Competition, Uncertainty, and Misallocation*

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Abstract

Uncertainty delays investment that involves disruption cost or time-to-build, resulting in capital misallocation from a static point of view. However, theory predicts that the extent to which uncertainty affects investment, and hence static misallocation, depends on the degree of product market competition. Using a large panel dataset of manufacturing plants in Japan, we find that although uncertainty results in static misallocation, the effect is stronger for industries with severer product market competition. We further find that competition worsens uncertainty-driven misallocation both through the less elastic investment response to the variability of the marginal revenue of capital and through the higher variability of the optimal level of capital. To improve allocative efficiency, reduced uncertainty complements competition policies.

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1. Introduction

It is now well known that dispersion in (revenue-based) productivity across producers within narrowly-defined industries results in misallocation of resources and lower aggregate productivity (Restuccia and Rogerson, 2008 Hsieh and Klenow, 2009). Among other possible factors that cause misallocation such as taxes, regulations, and financial frictions, grater uncertainty is likely to result in capital misallocation from a static point of view as it tends to delay investment that involves disruption cost or time-to-build. Figure 1 shows that the annual change in the marginal revenue of capital (MRPK) is positively correlated with the annual change in the revenue-based productivity (TFPR), suggesting that firms do not adjust capital in response to the TFPR shock within a year.[1] [2] Asker, Collard-Wexler, and De Loecker (2014) (ACL hereafter), use nine datasets spanning 40 countries and find that industries with greater time-series volatility of productivity have greater cross-sectional dispersion of the marginal revenue product of capital (MRPK). Their results suggest that higher volatility in productivity shocks results in the misallocation of capital from the static view, even if it is allocated efficiently from the dynamic view when adjustment costs are taken into account.

[Insert Figure 1 here]

While their results are convincing, they do not consider that the impact of uncertainty on investment, and hence on the allocation of capital, may depend on the degree of competition in the product market. Extant theoretical studies show that the effect of uncertainty on investment depends on the product market competition as well as on the degree of returns to scale and the adjustment-cost asymmetries; while greater uncertainty should lower investment if investment is irreversible, product market is competitive, and production technology exhibits constant returns to scale (Pindyck 1988; Bertola 1988), it could increase investment if competition is nearly perfect and technology exhibits increasing returns to scale even under the assumption that investment is irreversible (Caballero, 1991). Theoretical studies using an options-game also posit that uncertainty is less likely to delay investment in a more competitive product market. Empirical results on the relationship between uncertainty and investment are mixed as well.[3]

[1] The definitions of TFPR and MRPK are explained in Section 4.2.

[2] Figure 1 depicts the changes in TFPR and MRPK over the period from 2012 to 2013, but we observe a similar correlation between the two over the other years.

[3] See Bloom (2014) for a survey.

Product market competition affects not only firms' investment responses to (revenue-based) productivity shocks but also the optimal level of capital; in a more competitive market, dispersion in (revenue-based) productivity leads to a larger variability in the optimal level of capital. It is therefore not clear a priori whether competition attenuates or worsens uncertainty-driven capital misallocation. This study aims to show how product market competition affects the adverse impact of uncertainty on static capital misallocation.

To this aim, we use a large dataset of manufacturing plants in Japan covering 1986 to 2013. We find that while industries with greater time-series volatility in productivity have greater cross-sectional dispersion of MRPK, which is consistent with ACL, the impact is significant only when the product market is competitive. We further find that competition worsens uncertainty-driven misallocation both through the less elastic investment response to the MRPK and through the higher variability of the optimal level of capital.

Although prior studies show that tougher competition improves allocative efficiency across firms through markup harmonization (Edmond, Midrigan and Xu, 2015), our results show that capital misallocation deteriorates in a severely competitive market with high uncertainty. Reductions in uncertainty complement competition policies to improve allocative efficiency.

The reminder of the paper proceeds as follows. In Section 2, we review the relevant literature on the impact of uncertainty on investment and misallocation. In Section 3, we present a simple model to show how competition affects the relationship between volatility and dispersion in MRPK. Section 4 describes our dataset and methodology. Section 5 presents our results. Finally, we conclude the paper with a discussion of our findings in Section 6.

2. Literature Review

This study investigates the effects of competition on the relationship between uncertainty and resource misallocation. We particularly focus on the mechanism through firms' investment decision. Two strands of literature are therefore related to our study.

The first strand discusses the effect of uncertainty on investment. The standard real options models predict a negative relationship between uncertainty and investment because firms delay investment decisions when the investment is irreversible and future demand is uncertain (McDonald and Siegel 1986; Pindyck 1988).[4]. On the other

[4] Dixit and Pindyck (1994) is an excellent introduction to real options theory.

hand, some argue that uncertainty has positive effects on investment (Abel 1983; Bar-Ilan and Strange 1996).[5] Empirical evidences are also mixed, but most find negative effects from uncertainty on investment.[6] Bloom, Bond, and Van Reenen (2007), for example, find that sales growth has a smaller effect on investment for publicly traded UK firms when the firms face higher volatility in stock returns.[7] Caballero (1991) introduced the effect of competition on the uncertainty-investment relationship into the real options framework by presenting a theoretical model to show that the relationship between price uncertainty and capital investment is not robust. The negative effects require both market power and asymmetric capital adjustment costs. Another strand investigates options exercise games. Williams (1993), Kulatilaka and Perotti (1998), and Grenadier (1996, 2002) find that option values erode under fierce competition because competitors may preempt the investment opportunity. The fear of preemption leads to early investment.

Several empirical studies provide support for the theoretical prediction that competition mitigates the negative effects of uncertainty on investment, while other studies obtain the opposite results. Porter and Spence (1982) conduct an early case study of preemptive investment in the wet corn milling industry. Guiso and Parigi (1999) explore the effect of uncertainty on investment using a measure of uncertainty based on the information on the subjective probability distribution of future demand with a database of Italian manufacturing firms. The negative effect of uncertainty on investment is smaller for firms with little market power measured by the profit margin. Using a panel data set of Italian firms, Bontempi, Golinelli, and Parigi (2010) show that an increase in competition weakens the effect of uncertainty on investment decisions. Bulan (2005) uses a panel of U.S. manufacturing firms to explore the effects of uncertainty measured as the volatility of firms' equity returns. The study splits the sample by industry concentration ratios and finds that competition reduces the negative impact of uncertainty on investment. Bulan, Mayer, and Somerville (2009) address the same issue using the data on real estate projects in Vancouver, Canada. Their main finding is that increases in volatility lead developers to delay new real estate development, but the impact is smaller when the number of potential competitors is large. Akdogu and MacKay (2008) split a sample into three groups according to the

[5] Oikawa (2010) provides a model in which firm-level uncertainty raises aggregate productivity growth.

[6] Bloom (2014) notes that the uncertainty literature provides "suggestive but not conclusive evidence that uncertainty damages short-run (quarterly and annual) growth, by reducing output, investment, hiring, consumption, and trade" (p.168).

[7] See Ogawa and Suzuki (2000) and Mizobata (2014) for cases in Japan.

Herfindahl-Hirschman index (HHI) and provide evidence that firm investment is less sensitive to changes in Tobin's q in monopolistic industries than in competitive industries. On the other hand, Ghosal and Loungani (2000) show the opposite result, finding that the negative effect of uncertainty on investment is higher in competitive industries. In their studies, competition is measured as the four-firm seller concentration ratio. While the results are mixed, all of these studies focus on investment at the firm or project level without considering the effect on allocative efficiency at the industry level.

The second related strand investigates resource misallocation across firms. Restuccia and Rogerson (2008) first establish the mechanism by which factor price distortion at the firm level reduces allocative efficiency in the aggregate economy. They calibrate U.S. data to show the large effect of resource misallocation. Hsieh and Klenow (2009) incorporate monopolistic competition into Restuccia and Rogerson's (2008) model. In Hsieh and Klenow's (2009) framework, resource misallocation depends on the dispersion of marginal revenue products. They find that the degrees of resource misallocation are larger in China and India than in the U.S.

A number of studies follow Hsieh and Klenow (2009) to specify the underlying mechanisms of the dispersion of marginal revenue products.[8] ACL is one such study, which investigates the role of productivity shocks and dynamic production factors on the static variation of marginal revenue.[9] ACL use a dynamic investment model to replicate the observed patterns in the large dispersion of MRPK. In the reduced-form estimation with nine datasets spanning 40 countries, ACL show that the higher time-series volatility of productivity shocks, measured as the variance of productivity growth rates across firms, contribute to larger resource misallocation within industries measured as the cross-sectional dispersion of MRPK. Their result suggests that welfare gains from reallocating production factors are not as large as implied by static models.

Many studies investigate capital misallocation arising from capital market frictions (Banerjee and Moll 2010; Midrigan and Xu 2014; Moll 2014), but do not focus on the roles of uncertainty and competition. Other researchers study the effect of competition on resource misallocation. Edmond, Midrigan, and Xu (2015) show that trade-induced competition causes markup harmonization through reduced market power in a monopolistic competition framework with a finite number of firms. Unlike

[8] See Hopenhayn (2014) and Restuccia and Rogerson (2017) for a survey. Andrews and Cingano (2014) empirically study the effects of various kinds of policies on allocative efficiency.

[9] Da Rocha and Pujolas (2011) also explore the effect of productivity shocks on resource misallocation theoretically.

them, we focus on the dynamic aspect of competition through uncertainty.

While existing studies reveal the various factors, including uncertainty, that induce misallocation, to our knowledge, no studies consider the possibility that the impact of uncertainty on misallocation depends on the degree of competition in the product market. This study therefore shows how product market competition affects the adverse impact of uncertainty on resource misallocation across firms.

3. Theoretical Framework

In this section, we posit a simple model to consider how the degree of competition affects the relationship between the volatility of revenue productivity and MRPK dispersion. We extend ACL's dynamic investment model, which incorporates time-to-build and the adjustment cost of capital, in two ways. First, we introduce the asymmetric adjustment cost between a positive and negative investment considering that preceding studies point out the importance of such an asymmetric adjustment cost in generating a negative uncertainty-investment relationship (Caballero, 1991, among others). Next, we decompose the total factor revenue productivity (TFPR) shocks into demand and productivity shocks. Although we cannot decompose TFPR shocks in the empirical analyses below, this decomposition is theoretically interesting given that demand and productivity shocks have opposite impacts on TFPR as we show below. In this section, we begin by describing a static model and then extending it to a dynamic one. Finally, we present simulation results.

3.1 Static Model

Following ACL, we model a profit maximizing plant facing demand and productivity shocks. This static model is the base of the dynamic model in the next subsection as well as that of the measurement in Section 4. Specifically, plant *i*, at time *t*, produces output Q_{it} using the following constant returns technology:

$$Q_{it} = A_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} M_{it}^{\alpha_M}, \tag{1}$$

where A_{it} is the (physical) productivity shock, K_{it} is the capital input, L_{it} is the labor input, M_{it} is materials, and we assume constant returns to scale in production, so $\alpha_K + \alpha_L + \alpha_M = 1$. The demand curve for the plant's product has a constant elasticity:

$$Q_{it} = B_{it} P_{it}^{-\varepsilon}. \tag{2}$$

Demand elasticity ε serves as the degree of competition and the implied markup, $\frac{1}{1-\frac{1}{\varepsilon}}$, as the inverse degree of competition. Combining (1) and (2), we obtain the sales-generating production function

$$S_{it} = \Omega_{it} K_{it}^{\beta_K} L_{it}^{\beta_L} M_{it}^{\beta_M}, \tag{3}$$

where $\Omega_{it} \equiv A_{it}^{1-\frac{1}{\varepsilon}} B_{it}^{\frac{1}{\varepsilon}}$ is revenue productivity and $\beta_X \equiv \alpha_X \left(1 - \frac{1}{\varepsilon}\right)$ for $X \in \{K, L, M\}$.

We call $\omega_{it} \equiv \ln(\Omega_{it})$ TFPR. That is,

$$\omega_{it} = \left(1 - \frac{1}{\varepsilon}\right) a_{it} + \frac{1}{\varepsilon} b_{it}, \tag{4}$$

where lower cases denote logs. Eq. (4) shows that a larger ε magnifies the productivity shock a_{it}, while it diminishes the demand shock b_{it}. We can rewrite the TFPR shock as

$$\omega_{it} = s_{it} - \beta_K k_{it} - \beta_L l_{it} - \beta_M m_{it}, \tag{5}$$

The *MRPK* measured in logs is

$$MRPK_{it} = \log(\beta_K) + s_{it} - k_{it}, \tag{6}$$

We can define the marginal revenue product of labor and materials similarly. It is easy to show that the optimal capital in the static point of view is proportional to $\varepsilon\omega_{it}$. In the competitive market, therefore, the amount of optimal capital strongly depends on productivity. In other words, given a magnitude of TFPR shock, larger amount of investment is required to the optimal level when the competition is tougher.

3.2 Dynamic Model

We now present a simple dynamic model of investment that builds on Dixit and Pindyck (1994), Caballero and Pindyck (1996), Cooper and Haltiwanger (2006), Bloom

(2009), and ACL in particular. In each period, we assume that firms can hire labor for a wage p_L and acquire materials at a price p_M. Both of these inputs involve no adjustment costs. This leads to a period profit of

$$\pi(\Omega_{it}, K_{it}) = \lambda \Omega_{it}^{1/(\beta_K+\varepsilon^{-1})} K_{it}^{\beta_K/(\beta_K+\varepsilon^{-1})}, \tag{7}$$

where

$$\lambda = (\beta_K + \varepsilon^{-1}) \left(\frac{\beta_L}{p_L} \right)^{\frac{\beta_L}{(\beta_K+\varepsilon^{-1})}} \left(\frac{\beta_M}{p_M} \right)^{\frac{\beta_M}{(\beta_K+\varepsilon^{-1})}}. \tag{8}$$

Capital evolves as

$$K_{it+1} = \delta K_{it} + I_{it}, \tag{9}$$

where δ is one minus the depreciation rate and I_{it} is investment. Eq. (9) incorporates our assumption of one-period time to build. We further assume that investment involves adjustment costs composed of the fixed disruption cost of investment and convex costs. We consider the possibility that both adjustment cost components are asymmetric between positive and negative investment. Specifically, the adjustment cost is

$$\begin{aligned} C(I_{it}, K_{it}, \Omega_{it}) &= I_{it} + C_K^{F+} 1(I_{it} > 0)\pi_{it}(\Omega_{it}, K_{it}) + C_K^{F-} 1(I_{it} < 0)\pi_{it}(\Omega_{it}, K_{it}) \\ &\quad + C_Q^{K+} K_{it} \left(\frac{I_{it}}{K_{it}} \right)^2 1(I_{it} > 0) + C_Q^{K-} K_{it} \left(\frac{I_{it}}{K_{it}} \right)^2 1(I_{it} < 0) \end{aligned} \tag{10}$$

We specify the TFPR shock process in three ways: the demand shock model, the productivity shock model, and the TFPR shock model. In the demand shock model, we assume that $a_{it} = 0$ across firms and time to focus on the role of demand shocks. Specifically, we assume that the demand shock follows an AR(1) process given by

$$b_{it} = \mu_b + \rho_b b_{it-1} + \sigma_b \kappa_{it}, \tag{11}$$

where $\kappa_{it} \sim N(0,1)$ is an independent and identically distributed (i.i.d) standard normal random variable. We see from Eq. (4) that

$$\omega_{it} = \frac{1}{\varepsilon} b_{it}. \tag{12}$$

Eq. (12) shows that a larger ε attenuates the effect of the demand shock on TFPR.

In the productivity shock model, assuming that $b_{it} = 0$ across firms and time, we specify the demand shock as following an AR(1) process given by

$$a_{it} = \mu_a + \rho_a a_{it-1} + \sigma_a \kappa_{it} \quad (13)$$

We see from Eq. (4) that

$$\omega_{it} = (1 - \frac{1}{\varepsilon}) a_{it} \quad (14)$$

In the TFPR shock model, we assume that $a_{it} = b_{it}$, and that $a_{it} (= b_{it})$ follows the AR(1) process given by (11). Although the former assumption may be implausible, we use this model to see the outcome when the shock process does not depend on ε. For this specification, from Eq. (4),

$$\omega_{it} = b_{it} \quad (15)$$

In either specification, the TFPR shock Ω follows an AR (1) process, and we can hence define the transition of Ω as $\phi(\Omega_{it+1} | \Omega_{it})$.

The firm's value function is given in recursive form as

$$\begin{aligned} V(\Omega_{it}, K_{it}) = \max \pi(\Omega_{it}, K_{it}) - C(I_{it}, K_{it}, \Omega_{it}) \\ + \beta \int_{\Omega_{it+1}} V(\Omega_{it+1}, \delta K_{it} + I_{it}) \varphi(\Omega_{it+1} | \Omega_{it}) d\Omega_{it+1} \end{aligned} \quad (16)$$

A few remarks are noteworthy. First, our framework encompasses the ACL model in that the TFPR shock model with symmetric adjustment cost ($C_K^{F+} = C_K^{F-}$ and $C_K^{Q+} = C_K^{Q-}$) corresponds to the ACL model.

Second, as is the case with the ACL model, this model generates no entry or exit because any firm can operate with a positive profit due to the decreasing returns to scale in the revenue function and the absence of fixed costs. Therefore, the cross-sectional standard deviations of TFPR in the three models are

$$\text{Demand shock model: } SD(\omega_{it}) = \frac{\sigma_b}{\varepsilon \sqrt{1 - \rho_b{}^2}} \quad (17)$$

$$\text{Productivity shock model: } SD(\omega_{it}) = (1 - 1/\varepsilon) \frac{\sigma_a}{\sqrt{1 - \rho_a{}^2}} \quad (18)$$

and

$$\text{TFPR shock model: } SD(\omega_{it}) = \frac{\sigma_b}{\sqrt{1-\rho_b^2}}. \tag{19}$$

Eqs. (17)-(19) show that while an increase in ε dampens demand shock volatility, it amplifies productivity shock volatility.

Finally, suppose that there are no adjustment costs or time to build. Then, the firm would choose the optimal level of capital to make MRPK equal to its rental rate, which is common across firms. In this model, however, the adjustment costs and time-to-build cause MRPK dispersion across firms, which, in turn, cause capital misallocation in the static sense. We therefore use the dispersion of MRPK as a measure of misallocation.[10]

3.3 Simulation Results

We simulate the above dynamic models and calculate the standard deviation of the log of MRPK, denoted by $\mathrm{SD}(MRPK_{it})$ for simplicity, as a measure of misallocation in the static sense. The simulations aim to see the effects of various values of ε on the relation between σ_b (or σ_a) and $SD(MRPK_{it})$. In the following simulations, we set all parameters except adjustment cost parameters, following ACL, who estimate their model using the US Census of Manufacturers. Table 1 summarizes our set parameters. We set p_L and p_M to make λ=1.0 when ε=4 in the TFPR shock model, as in ACL. We use two alternative sets of adjustment cost parameters. In the symmetric adjustment cost specification, we use ACL's estimates, while in the asymmetric adjustment cost specification, we set $C_K^{F+} = C_K^{Q+} = 0$ while maintaining the same C_K^{F+} and C_K^{Q+} values as those of the symmetric adjustment cost specification.

[Insert Table 1 here]

We first simulate the TFPR shock model with asymmetric adjustment costs. Figure 2A shows the $SD(MRPK_{it})$ for the simulated data. For each ε, $\mathrm{SD}(MRPK_{it})$

[10] If we extend the model to a general equilibrium one, different ε values may result in different real interest rates. However, MRPK would still be equalized across firms without adjustment costs or time to build.

tends to increase with σ_b, suggesting that higher TFPR shock volatility results in worse allocations of capital in the static sense, which is consistent with ACL. Our new finding here is that the slope is steeper as ε is higher, suggesting that increasing product market competition strengthens the deteriorating effect of TFPR shock volatility on allocation.

To investigate the mechanism that brings about such misallocation, we decompose investment into the extensive and intensive margins. Specifically, Figures 2B and 2C show the fraction of the firms that conduct positive and negative investment, respectively, while Figures 2D and 2E show the average net investment ratio of firms that conduct positive and negative investment, respectively. Figure 2B shows that for each ε, the fraction of the firms that conduct positive investment decreases with σ_b, suggesting that higher TFPR shock volatility results in a smaller fraction of expanding firms. The negative effect of the volatility on the fraction of expanding firms tends to be smaller as ε is higher, that is, as the product market is more competitive. Figure 2C shows that the effects of the volatility on the fraction of shrinking firms is just the opposite to that of expanding firms. Figure 2D shows that the net investment ratio of expanding firms tends to increase as the volatility increases, and this positive effect of volatility on the intensive margin of expanding firms is stronger as the product market is more competitive. On the other hand, the absolute value of the net investment ratio of shrinking firms is relatively small and do not change significantly as volatility changes. In sum, both the extensive and intensive margins seem to matter both for the volatility-misallocation relationship and the role of competition on that relationship.

To further investigate the role of the extensive and intensive margins, we decompose $\mathrm{Var}(\mathrm{MRPK})$ into the following three components：

$$
\begin{aligned}
Var(MRPK_t) &= p_{t-1}\mathrm{VAR}(\mathrm{MRPK}_t|\mathrm{I}_{t-1} \neq 0) + (1-p_{t-1})\mathrm{VAR}(\mathrm{MRPK}_t|\mathrm{I}_{t-1} = 0) \\
&+p_{t-1}(1-p_{t-1})\big(E(MRPK_t|\mathrm{I}_{t-1} \neq 0) - E(MRPK_t|\mathrm{I}_{t-1} = 0)\big)^2,
\end{aligned} \tag{20}
$$

where p_{t-1} denotes the share of firms that invested in the previous period. The term $\mathrm{VAR}(\mathrm{MRPK}_t|\mathrm{I}_{t-1} \neq 0)$ is the misallocation among firms that invested in the previous period, and $\mathrm{VAR}(\mathrm{MRPK}_t|\mathrm{I}_{t-1} = 0)$ is the misallocation among firms that did not invest. We hereafter call the former the active margin and the latter the inactive margin. Eq. (20) shows that we can decompose the overall misallocation $Var(MRPK)$ into the weighted average of the active and inactive margins, where the weight is the fractions of the active and inactive firms, and the residual third term. Figures 2E and 2F show the active and inactive margins, respectively, indicating that both the active and inactive margins tend to increase as the volatility increases, and the more so as the market is more competitive, although the active margin is larger than the inactive margin.

[Insert Figure 2 here]

Next, we simulate the TFPR shock model with symmetric adjustment costs. Figure 3A shows the $SD(MRPK_{it})$ for each ε, which is very similar to Figure 2A, which depicts the case of asymmetric adjustment cost both in the qualitative and quantitative aspects. However, the mechanism that brings about such misallocation seems to be different between asymmetric and symmetric adjustment costs. Figure 3B shows that the share of expanding firms is close to unity except for a low range of volatility in the case of $\varepsilon = 2$, where the share of expanding firms tends to increase as the volatility increases. On the other hand, Figure 3C shows that the share of shrinking firms is very low. When adjustment costs are symmetric, misallocation is likely to be brought about by the low investment volume by expanding firms, i.e., intensive margin. We can confirm the significant role of the active margin by comparing Figures 3D and 3E, which show the active and inactive margins, respectively.

Finally, we simulate the demand shock model with symmetric and asymmetric adjustment costs. While a higher ε dampens the demand shock volatility and lowers TFPR volatility (Eq. (17)), a higher ε strengthens the effect of TFPR shock volatility on SD(MRPK) (Figures 2A and 3A). The simulation results show that the former effect outweighs the latter. That is, a higher ε weakens the positive effect of demand shock volatility on SD(MRPK). Note that the supply shock model is qualitatively similar to the TFPR shock model because a higher ε amplifies technology shock volatility and increases TFPR volatility.

In sum, the simulation results suggest that while volatility tends to worsen capital allocation for all of the specifications we simulate, whether competition attenuates this adverse effect of volatility on allocation depends on the source of volatility. Our results suggest that if demand shocks dominate TFPR shocks, competition tends to attenuate the adverse effect of volatility on allocation. However, the more empirically important results are that higher TFPR volatility worsens capital allocation and that competition worsens the misallocation driven by TFPR volatility. We examine whether these simulation results are supported empirically by data from Japanese manufacturing establishments below.

4. Data and Empirical Methodology

4.1 Data

Our main data source is the *Census of Manufacture* published by the Ministry of Economy, Trade, and Industry (METI) in Japan. The main purpose of this annual survey is to gauge the activities of Japanese plants in manufacturing industries quantitatively, including sales, number of employees, wages, materials and tangible fixed assets. The census covers all establishments in years ending with 0, 3, 5, and 8 of the calendar years from 1981 to 2009. For other years, the Census covers establishments with four or more employees.

The *Census of Manufacture* contains two types of surveys: one for plants with more than 30 employees (*Kou Hyou*), and the other is for plants with 29 or less employees (*Otsu Hyou*). The Otsu Hyou does not include some pieces of information, including fixed asset, especially after 2001. For this reason, we construct the panel dataset from 1986 to 2013 using the Kou Hyou.

To construct the data for output and factor inputs, first, we use each plant's shipments as the nominal gross output and then deflate the nominal gross output by the output deflator in the Japan Industrial Productivity Database (JIP) 2015 to convert it into values in constant prices (i.e., real gross output (Q_{it}) based on the year 2000. Second, we define the nominal intermediate input as the sum of raw materials, fuel, electricity, and subcontracting expenses for the plant's consigned production. Using the Bank of Japan's Corporate Good Price Index (CGPI), we convert the nominal intermediate input into values in constant prices (i.e., real intermediate input (M_{it})) for 2000. Third, we use each plant's total number of workers as labor input (L_{it}).

We construct the data for tangible capital stock as follows. First, we define capital input (K_{it}) as the nominal book value of tangible fixed assets from the Census multiplied by the book-to-market value ratio for each industry ($\alpha_{IND,t}$) for each data point corresponding to K_{it}. We calculate the book-to-market value ratio for each industry ($\alpha_{IND,t}$) by using the data for real capital stock ($K_{IND,t}^{JIP}$) and real value added ($Y_{IND,t}^{JIP}$) at each data point taken from the JIP database as follows:

$$\frac{Y_{IND,t}^{JIP}}{K_{IND,t}^{JIP}} = \frac{\sum_i Y_{IND,i,t}^{\text{Census}}}{\sum_i BVK_{IND,i,t}^{\text{census}} * \alpha_{IND,t}}$$

where $\sum_i Y_{IND,i,t}^{\text{Census}}$ is the sum of the plants' value added (i is the index of a plant), and $\sum_i BVK_{IND,i,t}^{\text{Census}}$ is the sum of the nominal book value of tangible fixed assets of industry *IND* in the Census.[11]

4.2 Variable Measurement

Production Function

We estimate the sales-generating production function (3) for each 4-digit Japan Standard Industrial Classifications (JSIC) using the system generalized method of moments (GMM) estimator following Blundell and Bond (2000). Specifically, we estimate the following function:

$$LN(Y)_{i,t} = \beta_K LN(K)_{i,t} + \beta_L LN(L)_{i,t} + \beta_M LN(M)_{i,t} + \eta_i + year_t + \omega_{i,t} + \varepsilon_{i,t}, \tag{21}$$

where

$$\omega_{i.t} = \rho\omega_{i.t-1} + \xi_{i,t}, \quad |\rho| < 1 \tag{22}$$
$$\varepsilon_{it}, \xi_{i,t} \sim MA(0).$$

The left hand-side of equation (21) accounts for the natural logarithm of output produced by firm i in period t. As production inputs, $LN(K)_{i,t}$ denotes the natural logarithm of firm i's capital input at the beginning of period t and $LN(L)_{i,t}$ and $LN(M)_{i,t}$ denote the natural logarithms of labor input and intermediate goods, respectively. We measure these variables at the end of period t. Following the literature, we include the firm-level fixed effect η_i, year fixed effect $year_t$, and the TFPR $\omega_{i,t}$. We assume that $\omega_{i,t}$ follows the AR(1) process described by equation (11). The disturbance term, $\varepsilon_{i,t}$, represents measurement error. This model has a dynamic (common factor) presentation

$$\begin{aligned} LN(Y)_{i,t} = {} & \beta_K LN(K)_{i,t} - \rho\beta_K LN(K)_{i,t-1} + \beta_L LN(L)_{i,t} - \rho\beta_L LN(L)_{i,t-1} \\ & + \beta_M LN(M)_{i,t} - \rho\beta_M LN(M)_{i,t-1} \\ & + \rho LN(Y)_{i,t-1} + \eta_i(1-\rho) + year_t - \rho year_{t-1} + \xi_{i,t} + \varepsilon_{i,t} - \rho\varepsilon_{i,t-1} \end{aligned} \tag{23}$$

[11] The real value added is negative only for the iron and steel industry in 2010. The book-to-market ratio is interpolated from the ratio as of t-1 and t+1.

or

$$LN(Y)_{i,t} = \pi_1 LN(K)_{i,t} + \pi_2 LN(K)_{i,t-1} + \pi_3 LN(L)_{i,t} + \pi_4 LN(L)_{i,t-1} + \pi_5 LN(M)_{i,t} + \pi_6 LN(M)_{i,t-1} + \pi_7 LN(Y)_{i,t-1} + \eta_i^* + year_t^* + \omega_{i,t} \tag{24}$$

subject to three non-linear (common factor) restrictions: $\pi_2 = -\pi_1\pi_7$, $\pi_4 = -\pi_3\pi_7$, $\pi_6 = -\pi_5\pi_7$. We first obtain consistent estimates of the unrestricted parameter $\pi = (\pi_1,,,\pi_7)$ and var(π) using the system GMM (Blundell and Bond, 1998). Since $\omega_{i,t} \sim MA(1)$, we use the following moment conditions:

$$\mathrm{E}\left(x_{i,t-s}\Delta\omega_{i,t}\right) = 0 \tag{25}$$
$$\mathrm{E}\left(\Delta x_{i,t-s}(\eta_i^* + \omega_{i,t})\right) = 0, \tag{26}$$

where $x_{i,t} = \left(LN(K)_{i,t}, LN(L)_{i,t}, LN(M)_{i,t}, LN(Y)_{i,t}\right)$ and $s \geq 3$. Next, using consistent estimates of the unrestricted parameters and their variance-covariance matrix, we impose the above restrictions by minimum distance to obtain the restricted parameter vector $(\beta_K, \beta_L, \beta_M, \rho)$.We first estimate the production function, using the data of all plants. Then we drop the 1% tails of TFPR and MRPK as outliers in each year and reestimate the production function.

Markup

From the definition of β_X and the assumption of constant returns to scale, we can derive the markup as $\frac{\varepsilon}{\varepsilon-1} = \frac{1}{\beta_K+\beta_L+\beta_M}$. Using the industry-level estimates of $(\beta_K, \beta_L, \beta_M)$, we obtain the industry-level, time-invariant markup:

$$Markup1_s = \frac{1}{\hat{\beta}_{Ks}+\hat{\beta}_{Ls}+\hat{\beta}_{Ms}} \tag{27}$$

We use this markup measure as an inverse measure of competition.

Later, we use an alternative measure of markup following De Loecker and Warzynski (2012). We allow adjustment costs only for capital, suggesting that the static profit maximization condition holds for materials. Therefore, the marginal product of materials, in particular, is equal to its price, which leads to

$$\beta_{Ms} = \frac{P_{it}^M M_{it}}{S_{it}} \tag{28}$$

where P_{it}^M is the price of materials and β_{Ms} is the output elasticity of materials in industry *s*. Eq. (28) shows that β_{Ms} is equal to the cost share of materials in sales. Combining Eq. (24) and $\beta_{Ms} = \left(1 - \frac{1}{\varepsilon_i}\right)\alpha_{Ms}$, we obtain the mark up as

$$\frac{1}{1-\frac{1}{\varepsilon_{it}}} = \frac{\alpha_{Ms}}{\frac{P_{it}^M M_{it}}{S_{it}}} \tag{29}$$

In practice, we follow the method of replacing α_{Ms} in Eq. (29) with the estimated value of β_{Ms}, $\widehat{\beta_{Ms}}$, and take the median value of the markup among the plants within each industry:

$$Markup2_{St} = Median\left(\frac{\widehat{\beta_{Ms}}}{\frac{P_{it}^M M_{it}}{S_{it}}}\right) \tag{30}$$

We use this industry-level, time-variant markup measure as a robustness test.

Volatility

To measure uncertainty, we employ two alternative measures of the volatility of productivity, ω_{it}. The first is the standard deviation of the productivity shocks across plants within an industry in a given year:

$$Volatility1_{st} = SD_{st}(\omega_{it} - \omega_{it-1}), \tag{31}$$

where *s* denotes the industry of plant *i*.

The other measure is based on the assumption that ω_{it} follows the stationary AR(1) process and is defined as

$$Volatility2_{st} = SD_{st}(\omega_{it} - \hat{\rho}\omega_{it-1}). \tag{32}$$

Note that both of these volatility measures are time variant and defined at the industry level. Note also that multiplicative shocks that are common to all establishments within an industry are absorbed when calculated the standard deviation of the log of TFPR and hence do not have effects on the volatility measures by definition.

Static Misallocation

Without adjustment costs or distortions, the marginal revenue of inputs should be equalized at their unit input cost across plants. To the extent that marginal revenues of inputs are dispersed across plants, aggregate total factor productivity (TFP) would be lower than that of the optimal allocation in which marginal revenues of inputs are equalized (Hsieh and Klenow, 2009). We therefore employ the standard deviation of $MRPK_{it}$ across plants in industry s in year t: $SD_{st}(MRPK_{it})$ as a baseline measure of static misallocation. The result below is robust to whether we use the $SD_{st}(MRPK_{it})$ or $Var_{st}(MRPK_{it})$.

Table 2 summarizes the descriptive sample statistics of the variables. We report the sample statistics of the dispersion in the marginal revenue products of labor and materials, $SD_{st}(MRPL_{it})$ and $SD_{st}(MRPM_{it})$ to compare with $SD_{st}(MRPK_{it})$ in Table 2, illustrating that $SD_{st}(MRPK_{it}) > SD_{st}(MRPL_{it}) > SD_{st}(MRPM_{it})$ on average. This evidence supports our approach focusing on the adjustment cost of capital rather than that of labor or materials.[12]

Figure 4 plots the standard deviation of $\text{Log}(\text{MRPK}_{it})$ and $\text{Log}(\text{MRPK}_{it}/\overline{MRPK}_{st})$ for each year, where $\overline{MRPK}_{st}$ denotes the average MRPK in industry *s*, which establishment *i* belongs to. The former shows the overall capital misallocation while the latter shows capital misallocation within the industry. Figure 4 shows that while the overall capital misallocation tends to decrease, the within-industry capital misallocation tends to increase over the last three decades.[13]

[Insert Table 2 here]

[Insert Figure 4 here]

Figure 5 shows the fraction of establishments with positive, zero, and negative investment where we define the zero investment as $\left|\frac{I_{t-1}}{K_{t-1}}\right| \leq 0.05$, where I_t is gross investment measured by tangible fixed assets acquired, and K_{t-1} represents the tangible fixed assets at the beginning of the previous year. We use the threshold value of 0.05 rather than 0 because a very small-scaled investment is not likely to involve with adjustment costs. While the average fractions of positive and zero investment are 0.56 and 0.41, respectively, the average fraction of negative investment is as small as 0.03.

[12] ACL report a similar magnitude of the standard deviation of each input for the US economy (0.81 for capital, 0.63 for labor, and 0.54 for materials) (Table 7, pp. 1036).

[13] The hike in 2011-12 possibly reflect the Tohoku Earthquake on March 11, 2011.

Figure 6 shows changes in the standard deviation of Log($\text{MRPK}_{it}/\overline{MRPK_{st}}$) among establishments with positive, zero, and negative investment, revealing that among establishments with positive investment, capital misallocation tends to decrease. Positive investment tended to help improve capital allocation.

[Insert Figure 5 here]

[Insert Figure 6 here]

4.3 Methodology

We examine how the time-series process of TFPR shocks affect the cross-sectional dispersion of MRPK depending on the markup levels. Our working hypothesis is that while greater uncertainty reduces investment and results in static misallocation, the impact of uncertainty on misallocation is stronger in more competitive markets. To test these hypotheses, we estimate the following baseline specifications:

$$Misallocation_{st} = \beta Volatility_{st} + FE_s + \varphi_{st} \tag{33}$$

$$Misallocation_{st} = \beta_1 Volatility_{st} + \beta_2 Volatility_{st} * Markup_s + FE_s + \varphi_{st} \tag{34}$$

The unit of observation is industry-year. The dependent variable is the static misallocation measure described above. The independent variables are one of the volatility measures or their interaction with the markup. If higher volatility results in worse static allocation, β should be positive. On the other hand, if market competition (that is, a lower markup) increases the impact of volatility on static misallocation, β_2 should take a negative value.. Because we include the industry-level fixed effect, we do not include the markup measure on its own, which is time-invariant.

We further control for the previous year's misallocation measure and estimate the following equation using the difference GMM in Arellano and Bond (1991):

$$Misallocation_{st} = \beta_0 Misallocation_{st-1} + \beta_1 Volatility_{st} + FE_s + \varphi_{st} \tag{35}$$

In all estimations, we drop the industry-year observations with the volatility variable is higher than the top 1 percentile. The standard errors are clustered at industry level.

5. Results

5.1 Overall Misallocation

Figure 7 plots the relationship between the main static misallocation measure,

$SD_{st}(MRPK_{it})$, and Volatility1_{st}. The figure shows a positive correlation between the misallocation measure and volatility, consistent with the hypothesis that uncertainty worsens static allocation.

[Insert Figure 7 here]

To illustrate the role of competition in the volatility-misallocation relationship, in Figure 8, we divide the industries into those with their markup above the median and those with their markup below the median, and depict the relationship between $SD_{st}(MRPK_{it})$ and the percentile of Volatility1_{st}. The figure shows that the slope is steeper for the lower-markup industries, suggesting that competition strengthens the volatility-misallocation relationship.

[Insert Figure 8 here]

Table 3 reports the baseline estimation results when we use $SD_{st}(MRPK_{it})$ as a misallocation measure, Volatility1_{st} as a volatility measure, and $Markup1_{st}$ as a markup measure. In Columns (1) and (2), we include only the current volatility measure, finding that higher TFPR volatility results in a larger MRPK dispersion regardless of whether we include industry fixed effects or not. In Columns (3) and (4), we add the lagged MRPK dispersion and estimate using GMM with industry-fixed effects. The one- to three-year lagged MRPK dispersion are all positive and significant. Importantly, even with these lagged MRPK dispersion, the current volatility still takes a positive and significant coefficient. In Column (6), we add the interaction of markup and volatility, and find that the interaction term is negative and weekly significant, suggesting that lower markup, i.e., severer competition, strengthens the adverse effect of volatility on capital misallocation. In Columns (7) to (12), we split the industries depending on whether the markup is higher or lower than the median. In Columns (7) and (8) we include only the current volatility measure, showing that while volatility takes positive and significant coefficients in both subsamples, the coefficient is larger for the sample with relatively lower markup. In Columns (9) and (10), we add the lagged MRPK and find that volatility takes a positive and significant coefficient only for the industries with lower markup. Finally, in Columns (11) and (12), we control for year fixed effects as well as industry fixed effects. Again we find a positive and marginally significant coefficient on volatility only for the industries with lower markup. All these results suggest that volatility worsens capital misallocation and that competition strengthens this volatility-misallocation relationship.

[Insert Table 3 here]

Next, in Table 4, we change the volatility measure from $Volatility1_{st}$ to $Volatility2_{st}$ in Columns (1)-(3) and the markup measure from $Markup1_{st}$ to $Markup2_{st}$ in Columns (4) and (5). We report only the results for OLS estimation of Eqs. (33); the results for the GMM of Eq. (35) are virtually the same. Table 4 shows that the baseline results do not qualitatively change.[14]

[Insert Table 4 here]

5.2 Quantitative effects of uncertainty on aggregate TFP

Based on the above estimation results, we quantify the effect of uncertainty on aggregate TFP and see to what extent competition magnifies this effect. To this aim, we follow Chen and Irarrazabal (2015). They assume that TFP shock and the capital wedge follow a joint log normal distribution, show that

$$\log(TFP_s) = \log(TFP_s^e) - \frac{\varepsilon_s}{2} var(\log(TFPR_{si})) - \frac{\alpha_{Ks}(1-\alpha_{Ks})}{2} \mathrm{var}(\log(1+\tau_{Ksi}))$$

and, without distortions output (i.e., $\tau_{Ysi} = 0$ for all si),

$$var(\log(TFPR_{si})) = \alpha_s^2 \mathrm{var}(\log(1+\tau_{Ksi})).$$

Combining these two and $var(\log(MRPK_{si})) = var(\log(1+\tau_{Ksi}))$, we obtain the loss of TFP as

$$\log(TFP_s^e) - \log(TFP_s) = \frac{\alpha_s}{2}\big(1+\alpha_s(\varepsilon_s - 1)\big) var(\log(MRPK_{si})) \qquad (36)$$

We measure the industry-level TFP losses defined by Eq. (36) and aggregate them using

[14] We have thus far implicitly assumed that TFPR shocks are independent across establishments. But TFPR shocks may correlate across establishments within a firm. To exclude this possibility, we restrict our sample to the firms with single establishments. Using $Volatility1_{st}$ as a volatility measure and split sample by median of $Markup1_{st}$, we again find that the volatility is positive and significant only for the lower markup subsample.

simple average after dropping the industries within the top and bottom 1% of TFP losses. We show the results in Table 5.

[Insert Table 5 here]

Column 1 shows that the average TFP loss due to capital misallocation is 5-8% depending on year and 6.1% on average over 1987-2013. Column 2 shows the effect of volatility on the TFP losses, calculated from the estimation similar to Column (2) in Table 3.[15] If volatility were zero, the average TFP would increase by 0.35% on average. The quantitative impact of volatility is small relative to the overall TFP losses.

Next, we restrict our sample to the industry-years with markup smaller than the median. Column 3 shows that if we restrict the sample to the more competitive industries, the average TFP loss is 7.3%. Column 4 shows the effect of volatility on the TFP losses for the subsample of the more competitive industry-years, showing that TFP increases 0.65% on average, which is larger than the full sample result, and constitutes a non-negligible part of the overall TFP losses.

5.3 Plant-level evidence

To investigate the mechanism through which competition worsens uncertainty-driven misallocation, we estimate the extensive and intensive margins of plant-level investment. First, to investigate the extensive margin, we run the following linear probability model of whether the plant conducts positive investment or not after dropping the plant-year observations with negative ($\frac{I_{it}}{K_{it}} < 0.05$) investment.

$$1\left(\frac{I_{it}}{K_{it}} > 0.05\right) = \beta_1 \log(MRPK_{it}) + \beta_2 Volatility_{st} + \beta_3 \log(MRPK_{it}) \times Volatility_{st} + FE_i + FE_t + \varphi_{it}, \tag{37}$$

where the dependent variable is a dummy for positive investment. We expect that β_1 takes a positive coefficient while β_2 and β_3 to take negative coefficients if volatility reduces the likelihood of positive investment and weakens the plant's response to the change in (the logarithm of) MRPK. We control for fixed effects in two ways. One is to control for plant- and year-level fixed effects additively, and the other is

[15] We calculate TFP losses in Columns (2) and (4) based on the estimation in which we replace SD(Log(MRPK)) with Var(Log(MRPK)) as the dependent variable.

to control for both of plant- and industry-year fixed effects. In the latter specification, we drop the single term of $Volatility_{st}$. We conduct the full sample estimation and the subsample estimation where industries are divided into the more competitive and less competitive ones depending on whether $Markup1_{st}$ is above or below the median.

We further estimate the linear probability model of negative investment after dropping the observations with positive $(\frac{I_{it}}{K_{it}} > 0.05)$ investment as follows:

$$1\left(\frac{I_{it}}{K_{it}} < -0.05\right) = \beta_1 \log(MRPK_{it}) + \beta_2 Volatility_{st} + \beta_3 \log(MRPK_{it}) \times Volatility_{st} + FE_i + FE_t + \varphi_{it}. \qquad (38)$$

Table 6 reports the results from using $Volatility1_{st}$ as a volatility measure, though using $Volatility2_{st}$ leave the results essentially unchanged. Columns (1)-(6) show the results for positive investment and Columns (7)-(12) for negative investment. In Columns (1)-(3) and (7)-(9), we control for plant- and year-fixed effects additively while in Columns (4)-(6) and (10)-(12), we control for plant- and industry-year fixed effects.

In Columns (1)-(3), β_1 is positive and significant while β_2 and β_3 are negative and significant, suggesting that while higher MRPK tends to induce positive investment, volatility reduces the likelihood of positive investment and weakens the plant's response to the change in MRPK. To compare Columns (2) and (3), we find that the absolute values of both β_2 and β_3 are larger for the industries with lower markup, suggesting that competition strengthens depressing effect of volatility on investment and on the sensitivity of investment to MRPK. In Columns (4)-(6), we control for time-varying industry fixed effects. β_1 still takes a positive and significant coefficient. β_3 takes a negative coefficient for the whole industries and the more competitive, but not for the less competitive industries. This result suggest that volatility weakens the positive response to MRPK only for relatively competitive industries.

Columns (7)-(12) show that in the case of negative investment, only β_1 is negative and significant. β_2 and β_3 are not significant, suggesting that volatility does not seem to affect the negative investment or the investment sensitivity to MRPK.

[Insert Table 6 here]

Next we turn to the intensive margin. We estimate the following equation for the full sample and subsamples divided by whether the plant-year conducts positive or negative investment:

$$\frac{I_{it}}{K_{it}} = \beta_1 \log(MRPK_{it}) + \beta_2 Volatility_{st} + \beta_3 \log(MRPK_{it}) \times Volatility_{st} + FE_i + FE_t + \varphi_{it}, \quad (39)$$

Note that we control for the time-varying industry fixed effects and hence drop the single term of $Volatility_{st}$. We expect β_1 to be positive and β_2 to be negative.

Columns (1) to (3) show the results from the sample that we do not divide by the investment status. They show that β_1 is positive and significant, while β_2 is negative and significant only for the smaller-markup industries, suggesting that competition strengthens the adverse effect of volatility on the intensive margin of investment sensitivity to MRPK. Columns (4) to (6) show the results from the restricted sample of plant-year observations with positive investment. The results are similar to those in Columns (1)-(3), although estimated β_1 is larger for this restricted sample. Columns (7) to (9) show the results from the restricted sample of plant-year observations with negative investment, showing that neither β_1 or β_2 is significant.

[Insert Table 7 here]

These estimation results suggest that uncertainty decreases both the likelihood (i.e., extensive margin) and the extent (i.e., intensive margin) of positive investment, and product market competition strengthens these adverse effects.

6. Conclusion

Uncertainty delays investment that involves disruption cost or time-to-build, resulting in capital misallocation from the static viewpoint. However, theory predicts that the impact of uncertainty on investment, and hence on static misallocation, may depend on the degree of product market competition. Using a large panel dataset of manufacturing plants in Japan, we find that uncertainty results in static misallocation and that this impact is stronger for industries with severe product market competition. We further find that competition worsens uncertainty-driven misallocation both through the less elastic investment response to the variability of the marginal revenue of capital and through the higher variability of the optimal level of capital. To improve allocative efficiency, reduced uncertainty complements competition policies.

While this study sheds new lights on the role of competition in the uncertainty-misallocation relationship, we have not yet explored the durability of uncertainty-driven misallocation. If the major source of such misallocation is time-to-build, then uncertainty-driven misallocation may be short-lived. Using annual data, we find a relatively small quantitative impact of volatility, which may reflect the short-run effect of uncertainty. We explore this issue in future work.

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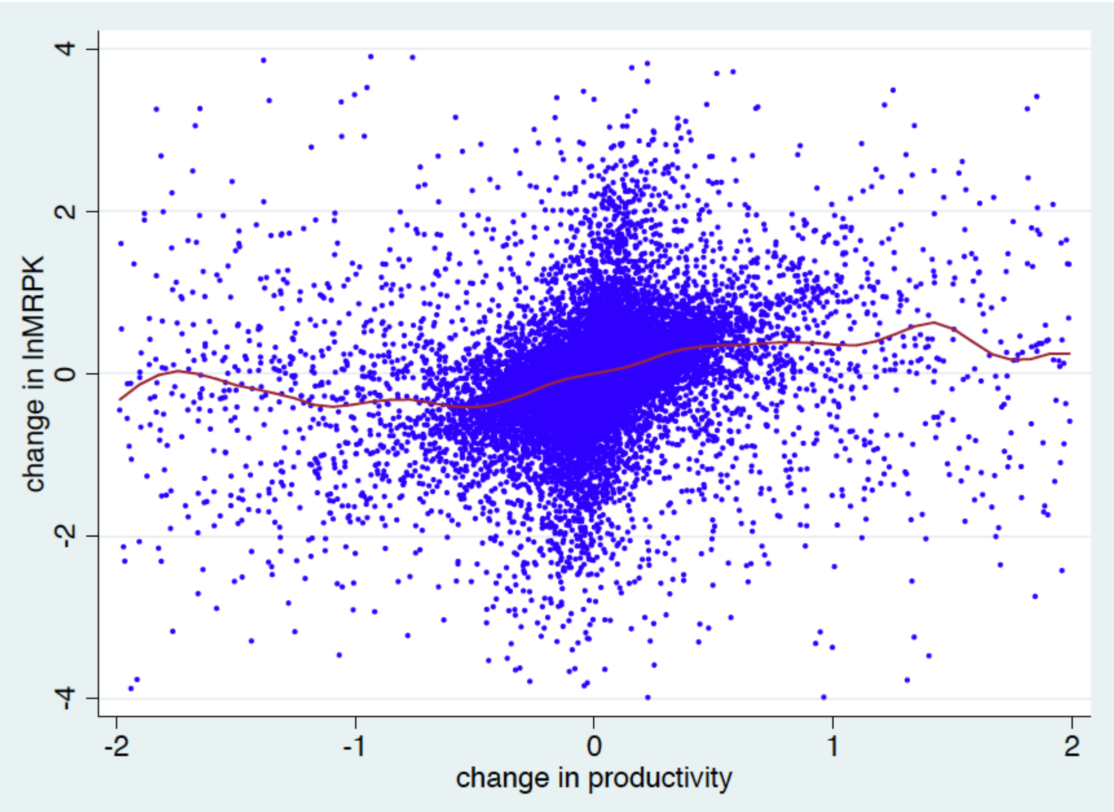
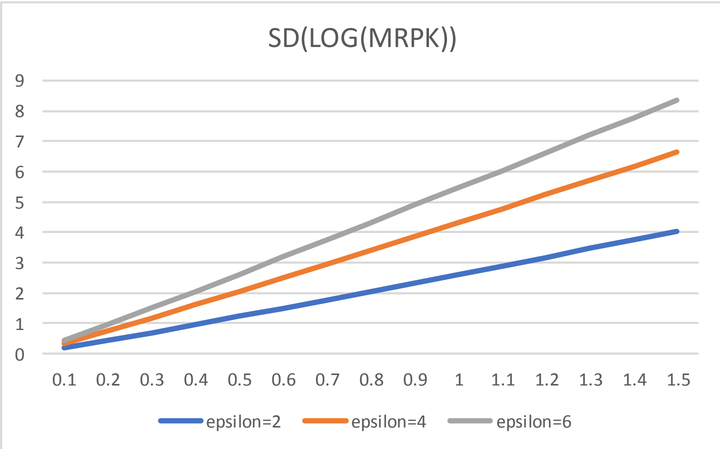
Figure 1. Establishment-level changes in TFPR and MRPK



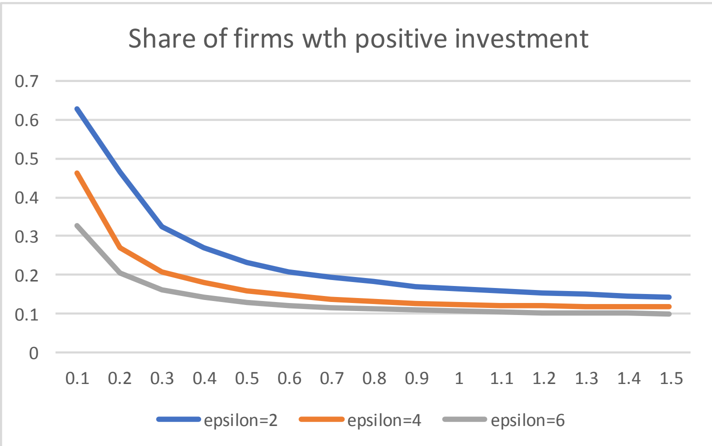
Note. This figure depicts changes in TFPR and MRPK over the period from 2012 to 2013.

Figure 2. Simulation Results: TFPR shock model with asymmetric adjustment cost

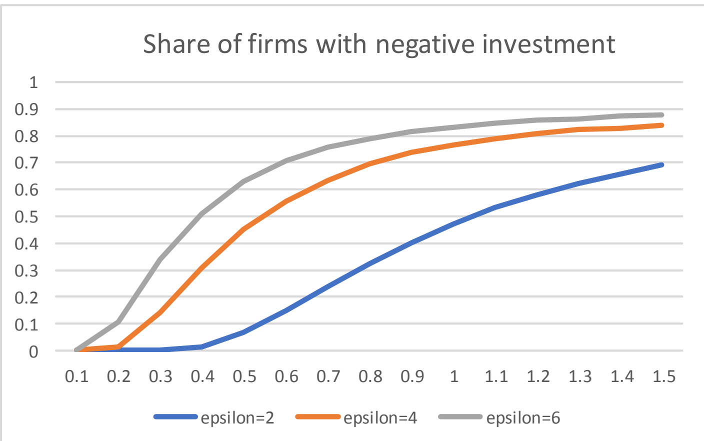
A. $\mathrm{SD}(MRPK_{it})$



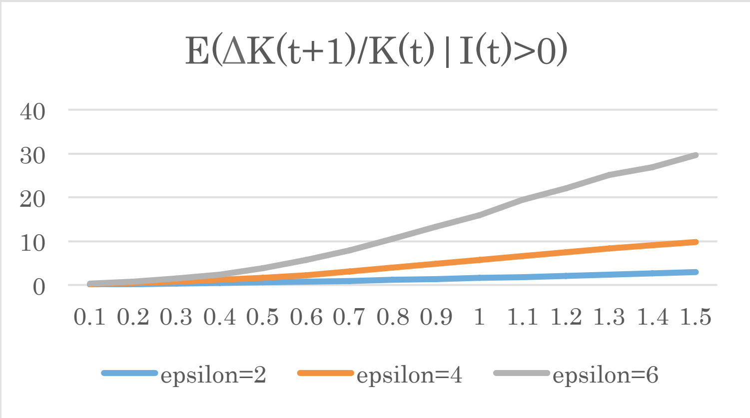
B. Share of firms with $\mathrm{I}_t > 0$



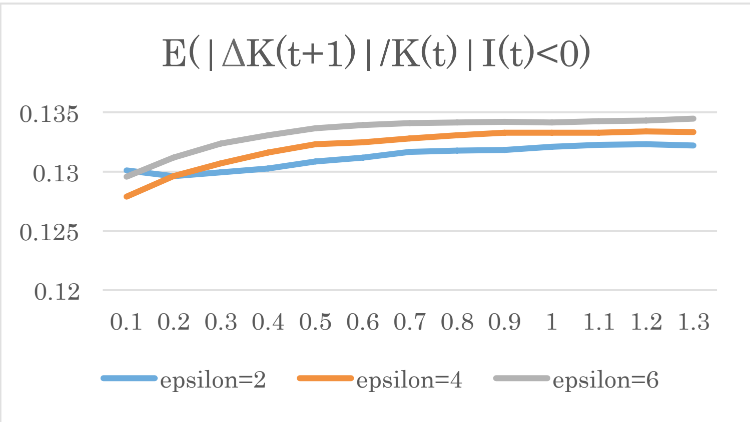
C. Share of firms with $\mathrm{I}_t < 0$



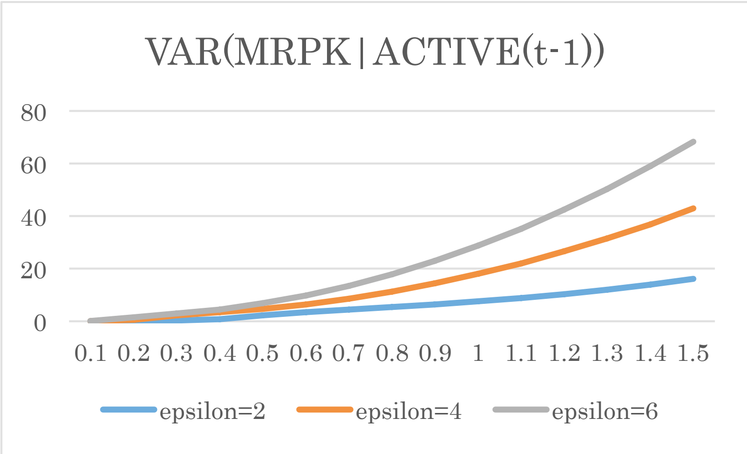
D. Average $\frac{\Delta K_{t+1}}{K_t}$ for firms with $I_t > 0$



E. Average $\frac{-\Delta K_{t+1}}{K_t}$ for firms with $I_t < 0$



F. Active margins



G. Inactive margins

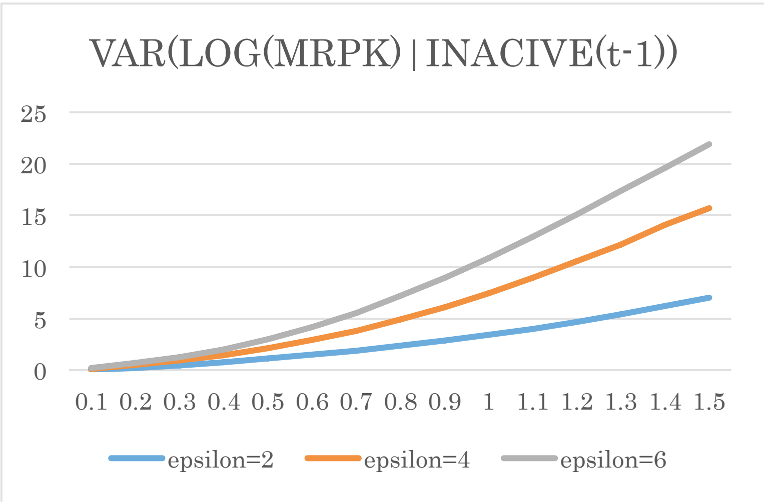
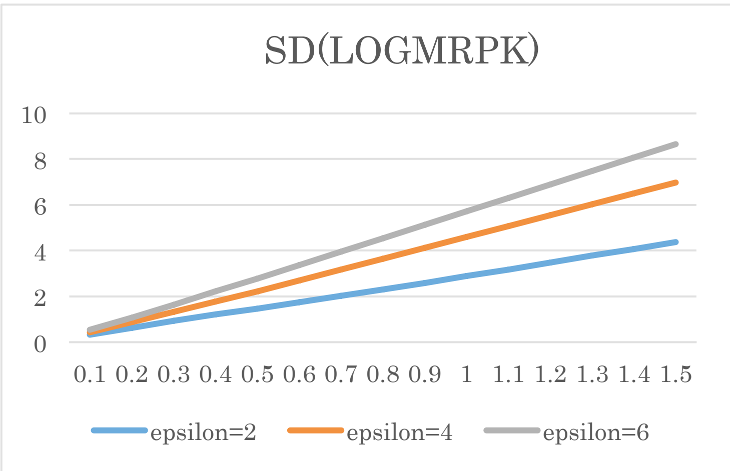
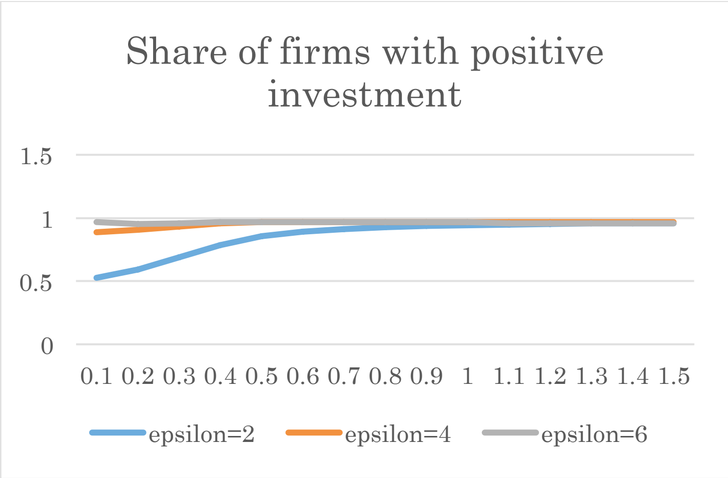


Figure 3. Simulation Results: TFPR shock model with symmetric adjustment cost

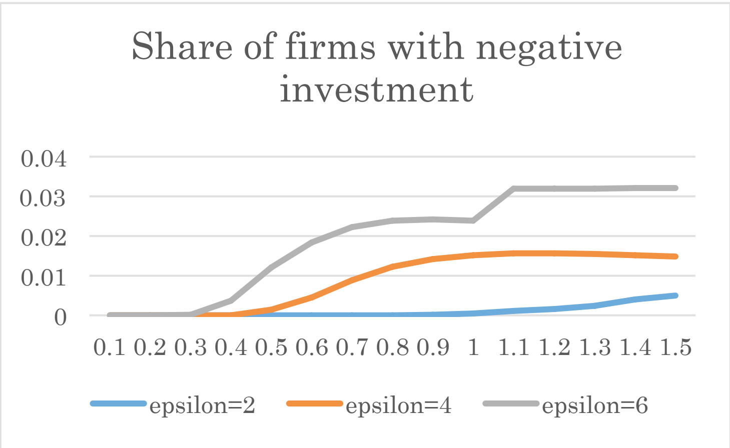
A. SD($MRPK_{it}$)



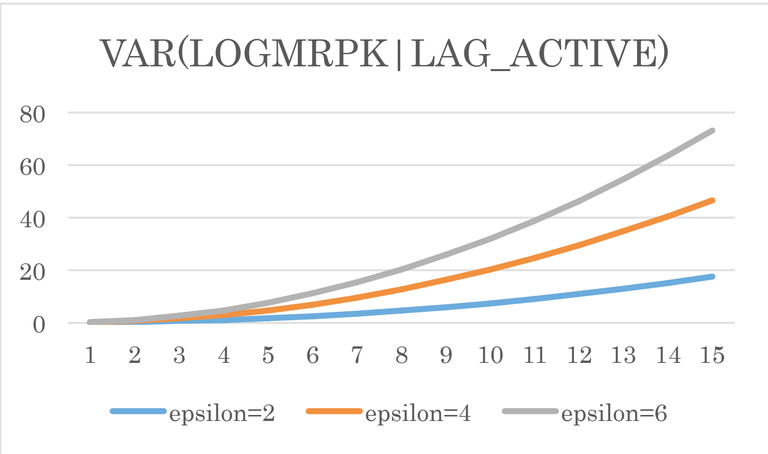
B. Share of firms with $I_t > 0$



C. Share of firms with $I_t < 0$



D. Active margin



E. Inactive margin

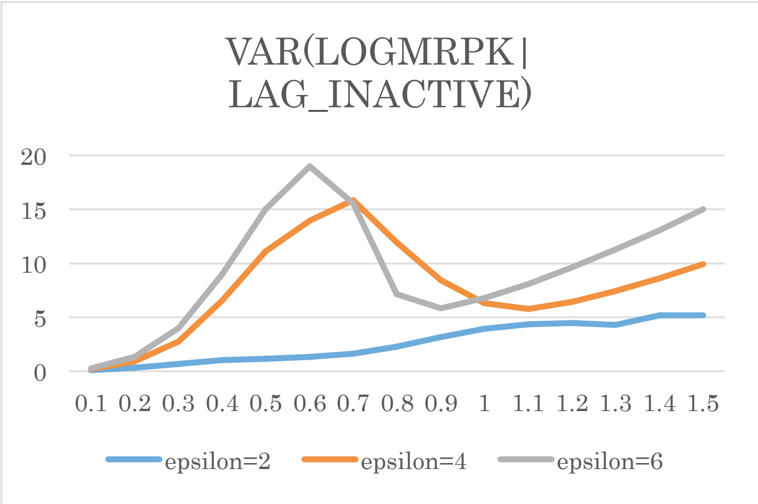

VAR(LOGMRPK|
LAG_INACTIVE)
20
15
10
5
0
0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1 1.1 1.2 1.3 1.4 1.5
epsilon=2
epsilon=4
epsilon=6

Figure 4. Standard deviation of LOG(MRPK)

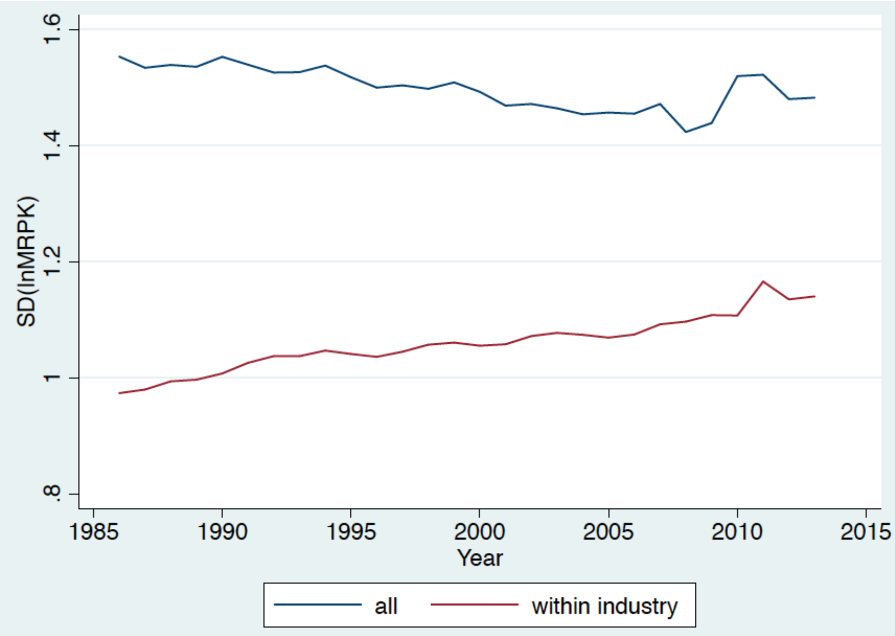
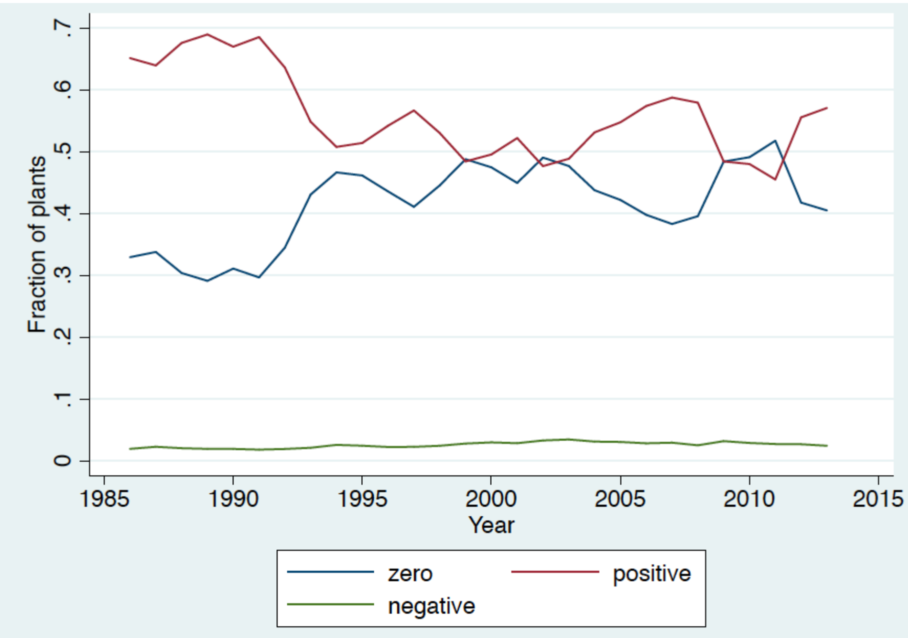
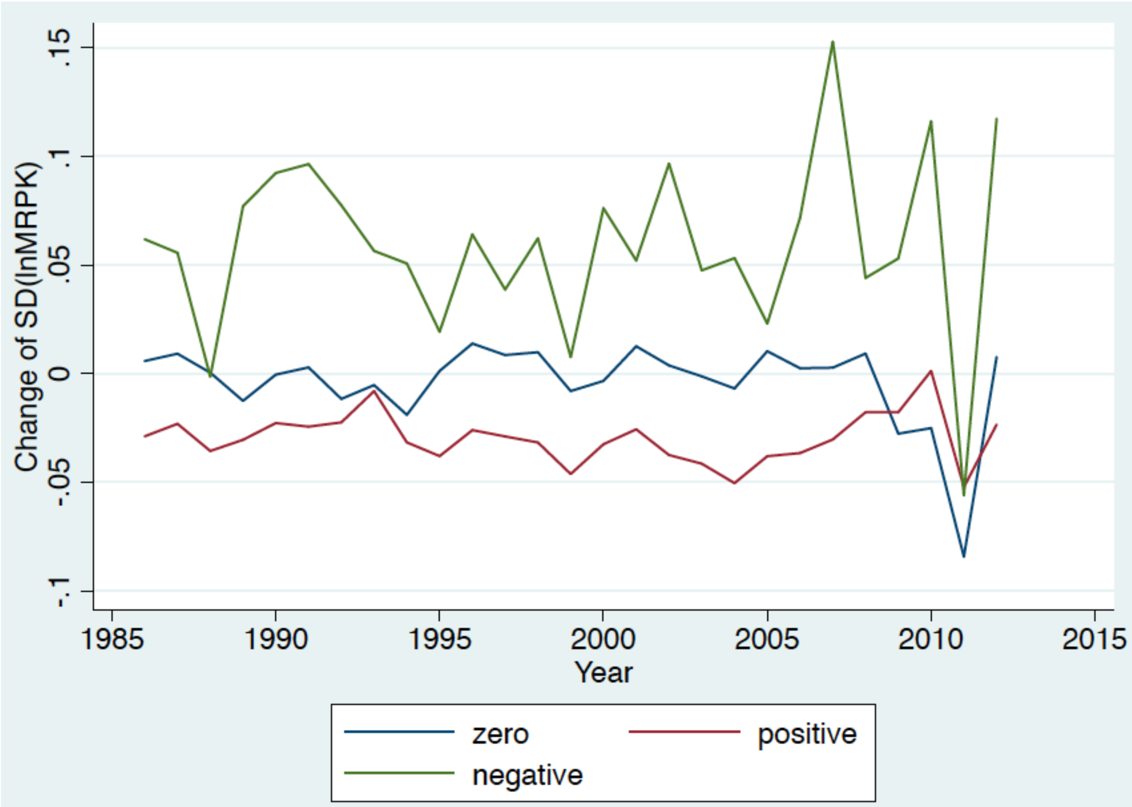


Figure 5. Fraction of establishments with positive, zero, and negative investment.



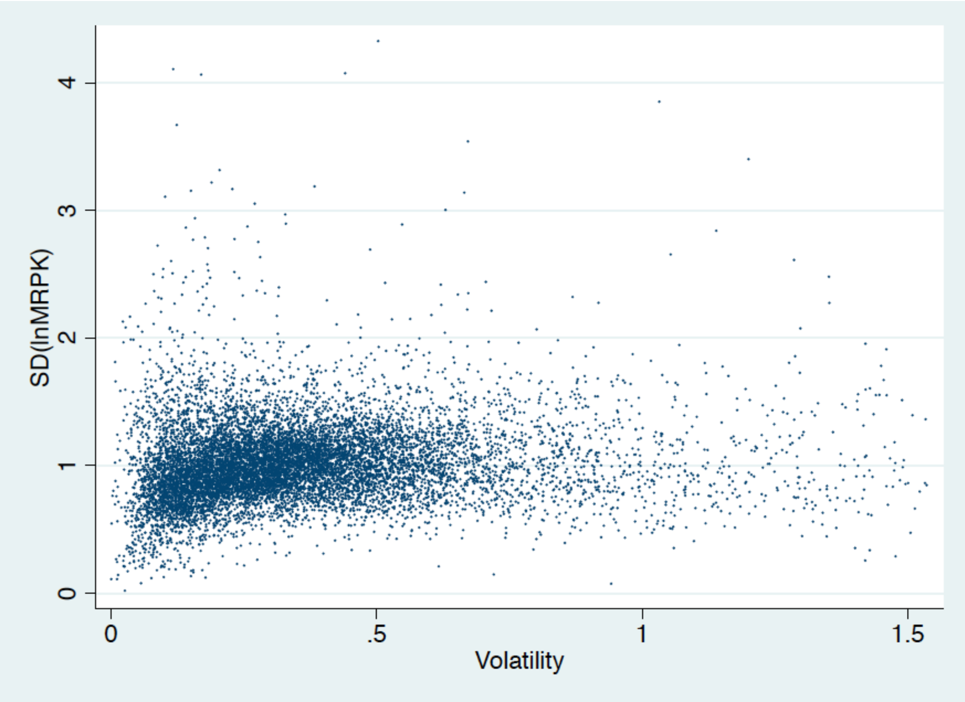
Note. We define zero investment as $\left|\frac{I_{t-1}}{K_{t-1}}\right| \leq 0.05$. We accordingly define positive and negative investment using the same threshold.

Figure 6. Changes in within-industry capital misallocation ($SD(Log\left(\frac{MRPK_{it}}{MRPK_{st}}\right))$) among establishments with positive, zero, and negative investment.



Note. We define zero investment as $\left|\frac{I_{t-1}}{K_{t-1}}\right| \leq 0.05$. We accordingly define positive and negative investment using the same threshold.

Figure 7. Volatility and Dispersion in MRPK



Note: Volatility measure is $Volatility1_{st} \equiv SD_{st}(\omega_{it} - \omega_{it-1})$.

Figure 8. Volatility and Dispersion in MRPK by markup

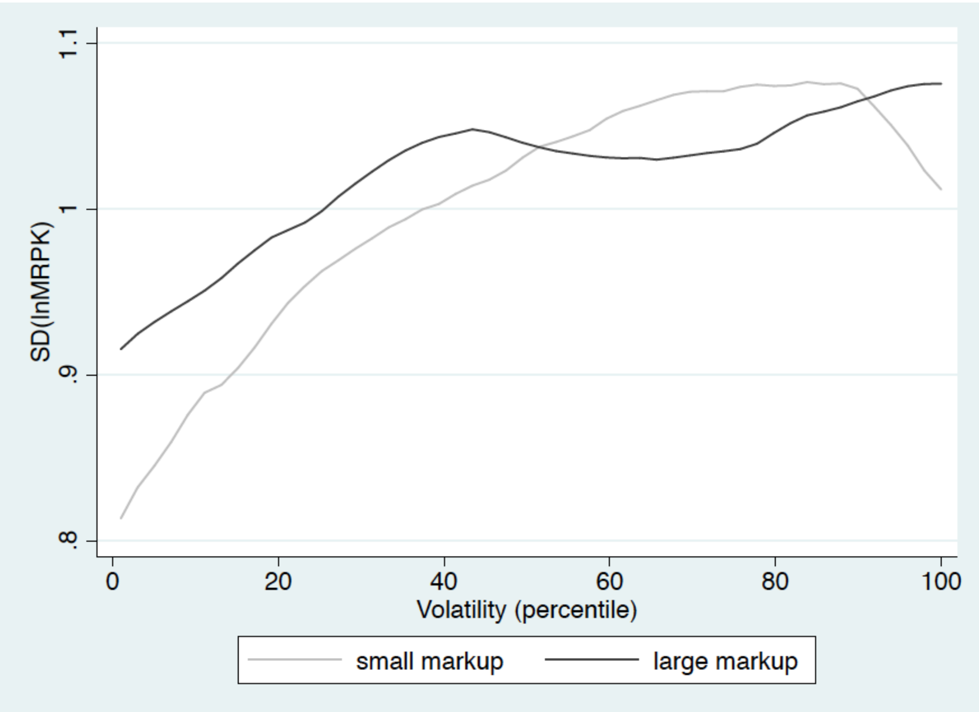


Table 1. Simulation Parameters

All specifications	
μ_b or μ_a	0.000
α_K	0.160
α_L	0.307
α_M	0.533
δ	0.900
β	1/(1+0.065)
p_L	0.182
p_M	0.182
ρ	0.850
Symmetric adjustment costs	
$C^{F+}{}_K$	0.090
$C^{Q+}{}_K$	8.800
$C^{F-}{}_K$	0.090
$C^{Q-}{}_K$	8.800
Asymmetric adjustment costs	
$C^{F+}{}_K$	0
$C^{Q+}{}_K$	0
$C^{F-}{}_K$	0.090
$C^{Q-}{}_K$	8.800

Table 2. Summary Statistics

Variable name	N	mean (p1-p99)	sd (p1-p99)	min	p5	median	p95	max
Plant-level variables								
ln(Productivity)	1,391,981	5.43	1.10	-6.71	3.65	5.34	7.54	14.24
Productivity growth rate	1,243,841	0.00	0.23	-11.66	-0.35	0.00	0.36	9.11
ln(MRPK)	1,333,909	-2.66	1.36	-16.53	-5.22	-2.63	-0.26	10.22
ln(MRPK) for zero investment plants	569,506	-2.85	1.43	-16.39	-5.48	-2.84	-0.31	9.65
ln(MRPK) for positive investment plants	787,808	-2.52	1.29	-16.53	-4.99	-2.50	-0.25	10.22
ln(MRPK) for negative investment plants	34,776	-2.67	1.44	-14.39	-5.30	-2.67	-0.06	7.84
ln(MRPL)	1,387,850	6.28	0.86	-6.19	4.64	6.33	7.73	12.47
ln(MRPM)	1,389,497	-0.19	0.59	-10.42	-1.06	-0.27	1.05	11.05
Investment rate	1,392,090	0.18	0.31	-31.16	-0.01	0.07	0.85	140462.83
Industry-level variables (time-variant)								
Number of plants	13,503	88	122	1	4	41	368	2681
Volatility1	12,842	0.36	0.25	0.00	0.08	0.30	0.91	3.83
Volatility2	12,842	0.36	0.15	0.00	0.12	0.35	0.65	3.15
SD(ln(MRPK))	11,734	1.00	0.26	0.02	0.59	0.98	1.53	4.33
SD(ln(MRPL))	12,985	0.69	0.19	0.00	0.39	0.67	1.07	2.10
SD(ln(MRPM))	13,177	0.53	0.23	0.00	0.21	0.49	1.00	3.46
Fraction of zero investment plants	13,503	0.41	0.18	0.00	0.13	0.40	0.70	1.00
Fraction of positive investment plants	13,503	0.57	0.18	0.00	0.26	0.57	0.86	1.00
Fraction of negative investment plants	13,503	0.02	0.03	0.00	0.00	0.02	0.08	1.00
Industry-level variables (time-invariant)								
Markup1	491	1.42	0.51	-32.06	0.97	1.29	2.47	10.93
Markup2	491	0.80	0.29	-0.10	0.33	0.79	1.33	5.96
Output elasticity of capital	491	0.04	0.05	-0.39	-0.03	0.04	0.13	0.31
Output elasticity of labor	491	0.30	0.15	-0.85	0.05	0.31	0.55	1.41
Output elasticity of materials	491	0.40	0.14	-0.05	0.16	0.40	0.62	1.03

Table 3. Baseline Estimation Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	OLS	OLS	GMM	GMM	GMM	OLS	OLS	OLS	GMM	GMM	OLS	OLS
volatility1	0.148***	0.0760***	0.0231**	0.0241**	0.0286***	0.0808***	0.0903***	0.0624***	0.0372***	0.0122	0.0462*	0.0289
	(5.176)	(4.340)	(2.488)	(2.551)	(2.925)	(4.769)	(3.482)	(2.627)	(2.706)	(0.967)	(1.903)	(1.116)
volatility_markup_crs_s						-0.00358*						
						(-1.750)						
L.sd_mrpk_all			0.430***	0.427***	0.453***				0.375***	0.550***		
			(27.07)	(26.14)	(25.65)				(18.51)	(27.81)		
L2.sd_mrpk_all				0.0585***	0.0582***							
				(5.004)	(4.774)							
L3.sd_mrpk_all					0.0292**							
					(2.491)							
Observations	11,207	11,207	10,665	10,239	9,814	11,207	5,558	5,649	5,276	5,389	5,558	5,649
Adjusted R-squared	0.013	0.441				0.441	0.367	0.512			0.398	0.532
Fixed effects	no	industry	industry	industry	industry	industry	industry	industry	industry	industry	industry+year	industry+year
Sample	all	all	all	all	all	all	markup smaller than median	markup larger than median	markup smaller than median	markup larger than median	markup smaller than median	markup larger than median

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Robustness Checks

	(1)	(2)	(3)	(4)	(5)
VARIABLES	OLS	OLS	OLS	OLS	OLS
volatility	volatility2	volatility2	volatility2	volatility1	volatility1
markup	markup1	markup1	markup1	markup2	markup2
volatility	0.185***	0.268***	0.111**	0.0919***	0.0621***
	(4.159)	(3.875)	(2.053)	(3.391)	(2.758)
Observations	11,317	5,626	5,691	5,549	5,658
Adjusted R-squared	0.437	0.373	0.503	0.519	0.365
Fixed effects	industry	industry	industry	industry	industry
Sample	all	markup smaller than	markup larger than median	markup smaller than	markup larger than median

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table5. TFP loss from capital misallocation (%)

Industry	all	all	markup smaller than median	markup smaller than median
Simulation	no capital misallocation	no volatility	no capital misallocation	no volatility
1987	4.83	0.37	5.18	0.47
1988	4.69	0.32	5.00	0.38
1989	4.63	0.31	4.92	0.41
1990	4.89	0.31	5.46	0.42
1991	5.03	0.30	5.58	0.40
1992	5.07	0.30	5.50	0.40
1993	4.97	0.29	5.42	0.37
1994	5.35	0.36	5.79	0.54
1995	5.27	0.31	5.92	0.64
1996	5.29	0.30	6.14	0.82
1997	5.57	0.29	6.29	0.65
1998	5.78	0.29	6.63	0.68
1999	5.76	0.34	7.21	0.46
2000	5.85	0.30	6.73	0.60
2001	5.88	0.30	6.96	0.71
2002	6.95	0.40	8.38	0.69
2003	7.06	0.34	8.76	0.79
2004	6.59	0.32	8.08	0.48
2005	6.78	0.31	8.15	0.76
2006	6.73	0.34	9.55	0.83
2007	7.02	0.38	9.28	0.70
2008	7.06	0.40	9.32	0.93
2009	7.13	0.43	8.23	0.95
2010	7.15	0.36	8.79	0.54
2011	7.65	0.54	10.55	1.08
2012	7.69	0.57	9.34	1.10
2013	7.93	0.37	11.00	0.87
mean	6.10	0.35	7.34	0.65

Table 6. Plant-level Estimation for Investment Status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Investment status	positive vs zero	positive vs zero	positive vs zero	positive vs zero	positive vs zero	positive vs zero	negative vs zero	negative vs zero	negative vs zero	negative vs zero	negative vs zero	negative vs zero
ln(MRPK)	0.0950***	0.109***	0.102***	0.126***	0.130***	0.127***	-0.00695***	-0.00813***	-0.00675***	-0.00814***	-0.0105***	-0.00735***
	(26.57)	(30.40)	(19.59)	(68.11)	(47.69)	(48.41)	(-5.686)	(-4.809)	(-3.514)	(-4.845)	(-4.164)	(-3.206)
volatility1	-0.0676***	-0.0839***	-0.0373**				0.00274	0.00536	-0.00435			
	(-6.253)	(-7.728)	(-2.670)				(0.366)	(0.508)	(-0.363)			
ln(MRPK)*volatility1	-0.0233***	-0.0279***	-0.0119***	-0.00824**	-0.0162***	-0.00335	0.000859	0.00350	-0.00217	-0.00350	0.000276	-0.00488
	(-6.538)	(-7.278)	(-3.039)	(-2.304)	(-2.941)	(-0.713)	(0.374)	(1.093)	(-0.601)	(-0.906)	(0.0498)	(-0.865)
Observations	1,185,147	622,315	558,119	1,185,138	622,307	558,118	254,082	126,503	123,288	252,770	125,859	122,610
Adjusted R-squared	0.274	0.280	0.279	0.289	0.292	0.292	0.262	0.269	0.258	0.268	0.273	0.267
Fixed effects	plant+year	plant+year	plant+year	plant + industry*year	plant + industry*year	plant + industry*year	plant+year	plant+year	plant+year	plant + industry*year	plant + industry*year	plant + industry*year
sample	all	markup smaller than median	markup larger than median	all	markup smaller than median	markup larger than median	all	markup smaller than median	markup larger than median	all	markup smaller than median	markup larger than median

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7. Plant-level Estimation of Investment Ratio

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Investment Status	all	all	all	positive	positive	positive	negative	negative	negative
ln(MRPK)	0.116***	0.126***	0.113***	0.174***	0.178***	0.177***	-0.00383	-0.000326	0.0197
	(72.08)	(51.29)	(50.98)	(71.35)	(49.85)	(49.49)	(-0.182)	(-0.00924)	(1.332)
ln(MRPK)*volatility1	-0.0132***	-0.0248***	-0.00258	-0.0205***	-0.0242***	-0.0110	-0.0490	-0.170	0.0561
	(-4.504)	(-5.451)	(-0.640)	(-4.419)	(-3.640)	(-1.568)	(-0.758)	(-1.165)	(1.243)
Observations	1,254,884	660,618	589,640	692,832	372,331	316,035	11,944	6,381	4,845
Adjusted R-squared	0.157	0.163	0.158	0.183	0.187	0.188	0.001	0.000	0.180
Fixed effects	plant + industry*year	plant + industry*year	plant + industry*year	plant + industry*year	plant + industry*year	plant + industry*year	plant + industry*year	plant + industry*year	plant + industry*year
Sample	all	markup smaller than median	markup larger than median	all	markup smaller than median	markup larger than median	all	markup smaller than median	markup larger than median

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1