f}_{-\mathrm{i}}(z_{si}) = \frac{\sum_{j \neq i}^{N} w_{sj} TFPR_{sj}}{\sum_{j \neq i}^{N} w_{sj}}$$

and $\pi(\cdot)$ is an indicator function which is one if $\mathrm{z_{si}}$ is between 5 percentile and 95 percentile of the distribution and zero otherwise.

The idea of cross-validation procedure is that one has to strike a balance between minimizing errors and improving efficiency of an estimate. Putting a large weight on $\mathrm{TFPR_{si}}$ to estimate $f(\mathrm{z_{si}})$ will reduce an error but will not use as much information from the adjacent observations $\mathrm{TFPR_{sj}}$, resulting in inefficiency. We penalize inefficiency by using $\hat{f}_{-i}(z_{si})$, or a leave one-out estimates in computing CV (h). Minimizing CV (h) amounts to choosing an optimal balance between error minimization and pursuit of efficiency.