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 uncertainty will affect investment, and hence static misallocation, depending 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 weaker for industries with less severe product market competition. We further find that competition worsens uncertainty-driven misallocation through the misallocation among firms that invested in the previous year (the active margin) rather than among those that did not (the inactive margin). While competition increases the probability of investment, it increases the variability of the optimal level of capital as well, which worsens misallocation. To improve allocative efficiency, reduced uncertainty complements competition policies.

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1. Introduction

Greater uncertainty is likely to reduce firm investments that involve disruption cost or time-to-build, while some evidence shows that uncertainty promotes research and development.¹ Thus, uncertainty could affect the aggregate economy through various channels, including aggregate demand or firm-level productivity. In this paper, we focus on a particular channel of uncertainty: its impact on resource misallocation.

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.

While their results are convincing, they do not consider that the impact of uncertainty on investment, and hence the allocation of capital, may depend on the degree of competition in the product market. Theoretical studies using an options-game posit that uncertainty is less likely to delay investment in a more competitive product market. However, given the variability of revenue-based productivity (TFPR) shocks, the optimal level of capital varies to a larger extent in a more competitive market. 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 resource 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 for the misallocation among firms that invested in the previous year (the active margin) rather than the misallocation among the firms that did not invest in the previous year (the inactive margin). This result suggests that competition worsens uncertainty-driven misallocation by increasing the variability of the optimal level of capital.² Although prior studies show that tougher competition improves allocative efficiency across firms through markup harmonization, our results show that capital misallocation deteriorates in a severely competitive market with high uncertainty. Reductions in uncertainty complement

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¹ See Bloom (2014) for a survey.
² Although firms that invested in the previous year partially shrank the distance from the optimal and actual levels of capital stock, they did so because their capital stock was far from the optimal level.
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 based on real options theory (McDonald and Siegel 1986; Pindyck 1988).\(^3\) 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. On the other hand, some argue that uncertainty has positive effects on investment (Abel 1983; Bar-Ilan and Strange 1996).\(^4\) Empirical evidences are also mixed, but most find negative effects from uncertainty on investment.\(^5\) 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.\(^6\)

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.\(^7\)

Several empirical studies provide support for the theoretical prediction that

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\(^3\) Dixit and Pindyck (1994) is an excellent introduction to real options theory.

\(^4\) Oikawa (2010) provides a model in which firm-level uncertainty raises aggregate productivity growth.

\(^5\) 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).

\(^6\) See Ogawa and Suzuki (2000) and Mizobata (2014) for cases in Japan.

\(^7\) 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.
competition mitigates the negative effects of uncertainty on investment. 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 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. All of these studies focus on investment at the firm or project level without considering the effect on allocative efficiency at the industry level.


A number of studies follow Hsieh and Klenow (2009) to specify the underlying mechanisms of the dispersion of marginal revenue products. ACL is one such study, which investigates the role of productivity shocks and dynamic production factors on the

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8 Porter and Spence (1982) conduct an early case study of preemptive investment in the wet corn milling industry. 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.

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 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.

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10 Da Rocha and Pujolas (2011) also explore the effect of productivity shocks on resource misallocation theoretically.
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:

\[
Q_{it} = A_{it} K_{it}^{\alpha_k} L_{it}^{\alpha_l} M_{it}^{\alpha_M},
\]

where \( A_{it} \) is the (physical) productivity shock, \( K_{it} \) is the capital input, \( L_{it} \) is the labor input, and \( M_{it} \) 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:

\[
Q_{it} = B_{it} P_{it}^{-\varepsilon}.
\]

Demand elasticity \( \varepsilon \) 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

\[
S_{it} = \Omega_{it} K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it}^{\beta_M},
\]

where \( \Omega_{it} \equiv A_{it}^{-\varepsilon} B_{it}^{-1} \) 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,

\[
\omega_{it} = \left(1 - \frac{1}{\varepsilon}\right) a_{it} + \frac{1}{\varepsilon} b_{it},
\]

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

\[
\omega_{it} = s_{it} - \beta_k k_{it} - \beta_l l_{it} - \beta_M m_{it},
\]
The \( MRPK \) measured in logs is

\[
MRPK_u = \log(\beta_K) + s_u - k_u, \tag{6}
\]

We can define the marginal revenue product of labor and materials similarly.

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

\[
\pi(\Omega_u, K_u) = \lambda \Omega_u^{(\beta_K + \varepsilon)} K_u^{\beta_K (\beta_K + \varepsilon)} , \tag{7}
\]

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

Capital evolves as

\[
K_{u+1} = \delta K_u + I_u, \tag{9}
\]

where \( \delta \) is one minus the depreciation rate and \( I_u \) 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

\[
C(I_u, K_u, \Omega_u) = I_u + C^F_u(I_u > 0)\pi_u(\Omega_u, K_u) + C^F_u(I_u < 0)\pi_u(\Omega_u, K_u)
+ C^K_u K_u \left( \frac{I_u}{K_u} \right)^2 l(I_u > 0) + C^K_u K_u \left( \frac{I_u}{K_u} \right)^2 l(I_u < 0) \tag{10}
\]

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 \( a_u = 0 \) 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

\[
b_{u} = \mu b + \rho b_{u-1} + \sigma \kappa_u, \tag{11}
\]

where \( \kappa_u \sim N(0,1) \) is an independent and identically distributed (i.i.d) standard
normal random variable. We see from Eq. (4) that
\[
\omega_a = \frac{1}{\varepsilon} b_{it}. \tag{12}
\]
Eq. (12) shows that a larger \( \varepsilon \) 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
\[
a_{it} = \mu_a + \rho_a a_{i,t-1} + \sigma_a \kappa_{it}. \tag{13}
\]
We see from Eq. (4) that
\[
\omega_a = \left(1 - \frac{1}{\varepsilon}\right) a_{it}. \tag{14}
\]

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 \( \varepsilon \). For this specification, from Eq. (4),
\[
\omega_a = b_{it}. \tag{15}
\]
In either specification, the TFPR shock \( \Omega \) follows an AR (1) process, and we can hence define the transition of \( \Omega \) as \( \phi(\Omega_{it+1}|\Omega_{it}) \).

The firm’s value function is given in recursive form as
\[
V(\Omega_{it}, K_{at}) = \max \pi(\Omega_{at}, K_{at}) - C(I_{at}, K_{at}, \Omega_{at})
+ \beta \int V(\Omega_{at+1}, \delta K_{at} + I_{at}) \phi(\Omega_{at+1}|\Omega_{at}) d\Omega_{at+1} \tag{16}
\]

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

Demand shock model: \( SD(\omega_{it}) = \frac{\sigma_0}{\varepsilon \sqrt{1 - \rho^2}} \tag{17} \)

Productivity shock model: \( SD(\omega_{it}) = (1 - 1/\varepsilon) \frac{\sigma_0}{\sqrt{1 - \rho^2}} \tag{18} \)
TFPR shock model: \[ SD(\omega_b) = \frac{\sigma_b}{\sqrt{1 - \rho^2}}. \] (19)

Eqs. (17)-(19) show that while an increase in \( \epsilon \) 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.\(^1\)

3.3 Simulation Results

We simulate the above dynamic models and calculate the standard deviation of the log of MRPK, denoted by \( SD(MRPK_{it}) \) for simplicity, as a measure of misallocation in the static sense. The simulations aim to see the effects of various values of \( \epsilon \) on the relation between \( \sigma_b \) (or \( \sigma_a \)) 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 \( \lambda = 1.0 \) when \( \epsilon = 4 \) 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 symmetric adjustment costs. Figure 1A shows the \( SD(MRPK_{it}) \) for the simulated data. For each \( \epsilon \), \( SD(MRPK_{it}) \) tends to increase with \( \sigma_b \), suggesting that higher TFPR shock volatility results in worse allocations of capital in the static sense, which is consistent with ACL. Our new finding

\(^{1}\) If we extend the model to a general equilibrium one, different \( \epsilon \) values may result in different real interest rates. However, MRPK would still be equalized across firms without adjustment costs or time to build.
here is that the slope is steeper as \( \varepsilon \) is higher, suggesting that increasing product market competition strengthens the deteriorating effect of TFPR shock volatility on allocation. To see why this is the case, we decompose \( \text{Var}(\text{MRPK}) \) into the following three components:

\[
\text{Var}(\text{MRPK}_t) = p_{t-1} \text{Var}(\text{MRPK}_t|I_{t-1} \neq 0) + (1 - p_{t-1}) \text{Var}(\text{MRPK}_t|I_{t-1} = 0) + p_{t-1}(1 - p_{t-1}) (E(\text{MRPK}_t|I_{t-1} \neq 0) - E(\text{MRPK}_t|I_{t-1} = 0))^2 ,
\]

(20)

where \( p_{t-1} \) denotes the share of firms that invested in the previous period. The term \( \text{Var}(\text{MRPK}_t|I_{t-1} \neq 0) \) is the misallocation among firms that invested in the previous period, and \( \text{Var}(\text{MRPK}_t|I_{t-1} = 0) \) 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 \( \text{Var}(\text{MRPK}) \) 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 1B-1D show the fraction of the active firms, active margin, and inactive margin, respectively. Figure 1B shows that competition has a non-monotonic effect on the share of active firms: competition tends to increase the share of active firms for a range of low volatility, while it tends to decrease the share of active firms for a range of high volatility. Note that in our simulation, virtually all the active firms conduct a positive investment. Figures 1C and 1D show that competition tends to worsen both the active and inactive margins. However, the difference in the variance of MRPK across different values of \( \varepsilon \) is larger for the active margin than for the inactive margin, suggesting that the active margin mainly drives the mechanism through which competition worsens uncertainty-driven misallocation based on our simulation results.

Next, we simulate the TFPR shock model with asymmetric adjustment costs. We do not report the results here to save space, though they are very similar to the TFPR shock model with symmetric adjustment costs. This is natural given that the share of firms that conduct negative investment was virtually zero even for the symmetric adjustment cost model.

Finally, we simulate the demand shock model with symmetric and asymmetric adjustment costs. While a higher \( \varepsilon \) dampens the demand shock volatility and lowers TFPR volatility (Eq. (17)), a higher \( \varepsilon \) strengthens the effect of TFPR shock volatility on
SD(MRPK) (Figure 1A). The simulation results show that the former effect outweighs the latter. That is, a higher $\epsilon$ 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 $\epsilon$ 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. Moreover, our results show that the adverse effects of competition on misallocation driven by TFPR are mainly due to the active margin, that is, the misallocation among investing firms. 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 ($Q_a$) 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 \( M_t \)) for 2000. Third, we use each plant’s total number of workers as labor input \( L_t \).

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

\[
\frac{Y_{IP}^{IND,t}}{K_{IP}^{IND,t}} = \frac{\sum_{i} Y_{Census}^{IND,t,i}}{\sum_{i} BVK_{Census}^{IND,t,i} \times \alpha_{IND,t}}
\]

where \( \sum_{i} Y_{Census}^{IND,t,i} \) is the sum of the plants’ value added (\( i \) is the index of a plant), and \( \sum_{i} BVK_{Census}^{IND,t,i} \) is the sum of the nominal book value of tangible fixed assets of industry \( IND \) in the Census. \(^{12}\)

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:

\[
LN(Y)_{Lt} = \beta_K LN(K)_{Lt} + \beta_L LN(L)_{Lt} + \beta_M LN(M)_{Lt} + \eta_t + \gamma year_t + \omega_{Lt} + \varepsilon_{Lt},
\]

(21)

where

\(^{12}\) 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 \( t+1 \).
\[ \omega_{it} = \rho \omega_{i,t-1} + \xi_{it}, \quad |\rho| < 1 \]  
\[ \varepsilon_{it}, \xi_{it} \sim MA(0). \]

The left hand-side of equation (21) accounts for the natural logarithm of output produced by firm \( i \) in period \( t \). As production inputs, \( LN(K)_{it} \) denotes the natural logarithm of firm \( i \)'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 firm-level fixed effect \( \eta_i \), year fixed effect \( \gamma_{it} \), and the TFPR \( \omega_{it} \). We assume that \( \omega_{it} \) follows the AR(1) process described by equation (11). The disturbance term, \( \varepsilon_{it} \), represents measurement error. This model has a dynamic (common factor) presentation

\[
LN(Y)_{it} = \beta_K LN(K)_{it} - \rho \beta_K LN(K)_{i,t-1} + \beta_L LN(L)_{it} - \rho \beta_L LN(L)_{i,t-1} \\
+ \beta_M LN(M)_{it} - \rho \beta_M LN(M)_{i,t-1} \\
+ \rho LN(Y)_{i,t-1} + \eta_i (1 - \rho) + \gamma_{it} - \rho \gamma_{i,t-1} + \xi_{it} + \varepsilon_{it} \\
- \rho \varepsilon_{i,t-1} 
\]

or

\[
LN(Y)_{it} = \pi_1 LN(K)_{it} + \pi_2 LN(K)_{i,t-1} + \pi_3 LN(L)_{it} + \pi_4 LN(L)_{i,t-1} + \pi_5 LN(M)_{it} \\
+ \pi_6 LN(M)_{i,t-1} + \pi_7 LN(Y)_{i,t-1} + \eta_i^* + \gamma_{it}^* \\
+ \omega_{it} \]

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 \( \pi = (\pi_1, \ldots, \pi_7) \) and \( \text{var}(\pi) \) using the system GMM (Blundell and Bond, 1998). Since \( \omega_{i,t} \sim MA(1) \), we use the following moment conditions:

\[ E(x_{it-s} \Delta \omega_{it}) = 0 \]  
\[ E(\Delta x_{it-s} (\eta_i^* + \omega_{it})) = 0, \]

where \( x_{it} = (LN(K)_{it}, LN(L)_{it}, LN(M)_{it}, LN(Y)_{it}) \) 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 $\beta_X$ and the assumption of constant returns to scale, we can derive the markup as

$$\epsilon = \frac{1}{\beta_K + \beta_L + \beta_M}.$$  

Using the industry-level estimates of $(\beta_K, \beta_L, \beta_M)$, we obtain the industry-level, time-invariant markup:

$$\text{Markup1}_s = \frac{1}{\beta_K + \beta_L + \beta_M}$$  

(27)

We use the quartile dummies of 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 labor. Therefore, the marginal product of labor, in particular, is equal to wage, which leads to

$$\beta_L = \frac{P_L}{S_{it}}$$  

(28)

where $P_L$ is the wage rate and $\beta_L$ is the output elasticity of labor in industry $s$. Eq. (28) shows that $\beta_L$ is equal to the share of the wage bill in sales. Combining Eq. (24) and $\beta_{LS} = \left(1 - \frac{1}{\epsilon_{it}}\right) \alpha_{LS}$, we obtain the mark up as

$$\frac{1}{1 - \frac{1}{\epsilon_{it}}} = \frac{\alpha_{LS}}{P_L S_{it}}$$  

(29)

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

$$\text{Markup2}_{st} = \text{Median} \left( \frac{\beta_{LS}}{\frac{P_{L_{st}}}{S_{it}}} \right)$$  

(30)

We use the quartile dummies of 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, $\omega_y$. The first is the standard deviation of the productivity shocks across
plants within an industry in a given year:

\[ \text{Volatility}^{1st}_{st} = SD_{st}(\omega_{it} - \omega_{it-1}), \]  

where \( s \) denotes the industry of plant \( i \).

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

\[ \text{Volatility}^{2nd}_{st} = SD_{st}(\omega_{it} - \hat{\rho}\omega_{it-1}). \]  

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 \( \text{MRPK}_{it} \) across plants in industry \( s \) in year \( t \): \( SD_{st}(\text{MRPK}_{it}) \) as a baseline measure of static misallocation. The result below is robust to whether we use the \( SD_{st}(\text{MRPK}_{it}) \) or \( Var_{st}(\text{MRPK}_{it}) \).

In decomposing \( Var_{st}(\text{MRPK}_{it}) \), we define active firms as those with \( \left| \frac{l_{it} - 1}{K_{it-1}} \right| > 0.02 \) and inactive firms as those with \( \left| \frac{l_{it} - 1}{K_{it-1}} \right| \leq 0.02 \), where \( l_t \) 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 0.02 rather than 0 because a very small-scaled investment is not likely to involve with adjustment costs. We also use another measure of investment as tangible fixed assets acquired minus those retired.

Table 2 summarizes the descriptive sample statistics of the variables. Figure 2 plots the change in the three components of \( Var_{st}(\text{MRPK}_{it}) \), \( 1,3 \) illustrating that the

---

1,3 In Figure 2, we fix the set of plants over two consecutive years to define the change
change in active margin tended to help improve misallocation more than the change in inactive margin. The average changes in the active and inactive margins are -3.6 and 2.0, respectively. \(^{14}\) Investment tended to help improve capital allocation.

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. \(^{15}\)

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:

\[
\begin{align*}
    Misallocation_{st} &= \beta V\text{olatility}_{st} + FE_s + FE_t + \varphi_{st} \quad (33) \\
    Misallocation_{st} &= \sum_{i=1}^{4} \beta_{qi} V\text{olatility}_{st} \times Markup\_Quartile\_Dummy_{s} + FE_s + FE_t + \varphi_{st} \\
    & \quad (34)
\end{align*}
\]

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 quartile dummies. If higher volatility results in worse static allocation, \(\beta\) should be positive. On the other hand, if market competition (that is, a lower markup) increases the impact of volatility on static

in the active margin as

\[
\Delta Var_{st}(MRPK_{it}) = Var_{st} \left( MRPK_{it} \bigg| \frac{l_{t-1}}{K_{t-1}} - V > 0.02 \right) - Var_{st-1} \left( MRPK_{it-1} \bigg| \frac{l_{t-1}}{K_{t-1}} - V > 0.02 \right).
\]

We define the change in the inactive margin and that in the residual similarly.

\(^{14}\) Both the active and inactive margins show a large negative value in 2011, when the Tohoku Earthquake hit Japan. The average active and inactive margins excluding 2011 are -2.8 and -1.7, respectively.

\(^{15}\) 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).
misallocation, $\beta_{qi}$ should take a positive and larger value for smaller $i$. 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):

$$ Misallocation_{st} = \beta_0 Misallocation_{st-1} + \sum_{i=1}^{4} \beta_{qi} Volatility_{st} \times Markup\_Quartile\_Dummy_s + FE_s + FE_t + \varphi_{st} $$

(35)

In all estimations, the standard errors are clustered at industry level.

5. Results

5.1 Overall Misallocation

Figure 3 plots the relationship between the main static misallocation measure, $SD_{st}(MRPK_{it})$, and $Volatility_{1st}$. The figure shows a positive correlation between the misallocation measure and volatility, consistent with the hypothesis that uncertainty worsens static allocation.

Table 3 reports the baseline estimation results when we use $SD_{st}(MRPK_{it})$ as a misallocation measure, $Volatility_{1st}$ as a volatility measure, and the quartile dummies of $Markup_{1st}$ as a markup measure. Columns (1)-(7) report the OLS estimation results of Eqs. (33) and (34). In Columns (1) and (2), we include only the volatility measure, finding that higher TFPR volatility results in a larger MRPK dispersion. In Column (3), we add the interaction of volatility and the markup quartiles. Only the interaction of volatility and the first quartile of the markup is positive and significant, suggesting that volatility results in misallocation only when the market is competitive. In Columns (4)-(7), we split the sample by quartiles of markup and regress the misallocation measure on the volatility measure for each quartile. They again show that the volatility is positive and significant only for the lowest quartile of the markup. Columns (8)-(11) report the GMM estimation results of Eq. (35), showing that all results from OLS remain essentially unchanged.

[Insert Figure 3 here]

Table 3 reports the baseline estimation results when we use $SD_{st}(MRPK_{it})$ as a misallocation measure, $Volatility_{1st}$ as a volatility measure, and the quartile dummies of $Markup_{1st}$ as a markup measure. Columns (1)-(7) report the OLS estimation results of Eqs. (33) and (34). In Columns (1) and (2), we include only the volatility measure, finding that higher TFPR volatility results in a larger MRPK dispersion. In Column (3), we add the interaction of volatility and the markup quartiles. Only the interaction of volatility and the first quartile of the markup is positive and significant, suggesting that volatility results in misallocation only when the market is competitive. In Columns (4)-(7), we split the sample by quartiles of markup and regress the misallocation measure on the volatility measure for each quartile. They again show that the volatility is positive and significant only for the lowest quartile of the markup. Columns (8)-(11) report the GMM estimation results of Eq. (35), showing that all results from OLS remain essentially unchanged.

[Insert Table 3 here]
Next, in Table 4, we change the volatility measure from Volatility\(_{1st}\) to Volatility\(_{2st}\) in Columns (1)-(8) and the markup measure from Markup\(_{1st}\) to Markup\(_{2st}\) in Columns (9) and (10). We report only the results for OLS estimation of Eqs. (33) and (34); the results for the GMM of Eq. (35) are virtually the same. Table 4 shows that the baseline results do not qualitatively change.\(^6\)

5.2 Active and Inactive Margins

To explore the mechanism through which competition worsens volatility-driven misallocation, we examine the effects of competition on the active and inactive margins of Var\(_{st}(MRPK_{st})\).

Table 5 reports the estimation results of Eqs. (33)-(35), where the dependent variable is the active margin in Columns (2), (5), (7), and (9) and is the inactive margin in Columns (3), (6), (8), and (10). In Columns (1)-(3), we used only Volatility\(_{1st}\) (as well as industry and year fixed effects) as an explanatory variable, while in Columns (4)-(10), we add its interaction with the quartile dummies of Markup\(_{1st}\). Columns (1)-(3) show that the volatility measure takes a positive and significant coefficient only for the active margin. In addition, Columns (4)-(6) show that among the interaction terms of volatility with quartile dummies of markup, only the interaction of volatility and the bottom quartile is positive and significant for the active margin, while none of the interaction terms is significant for the inactive margin. This suggests that competition worsens volatility-driven misallocation through the active margin. In Columns (7) and (8), the GMM estimation of Eq. (35) also shows that only the interaction of volatility and the bottom quartile is positive and significant for the active margin. These results hold when we change the definition of active plants from gross investment to net investment, that is, tangible fixed assets acquired minus those retired. Columns (9) and (10) show that the coefficients of volatility for competitive industries are significantly positive only for the active margin.

---

\(^6\) 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 Volatility\(_{1st}\) as a volatility measure and the quartile dummies of Markup\(_{1st}\) as a markup measure, we again find that the volatility is positive and significant only for the lowest quartile of the markup.
These effects result from the fact that in a more competitive market, the optimal level of capital fluctuates more than in a less competitive market, given the volatility of TFPR.

5.3 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

\[
\log(TFP_s) = \log(TFP^e_s) - \frac{\varepsilon_s}{2} \text{var}(\log(TFPR_{sl})) - \frac{\alpha_{KS}(1 - \alpha_{KS})}{2} \text{var}(\log(1 + \tau_{KS}))
\]

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

\[
\text{var}(\log(TFPR_{sl})) = \alpha_s^2 \text{var}(\log(1 + \tau_{KS})).
\]

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

\[
\log(TFP^e_s) - \log(TFP_s) = \frac{\alpha_{KS}}{2} (1 + \alpha_s (\varepsilon_s - 1)) \text{var}(\log(MRPK_{sl}))
\]

We measure the industry-level TFP losses defined by Eq. (36) and aggregate them using sales share as a weight. We show the results in Table 6.

[Insert Table 6 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 that if we restrict the sample to the most competitive industries, i.e., industries with markup lower than the lowest quantile, the average TFP loss is 9.13%.

Next, Column 3 shows the effect of volatility on the TFP losses, calculated from Table 3 (2). If volatility were zero, the average TFP would increase by 0.10-0.13%. The quantitative impact of volatility is small relative to the overall TFP losses. However, Column 4 shows that if we restrict the sample to the most competitive industries and
calculate the TFP loss from Table 3 (3), the average TFP would rise by about 0.5%, which is not a negligible part of the overall TFP losses.

5.4 Plant-level evidence

To investigate the mechanism through which competition worsens uncertainty-driven misallocation, we run the following linear probability model of whether the plant invests or not by dividing the sample by whether $\text{Markup}_{1, it}$ is above or below its median.

$$1 \left( \frac{\ln K_{it}}{\bar{K}} > 0.02 \right) = \beta_1 \text{MRPK}_{it} + \beta_2 \text{MRPK}_{it} \times \text{Volatility}_{st} + FE_i + FE_t + \varphi_{st}, \quad (36)$$

where the dependent variable is a dummy for an active plant.

Table 7 reports the results from using Volatility$_{1, it}$ as a volatility measure, though using Volatility$_{2, it}$ leave the results essentially unchanged. Columns (1)-(4) show the results for the whole sample. In Columns (1)-(3), we include only $\text{MRPK}_{it}$ as an explanatory variable as well as the plant (or industry) and year fixed effects. The $\text{MRPK}_{it}$ takes a positive and significant coefficient. A higher MRPK indicates less capital relative to its optimal level, triggering investment. In Column (4), we add the interaction of $\text{MRPK}_{it}$ and $\text{Volatility}_{1, it}$. This interaction term is negative, indicating that a higher TFPR volatility dampens the positive effect of MRPK on the plant's investment probability. Columns (5) and (6) show the results from the sample of more competitive (with $\text{Markup}_{1, it}$ below the median) and less competitive (with $\text{Markup}_{1, it}$ above the median) markets, respectively. They show that volatility dampens the positive effect of MRPK on the plant’s investment probability only for the less competitive markets.

[Insert Table 7 here]

These estimation results show that uncertainty delays investment, but a competitive product market dampens these adverse effects. Although TFPR shocks negatively affect capital allocation efficiency in competitive markets, the decision of whether to invest is improved. Although competition increases both the probability of investment and the optimal capital level, because the latter effect is larger than the former, the actual capital deviates more from its optimal level in a more competitive market.

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 although uncertainty results in static misallocation, this impact is stronger for industries with severe product market competition. We further find that competition worsens uncertainty-driven misallocation through the misallocation among the plants that invested in the previous year (the active margin) rather than that among the plants that did not (the inactive margin). On the other hand, competitive markets mitigate the adverse effects of uncertainty on the probability of investment. While competition increases the probability of investment, it increases the variability of the optimal level of capital as well, which worsens misallocation. To improve allocative efficiency, reduced uncertainty complements competition policies.
References


Figure 1. Simulation Results: TFPR shock model with symmetric adjustment cost

A. \( SD(MRPK_t) \)

\[ SD(\log(MRPK)) \]

B. Share of firms with \( I_{t-1} \neq 0 \)

\[ \text{Share of Active Firms} \]
C. \( \text{VAR}(\text{MRPK}_t | I_{t-1} \neq 0) \)

\[
\text{VAR} (\text{MRPK} | \text{LAG_ACTIVE})
\]

\begin{center}
\begin{tabular}{c c c c c c c c c c c c c c c c}
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 \\
0 & 10 & 20 & 30 & 40 & 50 & 60 & 70 & \\
\end{tabular}
\end{center}

\begin{itemize}
\item \( \text{sigma}_b \)
\end{itemize}

\begin{itemize}
\item \text{epsilon}=2
\item \text{epsilon}=4
\item \text{epsilon}=6
\end{itemize}

D. \( \text{VAR}(\text{MRPK}_t | I_{t-1} = 0) \)

\[
\text{VAR} (\text{LOGMRPK} | \text{LAG_INACTIVE})
\]

\begin{center}
\begin{tabular}{c c c c c c c c c c c c c c c c}
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 \\
0 & 10 & 20 & 30 & 40 & 50 & 60 & 70 & \\
\end{tabular}
\end{center}

\begin{itemize}
\item \( \text{sigma}_b \)
\end{itemize}

\begin{itemize}
\item \text{epsilon}=2
\item \text{epsilon}=4
\item \text{epsilon}=6
\end{itemize}
Figure 2. Changes in the Components of Var(MRPK)

Decomposition of Var(MRPK)

Δ active margin  Δ inactive margin  residual
Figure 3. Volatility and Dispersion in MRPK

Note: Volatility measure is $Volatility_t \equiv SD_t (\omega_t - \omega_{t-1})$. 
Table 1. Simulation Parameters

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Table 3. Baseline Estimation Results

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<td>11,131</td>
<td>11,131</td>
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<td>2,793</td>
<td>2,770</td>
<td>2,765</td>
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<td>10,278</td>
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<td>0.064</td>
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<td>10,278</td>
<td>10,278</td>
<td>5,165</td>
<td>5,113</td>
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Robust t-statistics in parentheses

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

31
Table 4. Robustness Checks

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<td>OLS</td>
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<td>0.0996***</td>
<td>0.000910</td>
<td>0.0496</td>
<td>0.0147</td>
<td>0.0566*</td>
<td>0.0113</td>
<td>0.0242***</td>
<td>0.0235*</td>
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<td>0.0239</td>
<td>0.397</td>
<td>0.0153</td>
<td>0.534</td>
<td>0.448***</td>
<td>0.438***</td>
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<td>0.397</td>
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<td>0.397</td>
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<td>Lagged sd(mrpk)</td>
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<td>0.066</td>
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<td>2,803</td>
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<td>2,770</td>
<td>2,765</td>
<td>5,165</td>
<td>5,113</td>
<td>11,131</td>
<td>11,131</td>
</tr>
<tr>
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<td>0.067</td>
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<td>0.050</td>
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<tr>
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<td>year + industry</td>
<td>year + industry</td>
<td>year + industry</td>
<td>year + industry</td>
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<td>423</td>
<td>107</td>
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<td>210</td>
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Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Table 5. Estimation Results for Decomposed Misallocation

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<th>(3)</th>
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<th>(5)</th>
<th>(6)</th>
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<td>OLS</td>
<td>OLS</td>
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<td>OLS</td>
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<td>GMM</td>
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<td>gross</td>
<td>gross</td>
<td>gross</td>
<td>gross</td>
<td>gross</td>
<td>gross</td>
<td>gross</td>
<td>gross</td>
<td>net</td>
</tr>
</tbody>
</table>

| Volatility1      | 0.0418*** | 0.0402** | 0.0238 | 0.0841*** | 0.0795** | 0.0286 | 0.0500* | 0.00149 | 0.0817*** | 0.0202 |
|                 | (2.611)   | (2.197)   | (1.337) | (2.671)   | (2.364)   | (1.126) | (1.939) | (0.0518) | (2.276)   | (0.775) |

| Vol1*markup_smallest | 0.0478 | 0.0929** | 0.0321 | 0.0335 | 0.0687 | 0.0948* | 0.0433 | 0.0113 | 0.0362 |                |
|                      | (1.414) | (2.164)   | (0.796) | (0.858) | (1.152) | (1.797) | (1.238) | (0.607) | (0.362) |                |

| Vol1*markup_second  | 0.00311 | -0.0576 | 0.0360 | 0.0614 | 0.0563 | -0.0493 | 0.0326 | 0.0136 | 0.0362 |                |
|                     | (0.0852) | (-1.331) | (0.566) | (1.043) | (1.206) | (-1.126) | (0.607) | (0.362) | (0.930) |                |

| Vol1*markup_third   | 0.0109 | 0.0119 | 0.0119 | -0.0275 | 0.0468 | 0.0113 | 0.0362 |                |                |                |
|                     | (0.430) | (0.431) | (0.372) | (-0.948) | (1.158) | (0.436) | (0.930) |                |                |                |

| Vol1*markup_largest |                |                |                | 0.138*** | 0.0559*** | 0.0559*** | 0.0559*** | 0.0559*** | 0.0559*** | 0.0559*** |
|                     |                |                |                | (3.966) | (2.734)   | (2.734)   | (2.734)   | (2.734)   | (2.734)   | (2.734)   |

| Observations       | 11,131 | 11,131 | 11,131 | 11,131 | 11,131 | 10,278 | 10,278 | 11,131 | 11,131 | 11,131 |
|                   |       |       |       |       |       |       |       |       |       |       |
| Adjusted R-squared | 0.074 | 0.043 | 0.026 | 0.075 | 0.045 | 0.026 | 0.046 | 0.024 |       |       |
| Fixed Effect       | year + | year + | year + | year + | year + | year + | year + | year + | year + | year + |
| Number of industry | 423   | 423   | 423   | 423   | 423   | 423   | 423   | 423   | 423   | 423   |

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1
<table>
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<td>0.0348*** (9.432)</td>
<td>0.00800*** (9.414)</td>
</tr>
<tr>
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<td>-0.00294** (-2.187)</td>
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<td>year + firm</td>
<td>year + firm</td>
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</tr>
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<td>** p&lt;0.05, * p&lt;0.1</td>
<td>*** p&lt;0.01, ** p&lt;0.05, * p&lt;0.1</td>
<td>*** p&lt;0.01, ** p&lt;0.05, * p&lt;0.1</td>
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