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Does Product Differentiation Reduce the Productivity Dispersion Caused by Uncertainty?*

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Abstract

Uncertainty affects investment that involves adjustment costs or time-to-build, resulting in dispersion in marginal revenue productivity of capital (MRPK) and consequently in aggregate total factor productivity (TFP). This paper sheds new light on this relationship from the perspective of product differentiation. Using a simple dynamic model and a large panel dataset of manufacturing plants in Japan, we find that while industries with greater time-series volatility in revenue-based productivity (TFPR) have greater cross-sectional dispersion of MRPK, such an impact is stronger for the industries of less differentiated goods. We also obtain supporting evidence that plant-level investment decreases more in response to the volatility in TFPR in the industries of less differentiated goods. Based on the structural estimation result, we find that the effects of the volatility in TFPR on the aggregate TFP are economically sizable and much larger for the industries of less differentiated goods.

Keywords: Uncertainty, Product Differentiation, Productivity dispersion, Aggregate productivity.

JEL Classification: O11, O47.

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1. Introduction

It is now well known that the dispersion in revenue-based productivity (TFPR) across firms or plants is quite large even within narrowly defined industries. However, the reasons for the dispersion in productivity are still controversial. Many preceding studies posit that the distortions such as taxes, regulations, financial frictions, and markups that vary across producers result in the dispersion in productivity, which, in turn, cause misallocation of resources and lower aggregate productivity (Restuccia and Rogerson, 2008, Hsieh and Klenow, 2009). More recent studies show that uncertainty results in the dispersion in revenue-based productivity as it affects investment that involves adjustment costs or time-to-build.[1] Asker et al. (2014) show that higher time-series volatility in productivity shocks results in the greater dispersion in the marginal revenue of capital (MRPK) among plants within an industry, even if capital is allocated efficiently from the dynamic view when adjustment costs are considered. However, following studies (Kehrig and Vincent, 2019; David and Venkateswaren, 2019, among others) obtain mixed results as to the importance of adjustment costs as a source of misallocation, as Hopenhayn (2014) stresses in his survey of misallocation.

Given such controversy, it is useful to provide new evidence on the role of uncertainty in the dispersion in TFPR. Figure 1 shows the cross-sectional relationship between the plant-level annual changes in MRPK and in TFPR in Japan. These two variables should not be correlated if plants immediately adjust their capital at the optimal level that equates MRPK to the marginal cost of capital and if no distortions on capital exist and hence the marginal cost of capital is common across plants. The figure indicates that these two are positively correlated, suggesting that plants do not adjust capital in response to the TFPR shock within a year.[2]

[Insert Figure 1 here]

Moreover, the effects of uncertainty on investment, and hence on the dispersion in MRPK are likely to depend on various firm- and industry-specific factors. Exploring such factors will contribute to our understanding to the mechanism through which uncertainty results in the dispersion in MRPK and aggregate productivity.

In this paper, we focus on the industry-level difference in the degree of product differentiation as a potential source for the variety in the relationship between the volatility in TFPR and the dispersion in MRPK; firms in the industries of more differentiated goods face more stable demand, and therefore, reduce investment by less in response to the TFPR shocks, which results in a smaller dispersion in MRPK within the industry for the volatility in the TFPR shocks. Despite such

[1] Mismeasurement is another potential reason for the dispersion in measured TFPR (e.g., Bils et al., 2021).

[2] We describe the data in Section 4.1 and the definition of TFPR and MRPK in Section 4.2 in detail. Figure 1 depicts the plant-level changes in TFPR and MRPK over the period from 2012 to 2013, although we observe a similar correlation between the two over the other years in our sample.

potential importance, no study examines the role of product differentiation in transmitting the volatility in TFPR shocks to the dispersion in MRPK. Therefore, this study aims at providing evidence on to what extent uncertainty affects dispersion in MRPK and aggregate productivity depending on the product differentiation. Our contribution to the literature is to take product differentiation into account when we estimate the effect of uncertainty on the dispersion in MRPK and aggregate productivity.

We use a simple dynamic model and a large dataset of manufacturing plants in Japan covering 1986 to 2013. We find that while industries with greater time-series volatility in TFPR have greater cross-sectional dispersion of MRPK, which is consistent with Asker et al. (2014), such a relationship is stronger for the industries of less differentiated goods. We also provide supporting evidence that the sensitivity of plant-level investment to the volatility in TFPR is higher for industries of less differentiated goods. Based on the structural estimation results, we further conduct counterfactual experiments to quantify to what extent the effects of the volatility in TFPR on the dispersion in MRPK and aggregate productivity depend on the degree of product differentiation. Specifically, we assume that the volatility in TFPR decreases by 50%. Then, we find that while the dispersion in MRPK decreases almost by 50% regardless of the degree of product differentiation, the gains of the aggregate productivity relative to the hypothetical aggregate productivity that would be achieved without adjustment costs or time-to-build are 5.6-6.0% for the industries of less differentiated goods and 1.4-1.5% for the industries of more differentiated goods.

The reminder of the paper proceeds as follows. In Section 2, we review the relevant literature on the impact of uncertainty on investment and dispersion in MRPK. In Section 3, we present a simple model to show how product differentiation affects the relationship between volatility of TFPR shocks and dispersion in MRPK. Section 4 describes our data and variables. Section 5 describes the methodology for our reduced-form estimation for the dispersion in MRPK and presents the results. We further show the regression results for plant-level investment. Section 6 presents the results from the structural estimation and the counterfactual experiments. Finally, we conclude the paper with discussion of our findings in Section 7.

2. Literature Review

This study investigates the effects of product differentiation on the relationship between uncertainty and dispersion in TFPR, and contributes to the literature on resource misallocation across firms and plants. 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 losses of aggregate TFP due to resource misallocation are larger in China by 30%-50% and

India by 40%-60% 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.[3] Asker et al. (2014) is one such study, which investigates the role of productivity shocks and dynamic production factors on the static variation of marginal revenue.[4] They 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, Asker et al. (2014) show that the higher time-series volatility of productivity shocks, measured as the variance of productivity growth rates across firms, contributes 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. Kehrig and Vincent (2019) first document that dispersion in MRPK occurs across plants within rather than between firms and then build a model in which multi-plant firms optimally allocate resources across plants that face idiosyncratic productivity shocks and non-convex adjustment costs of investment. Based on this framework, they show that dispersion one-quarter of the total variance of revenue products reflects good dispersion in the sense that eliminating frictions increases productivity dispersion and raises overall output. David and Venkateswaran (2019) disentangle sources of the dispersion in the ratio of value-added to capital into technological and informational frictions and various firm-specific factors. They find that adjustment costs and uncertainty explain only a modest fraction of the dispersion in Chinese manufacturing firms while adjustment costs account the dispersion more for large U.S. firms In addition to uncertainty, capital market frictions such as external finance constraints have been investigated as a source of capital misallocation by many researchers (e.g., Banerjee and Moll, 2010; Midrigan and Xu, 2014; Moll, 2014). They are also related with this study to the extent that financial constraints work as adjustment costs of capital. However, none of them focus on the roles of product differentiation.

Thus, we contribute to the extant literature by taking product differentiation into account when we estimate the effect of uncertainty on the dispersion in MRPK. In addition, we estimate the effects of uncertainty on aggregate TFP as well as the dispersion in MRPK.

3. Theoretical Framework

In this section, we posit a simple dynamic investment model to consider how the degree of product differentiation affects the relationship between the TFPR volatility and MRPK dispersion. The model builds on Dixit and Pindyck (1994), Caballero and Pindyck (1996), Cooper and Haltiwanger

[3] 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. Osotimehin (2019) and Hosono and Takizawa (2021) extend the Hsieh-Klenow (2009)'s approach to a dynamic setting. Baqaee and Farhi (2019) extend the formula of Hsieh and Klenow (2009) to arbitrary input-output network linkages, numbers of factors, microeconomic elasticities of substitution, and distributions of distortion wedges.

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

(2006), Bloom (2009), and Asker et al. (2014) in particular. We first describe a model environment and proceed to a simplified model that incorporates only time-to-build to analytically solve the model. Then we proceed to a more general model that introduces asymmetric adjustment costs between a positive and negative investment as well as time-to-build. This is an important extension of Asker et al. (2014) because preceding studies point out a significant role of asymmetric adjustment costs in generating a negative uncertainty-investment relationship (Caballero, 1991). We numerically solve the model that incorporates adjustment costs and simulate it to obtain a testable hypothesis on the role of product differentiation in the relationship between the TFPR volatility and the MRPK dispersion.

3.1 Environment

There are a unit mass of intermediate good producers i and a final good producer. The final good producer combines differentiated product Q_{it} to produce output Q_t using a constant elasticity of substitution (CES) production technology:

$$Q_t = \left(\int (B_{it}Q_{it})^{\frac{\varepsilon-1}{\varepsilon}} di\right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{1}$$

where B_{it} denotes a quality of the differentiated product i at time *t*. Eq. (1) leads to the demand curve for differentiated good *i* as

$$Q_{it} = B_{it}^{\varepsilon-1} P_{it}^{-\varepsilon}. \tag{2}$$

We standardize $P_t^{\varepsilon} Q_t = 1$, where $P_t = (\int (P_{it}/B_{it})^{1-\varepsilon} di)^{\frac{1}{1-\varepsilon}}$. Demand elasticity ε serves as the inverse degree of product differentiation and the implied markup, $\varepsilon/(\varepsilon-1)$, as the degree of differentiation. Differentiated-good producer *i*, which we call a plant hereafter, at time *t*, produces output Q_{it} using the following constant-returns-to-scale technology:

$$Q_{it} = A_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} M_{it}^{\alpha_M}, \tag{3}$$

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 $\alpha_K + \alpha_L + \alpha_M = 1$. Combining (2) and (3), we obtain sales as

$$S_{it} = \Omega_{it} K_{it}^{\beta_K} L_{it}^{\beta_L} M_{it}^{\beta_M}, \tag{4}$$

where $\Omega_{it} = (A_{it}B_{it})^{1-\frac{1}{\varepsilon}}$ is revenue productivity and $\beta_X = \alpha_X\left(1-\frac{1}{\varepsilon}\right)$ for $X \in \{K, L, M\}$.[5] We call $\omega_{it} = \ln(\Omega_{it})$ TFPR. That is,

$$\omega_{it} = \left(1-\frac{1}{\varepsilon}\right)(a_{it} + b_{it}), \tag{5}$$

where lower cases denote logs of the variables. Eq. (5) shows that TFPR shocks depend on the sum of demand and technology shocks and that a larger ε, or less differentiation, magnifies these shocks. The MRPK is defined in logs as

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

It is easy to show that the optimal capital is proportional to $\varepsilon\omega_{it}$ if investment involves with no time-to-build or adjustment costs. In this hypothetical setting, therefore, optimal capital depends more on productivity if the product is less differentiated (i.e., if ε is high). In this hypothetical setting, therefore, given a magnitude of TFPR shock, larger amount of investment, or capital reallocation, is required to achieve the optimal level when the product is less differentiated.

Now we proceed to a dynamic aspect of the model. We assume that plants can hire labor for a wage P_L and acquire materials at a price P_M without incurring any adjustment costs in each period. This leads to a period profit of

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

where $\lambda = (\beta_K + 1/\varepsilon)(\beta_L/P_L)^{\frac{\beta_L}{\beta_K+1/\varepsilon}}(\beta_M/P_M)^{\frac{\beta_M}{\beta_K+1/\varepsilon}}$. Capital evolves as

$$K_{it+1} = \delta K_{it} + I_{it}, \tag{8}$$

where δ is one minus the depreciation rate and I_{it} is investment. Eq. (8) incorporates our

[5] Our definition of TFPR, Ω_{it}, is the same as Asker et al. (2014), but different from Hsieh and Klenow (2009)'s. Hsieh and Klenow define TFPR as $TFPR_{HKi} = P_i A_i = S_i/\left(K_i^{\alpha_K} L_i^{\alpha_L} M_i^{\alpha_M}\right)$ if materials are included as a production factor. The two definitions are related with each other as $TFPR_{HKi} = \Omega_i\left(K_i^{\alpha_K} L_i^{\alpha_L} M_i^{\alpha_M}\right)^{-\frac{1}{\varepsilon_s}}$. We choose our definition because Ω_{it} is composed of demand and technology shocks and hence can be safely regarded as exogenous shocks. The TFPR based on the Hsieh and Klenow's definition should be used to compute aggregate TFP. Using the terminology of Foster et al. (2017), Ω_{it} is the regression-residual based TFPR while $TFPR_{HKi}$ is the cost-share based TFPR.

assumption of one-period time to build.

We specify the TFPR shock process as the AR(1) process:

$$\omega_{it} = \mu + \rho\omega_{it-1} + \sigma\kappa_{it}, \tag{9}$$

where κ_{it} is an i.i.d. random variable, and $|\rho| < 1$. Note that we assume that the volatility of TFPR shock is independent of ε despite Eq. (5) in order to compare the dispersion in MRPK across different ε's controlling for the dispersion in TFPR shock.

As is the case with the model of Asker et al. (2014), this model generates no entry or exit because any plant 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 deviation of TFPR is

$$\mathrm{SD}(\omega_{it}) = \frac{\sigma}{\sqrt{1-\rho^2}}. \tag{10}$$

3.2 Time-to-build Model

To analytically solve the model, we first consider only time-to-build and assume no adjustment costs of investment. In this simplified model, the plant's problem can be written as the following two-period problem,

$$\max_{K_i} \mathrm{E}(\pi(\Omega_i, K_i)|\Omega_{-1i}) - P_K K_i\,, \tag{11}$$

where P_K denotes the rental cost of capital and $\pi(\Omega_i, K_i)$ is defined by Eq. (7). We omit time subscript $t+1$ for brevity and $\Omega_{-1i} = \Omega_{it}$. Appendix shows that aggregating the output and inputs across plants yields aggregate productivity. Comparing the aggregate productivity with and without time-to-build yields

$$TFPratio = \frac{A}{A^*} = \frac{\left(\int u_i^{\frac{1}{1-\left(1-\frac{1}{\varepsilon}\right)(1-\alpha_K)}} di\right)^{\frac{\varepsilon}{\varepsilon-1}-(1-\alpha_K)}}{\left(\int u_i^{\varepsilon} di\right)^{\frac{1}{\varepsilon-1}}}, \tag{12}$$

where A and A^* respectively denote the aggregate TFPs with and without time-to-build, and $u_i = e^{\mu+\sigma\kappa_i}$. Suppose further that the shock is log-normally distributed with $\mathrm{V}(\ln u_i) = \sigma^2$. Then,

$$\mathrm{SD}(MRPK_i) = \left(\frac{\sigma}{1 - \left(1 - \frac{1}{\varepsilon}\right)(1 - \alpha_K)} \right) \tag{13}$$

$$\ln TFPratio = -\frac{\varepsilon\alpha_K}{1 - \left(1 - \frac{1}{\varepsilon}\right)(1 - \alpha_K)}\sigma^2. \tag{14}$$

Eqs. (13) and (14) show that the inability to adjust capital instantaneously increases the dispersion in MRPK and lowers aggregate TFP even though plants dynamically optimize capital. In addition, the dispersion in MRPK and aggregate TFP relative to the no-time-to-build case is lower when the volatility of TFPR shock is higher and even more so when the product is less differentiated (i.e., for higher ε).[6] As we will show in Section 3.3, these implications carry over to the more general cases where we account for adjustment costs.

3.3 Time-to-build and Adjustment Costs Model

Now we 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 expressed as

$$\begin{aligned} C(I_{it}, K_{it}, \Omega_{it}) = I_{it} &+ C_K^{F+} 1_{\{I_{it}>0\}} \pi(\Omega_{it}, K_{it}) + C_K^{F-} 1_{\{I_{it}<0\}} \pi(\Omega_{it}, K_{it}) \\ &+ C_K^{Q+} 1_{\{I_{it}>0\}} K_{it} \left(\frac{I_{it}}{K_{it}}\right)^2 + C_K^{Q-} 1_{\{I_{it}<0\}} K_{it} \left(\frac{I_{it}}{K_{it}}\right)^2. \end{aligned} \tag{15}$$

C_K^{F+} and C_K^{F-} denote the disruption costs for positive and negative investment, respectively. C_K^{Q+} and C_K^{Q-} denote the convex adjustment costs for positive and negative investment, respectively. Defining the transition of TFPR Ω_{it} as $\phi(\Omega_{it+1} \mid \Omega_{it})$, we express the plant's value function in recursive form as

$$V(\Omega_{it}, K_{it}) = \max \pi(\Omega_{it}, K_{it}) - C(I_{it}, K_{it}, \Omega_{it}) + \beta \int V(\Omega_{it}, \delta K_{it} + I_{it}) \phi(\Omega_{it+1} \mid \Omega_{it}) d\Omega_{it+1}. \tag{16}$$

We numerically solve and simulate Eq. (16) to obtain the standard deviation of the log of MRPK, $\mathrm{SD}(MRPK_{it})$, in the stationary state.[7] The simulations aim to see the effects of various values

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[6] If we extend the model to a general equilibrium one, different ε values should result in different real interest rates. However, MRPK would still be equalized across firms without frictions and a larger dispersion in MRPK would result in a larger TFP loss relative to the frictionless economy (Hsieh and Klenow, 2009).

[7] Specifically, we simulate the model for 10,000 firms over 550 periods and discard data from initial 50 periods. Then

of ε on the relation between σ and $\mathrm{SD}(MRPK_{it})$. In the following simulations, we set all parameters except for σ based on the estimation results from Japanese plant-level data. The estimation method we use is described in Section 6.1. For σ, we set arbitrarily from 0.1 to 1.5 although the actual average value of σ is 0.36. Table 1 summarizes our set parameters. We use three alternative sets of adjustment cost parameters. In the asymmetric adjustment cost specification, we assume that $C_K^{F+} = C_K^{Q+} = 0$, while in the symmetric adjustment cost specification, we impose the restriction that $C_K^{F+} = C_K^{F-}$ and $C_K^{Q+} = C_K^{Q-}$. Finally, in no adjustment cost specification, we set all the adjustment cost parameters at zero.

[Insert Table 1 here]

A. Asymmetric adjustment costs

We first simulate the asymmetric adjustment cost model. In Table 2, columns labelled "Asym AC" show $\mathrm{SD}(MRPK_{it})$ for the simulated data from this specification. The first panel of Figure 2A illustrates that for each ε, $\mathrm{SD}(MRPK_{it})$ tends to increase with σ, suggesting that higher TFPR shock volatility results in grater dispersion in MRPK, which is consistent with Asker et al. (2014). Our new finding here is that the slope is steeper as ε is higher, suggesting that the effect of TFPR shock volatility on the dispersion in MRPK is stronger as the product is less differentiated.

[Insert Table 2 here]

To investigate the mechanism that causes such dispersion, we decompose investment into the extensive and intensive margins. Specifically, the second and third panels of Figure 2A show the fraction of the plants that conduct positive and negative investment, respectively, while the lower-right panel of Figure 2A shows the average investment ratio of plants that conduct positive investment. The second panel shows that for each ε, the fraction of the plants that conduct positive investment decreases with σ, suggesting that higher TFPR shock volatility results in a smaller fraction of expanding plants. The negative effect of the volatility on the fraction of expanding plants tends to be smaller as ε is higher, that is, as the product market is less differentiated. The third panel shows that the effects of the volatility on the fraction of shrinking plants is just the opposite to that of expanding plants. The last panel shows that the investment ratio of expanding plants tends to increase as the volatility increases, and this positive effect of volatility on the intensive margin of expanding plants is stronger as the product market is less differentiated. Although not reported to save space, the absolute value of the investment ratio of shrinking plants is relatively small, ranging between 17% and 27%,

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we compute $\mathrm{SD}(MRPK_{it})$ for the pooled $10{,}000 \times 500$ firm-period data. We have confirmed that $\mathrm{SD}(MRPK_{it})$ for 10,000 firms at any particular period t is close to the counterpart from the pooled data.

and do not change significantly as volatility changes. In sum, the extensive margin seems to matter both for the volatility-MRPK dispersion relationship and the role of product differentiation on that relationship.

[Insert Figure 2 here]

Finally, we investigate how the dispersion in MRPK is related to aggregate productivity. To this aim, we compute the aggregate TFP, A_t, using simulated data and compare it with the hypothetical aggregate TFP that would be realized if investment did not involve with time-to-build or adjustment costs. In this hypothetical setting, it is easy to show that aggregate TFP is

$$A_t^* = \left(\int \Omega_{it}^{\varepsilon} di \right)^{\frac{1}{\varepsilon - 1}} \tag{17}$$

Table 3 shows the average ratio of A_t/A_t^*. The higher dispersion in MRPK results in lower aggregate TFP relative to the hypothetical TFP. In addition, as ε is higher, the difference in A_t/A_t^* between low σ and high σ becomes larger.

[Insert Table 3 here]

B. Symmetric adjustment costs

Next, we simulate the symmetric adjustment cost model. In Table 2, columns labelled "Sym AC" show $\mathrm{SD}(MRPK_{it})$ from the simulated data from this specification. Table 2 and the top panel of Figure 2B show that $\mathrm{SD}(MRPK_{it})$ for each ε is similar to the asymmetric adjustment cost case, although $\mathrm{SD}(MRPK_{it})$ is larger and A_t/A_t^* is slightly smaller for the symmetric adjustment costs than for the asymmetric adjustment costs.

The mechanism that causes such dispersion in MRPK, however, is different between asymmetric and symmetric adjustment costs. The second panel of Figure 2B shows that the share of expanding plants tends to increase as the volatility increases. On the other hand, the third panel of Figure 2B shows that the share of shrinking plants is very low. As for the intensive margins, the bottom panel of Figure 2B shows that the relationship between the investment ratio of expanding plants and volatility tends to decrease as the volatility increases, and this negative effect of volatility on the intensive margin of expanding plants is weaker as the product is less differentiated. In sum, the intensive margin seems to matter both for the volatility-MRPK dispersion relationship and the role of product differentiation on that relationship.

C. No adjustment costs

Finally, we simulate the model with no adjustment costs. Note that we still assume the time-to-build: one-period lag between current-period investment and capital that serves production.

Table 2 compares $\mathrm{SD}(MRPK_{it})$ in the case of no adjustment costs to the cases of asymmetric and symmetric adjustment costs. It shows that while $\mathrm{SD}(MRPK_{it})$ of no adjustment costs is slightly smaller than those of asymmetric and symmetric adjustment costs for most of the parameter sets we examine, the differences between the cases of no adjustment costs, symmetric adjustment costs, and symmetric adjustment costs are small. This finding is not surprising given that the estimated parameters of adjustment costs are small. In terms of aggregate TFP relative to the hypothetical TFP, A_t/A_t^*, it is slightly higher in the case of no adjustment costs than in the cases of asymmetric and symmetric adjustment costs.

The third panel of Figure 2C shows that in the case of no adjustment costs, the share of plants that conduct negative investment is much larger than in the cases of asymmetric and symmetric adjustment costs. Combining the second and third panels of Figure 2C indicate that, without adjustment costs but with time to build, the share of inactive plants (i.e., those plants that do not invest or divest) is zero for all of the parameter sets we examine. These results suggest that adjustment costs play a significant role in accounting for the distribution of investment.

In sum, the simulation results suggest that volatility tends to cause greater dispersion in MRPK and that product differentiation causes smaller dispersion in MRPK driven by TFPR volatility. In addition, the dispersion in MRPK results in lower aggregate TFP relative to the hypothetical TFP that would be realized without time-to-build or adjustment costs. Finally, the specification of adjustment costs matters for the intensive and extensive margins of investment. We examine whether these simulation results are supported empirically by data from Japanese manufacturing plants below.[8]

4. Data and Variables

4.1 Data

Our main data source is the Census of Manufacture conducted by the Ministry of Economy, Trade, and Industry (METI) and the Economic Census for Business Activity conducted by the METI and the Ministry of Internal Affairs and Communications (MIC) in Japan. The main purpose of the annual surveys 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 30 employees or more (Kou Hyou), and the other is for plants with less than 30 employees (Otsu Hyou). We construct the panel dataset

[8] We use plants and establishments interchangeably throughout this paper.

from 1986 to 2013 using the Kou Hyou because the Otsu Hyou does not include some pieces of information, including fixed asset.

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 $\alpha_{s't}$ for each data point corresponding to K_{it}. We calculate the book-to-market value ratio for each industry $\alpha_{s't}$ by using the data for real capital stock ($K_{s't}^{JIP}$) and real value added ($Y_{s't}^{JIP}$) at each data point taken from the JIP database as follows:

$$\frac{Y_{s't}^{JIP}}{K_{s't}^{JIP}} = \frac{\sum_{i\in s'} Y_{it}^{\text{Census}}}{\sum_{i\in s'} BVK_{it}^{\text{Census}} * \alpha_{s't}}$$

where $\sum_{i\in s'} Y_{it}^{\text{Census}}$ is the sum of the plants' value added, and $\sum_{i\in s'} BVK_{it}^{\text{Census}}$ is the sum of the nominal book value of tangible fixed assets of industry s' in the Census.[9]

4.2 Variable Measurement

4.2.1 Production Function

We estimate the sales-generating production function (4) 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:

$$\ln Y_{it} = \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_M \ln M_{it} + \eta_i + year_t + \omega_{it} + \varepsilon_{it}, \tag{18}$$

where

$$\omega_{it} = \rho\omega_{it-1} + \xi_{it}, \tag{19}$$

[9] 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 2009 and 2011.

$|\rho| < 1$, and $\varepsilon_{it}, \xi_{it} \sim MA(0)$.

The left hand-side of equation (18) accounts for the natural logarithm of output produced by plant *i* in period *t*. As production inputs, $\ln K_{it}$ denotes the natural logarithm of plant *i*'s capital input at the beginning of period *t* and $\ln L_{it}$ and $\ln M_{it}$ 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 plant-level fixed effect η_i, year fixed effect $year_t$, and the TFPR ω_{it}. We assume that ω_{it} follows the AR(1) process described by equation (10). The disturbance term, ε_{it}, represents measurement error. This model has a dynamic (common factor) presentation

$$\begin{aligned}\ln Y_{it} = \beta_K \ln K_{it} - \rho\beta_K \ln K_{it-1} + \beta_L \ln L_{it} - \rho\beta_L \ln L_{it-1} + \beta_M \ln M_{it} - \rho\beta_M \ln M_{it-1} \\ +\rho \ln Y_{it-1} + (1-\rho)\eta_i + year_t - \rho year_{t-1} + \xi_{it} + \varepsilon_{it} - \rho\varepsilon_{it-1} \qquad (20)\end{aligned}$$

$$\begin{aligned}\ln Y_{it} = \pi_1 \ln K_{it} + \pi_2 \ln K_{it-1} + \pi_3 \ln L_{it} + \pi_4 \ln L_{it-1} + \pi_5 \ln M_{it} + \pi_6 \ln M_{it-1} \\ +\pi_7 \ln Y_{it-1} + \eta_i^* + year_t^* + \omega_{it} \qquad (21)\end{aligned}$$

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 parameters $\pi = (\pi_1, \pi_2, \pi_3, \pi_4, \pi_5, \pi_6, \pi_7)$ and $\mathrm{V}(\pi)$ using the system GMM (Blundell and Bond, 1998). Since $\omega_{it} \sim MA(1)$, we use the following moment conditions:

$$\mathrm{E}(x_{it-s}\Delta\omega_{it}) = 0 \qquad (22)$$

$$\mathrm{E}\big(\Delta x_{it-s}(\eta_i^* + \omega_{it})\big) = 0, \qquad (23)$$

where $x_{it-s} = (\ln K_{it-s}, \ln L_{it-s}, \ln M_{it-s}, \ln Y_{it-s})$ 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 estimate the production function again.

4.2.2 Markup

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

$$Markup1_s = \frac{1}{\hat{\beta}_{Ks} + \hat{\beta}_{Ls} + \hat{\beta}_{Ms}}. \qquad (24)$$

We use this markup measure as a measure of product differentiation. 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

$$\beta_{Ms} = \frac{P_{Ms} M_{it}}{S_{it}}, \tag{25}$$

where P_{Mit} is the price of materials and β_{Ms} is the output elasticity of materials in industry s. Eq. (25) shows that β_{Ms} is equal to the cost share of materials in sales. Combining Eq. (25) and $\beta_{Ms} = (1 - 1/\varepsilon_i)\alpha_{Ms}$, we obtain the markup as

$$\frac{\varepsilon_{it}}{\varepsilon_{it} - 1} = \frac{\alpha_{Ms} S_{it}}{P_{Ms} M_{it}}. \tag{26}$$

In practice, we follow the method of replacing α_{Ms} in Eq. (26) with the estimated value of β_{Ms}, $\hat{\beta}_{Ms}$, and take the median value of the markup among the plants within each industry:

$$Markup2_s = Median\left(\frac{\hat{\beta}_{Ms} S_{it}}{P_{Ms} M_{it}}\right). \tag{27}$$

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

4.2.3 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:

$$Volatility1_{st} = \mathrm{SD}_{st}(\omega_{it} - \omega_{it-1}), \tag{28}$$

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

$$Volatility2_{st} = \mathrm{SD}_{st}(\omega_{it} - \hat{\rho}\omega_{it-1}). \tag{29}$$

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 we calculate the standard deviation of the log of TFPR and hence do not have effects on the volatility measures. Nonetheless, it turns out that these volatility measures seem to be correlated with aggregate uncertainty shocks. Figure 3 depicts $Volatility1_{st}$ averaged over industries for each year and the Japan Policy Uncertainty Index.[10] Both $Volatility1_{st}$ and the Index spike in the late 1990s of the Japanese banking crisis, the 2008 global financial crisis, and the 2011 Tohoku Great Earthquake.

[Insert Figure 3 here]

4.2.4 Dispersion in MRPK

We focus on the standard deviation of $MRPK_{it}$ across plants in industry s in year t: $\mathrm{SD}_{st}(MRPK_{it})$ as a baseline measure of the dispersion in log of MRPK. The result below is robust to whether we use the $\mathrm{SD}_{st}(MRPK_{it})$ or $\mathrm{V}_{st}(MRPK_{it})$.

Table 4 summarizes the descriptive sample statistics of the variables. The standard deviation of $MRPK_{it}$ across plants in all industries is 1.36, which is larger than the U.S. counterpart (0.98) but close to the French, Romanian and Mexican counterparts (1.28, 1.38, and 1.40, respectively) reported in Table 2 of Asker et al. (2014). We also report the sample statistics of the dispersion in the marginal revenue products of labor and materials, $\mathrm{SD}_{st}(MRPL_{it})$ and $\mathrm{SD}_{st}(MRPM_{it})$ to compare with $\mathrm{SD}_{st}(MRPK_{it})$ in Table 4, illustrating that $\mathrm{SD}_{st}(MRPK_{it}) > \mathrm{SD}_{st}(MRPL_{it}) > \mathrm{SD}_{st}(MRPM_{it})$ on average. This evidence supports our approach focusing on the adjustment cost of capital rather than that of labor or materials.[11]

[Insert Table 4 here]

To see the time-series movement of the dispersion in log of MRPK, we depict in Figure 4 the standard deviations of logs of MRPK and the ratio of MRPK to average MRPK in industry for each year. The former shows the overall dispersion in MRPK while the latter shows the dispersion in MRPK within the industry. Figure 4 shows that while the overall MRPK dispersion tends to decrease, the within-industry MRPK dispersion tends to increase over the last three decades.[12]

[Insert Figure 4 here]

[10] This index is constructed by the Economic Policy Uncertainty Project, the Asia and Pacific Division of the International Monetary Fund (IMF), and the Research Institute of Economy, Trade, and Industry (RIETI) and available at http://www.rieti.go.jp/jp/database/policyuncertainty/. See Arbatli et al. (2022) in detail.
[11] Asker et al. (2014) report a similar magnitude of the standard deviation of each input for the U.S. economy (0.81 for capital, 0.63 for labor, and 0.54 for materials) (Table 7, pp. 1036).
[12] The hike in 2011-12 possibly reflect the Tohoku Earthquake on March 11, 2011.

5. Reduced-form Regression

In this section, we first conduct reduced-form regression analyses to examine how the time-series volatility in TFPR affects the cross-sectional dispersion of MRPK depending on the markup. Our working hypothesis is that while greater volatility in TFPR results in a larger dispersion in MRPK, this effect is stronger in industries with lower markups that represent less differentiation. Next, we estimate the plant-level investment. Our working hypothesis is that while greater volatility in TFPR results in lower plant-level investment, this negative effect is stronger in industries with lower markups, although the exact relationship between the markup and the effect of volatility in TFPR on investment may differ between the extensive and intensive margins of investment as we see Figure 2.

5.1 Dispersion in MRPK

To test the above hypotheses about the dispersion in MRPK, we estimate the following baseline specifications:

$$MRPK\ Dispersion_{st} = \beta Volatility_{st} + FE_s + \varphi_{st} \tag{30}$$

$$MRPK\ Dispersion_{st} = \beta_1 Volatility_{st} + \beta_2 Volatility_{st} * Markup_s + FE_s + \varphi_{st}. \tag{31}$$

The unit of observation is industry-year. The dependent variable is the MRPK dispersion measure described above. The independent variables are the volatility measures and their interaction with the markup. If higher volatility results in larger dispersion in MRPK, β should be positive. On the other hand, if product differentiation decreases, that is, if the markup is lower, the impact of volatility on the dispersion in MRPK should be lower, and hence β_2 should be negative. 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 dispersion in MRPK and estimate the following equation using the difference GMM in Arellano and Bond (1991):

$$MRPK\ Dispersion_{st} = \beta_0 MRPK\ Dispersion_{st-1} + \beta_1 Volatility_{st} + FE_s + \varphi_{st} \tag{32}$$

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

Panel A of Figure 5 plots $\mathrm{SD}_{st}(MRPK_{it})$ and $Volatility1_{st}$, indicating that there is a positive correlation between these two, which is consistent with the hypothesis that uncertainty increases the dispersion in MRPK. To illustrate the role of product differentiation in the volatility-MRPK dispersion relationship, Panel B of Figure 5, we divide the industries into two depending on whether the markups are above or below the median, and depict the relationship between $\mathrm{SD}_{st}(MRPK_{it})$ and the percentile of $Volatility1_{st}$. The figure shows that the slope is steeper for the lower-markup industries, suggesting that product differentiation weakens the volatility-MRPK dispersion relationship.

[Insert Figure 5 here]

Table 5 reports the baseline estimation results when we use $\mathrm{SD}_{st}(MRPK_{it})$ as a MRPK dispersion 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 to the specification in Column (2), and find that the interaction term is negative and weakly significant, suggesting that lower markup, i.e., less product differentiation, strengthens the adverse effect of volatility on MRPK dispersion. In Columns (7) to (10), 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. All these results suggest that volatility increases the dispersion in and that product differentiation weakens this volatility-MRPK dispersion relationship.

[Insert Table 5 here]

Next, in Table 6, we change the volatility measure from $Volatility1_{st}$ to $Volatility2_{st}$ in Columns (1)-(3) and the markup measure from $Markup1_{s}$ to $Markup2_{s}$ in Columns (4) and (5). We report only the results for OLS estimation of Eqs. (30) and (31); the results for the GMM of Eq. (32) are virtually the same. Table 6 shows that the baseline results do not qualitatively change.[13]

[Insert Table 6 here]

5.2 Plant-level Investment

[13] 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 the quartile dummies of $Markup1_{st}$ as a markup measure, we again find that the volatility is positive and significant only for the lower markup subsample.

To investigate the mechanism through which product differentiation decreases the effects of the volatility of TFPR on the dispersion in MRPK, 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,

$$1\left(\frac{I_{it}}{K_{it}} > 0.05\right) = \beta_1 MRPK_{it} + \beta_2 Volatility_{st} + \beta_3 MRPK_{it} \times Volatility_{st} + FE_i + FE_t + \varphi_{it}, \quad (33)$$

where I_{it} is gross investment measured by tangible fixed assets acquired, and K_{it} 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 time-to-build or adjustment costs. The dependent variable is a dummy for positive investment. We drop the plant-year observations with negative investment, $I_{it}/K_{it} < 0.05$. We expect that β_1 takes a positive coefficient. On the other hand, we expect β_2 to take either negative or positive coefficients depending on whether the adjustment costs are asymmetric or symmetric, as the second panels of Figures 2A and 2B show. Finally, we expect β_3 to be negative if volatility weakens the plant's response to the change in MRPK. We control for fixed effects in two ways. One is to control for plant and year fixed effects additively, and the other is to control for 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 those of more and less differentiated goods depending on whether $Markup1_s$ is above or below the median.

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

$$1\left(\frac{I_{it}}{K_{it}} < -0.05\right) = \beta_1 MRPK_{it} + \beta_2 Volatility_{st} + \beta_3 MRPK_{it} \times Volatility_{st} + FE_i + FE_t + \varphi_{it}. \quad (34)$$

Figure 6 shows the fraction of establishments with positive, zero, and negative investment over time. While the average fractions of positive and zero investment are 0.56 and 0.41, respectively, the average fraction of negative investment is only 0.03.

[Insert Figure 6 here]

Table 7 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 product differentiation weakens the negative effect of volatility on investment (as in the asymmetric adjustment cost model) 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 industries of less differentiated goods, but not for those of more differentiated goods. This result suggest that volatility weakens the positive response to MRPK only for industries of relatively less differentiated goods. 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 7 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:

$$\frac{I_{it}}{K_{it}} = \beta_1 MRPK_{it} + \beta_2 Volatility_{st} + \beta_3 MRPK_{it} \times Volatility_{st} + FE_i + FE_t + \varphi_{it}. \tag{35}$$

We expect β_1 to be positive. As for β_2, we expect it to be positive or negative depending on the adjustment costs are asymmetric or symmetric as the last panel of Figures 2A and 2B show. Finally, we expect β_3 to be negative if volatility weakens the plant's response to the change in MRPK. In the estimations, we drop the observations with the investment rate is higher than the top 1 percentile.

Table 8 reports the estimation results for the intensive margin. Columns (1)-(6) show the results from the sample of the observations that are included regardless of whether the plant-year conducts positive, zero, or negative investment. They show that β_1 is positive and significant, while β_2 and β_3 are negative and significant only for the industries with smaller markup, suggesting that product differentiation weakens the adverse effect of volatility on the intensive margin of investment sensitivity to MRPK. Columns (7)-(9) show the results from the restricted sample of plant-year observations with positive investment. The results are similar to those in Columns (4)-(6), although estimated β_1 is larger for this restricted sample. The negative β_2 for the industries with smaller markups does not seem to be consistent with the asymmetric or symmetric adjustment cost models.

However, we cannot simply compare the results with the model predictions because threshold level above which the investment ratio is regarded as positive is fixed at the 5% level here while the models predict a higher threshold with the volatility. Columns (10)-(12) show the results from the restricted sample of the observations with negative investment, showing that neither β_1 nor β_3 is significant.

[Insert Table 8 here]

These estimation results show that the volatility in TFPR decreases both the likelihood (i.e., extensive margin) and the extent (i.e., intensive margin) of positive investment, and product differentiation weakens these adverse effects. The negative impact of the volatility in TFPR on the likelihood and extent of positive investment, especially in industries of less differentiated goods, seem to result in a large dispersion in MRPK.

6. Structural analysis

In this section, we aim to quantitatively evaluate the role of product differentiation in transmitting the volatility in TFPR to the dispersion of MRPK and aggregate TFP using the model described in Section 3. To this aim, we first estimate the model parameters and then use the estimated parameters to conduct counterfactual experiments in which the volatility decreases by half.

6.1 Parameters

Assuming for simplicity that industries have common production technology, adjustment technology, and demand elasticity, we use the average estimated values for production function parameters, α_K, α_L, α_M, productivity process parameters, ρ, σ, and demand elasticity, ε, which governs the markup.[14] We set the other parameters except for the adjustment cost parameters, μ, δ, and β at conventional values following, e.g., Asker et al. (2014). Table 1 shows the parameters.

We estimate the adjustment cost parameters, $\theta = \left(C_K^{F+},\ C_K^{Q+},\ C_K^{F-},\ C_K^{Q-}\right)$ using a minimum-distance procedure similar to that in Cooper and Haltiwanger (2006) and Asker et al. (2014). Specifically, we search for θ that distance between the moments predicted by the model and those from the data. The moments we use are the proportion of plant-year observations with the investment ratio falling into each of the 5 intervals: $I_{it}/K_{it} < -0.2 <$, $-0.2 < I_{it}/K_{it} < -0.05$, $-0.05 < I_{it}/K_{it} < 0.05$, $0.05 < I_{it}/K_{it} < 0.2$, and $0.2 < I_{it}/K_{it}$; and the standard deviation of the investment ratio. We simulate the model forward for 550 years for 10,000 firms and discard the first 50 years to obtain the stationary moments from the model, which we denote as $\Psi(\theta)$. As for the actual data, we drop the outliers with the investment ratio either below 1 percentile or above 99 percentiles to compute the moments, which are denoted as $\widehat{\Psi}$. We adopt a criterion function given by the quadratic

[14] These parameters are virtually the same between industries with large markups and those with small markups.

form with weighting matrix W:

$$Q(\theta) = \left(\widehat{\Psi} - \Psi(\theta)\right)' W \left(\widehat{\Psi} - \Psi(\theta)\right). \tag{36}$$

We set $W = I$, the identity matrix because the scales of the moments are similar. In practice, it is computationally too heavy to estimate these four parameters at once. We therefore focus on the two restricted models: the asymmetric adjustment cost (Asym AC) model where the restrictions $C_K^{F+} = C_K^{Q+} = 0$ are imposed, and the symmetric adjustment cost (Sym AC) model where the restrictions $C_K^{F+} = C_K^{F-}$ and $C_K^{Q+} = C_K^{Q-}$ are imposed. The estimated values for each model are reported in Table 1 while the moments from the estimated models and the data are shown in Table 9. Just for comparison, we also report the moments from the simulated data of the no adjustment model (No AC). The No AC models fit the actual data much worse than the Asym AC and Sym AC models, especially in that the fraction of firms with $-0.05 < I_{it}/K_{it} < 0.05$ is much larger in the No AC model than its counterpart of the actual data. The Sym AC model mimics the proportion of the investment ratios falling into the five bins defined above better than the Asym AC model, but the standard deviation of the Sym AC model is much smaller than that of the Asym AC model and the actual data. Overall, the Asym AC model performs better than the Sym AC model in terms of the distance defined by equation (36).

[Insert Table 9 here]

6.2 Counterfactual experiments

To investigate the effects of the volatility in TFPR on the dispersion in MRPK and aggregate TFP, we decrease the volatility σ by half from the value of 0.36 to 0.18 and examine the standard deviation of MRPK and the ratio of aggregate TFP to its hypothetical level that would be reached without time-to-build or adjustment costs, A/A^*. We conduct this experiment for different markups to quantitatively investigate to what extent the volatility in TFPR affects industry-level TFP depending on the degree of product differentiation. Specifically, we choose $\varepsilon = 2.45, 3.40, 8.18$ so that the markup is equal to the average of the industries with their markups above the median, 1.69, the average of all industries, 1.42 and the average of the industries with their markups below the median, 1.14.

Table 10 shows the results from these counterfactual experiments from the asymmetric and symmetric adjustment cost models. We first confirm that given the volatility in TFPR σ, the aggregate TFP relative to the hypothetical level A/A^* is lower as the degree of product differentiation is lower (i.e., ε is higher). Next, we find that regardless of ε or the adjustment cost specifications, decreasing volatility by half results in a decrease in SD(MRPK) almost by half. However, the effect on the TFP relative to its hypothetical level depends significantly on the degree of competition. For $\varepsilon = 3.40$, which represents the average of all industries, the relative TFP increases by 2.3% for the Asym AC model, while for the less and more competitive industries ($\varepsilon = 2.45$ and 8.18), the relative TFP increases by 1.4% and 5.6%, respectively, for the Asym AC model. The counterparts for the Sym AC model are slightly larger: 2.5% for $\varepsilon = 3.40$, 1.5% for $\varepsilon = 2.45$, and 6.0% for $\varepsilon = 8.18$. These results indicate that industries of less differentiated goods can realize significantly larger TFP gains from less uncertainty as compared to industries of more differentiated goods.

[Insert Table 10 here]

7 . Conclusion

Uncertainty affects investment that involves adjustment costs or time-to-build, resulting in dispersion in MRPK and consequently in aggregate TFP, depending on the degree of product differentiation. Using a simple dynamic model and a large panel dataset of manufacturing plants in Japan, we find that while industries with greater time-series volatility in TFPR have greater cross-sectional dispersion of MRPK, such an impact is stronger for the industries of less differentiated goods. We also obtain supporting evidence that plant-level investment decreases more in response to the volatility in TFPR in the industries of less differentiated goods. Based on the structural estimation result, we find that the effects of the volatility in TFPR on the aggregate TFP are economically sizable and much larger for the industries of less differentiated goods. Given that the volatility in TFPR is associated with the policy uncertainty index, our results suggest that reducing policy uncertainty has heterogeneous impacts on the industry-level TFP depending on the degree of product differentiation.

While this study sheds new lights on the effects of uncertainty on the allocation of capital and aggregate TFP by focusing on the role of product differentiation, some issues are left for future work. First, we have focused on the industry-level difference in the degree of product differentiation. In fact, plants and firms within a narrowly defined industry produce goods with different degree of differentiation. Taking firm-level heterogeneity in the degree of product differentiation is an important path for future work. Second, we have not yet explored the durability of uncertainty-driven dispersion in MRPK. If the major source of such productivity dispersion is time-to-build, then uncertainty-driven dispersion in MRPK may be short-lived. We explore this issue also in future work.

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Appendix. Analytical solution to the simplified model

In this Appendix, we first derive aggregate TFP in the case where time-to-build exists, and then compare it with the aggregate TFP in the case where capital adjusts without time lag. In the presence of time-to-build, plant i's problem (11) leads to the following optimal inputs and output:

$$K_i = \left\{\left(1-\frac{1}{\varepsilon}\right)\left(\frac{\alpha_L}{P_L}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_L}\left(\frac{\alpha_M}{P_M}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_M}\right\}^{\varepsilon}$$
$$*\left\{\left(\frac{\alpha_K}{P_K}\right)\mathrm{E}\left[u_i^{\frac{1}{1-\left(1-\frac{1}{\varepsilon}\right)(\alpha_L+\alpha_M)}}\right]\right\}^{\varepsilon\left[1-\left(1-\frac{1}{\varepsilon}\right)(\alpha_L+\alpha_M)\right]}\Omega_{-1i}^{\rho\varepsilon}$$

$$L_i = \left\{\left(1-\frac{1}{\varepsilon}\right)\left(\frac{\alpha_L}{P_L}\right)^{\left(1-\frac{1}{\varepsilon}\right)(\alpha_L-1)+1}\left(\frac{\alpha_M}{P_M}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_M}\left(\frac{\alpha_K}{P_K}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_K}\right\}^{\varepsilon}$$
$$*\left\{\mathrm{E}\left[u_i^{\frac{1}{1-\left(1-\frac{1}{\varepsilon}\right)(\alpha_L+\alpha_M)}}\right]\right\}^{\varepsilon\left(1-\frac{1}{\varepsilon}\right)\alpha_K} u_i^{\frac{1}{1-\left(1-\frac{1}{\varepsilon}\right)(\alpha_L+\alpha_M)}}\Omega_{-1i}^{\rho\varepsilon}$$

$$M_i = \left\{\left(1-\frac{1}{\varepsilon}\right)\left(\frac{\alpha_L}{P_L}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_L}\left(\frac{\alpha_M}{P_M}\right)^{\left(1-\frac{1}{\varepsilon}\right)(\alpha_M-1)+1}\left(\frac{\alpha_K}{P_K}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_K}\right\}^{\varepsilon}$$
$$*\left\{\mathrm{E}\left[u_i^{\frac{1}{1-\left(1-\frac{1}{\varepsilon}\right)(\alpha_L+\alpha_M)}}\right]\right\}^{\varepsilon\left(1-\frac{1}{\varepsilon}\right)\alpha_K} u_i^{\frac{1}{1-\left(1-\frac{1}{\varepsilon}\right)(\alpha_L+\alpha_M)}}\Omega_{-1i}^{\rho\varepsilon}$$

$$B_iQ_i = \left(1-\frac{1}{\varepsilon}\right)^{\varepsilon}\left(\frac{\alpha_K}{P_K}\right)^{\varepsilon\alpha_K}\left(\frac{\alpha_L}{P_L}\right)^{\varepsilon\alpha_L}\left(\frac{\alpha_M}{P_M}\right)^{\varepsilon\alpha_M}$$
$$*\,u_i^{\frac{\frac{\varepsilon}{\varepsilon-1}}{1-\left(1-\frac{1}{\varepsilon}\right)(\alpha_L+\alpha_M)}}\left\{\mathrm{E}\left[u_i^{\frac{1}{1-\left(1-\frac{1}{\varepsilon}\right)(\alpha_L+\alpha_M)}}\right]\right\}^{\varepsilon\alpha_K}\Omega_{-1i}^{\frac{\rho\varepsilon^2}{\varepsilon-1}}\left(PQ^{\frac{1}{\varepsilon}}\right)^{-\frac{\varepsilon}{\varepsilon-1}},$$

where $u_i = e^{\mu+\sigma\kappa_{it}}$ and time subscript -1 denotes $t-1$.

Aggregating inputs and outputs across plants lead to

$$K = \left\{\left(1-\frac{1}{\varepsilon}\right)\left(\frac{\alpha_L}{P_L}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_L}\left(\frac{\alpha_M}{P_M}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_M}\left(\frac{\alpha_K}{P_K}\right)^{1-\left(1-\frac{1}{\varepsilon}\right)(\alpha_L+\alpha_M)}\right\}^{\varepsilon}\int\Omega_{-1i}^{\rho\varepsilon}di\left\{E\left[u_i^{\frac{1}{1-\left(1-\frac{1}{\varepsilon}\right)(\alpha_L+\alpha_M)}}\right]\right\}^{\varepsilon-(\varepsilon-1)(\alpha_L+\alpha_M)}$$

$$L = \left\{\left(1-\frac{1}{\varepsilon}\right)\left(\frac{\alpha_L}{P_L}\right)^{\left(1-\frac{1}{\varepsilon}\right)(\alpha_L-1)+1}\left(\frac{\alpha_M}{P_M}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_M}\left(\frac{\alpha_K}{P_K}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_K}\right\}^{\varepsilon}\int\Omega_{-1i}^{\rho\varepsilon}di\left\{\mathrm{E}\left[u_i^{\frac{1}{1-\left(1-\frac{1}{\varepsilon}\right)(\alpha_L+\alpha_M)}}\right]\right\}^{\varepsilon-(\varepsilon-1)(\alpha_L+\alpha_M)}$$

$$M=\left\{\left(1-\frac{1}{\varepsilon}\right)\left(\frac{\alpha_L}{P_L}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_L}\left(\frac{\alpha_M}{P_M}\right)^{\left(1-\frac{1}{\varepsilon}\right)(\alpha_M-1)+1}\left(\frac{\alpha_K}{P_K}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_K}\right\}^{\varepsilon}\int \Omega_{-1i}^{\rho\varepsilon}di\left\{\mathrm{E}\left[u_i^{\frac{1}{1-\left(1-\frac{1}{\varepsilon}\right)(\alpha_L+\alpha_M)}}\right]\right\}^{\varepsilon-(\varepsilon-1)(\alpha_L+\alpha_M)}$$

$$Q=\left(1-\frac{1}{\varepsilon}\right)^{\varepsilon}\left(\frac{\alpha_K}{P_K}\right)^{\varepsilon\alpha_K}\left(\frac{\alpha_L}{P_L}\right)^{\varepsilon\alpha_L}\left(\frac{\alpha_M}{P_M}\right)^{\varepsilon\alpha_M}\left\{\mathrm{E}\left[u_i^{\frac{\varepsilon}{\varepsilon-(\epsilon-1)(\alpha_L+\alpha_M)}}\right]\right\}^{\frac{\epsilon}{\epsilon-1}[\epsilon-(\epsilon-1)(\alpha_L+\alpha_M)]}\left\{\int \Omega_{-1i}^{\rho\epsilon}di\right\}^{\frac{\epsilon}{\epsilon-1}}.$$

Substituting these aggregate inputs and output to the definition of aggregate TFP, $A=Q/(K^{\alpha_K}L^{\alpha_L}M^{\alpha_M})$ yields

$$A=\left\{\int \Omega_{-1i}^{\rho\varepsilon}di\right\}^{\frac{1}{\varepsilon-1}}\left\{\mathrm{E}\left[u_i^{\frac{1}{1-\left(1-\frac{1}{\varepsilon}\right)(\alpha_L+\alpha_M)}}\right]\right\}^{\frac{\varepsilon}{\varepsilon-1}\left[1-\left(1-\frac{1}{\varepsilon}\right)(\alpha_L+\alpha_M)\right]}.$$

Next, we turn to the case where there exists no time-to-build. In this case, the optimal inputs and output are as follows.

$$K_i^*=\left\{\left(1-\frac{1}{\varepsilon}\right)\left(\frac{\alpha_K}{P_K}\right)^{1-\left(1-\frac{1}{\varepsilon}\right)(\alpha_L+\alpha_M)}\left(\frac{\alpha_L}{P_L}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_L}\left(\frac{\alpha_M}{P_M}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_M}\right\}^{\varepsilon}\left(u_i\Omega_{-1i}^{\rho}\right)^{\varepsilon}$$

$$L_i^*=\left\{\left(1-\frac{1}{\varepsilon}\right)\left(\frac{\alpha_L}{P_L}\right)^{\left(1-\frac{1}{\varepsilon}\right)(\alpha_L-1)+1}\left(\frac{\alpha_M}{P_M}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_M}\left(\frac{\alpha_K}{P_K}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_K}\right\}^{\varepsilon}\left(u_i\Omega_{-1i}^{\rho}\right)^{\varepsilon}$$

$$M_i^*=\left\{\left(1-\frac{1}{\varepsilon}\right)\left(\frac{\alpha_L}{P_L}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_L}\left(\frac{\alpha_M}{P_M}\right)^{\left(1-\frac{1}{\varepsilon}\right)(\alpha_M-1)+1}\left(\frac{\alpha_K}{P_K}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_K}\right\}^{\varepsilon}\left(u_i\Omega_{-1i}^{\rho}\right)^{\varepsilon}.$$

Aggregating these inputs across plants yields

$$K^*=\left\{\left(1-\frac{1}{\varepsilon}\right)\left(\frac{\alpha_K}{P_K}\right)^{1-\left(1-\frac{1}{\varepsilon}\right)(\alpha_L+\alpha_M)}\left(\frac{\alpha_L}{P_L}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_L}\left(\frac{\alpha_M}{P_M}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_M}\right\}^{\varepsilon}\int \Omega_{-1i}^{\rho\varepsilon}di\int (u_i)^{\varepsilon}\,di$$

$$L^*=\left\{\left(1-\frac{1}{\varepsilon}\right)\left(\frac{\alpha_L}{P_L}\right)^{\left(1-\frac{1}{\varepsilon}\right)(\alpha_L-1)+1}\left(\frac{\alpha_M}{P_M}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_M}\left(\frac{\alpha_K}{P_K}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_K}\right\}^{\varepsilon}\int \Omega_{-1i}^{\rho\varepsilon}di\int (u_i)^{\varepsilon}\,di$$

$$M^*=\left\{\left(1-\frac{1}{\varepsilon}\right)\left(\frac{\alpha_L}{P_L}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_L}\left(\frac{\alpha_M}{P_M}\right)^{\left(1-\frac{1}{\varepsilon}\right)(\alpha_M-1)+1}\left(\frac{\alpha_K}{P_K}\right)^{\left(1-\frac{1}{\varepsilon}\right)\alpha_K}\right\}^{\varepsilon}\int \Omega_{-1i}^{\rho\varepsilon}di\int (u_i)^{\varepsilon}\,di.$$

Aggregate output must satisfy (1). Substituting plant-level optimal inputs into (1) yields

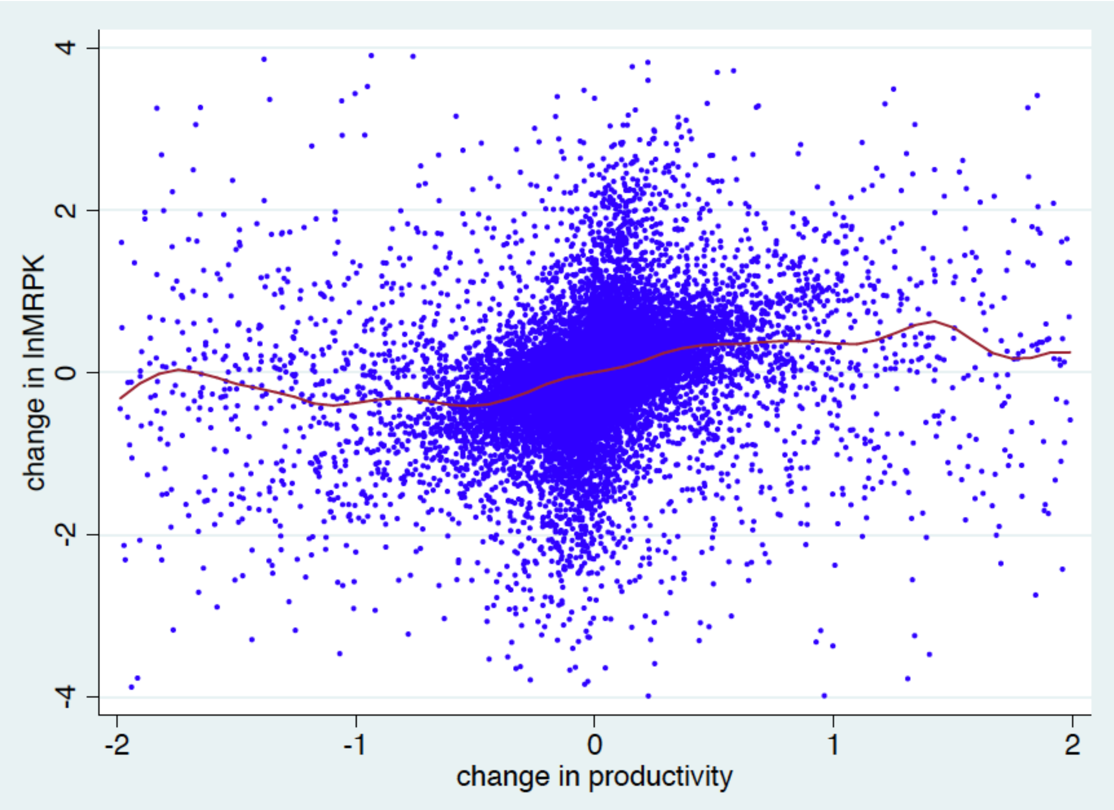
$$Q^*=\left(1-\frac{1}{\varepsilon}\right)^{\varepsilon}\left\{\left(\frac{\alpha_K}{P_K}\right)^{\alpha_K}\left(\frac{\alpha_L}{P_L}\right)^{\alpha_L}\left(\frac{\alpha_M}{P_M}\right)^{\alpha_M}\right\}^{\varepsilon}\left\{\int \Omega_{-1i}^{\rho\varepsilon}di\right\}^{\frac{\varepsilon}{\varepsilon-1}}\left\{\int (u_i)^{\varepsilon}\,di\right\}^{\frac{\varepsilon}{\varepsilon-1}}$$

Aggregate TFP without time-to-build is

$$A^{*}=\left\{\int \Omega_{-1i}^{\rho\varepsilon} di\right\}^{\frac{1}{\varepsilon-1}}\left\{\int (u_i)^{\varepsilon}\, di\right\}^{\frac{1}{\varepsilon-1}}$$

Comparing A and A^{*} leads to Eq. (12) in the main text.

Figure 1. Establishment-level changes in TFPR and MRPK



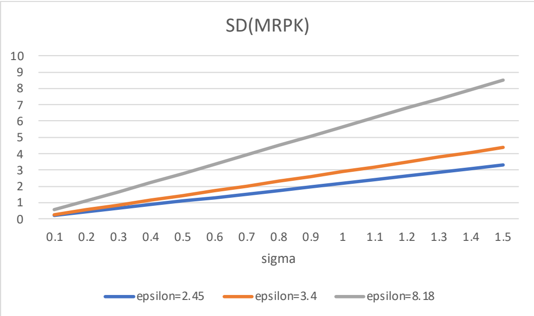
Notes: Each dot represents the manufacturing establishment in Japan. The figure shows the changes in TFPR and MRPK over the period from 2012 to 2013.

Source: Authors' calculations, based on the Census of Manufacture (METI) and the Economic Census for Business Activity (METI and MIC).

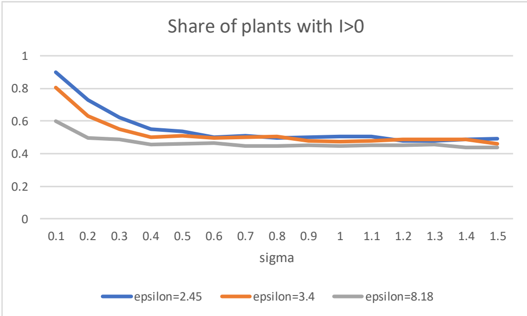
Figure 2. Simulation Results

A. Asymmetric adjustment costs

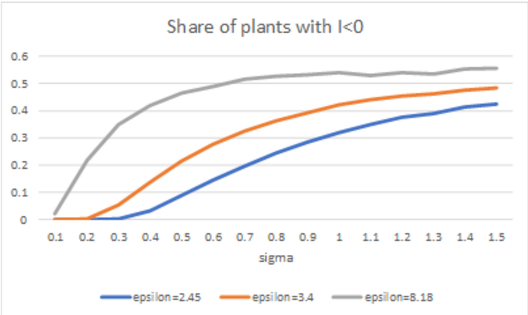
SD($MRPK_{it}$)



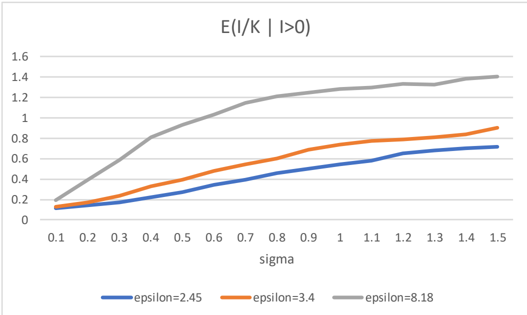
Share of plants with $I_{it} > 0$



Share of plants with $I_{it} < 0$

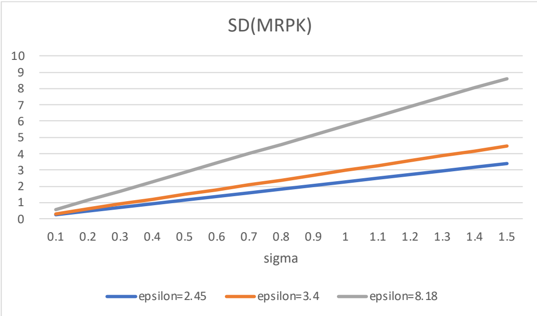


Average I_{it}/K_{it} for plants with $I_{it} > 0$

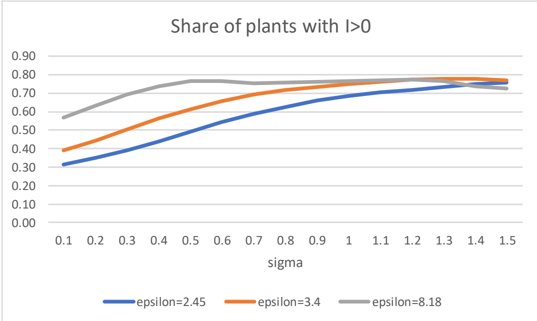


B. Symmetric adjustment costs

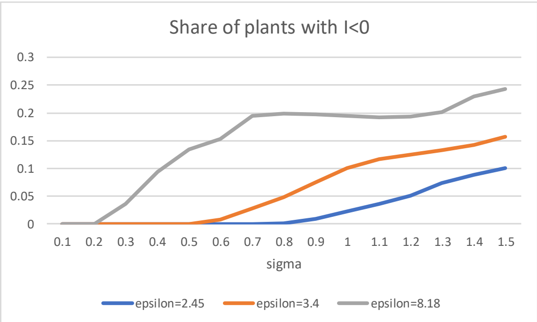
$\mathrm{SD}(MRPK_{it})$



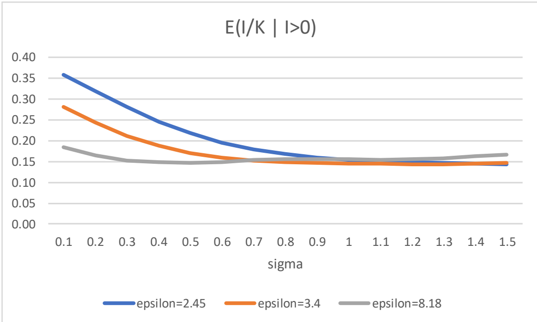
Share of plants with $I_{it} > 0$



Share of plants with $I_{it} < 0$

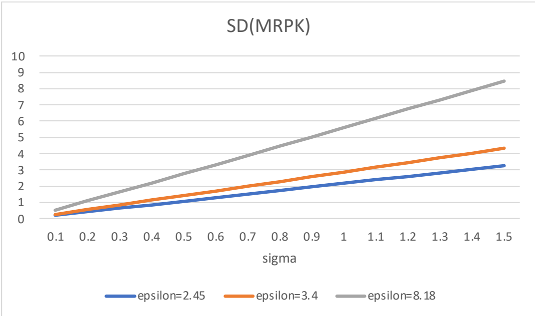


Average I_{it}/K_{it} for plants with $I_{it} > 0$

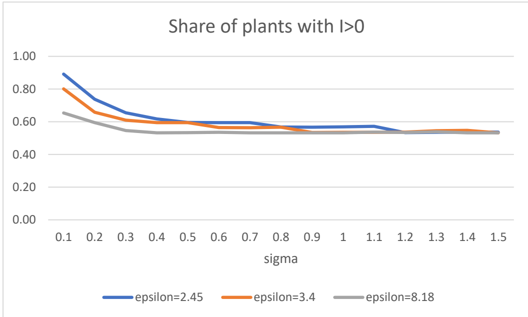


C. No adjustment costs with time to build

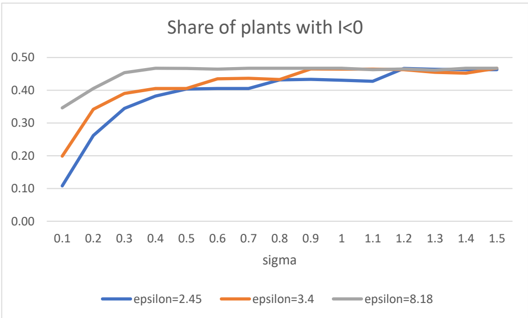
SD($MRPK_{it}$)



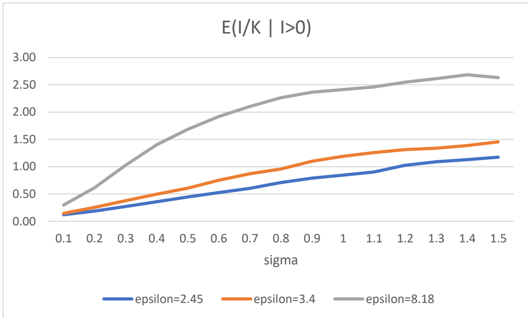
Share of plants with $I_{it} > 0$



Share of plants with $I_{it} < 0$

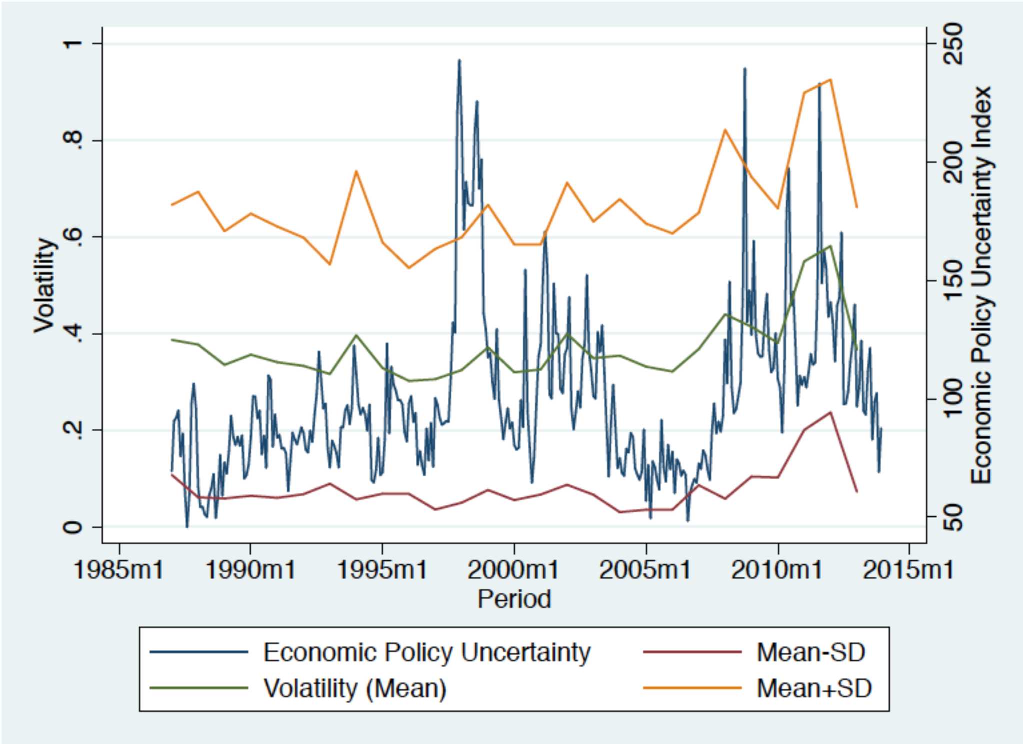


Average I_{it}/K_{it} for plants with $I_{it} > 0$



Source: Authors' calculations.

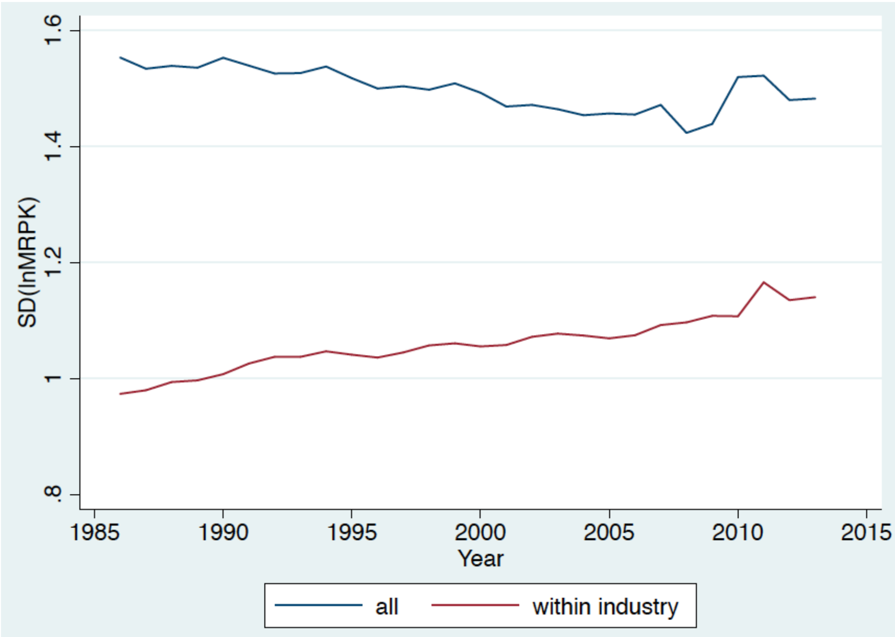
Figure 3. Average $Volatility1_{st}$ and Economic Policy Uncertainty Index



Note: Volatility measure is $Volatility1_{st} = \mathrm{SD}_{st}(\omega_{it} - \omega_{it-1})$.

Source: Authors' calculations, based on the Census of Manufacture (METI), the Economic Census for Business Activity (METI and MIC), and Arbatli et al. (2022).

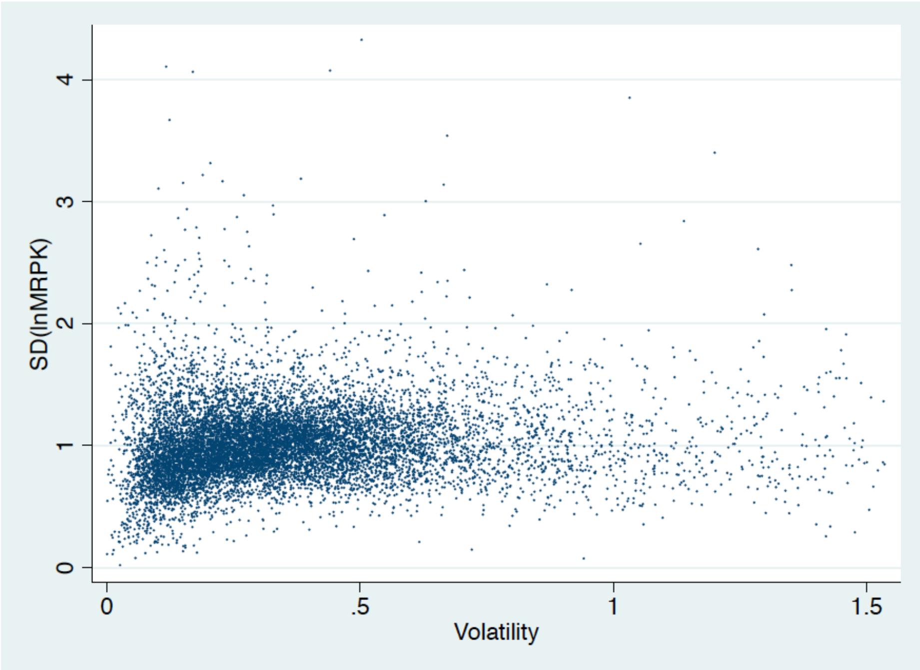
Figure 4. Dispersion in MRPK



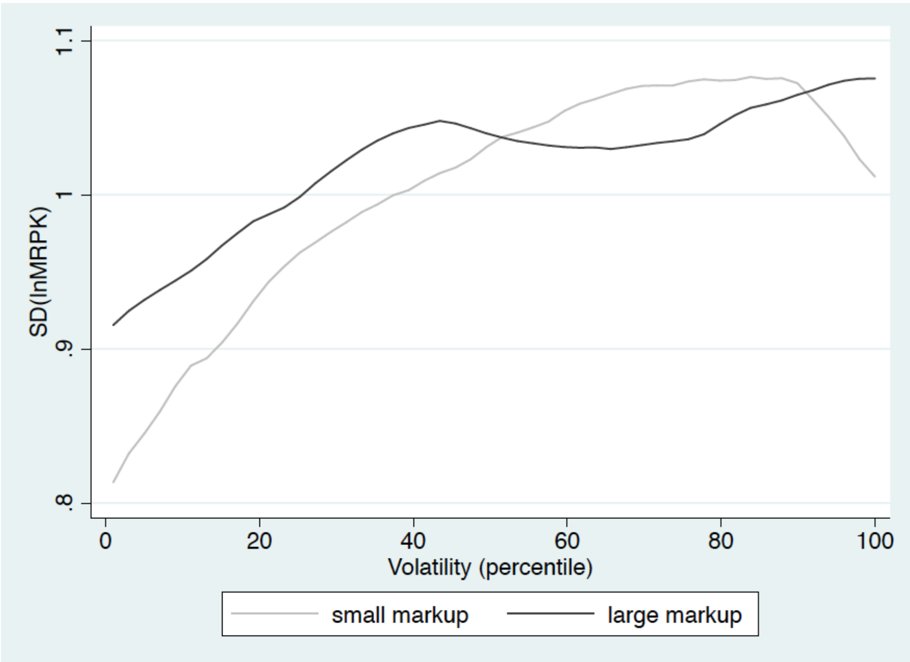
Source: Authors' calculations, based on the Census of Manufacture (METI) and the Economic Census for Business Activity (METI and MIC).

Figure 5. Volatility and Dispersion in MRPK

A. All industries



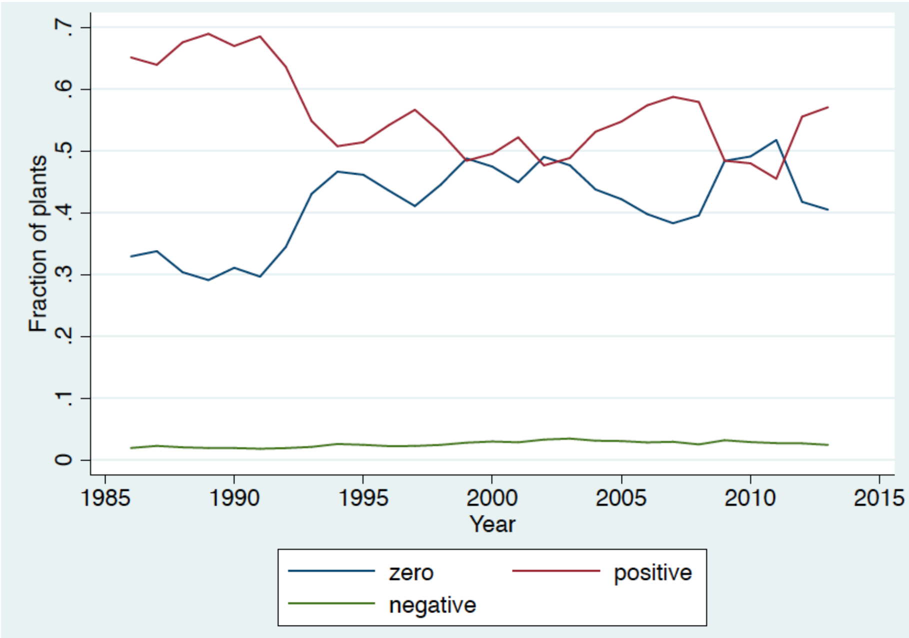
B. Divided by markups



Note: Volatility measure is $Volatility1_{st} = \mathrm{SD}_{st}(\omega_{it} - \omega_{it-1})$.

Source: Authors' calculations, based on the Census of Manufacture (METI) and the Economic Census for Business Activity (METI and MIC).

Figure 6. Fraction of establishments with positive, zero, and negative investment.



Notes: Zero investment is defined as the plants of $|I_{it-1}/K_{it-1}| \leq 0.05$. Positive and negative investment are defined accordingly by the same thresholds.

Source: Authors' calculations, based on the Census of Manufacture (METI) and the Economic Census for Business Activity (METI and MIC).

Table 1. Simulation Parameters

A. Parameters

	Value	Source
μ	0.000	
α_K	0.06	Mean of estimates
α_L	0.41	Mean of estimates
α_M	0.53	Mean of estimates
δ	0.900	
β	1/(1+0.065)	
p_L	0.193	Set to make λ=1
p_M	0.193	Set to make λ=1
ρ	0.31	Mean of estimates
σ	0.36	Mean of estimates

B. Adjustment costs

	No AC	Asym. AC	Sym. AC
C^{F+}_K	0	0	0.021
C^{Q+}_K	0	0	0.299
C^{F-}_K	0	0.021	0.021
C^{Q-}_K	0	0.092	0.299

Notes: Adjustment costs in Panel B are parameters are obtained by the minimum distance estimator. Demand elasticity is set as $\varepsilon = 2.45, 3.40, 8.18$. These values are obtained from the average values across the industries with the markup higher and lower than median values, respectively.

Source: Authors' compilations.

Table 2. Simulation Results of dispersion in MRPK

σ	ε = 2.45			ε = 3.40			ε = 8.18		
	No AC	Asym AC	Sym AC	No AC	Asym AC	Sym AC	No AC	Asym AC	Sym AC
0.1	0.22	0.22	0.27	0.29	0.29	0.32	0.55	0.56	0.57
0.2	0.43	0.44	0.49	0.57	0.58	0.62	1.10	1.11	1.15
0.3	0.65	0.66	0.71	0.86	0.87	0.92	1.65	1.67	1.72
0.4	0.87	0.88	0.94	1.14	1.16	1.21	2.21	2.23	2.29
0.5	1.08	1.10	1.16	1.43	1.45	1.50	2.77	2.79	2.86
0.6	1.30	1.32	1.38	1.72	1.73	1.80	3.33	3.36	3.44
0.7	1.52	1.53	1.60	2.01	2.02	2.09	3.89	3.93	4.01
0.8	1.74	1.75	1.83	2.30	2.32	2.39	4.46	4.50	4.59
0.9	1.96	1.97	2.05	2.59	2.61	2.68	5.03	5.07	5.16
1.0	2.18	2.19	2.27	2.88	2.90	2.98	5.60	5.64	5.74
1.1	2.39	2.42	2.50	3.17	3.20	3.28	6.17	6.22	6.31
1.2	2.62	2.64	2.72	3.46	3.49	3.58	6.74	6.79	6.89
1.3	2.84	2.86	2.94	3.75	3.79	3.87	7.31	7.36	7.46
1.4	3.06	3.08	3.17	4.05	4.08	4.17	7.88	7.94	8.04
1.5	3.28	3.31	3.39	4.34	4.38	4.47	8.46	8.51	8.61

Notes: This table shows the simulation results. The values represent the dispersion in MRPK, $\mathrm{SD}(MRPK_{it})$. Columns of "No AC", "Asym AC", and "Sym AC" show the results with no adjustment costs, asymmetric adjustment costs, and symmetric adjustment costs, respectively.

Source: Authors calculations, based on the parameters in Table 1.

Table 3. Simulation Results in TFP

σ	ε = 2.45			ε = 3.40			ε = 8.18		
	No AC	Asym AC	Sym AC	No AC	Asym AC	Sym AC	No AC	Asym AC	Sym AC
0.1	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99
0.2	0.99	0.99	0.99	0.99	0.99	0.99	0.96	0.96	0.96
0.3	0.99	0.99	0.98	0.98	0.98	0.97	0.93	0.93	0.92
0.4	0.98	0.98	0.97	0.96	0.96	0.96	0.91	0.91	0.90
0.5	0.97	0.97	0.96	0.95	0.95	0.94	0.89	0.89	0.88
0.6	0.96	0.96	0.95	0.94	0.93	0.93	0.88	0.87	0.87
0.7	0.95	0.95	0.94	0.92	0.92	0.92	0.87	0.86	0.86
0.8	0.94	0.94	0.93	0.91	0.91	0.90	0.86	0.86	0.85
0.9	0.93	0.93	0.92	0.90	0.90	0.89	0.85	0.85	0.84
1.0	0.92	0.92	0.91	0.89	0.89	0.88	0.85	0.85	0.84
1.1	0.91	0.91	0.90	0.88	0.88	0.88	0.84	0.84	0.83
1.2	0.90	0.90	0.89	0.88	0.88	0.87	0.84	0.84	0.83
1.3	0.90	0.89	0.89	0.87	0.87	0.86	0.84	0.84	0.83
1.4	0.89	0.89	0.88	0.87	0.87	0.86	0.84	0.84	0.83
1.5	0.88	0.88	0.87	0.86	0.86	0.85	0.83	0.83	0.82

Notes: This table shows the simulation results. The values represent the TFP ratio, A/A^{*}. Columns of "No AC", "Asym AC", and "Sym AC" show the results with no adjustment costs, asymmetric adjustment costs, and symmetric adjustment costs, respectively.

Source: Authors calculations, based on the parameters in Table 1.

Table 4. Summary Statistics

Variable	N	mean	sd	min	p5	median	p95	max
Plant level								
TFPR	1,391,981	5.43	1.10	-6.71	3.65	5.34	7.54	14.24
TFPR growth rate	1,243,841	0.00	0.23	-11.66	-0.35	0.00	0.36	9.11
MRPK	1,333,909	-2.66	1.36	-16.53	-5.22	-2.63	-0.26	10.22
MRPK for zero investment	569,506	-2.85	1.43	-16.39	-5.48	-2.84	-0.31	9.65
MRPK for positive investment	787,808	-2.52	1.29	-16.53	-4.99	-2.50	-0.25	10.22
MRPK for negative investment	34,776	-2.67	1.44	-14.39	-5.30	-2.67	-0.06	7.84
MRPL	1,387,850	6.28	0.86	-6.19	4.64	6.33	7.73	12.47
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	140,463
Industry level (time-variant)								
Number of plants	13,503	88	122	1	4	41	368	2,681
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(MRPK)	11,734	1.00	0.26	0.02	0.59	0.98	1.53	4.33
SD(MRPL)	12,985	0.69	0.19	0.00	0.39	0.67	1.07	2.10
SD(MRPM)	13,177	0.53	0.23	0.00	0.21	0.49	1.00	3.46
Fraction of zero investment	13,503	0.41	0.18	0.00	0.13	0.40	0.70	1.00
Fraction of positive investment	13,503	0.57	0.18	0.00	0.26	0.57	0.86	1.00
Fraction of negative investment	13,503	0.02	0.03	0.00	0.00	0.02	0.08	1.00
Industry level (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
Capital elasticity	491	0.04	0.05	-0.39	-0.03	0.04	0.13	0.31
Labor elasticity	491	0.30	0.15	-0.85	0.05	0.31	0.55	1.41
Materials elasticity	491	0.40	0.14	-0.05	0.16	0.40	0.62	1.03

Notes: Mean and SD are calculated from the observations from 1 to 99 percentiles. TFPR, MRPK, MRPL, and MRPM are the values after the natural logarithms are taken. Zero investment is defined as the plants of $|I_{it}/K_{it}| \leq 0.05$. Positive and negative investment are defined accordingly by the same thresholds.

Source: Authors' calculations, based on the Census of Manufacture (METI) and the Economic Census for Business Activity (METI and MIC).

Table 5. Baseline Estimation Results for the Dispersion in MRPK

Dependent variable: SD(MRPK)	(1)	(2)	(3)	(4)	(5)
Method	OLS	OLS	GMM	GMM	GMM
Volatility1	0.148***	0.0760***	0.0231**	0.0241**	0.0286***
	(5.176)	(4.340)	(2.488)	(2.551)	(2.925)
Lag1 SD(MRPK)			0.430***	0.427***	0.453***
			(27.07)	(26.14)	(25.65)
Lag2 SD(MRPK)				0.0585***	0.0582***
				(5.004)	(4.774)
Lag3 SD(MRPK)					0.0292**
					(2.491)
Industry fixed effect	no	yes	yes	yes	yes
Observations	11,207	11,207	10,665	10,239	9,814
Adjusted R-squared	0.013	0.441			
Sample	all	all	all	all	all

Dependent variable: SD(MRPK)	(6)	(7)	(8)	(9)	(10)
Method	OLS	OLS	OLS	GMM	GMM
Volatility1	0.0808***	0.0903***	0.0624***	0.0372***	0.0122
	(4.769)	(3.482)	(2.627)	(2.706)	(0.967)
Volatility1*Markup	-0.00358*				
	(-1.750)				
Lag1 SD(MRPK)				0.375***	0.550***
				(18.51)	(27.81)
Industry fixed effect	yes	yes	yes	yes	yes
Observations	11,207	5,558	5,649	5,276	5,389
Adjusted R-squared	0.441	0.367	0.512		
Sample	all	small markup	large markup	small markup	large markup

Notes: Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In Columns (7) and (9), the sample comprises the industries with the markup lower than median value. In Columns (8) and (10), the sample comprises the industries with the markup higher than median value.

Source: Authors' estimations, based on the Census of Manufacture (METI) and the Economic Census for Business Activity (METI and MIC).

Table 6. Robustness Checks for the Dispersion in MRPK

Dependent variable: SD(MRPK)	(1)	(2)	(3)	(4)	(5)
Method	OLS	OLS	OLS	OLS	OLS
Volatility measure	Volatility2	Volatility2	Volatility2	Volatility1	Volatility1
Markup measure	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)
Industry fixed effect	yes	yes	yes	yes	yes
Observations	11,317	5,626	5,691	5,549	5,658
Adjusted R-squared	0.437	0.373	0.503	0.519	0.365
Sample	all	small markup	large markup	small markup	large markup

Notes: Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In Columns (2) and (4), the sample comprises the industries with the markup lower than median value. In Columns (3) and (5), the sample comprises the industries with the markup higher than median value.

Source: Authors' estimations, based on the Census of Manufacture (METI) and the Economic Census for Business Activity (METI and MIC).

Table 7. Plant-level Estimation for Investment Status

Positive vs zero	(1)	(2)	(3)	(4)	(5)	(6)
MRPK	0.0950***	0.109***	0.102***	0.126***	0.130***	0.127***
	(26.57)	(30.40)	(19.59)	(68.11)	(47.69)	(48.41)
Volatility1	-0.0676***	-0.0839***	-0.0373**			
	(-6.253)	(-7.728)	(-2.670)			
MRPK*Volatility1	-0.0233***	-0.0279***	-0.0119***	-0.00824**	-0.0162***	-0.00335
	(-6.538)	(-7.278)	(-3.039)	(-2.304)	(-2.941)	(-0.713)
Plant fixed effect	yes	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	no	no	no
Industry-year fixed effect	no	no	no	yes	yes	yes
Observations	1,185,147	622,315	558,119	1,185,138	622,307	558,118
Adjusted R-squared	0.274	0.280	0.279	0.289	0.292	0.292
Sample	all	small markup	large markup	all	small markup	large markup

Negative vs zero	(7)	(8)	(9)	(10)	(11)	(12)
MRPK	-0.00695***	-0.00813***	-0.00675***	-0.00814***	-0.0105***	-0.00735***
	(-5.686)	(-4.809)	(-3.514)	(-4.845)	(-4.164)	(-3.206)
Volatility1	0.00274	0.00536	-0.00435			
	(0.366)	(0.508)	(-0.363)			
MRPK*Volatility1	0.000859	0.00350	-0.00217	-0.00350	0.000276	-0.00488
	(0.374)	(1.093)	(-0.601)	(-0.906)	(0.0498)	(-0.865)
Plant fixed effect	yes	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	no	no	no
Industry-year fixed effect	no	no	no	yes	yes	yes
Observations	254,082	126,503	123,288	252,770	125,859	122,610
Adjusted R-squared	0.262	0.269	0.258	0.268	0.273	0.267
Sample	all	small markup	large markup	all	small markup	large markup

Notes: Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In Columns (2), (5), (8) and (11), the sample comprises the plants in the industries with the markup lower than median value. In Columns (3), (6), (9), and (12), the sample comprises the plants in the industries with the markup higher than median value. In addition, the sample is limited for the plants with positive and zero investment in Columns (1)-(6). The sample is limited for the plants with negative and zero investment in Columns (7)-(12).

Source: Authors' estimations, based on the Census of Manufacture (METI) and the Economic Census for Business Activity (METI and MIC).

Table 8. Plant-level Estimation for Investment Ratio

	(1)	(2)	(3)	(4)	(5)	(6)
Sample investment status	all	all	all	all	all	all
MRPK	0.0813***	0.0978***	0.0851***	0.116***	0.126***	0.113***
	(18.01)	(22.01)	(14.63)	(72.08)	(51.29)	(50.98)
Volatility1	-0.0535***	-0.0757***	-0.0156			
	(-5.542)	(-7.149)	(-1.420)			
MRPK*Volatility1	-0.0200***	-0.0267***	-0.00698*	-0.0132***	-0.0248***	-0.00258
	(-6.268)	(-7.823)	(-2.007)	(-4.504)	(-5.451)	(-0.640)
Plant fixed effect	yes	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	no	no	no
Industry-year fixed effect	no	no	no	yes	yes	yes
Observations	1,254,884	660,618	589,640	1,254,884	660,618	589,640
Adjusted R-squared	0.137	0.148	0.142	0.157	0.163	0.158
Sample	all	small markup	large markup	all	small markup	large markup
	(7)	(8)	(9)	(10)	(11)	(12)
Sample investment status	positive	positive	positive	negative	negative	negative
MRPK	0.174***	0.178***	0.177***	-0.00383	-0.000326	0.0197
	(71.35)	(49.85)	(49.49)	(-0.182)	(-0.00924)	(1.332)
MRPK*Volatility1	-0.0205***	-0.0242***	-0.0110	-0.0490	-0.170	0.0561
	(-4.419)	(-3.640)	(-1.568)	(-0.758)	(-1.165)	(1.243)
Plant fixed effect	yes	yes	yes	yes	yes	yes
Industry-year fixed effect	yes	yes	yes	yes	yes	yes
Observations	692,832	372,331	316,035	11,944	6,381	4,845
Adjusted R-squared	0.183	0.187	0.188	0.001	0.000	0.180
Sample	all	small markup	large markup	all	small markup	large markup

Notes: Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In Columns (2), (5), (8) and (11), the sample comprises the plants in the industries with the markup lower than median value. In Columns (3), (6), (9), and (12), the sample comprises the plants in the industries with the markup higher than median value. In addition, the sample is limited for the plants with positive investment in Columns (7), (8), and (9). The sample is limited for the plants with negative investment in Columns (10), (11), and (12).

Source: Authors' estimations, based on the Census of Manufacture (METI) and the Economic Census for Business Activity (METI and MIC).

Table 9. Moments from actual and simulated data

Moments	Actual	No AC	Asym AC	Sym AC
I/K<-0.2	0.01	0.19	0.05	0.00
-0.2<I/K<-0.05	0.02	0.16	0.05	0.00
-0.05<I/K<0.05	0.41	0.12	0.44	0.46
0.05<I/K<0.2	0.30	0.13	0.17	0.30
0.2<I/K	0.26	0.41	0.29	0.24
SD(I/K)	0.30	0.46	0.25	0.11
Squared Difference		0.216	0.025	0.038

Note: "No AC", "Asym AC", and "Sym AC" denote the moments of simulated data from no adjustment cost model, asymmetric adjustment cost model, and symmetric adjustment cost model, respectively.

Source: Authors' calculations, based on the Census of Manufacture (METI) and the Economic Census for Business Activity (METI and MIC).

Table 10. Counterfactual experiments

A. Asymmetric adjustment cost

	ε = 2.45	ε = 3.40	ε = 8.18
σ=0.36			
SD(MRPK)	0.79	1.04	2.01
TFP/Efficient TFP	0.98	0.97	0.91
σ=0.18			
SD(MRPK)	0.39	0.52	1.00
TFP/Efficient TFP	1.00	0.99	0.97
% change			
SD(MRPK)	-50.3%	-49.9%	-50.1%
TFP/Efficient TFP	1.4%	2.3%	5.6%

B. Symmetric adjustment cost

	ε = 2.45	ε = 3.40	ε = 8.18
σ=0.36			
SD(MRPK)	0.85	1.09	2.06
TFP/Efficient TFP	0.98	0.97	0.91
σ=0.18			
SD(MRPK)	0.45	0.56	1.03
TFP/Efficient TFP	0.99	0.99	0.96
% change			
SD(MRPK)	-47.4%	-48.5%	-49.9%
TFP/Efficient TFP	1.5%	2.5%	6.0%

Source: Authors' estimations, based on the Census of Manufacture (METI) and the Economic Census for Business Activity (METI and MIC).