A New Look at Uncertainty Shocks: Imperfect Information and Misallocation

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14 July, 2014

Abstract

Uncertainty faced by individual firms appears to be heterogeneous: some firms are more confident than others about a particular future event. This paper studies the role of heterogeneous uncertainty in propagating uncertainty shocks within a model with imperfect information. Towards that goal, I first construct an empirical measure of firm-level uncertainty with data from the IBES, and I document its features. I then build a heterogeneous firm model with learning to account for heterogeneous uncertainty, and I conduct stochastic simulations with both TFP and uncertainty shocks. The model features heterogeneity in productivity and confidence about it: firms are differently informed about own productivity due to learning. By calibrating the process of the two types of aggregate shocks to match the level and cyclicality of the plant level productivity growth rates as well as the empirical series of Solow residuals, I show that this model reproduces rapid drops and slow recoveries in aggregates following uncertainty shocks. In addition, the simulation results reveal that uncertainty shocks explain a large fraction of the U.S. business cycles and reproduce the negative correlation between hours and labour productivity, consistent with data. These results imply the greater importance of uncertainty shocks when interacted with imperfect information.

JEL Classification: D83, E10, E22, E32

Keywords: Uncertainty, imperfect information, learning, misallocation, business cycles

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*I am grateful to Aubhik Khan and Julia Thomas for the valuable advice they have provided throughout this project. I would also like to thank comments from Nick Bloom, Paul Evans, Joe Kaboski, Munechika Katayama, Pok-sang Lam, Enrique Mendoza, Shuhei Takahashi, Tamon Takamura, Takayuki Tsuruga, Katsunori Yamada, and seminar participants at the Bank of Canada, Kyoto and Ohio State. All remaining errors are mine.

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1 Introduction

There is little doubt that firms differently assess uncertainty. For example, some firms can be more confident about the price of oil tomorrow than others. This feature of firm-level uncertainty, which is referred to as heterogeneous uncertainty, is studied in this paper. Towards that goal, I develop a heterogeneous firm model with Bayesian learning and study the role of heterogeneous uncertainty in propagating uncertainty shocks. By calibrating the model to match the level and cyclicality of the plant level productivity growth rates as well as the empirical series of Solow residuals, I show that this model reproduces rapid drops and slow recoveries in aggregates following uncertainty shocks. In addition, I find the greater importance of uncertainty shocks in explaining business cycle fluctuations when interacted with heterogeneous uncertainty, and I further demonstrate that uncertainty shocks can resolve some puzzles that cannot be explained by a standard business cycle model with only TFP shocks.

A key feature of this paper is that uncertainty faced by firms is not only time-varying but also heterogeneous. That is, the conditional variance of idiosyncratic shocks is heterogeneous among firms.[1] To account for heterogeneous uncertainty, I integrate learning á la Jovanovic (1982) into a standard heterogeneous firm model. Firms are heterogeneous in both productivity and confidence about it: the more informed, the smaller the conditional variance. Due to Bayesian learning, two different firms could have the same posterior mean, while being different about their posterior variance. Heterogeneous uncertainty due to imperfect information turns out to have an important mechanism by which uncertainty shocks cause prolonged recessions.[2]

The model developed in this paper builds on a standard heterogeneous firm model. I deviate from this standard model in three ways. First, idiosyncratic productivity has two components: an i.i.d. transitory component around a base component for each firm. These components cannot be observed separately, and therefore each firm must learn the true value

[1] A conventional source of uncertainty in the literature is the volatility of idiosyncratic shocks. All agents know the true distribution of the shock, including the volatility, and the uncertainty of agents is the future draw of shocks from that distribution. In uncertain times, the volatility, that every firm faces equally, is high, which causes recessions in the presence of adjustment costs.

[2] Bachman, Elstner and Sims (2013) argue that "wait-and-see" effects is not entirely consistent with the U.S. data showing the persistent and prolonged dynamics following a rise in uncertainty.

of its base component in a Bayesian way. Second, the base component is randomly reset. When it is reset, a new one is drawn from the distribution known to all firms. Whereas firms know when it is reset, they do not know the true value of its new base component, and thus they restart learning. Otherwise, firms maintain its current base component and keep learning it. This structure allows me to integrate learning into a model of heterogeneous firms that are subject to persistent shocks to idiosyncratic productivity as in Hopenhayn (1992). Third, I assume that the reset probability of base components is stochastic: two-state Markov process. The high reset probability induces that many more firms change productivity, and hence they lose information and restart learning. This, in fact, leads to the larger variance of TFP growth rates across the distribution of firms, which is an important empirical observation that has been captured by the previous leading work of uncertainty shocks (Bloom et al. 2012). There, each firm faces the larger variance of shocks to idiosyncratic productivity. Instead, more firms change productivity here. Furthermore, the Oi-Hartman-Abel effect is absent as the distribution of plant level productivity level is time-invariant.[3] Uncertainty shocks, defined as the high reset probability, together with aggregate TFP shocks drive business cycle fluctuations in this model.

Main findings are as follows. First, the model reproduces rapid drops and slow recoveries in aggregates following uncertainty shocks. Second, uncertainty shocks explain a large fraction of the U.S. business cycles and reproduce the negative correlation between hours and labour productivity, consistent with data.[4] Third, aggregate TFP shocks are also an important driver of business cycle fluctuations, and they elicit standard business cycle properties. Overall, these results imply the greater importance of uncertainty shocks when interacted with imperfect information.

The mechanism behind these results come from the following two effects: one precautionary and one distributional. First, precautionary effects are that all firm anticipate the higher reset probability, implying that they take care of the likelihood of the larger changes in productivity. Consequently, they change their target level of capital stock. Firms that

[3]With decreasing returns to scale in production, inputs for production, capital and labour in this paper, are convex in productivity. Therefore, a higher variance of productivity implies a larger capital investment and employment on avarage.

[4]See Takahashi (2014) that reproduces the negative correlation between hours worked and average labour productivity with a heterogeneous households model. Ohanian and Raffo (2011) documents the empirical evidence.

believe that their base component is higher than the mean reduces their capital stock. On the other hand, firms that believe that they are in the bottom half increase their capital stock. Given that the distribution of the base component of productivity is symmetric and the production function has decreasing returns to scale, the net impact is negative. The precautionary response is immediately reversed when the shock ends, which in turn results in an expansion of the pent-up investment demand.[5] However, this fails to spur aggregate investment because of the offsetting impact of the distributional effects. As a large number of firms experience the reset of base components, the economy gets more populated by uninformed firms in recessions. They lose information and restart learning, and therefore the conditional variance of idiosyncratic shocks is large, suggesting that they are still cautious after recessions. The population share of uninformed firms remains higher for a while until they become informed, and thus aggregate negative effects persist.

At the start of the recession, the precautionary and distributional effects compound each other and this leads to a rapid drop in aggregates. However, in the recovery phase, the precautionary and distributional effects offset each other; their relative strength must be quantitatively assessed, and this paper shows that the distributional effect dominates and aggregate variables gradually recover to their pre-recession level. This establishes the importance of examining distributional effects on aggregate fluctuation in business cycle studies.[6]

To quantitatively assess the aggregate implications of the mechanism, I use micro data to calibrate the following parameters are crucial for the results of this paper. First, the variance of both base and transitory components are set to match the empirical moments of the establishment level investment rates from the LRD: the standard deviation and serial correlation. When the variance is large, firms take more time to understand the true value of base components, while the small variance implies little roles of learning in the model. The source of the misallocation of resources is firm's over- or under-capacity due to learning. Unless firms are fully informed about their base component, capital stock is either excess or

[5]In a seminal work of Bloom (2009), the region of inaction of investment and employment expands following a shock that increases idiosyncratic volatility, and this region shrinks after the shock is turned off. Pent-up investment demand, which causes a relatively quick rebound of the economy, arises due to the fact that there are many firms staying around the thresholds between inaction and action regions.

[6]In a (S,s) model of price settings, Vavra (2013) argue that the impacts of volatility shocks iclude a direct effect pushing more firms into the region of action and an indirect effect widening the region of inaction.

insufficient relative to the efficient level consistent with the true value of base components and the interest rate. Therefore, the longer firms take time to learn, the more severe resource misallocation is. Second, the process of the two aggregate shocks are set to match the level and cyclicality of the plant level productivity growth rates as well as the empirical series of Solow residuals. Specifically, I identify the both high and low reset probability as well as the transition probabilities on the U.S. census plant data. The variation of the reset probability leads to the fluctuation of measured TFP in the model. I set the parameters that control the process of aggregate TFP shocks to capture the empirical series of the Solow residuals that are not explained by uncertainty shocks. This allows me to decompose each shock's contribution to business cycle fluctuations, and I show that uncertainty shocks explain a large fraction of the U.S. business cycles and reproduce the negative correlation between hours and labour productivity.

Finally, I conduct a simulation on the Great Recession in the U.S. economy. By recalibrating the size of the shocks to replicate the plant-level productivity growth rate distribution for both the 2005-06 and 2008-09 U.S. economy, the simulation reveals that the model explains 80% of the decline in GDP and 74% in the decline in investment. A massive and rapid drop in aggregates is followed by a slow recovery—the half-life of the impulse response of output to an uncertainty shock is 6 years.

Related Literature Understanding the aggregate implications of uncertainty at the micro level has been one of the central interest in business cycle studies.[7] The seminal contribution in this literature by Bloom (2009) and Bloom et al. (2012) show that high uncertainty at the micro level causes the "wait-and-see" effects on firm's investment and employment decisions in the presence of non-convex adjustment costs. Whereas the earlier theories of uncertainty shocks lead to short recessions and quick recoveries, Bachman, Elstner and Sims (2013) argue that "wait-and-see" effects is not entirely consistent with the U.S. data, and they show the persistent and prolonged dynamics following a rise in uncertainty.[8] I contribute to this literature by conducting a quantitative exploration of the role of imperfect information in shaping the long-lasting recession. My paper is related to some

[7]See Bloom (2014) for the overview on the growing developments in the literature.

[8]There, it is suggested that financial frictions are one mechanism to produce persistent reductions in aggregates (e.g. Gilchrist, Sim, and Zakrajsek (2010), Arellano, Bai, and Kehoe (2012), Christiano, Motto, and Rostagno (2010)).

recent work that studies the interaction of information dynamics and the aggregate economy (e.g. Fajgelbaum, Schaal and Taschereau-Dumouchel (2013) offer an endogenous mechanism of prolonged recession through a rise in uncertainty). An early contribution is Caplin and Leahy (1993) that provided a theory that the interaction between imperfect information and irreversible investment causes aggregate fluctuations.

As for the empirical strategy, I follow the literature that view ex-ante forecast disagreement as a proxy for uncertainty. Bachman, Elstner and Sims (2013) use survey data from the IFO-BCF, especially micro-data of the survey, to extensively study various measures of uncertainty and show the usefulness of forecast disagreement to measure uncertainty. I use data on market analysts' forecasts and show that a new measure of uncertainty, constructed from ex-ante forecast disageement, exhbits the heterogeneity and countercyclicality of uncertainty at the firm-level.[9]

My paper is also related and complementary to existing papers that study the role of the allocation of resources across heterogeneous agents and its impacts on aggregate productivity (e.g. Restuccia and Rogerson (2008)). Hsieh and Klenow (2009) argue that misallocation of resources have a substantial impact on aggregate TFP in India and China. In particular, more recently, the role of financial frictions generating capital misallocation and its aggregate implications has been studied in a quantitative framework (Khan and Thomas (2013), Buera and Moll (2013), Buera, Kaboski and Shin (2011)). My paper is distinct from these papers in focusing on how information frictions cause capital misallocation over business cycles. In terms of the focus on information frictions and misallocation, David, Hopenhayn and Venkateswaran (2013) offer a theory to explain the cross-country difference of aggregate TFP caused by information frictions.

To introduce imperfect information, I develop a fully specified DSGE model that builds on Jovanovic's (1982) learning. Alti (2003) studies the disparate sensitivity of investment for young and old firms in a model with learning. Timoshenko (2013) examines product switching behavior of exporters in a model of demand learning.

The rest of the paper is organized as follows. Section 2 reports empirical results. In Section 3, the model of heterogeneous firms with Bayesian learning is developed. Section 4 describes the calibration of this model to match a variety of micro level moments as well

[9] See Diether, Malloy, and Scherbina (2002) and Johnson (2004) for what analysts disagreement tells us about uncertainty and risk. See also Janunts (2010) for an extensive study on this agenda.

as a set of standard aggregate moments in business cycle studies. Section 5 presents my quantitative results both in stationary equilibrium and dynamic transitions, and Section 6 concludes. Computational methods and details of data set are explained in the Appendix.

2 Empirical facts

This section explains the data and empirical facts that support my theoretical results. First, the data reveals heterogeneous uncertainty among firms. Second, the cross-sectional dispersion of micro level uncertainty exhibits countercyclicality for both ex-ante forecasts-based and ex-post performance-based measures. In addition, these two measures on micro level uncertainty are correlated each other. Finally, the comparison of postwar recessions including the latest 07-09 recession is shown, and I show that the pace of recovery from the latest recession is an order of magnitude too slow.

In general, uncertainty is not easy to observe.[10] A large literature has been developing various proxies for uncertainty, including ex-post forecast errors, ex-ante forecast disagreement, and other measures (e.g. stock price volatility). I follow the literature in using forecast disagreement as a proxy for uncertainty (e.g. Bachman, Elstner and Sims (2013)), and, I particularly use the dispersion of analysts' forecasts to examine uncertainty faced by firms, as argued in Johnson (2004), Bond, Moessner, Mumtaz and Syed (2005), and Janunts (2010).

As argued in the literature, viewing forecast disagreement as a proxy for uncertainty raise some questions: what is and is not measured by this proxy and how to interpret this. In the following sections, I explore the cross-sectional distribution of this measure as well as its cyclical properties, and I report similar results to that obtained by previous studies.

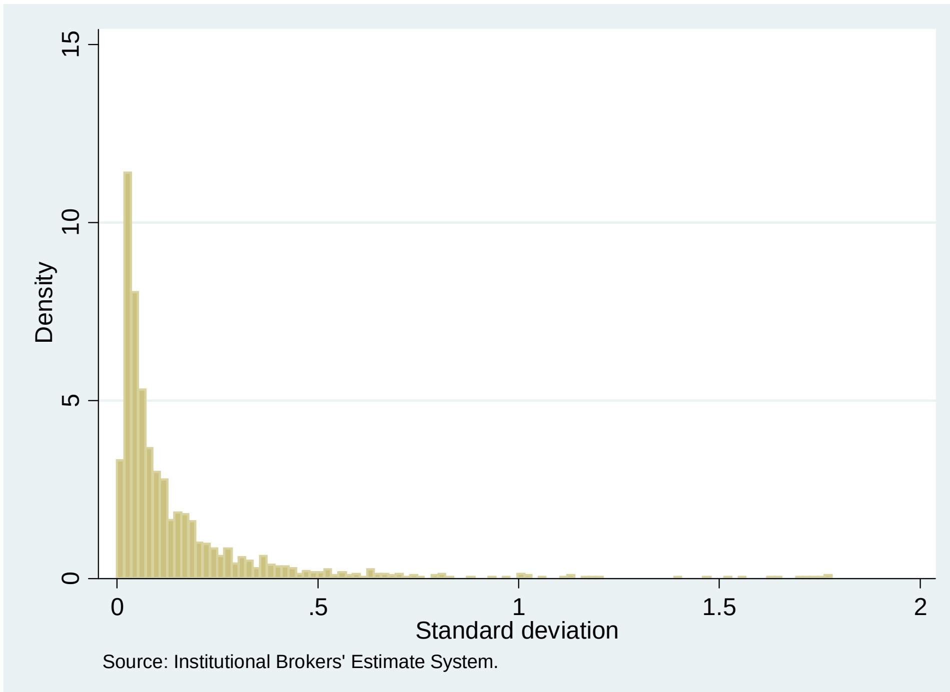
2.1 Data and sample selection

The data is taken from the Institutional Brokers' Estimate System (I/B/E/S). For each firm, the data set contains a point forecast by an individual analyst. One can calculate

[10] An ideal data is managers' subjective distributions for future events. See Guiso and Parigi (1999) for cross-sectional survey data for Italian firms. Bloom, Bond and Van Reenen (2007) discuss the usefullness of other uncertainty measures.

the cross-analyst standard deviation for each firm at any given date, and further the cross-sectional distribution of this measure can be obtained.

Figure 1: Distribution of EPS forecasts (earnings per share)



To infer firm-specific uncertainty, it is ideal to have as many forecasts as possible. Therefore, the analysis in this section focus on firms that have more than twenty forecasts of EPS. The resulting sample contains data on 1,345 U.S. firms between 1975 and 2013. Figure 1 reports the cross-sectional distribution of standard deviation of EPS forecasts. As shown in the figure, there is a clear evidence that there is a substantial heterogeneity in the conditional variance of idiosyncratic shocks measured by EPS forecasts among firms.

2.2 EPS-based and TFP-based measure of uncertainty

In light of the evidence on heterogeneous uncertainty, I then examine the time series properties of the distribution of firm-specific uncertainty. To do so, I construct a measure of uncertainty based on EPS forecasts dispersion, by taking the cross-sectional mean of the standard deviation of EPS forecasts for each year.

Figure 2: Cyclicality of Uncertainty (EPS based)

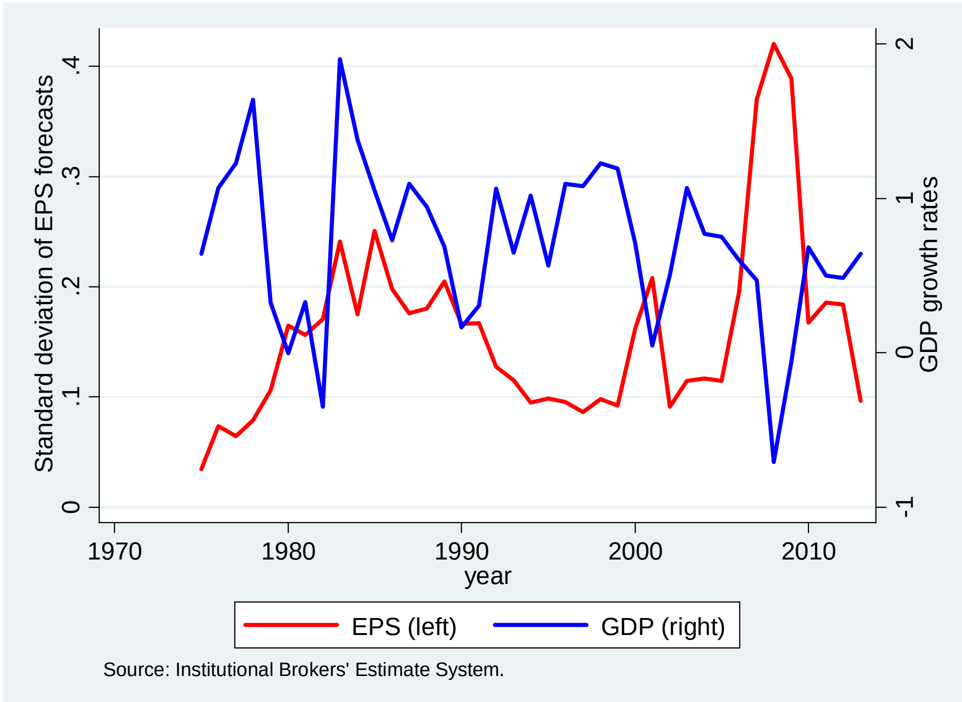
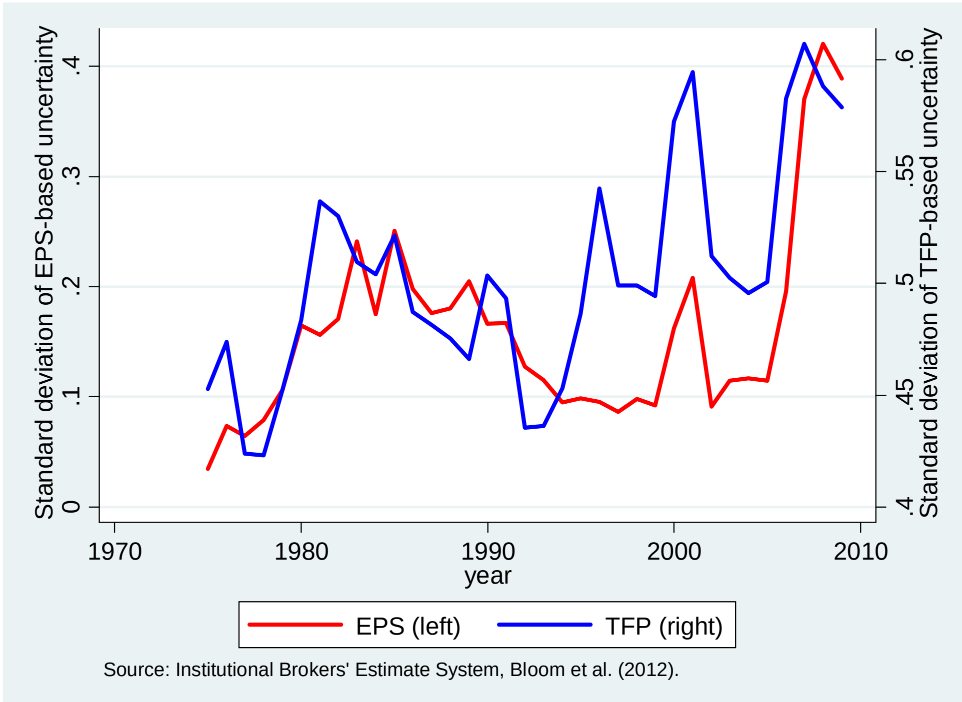


Figure 2 plots the time series of the constructed measure along with historical series of real GDP growth rates. The correlation between the EPS-based uncertainty measure and GDP growth rates is -0.464, suggesting that the ex-ante forecasts-based measure of uncertainty is countercyclical. In recessions, the population share of uninformed firms, that anticipate the higher conditional variance of next period's idiosyncratic shocks, gets larger. This new micro evidence on firm specific uncertainty supports the mechanism of this paper as the following sections show in detail.

Next, I examine the correlation between the EPS-based uncertainty measure and TFP-based uncertainty measure studied by Bloom et al. (2012). Figure 3 shows both the historical series of TFP-based uncertainty measure and real GDP growth rates.

Figure 3: Cyclicality of Uncertainty (TFP based)



The data for the series of TFP-based measure on uncertainty is taken from Bloom et al. (2012). Among various series of uncertainty measures reported in the paper, their baseline sample is chosen here.[11] The correlation with GDP growth rates is -0.467: a well-known countercyclical property of the standard deviation of the cross-sectional TFP shocks, defined as establishment specific shocks to productivity that is not explained either by establishment-level fixed effect or a year fixed effect. The summary statistics of the two measures are shown in Table 1. First, the EPS-based and TFP-based measures are correlate each other. Second, both measures are persistent and countercyclical.

Table 1: Statistics of uncertainty measures

	EPS-based	TFP-based
Standard deviation	0.08	0.52
Skewness	1.47	-0.34
Kurtosis	5.21	3.53
First order autocorrelation	0.70	0.69
Correlation with EPS-based	1.00	0.69
Correlation with TFP-based	0.69	1.00
Correlation with GDP growth rate	-0.464	-0.467

[11]See Bloom et al. (2012) for detailed description of the measure.

2.3 Comparison of postwar recessions

Figure 4: Comparison of Postwar Recessions

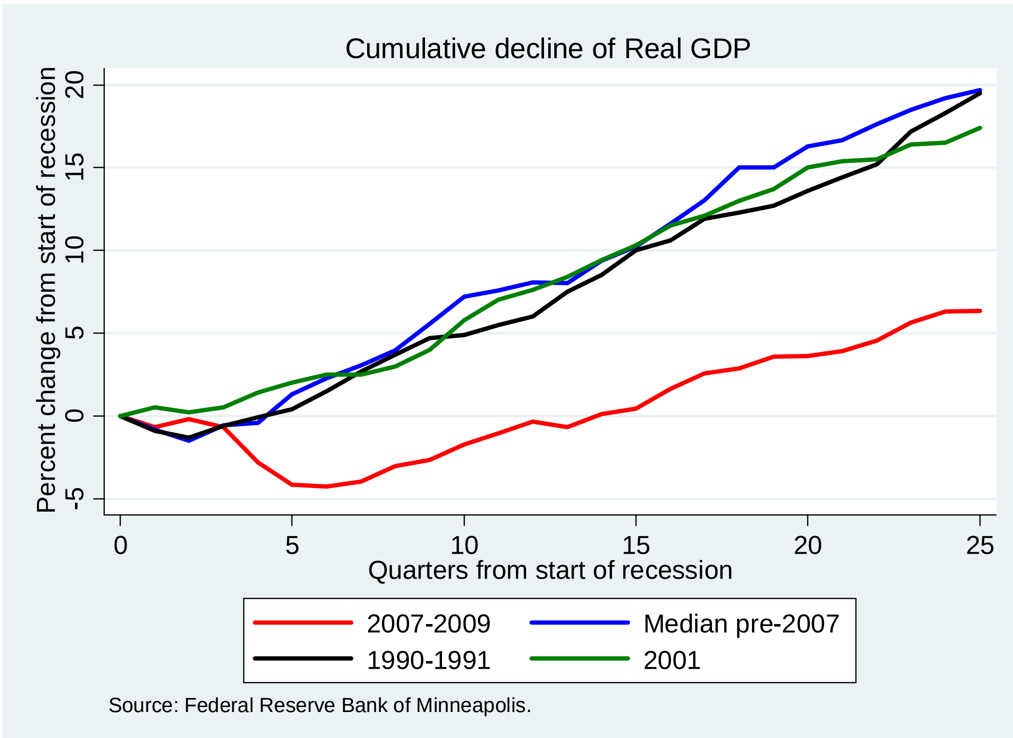


Figure 4 shows the comparisons of eleven postwar recessions including the Great Recession from 2007. The data is taken from the Federal Reserve Bank of Minneapolis, and I extend the length of periods shown. The comparison is about cumulative decline of real GDP from the start of recession over eleven recessions. Notice that the red line, which shows the Great Recession, is far below compared to the last two preceding recession, the 2001 and 1990-1991, and the median path of the postwar recessions.

3 Models

This section describes the model economy. I take a standard model with heterogeneous firms and extend it as follows. First, idiosyncratic productivity has both persistent and temporary components, and these two components cannot be observed separately. Since I assume that the temporary component is i.i.d., each firm must learn its persistent component as in Jovanovic (1982). Second, each firm is subject to exogenous shocks to its persistent component. In each period, each firm retains its current persistent component with probability π, but loses the current level and draws a new one with probability $1 - \pi$. The new persistent component is drawn from a time-invariant distribution and independent of last period's productivity level, and each firm restarts learning. Third, I assume that π is time-varying. An uncertain time in this model is when π is high, which implies that unusually many firms change their productivity level and restart learning.

3.1 Production, learning

The model economy is perfectly competitive and has an infinite horizon. There are competitive firms producing a homogenous good. Each firm uses capital stock k, and labor n, via an increasing and concave production function,

$$y = z\varepsilon F(k, n), \tag{1}$$

where $F(k, n) = (k^{\alpha} n^{1-\alpha})^{\nu}$, with $0 < \alpha < 1$ and $0 < \nu < 1$.

There are two productivity components attached to the production function, one aggregate z and one idiosyncratic ε. z represents an exogenous stochastic total factor productivity common across all firms: $z \in \{z_1, \ldots, z_{N_z}\}$, where $\Pr(z' = z_m \mid z = z_l) \equiv \pi^z_{lm} \geq 0$, and $\sum_{m=1}^{N_z} \pi^z_{lm} = 1$ for each $l = 1, \ldots, N_z$. For a firm-specific idiosyncratic counterpart, I assume that ε is the sum of two components: a persistent one θ and a transitory one a;

$$\varepsilon = \theta + a. \tag{2}$$

A firm specific productivity, θ, changes infrequently and the timing of changes, though not their value, is known to the firm. With probability $1 - \pi$, the current persistent is maintained. With probability π, the current persistent component is lost and it is newly drawn, irrespective of the current state. A transitory component, a, is independently and identically distributed through time. The distributions of both θ and a are known to all firms: $\theta \sim N(\overline{\theta}, \sigma^2_{\theta})$ and $\varepsilon \sim N(0, \sigma^2_{\varepsilon})$.

Firms observe ε, but θ and a are not observed separately. Firms can extract information about their θ by accumulating observations of ε, and these observations are affected by i.i.d. draws of a every period.

We formalize this learning process as follows. Consider a firm with $\overline{\varepsilon}$ —the mean of the observations of idiosyncratic shocks ε_i for $i = 1, \ldots, t$, where t is the number of observations. To form a belief about persistent component θ, $(\overline{\varepsilon}, t)$ are the sufficient information in this setting. Therefore, a firm with $(\overline{\varepsilon}, t)$ infers the posterior distribution: $\theta \sim N(A, B)$ with

$$A = \frac{\sigma_a^2}{\sigma_a^2 + t\sigma_\theta^2}\overline{\theta} + \frac{t\sigma_\theta^2}{\sigma_a^2 + t\sigma_\theta^2}\overline{\varepsilon} \tag{3}$$

$$B = \frac{\sigma_a^2\sigma_\theta^2}{\sigma_a^2 + t\sigma_\theta^2} \tag{4}$$

where $\overline{\varepsilon} = (\sum_{i=1}^t \varepsilon)/t$ and t is the number of observations. By accumulating observations, the posterior distribution of θ is updated, and it converges to the true value of θ as t becomes large enough.

3.2 Distribution of firms

The exogenous aggregate state is summarized by $s = (z, \pi)$. In addition, a non-trivial, time-varying distribution of firms is a part of the aggregate state in this model. As shown in the last section, firms take expectations over their productivity in the next period. Starting with the last period when their base component is reset, firms keep observing their productivity, and the mean of these observations and the number of observations are a part of each firm's state. The number of observations can be considered as time-since-reset. Thus, firms at the beginning of each period are identified by the mean of their observations of idiosyncratic shocks, $\overline{\varepsilon}$, the number of these observations, t, and their current productivity draw, ε, alongside their predetermined capital stock, k. I summarize the distribution of firms over $(\overline{\varepsilon}, t, \varepsilon, k)$ using the probability measure μ defined on the Borel algebra, $\mathcal{S}$, generated by the open subsets of the product space, $\mathcal{S} = \mathbb{R}_+ \times \mathbb{Z} \times \mathbb{R}_+ \times \mathbb{R}_+$.

Given the distribution of firms, the aggregate state of the economy is fully summarized by (s, μ), and the distribution of firms evolves over time according to a mapping, Γ, from the current aggregate state; $\mu' = \Gamma(s, \mu)$.

3.3 Firm's problem

Firms solve the following problem given their firm-level state together with the aggregate state. The problem consists of choosing capital stock in the following period, k', and labour input for this period, n. Let $V(\overline{\varepsilon}, t, \varepsilon, k; s, \mu)$ be the value function of a firm;

$$\begin{aligned} V(\overline{\varepsilon}, t, \varepsilon, k; s, \mu) &= \max_{n,k'} \Big[z\varepsilon(k^{\alpha} n^{1-\alpha})^{\nu} - \omega n + (1-\delta)k - k' \\ &+(1-\pi) E_{s'|s} d\left(s', s, \mu\right) E_{\overline{\varepsilon}'|\overline{\varepsilon},t} V(\overline{\varepsilon}', t+1, \varepsilon', k'; s', \mu') \\ &+\pi E_{s'|s} d\left(s', s, \mu\right) E_{\varepsilon'} V(\frac{\overline{\theta} + \varepsilon'}{2}, 2, \varepsilon', k'; s', \mu') \Big] \end{aligned} \tag{5}$$

$$\text{subject to} \quad : \quad \overline{\varepsilon}' = \frac{t\overline{\varepsilon} + \varepsilon'}{t+1}, \tag{6}$$

$$\text{and} \quad : \quad \mu' = \Gamma(s, \mu). \tag{7}$$

Each firm's profits are its output less wage payments and investment. With probability $1-\pi$, the current persistent component is maintained and hence their expectation over ε' and thus $\overline{\varepsilon}'$ are conditional on $(\overline{\varepsilon}, t)$. Furthermore, they discount the next period value by the state contingent discount factor, $d\left(s', s, \mu\right)$. With probability π, the current persistent component is lost and it is newly drawn, independently in terms of the current state. In the first period after the reset of the base component, firms take an average of the mean value of $\overline{\theta}$ and the first draw of ε'. The same state contingent discount factor is used. The state contingent discount factor is determined through the following household behavior.

3.4 Households

There is a large number of identical households in this economy and I assume a unit measure of households. Households choose consumption, supply labor, and hold their wealth in firm shares to maximize lifetime expected utility as follows.

$$V^h(\lambda, \phi; s, \mu) = \max_{c, n^h, \phi', \lambda'} \left[U\left(c, 1 - n^h\right) + \beta E_{s'|s} V^h\left(\lambda'; s', \mu'\right) \right] \tag{8}$$

$$\text{subject to} \quad : \quad c + \int_{\mathbf{S}} \rho_1\left(\overline{\varepsilon}', t+1, \varepsilon', k'; s, \mu\right) \lambda'\left(d\left[\overline{\varepsilon}' \times t+1 \times \varepsilon' \times k'\right]\right) \leq$$

$$w(s, \mu) n^h + \int_{\mathbf{S}} \rho_0(\overline{\varepsilon}, t, \varepsilon, k; s, \mu) \lambda(d[\overline{\varepsilon} \times t \times \varepsilon \times k]) \tag{9}$$

$$: \quad \mu' = \Gamma(s, \mu) \tag{10}$$

Households hold the one-period shares in firms, which is denoted by the measure λ. Given the prices—the real wage, $w(s, \mu)$, and the prices of shares, $\rho_0(\overline{\varepsilon}, t, \varepsilon, k; s, \mu)$ and $\rho_1\left(\overline{\varepsilon}', t+1, \varepsilon', k'; s, \mu\right)$, households choose their current consumption, c, hours worked, n^h, and the numbers of new shares, $\lambda'\left(\overline{\varepsilon}' \times t+1 \times \varepsilon' \times k'\right)$.

Let $C^h(\lambda; s, \mu)$ and $N^h(\lambda; s, \mu)$ represent the household decision rules for consumption, hours worked, and let $\Lambda^h(\overline{\varepsilon}', t+1, \varepsilon', k', \lambda; s, \mu)$ be the household decision rule for shares purchased in firms that will begin the next period with $(\overline{\varepsilon}' \times t+1 \times \varepsilon' \times k')$.

3.5 Recursive equilibrium

A recursive competitive equilibrium is a set of functions

$$\begin{aligned} \text{prices} \quad &: \quad (\omega, d, \rho_0, \rho_1) \\ \text{quantities} \quad &: \quad (N, K, C, N^h, \Lambda^h) \\ \text{values} \quad &: \quad (V, V^h) \end{aligned}$$

that solve firm and household problems and clear the markets for assets, labor, and output:

1. V satisfies (5) - (7), and (N, K) are the associated policy functions for firms.

2. V^h satisfies (8) - (10), and (C, N^h, Λ^h) are the associated policy functions for households.

3. $\Lambda^h(\overline{\varepsilon}, t, \varepsilon, k, \mu; s, \mu) = \mu(\overline{\varepsilon}, t, \varepsilon, k)$ for each $(\overline{\varepsilon}, t, \varepsilon, k) \in \mathcal{S}$.

4.

$$\begin{aligned} N^h(\mu; s, \mu) &= \int_{\mathbf{S}} [N(\overline{\varepsilon}, t, \varepsilon, k)] \cdot \mu(d[\overline{\varepsilon} \times t \times \varepsilon \times k]) \\ C(\mu; s, \mu) &= \int_{\mathbf{S}} [z\varepsilon F\left(k, N(\overline{\varepsilon}, t, \varepsilon, k)\right) - (K(k, b, \varepsilon; z, \mu) - (1-\delta)k)] \cdot \mu(d[\overline{\varepsilon} \times t \times \varepsilon \times k]) \end{aligned}$$

5. the resulting individual decision rules for firms and households are consistent with the aggregate law of motion, Γ, where Γ defines the mapping from μ to μ' with $K(\overline{\varepsilon}, t, \varepsilon, k; s, \mu)$.

Using $C(s, \mu)$ and $N(s, \mu)$ to describe the market-clearing values of household consumption and hours worked, it is straightforward to show that market-clearing requires that (a) the real wage equal the household marginal rate of substitution between leisure and consumption:

$$w\left(s, \mu\right) = D_2 U\Big(C(s, \mu), 1 - N(s, \mu)\Big) / D_1 U\Big(C(s, \mu), 1 - N(s, \mu)\Big),$$

that (b) the risk-free bond price, q_0^{-1}, equals the expected gross real interest rate:

$$q_0\left(s, \mu\right) = \beta E_{s'|s} D_1 U\Big(C(s', \mu'), 1 - N(s', \mu')\Big) / D_1 U\Big(C(s, \mu), 1 - N(s, \mu)\Big)$$

and that (c) firms' state-contingent discount factors are consistent with the household marginal rate of substitution between consumption across states:

$$d\left(s', s, \mu\right) = \beta D_1 U\Big(C(s', \mu'), 1 - N(s', \mu')\Big) / D_1 U\Big(C(s, \mu), 1 - N(s, \mu)\Big).$$

4 Calibration

In this section, I present my calibration strategy to match both the micro and macro level moments. I first present some micro-level and cross-sectional properties of the model, and I show that several prerequisites are captured: TFP shock and investment rate distribution at the establishment level. Having captured the micro level moments, I present a collection of aggregate moments that are standard in business cycle studies and compare them to those in the model.

4.1 Functional forms and stochastic processes

I assume that the representative household's period utility is $u(c, L) = \log c + \eta L$, as in the models of indivisible labor (e.g. Hansen (1985), Rogerson (1988)). As seen in the previous sections, we assume that each heterogeneous firm undertakes production via Cobb-Douglas production function: $z\varepsilon(k^{\alpha}n^{1-\alpha})^{\nu}$, where α determines capital's share of income and ν governs returns to scale in this economy. For the aggregate and idiosyncratic productivity processes: z and $\varepsilon = \theta + a$, I assume

$$
\begin{aligned}
\log z' &= \rho_z \log z + \eta'_z \quad \text{with } \eta'_z \sim N\left(0, \sigma^2_{\eta_z}\right) \quad \text{and} && (11)\\
\varepsilon &= \theta + a \\
&: \ \theta \sim N(\overline{\theta}, \sigma^2_{\theta}) \ \text{ and} \\
&: \ a \sim N(0, \sigma^2_a). && (12)
\end{aligned}
$$

$\overline{\theta}$ is the mean and σ^2_{θ} is the variance of the persistent component of idiosyncratic TFP, and σ^2_a is the variance of the temporary component of idiosyncratic TFP.

For time-varying π, I assume that π follows a two-state Markov chain with π_L and π_H. Transition matrix is $\Pi = \begin{bmatrix} \rho_L & 1-\rho_L \\ 1-\rho_H & \rho_H \end{bmatrix}$.

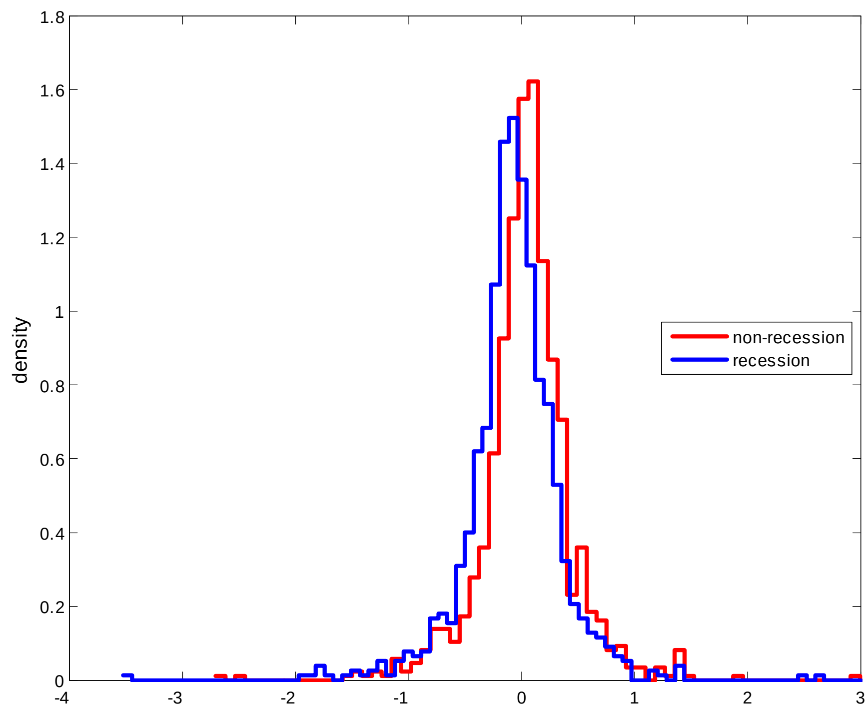
4.2 Micro level moments

4.2.1 TFP shock distribution

A prerequisite for this paper is that the dynamics of uncertainty at the micro level over business cycles are captured. Specifically, I calibrate this model to match the mean and variance of idiosyncratic TFP shocks in both non-recession and recession periods in the data. Bloom et al. (2012) show that the mean falls and the variance rises in recessions by calculating various moments taken form the Census of Manufactures (CM) and the Annual Survey of Manufactures (ASM) from the U.S. Census Bureau.

I identify the both high and low reset probability as well as the transition probabilities on the U.S. census plant data. The low reset probability, π_L, to match the variance of establishment-level TFP shocks in non-recession periods between 1972 and 2006. I set the high reset probability, π_H, to match the same target in recession periods between 1972 and 2006. The transition probabilities are determined using the NBER US business cycle expansions and contractions. Figure 1 compares the two distributions: non-recession and recession.

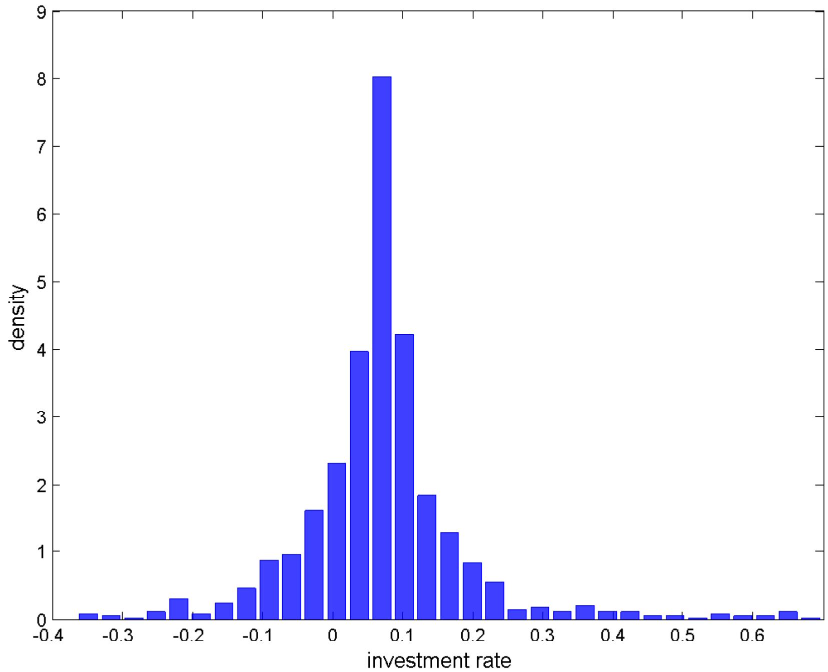
Figure 5: Distribution of idiosyncratic TFP shocks



4.2.2 Investment rate moments

To study how behaviors of micro-level investment shape aggregate investment dynamics during the recent recession, it is indispensable for this model to be consistent with the data on micro-level investment. Three parameters, (1) the mean of persistent component of firm level TFP $\overline{\theta}$, (2) the variance of temporary component of TFP σ_a, and (3) the variance of persistent component of TFP, σ_θ, are calibrated to match the Longitudinal Research Database (LRD) data on the plant-level investment rate moments, summarized by Cooper and Haltiwanger (2006). Figure 2 is based on a simulation of 1,000 firms for 2,000 periods. This model gets the mean (0.118), standard deviation (0.368) and serial correlation (0.007) of the typical plant's investment rate, defined as i/k, in the LRD data.

Figure 6: Distribution of firm-level investment rates



4.3 Macro level moments

For interpreting the business cycle implications of this model, this model must be consistent with a standard business cycle model in terms of the ability of replicating several aggregate moments. There are five parameters that are set to match the aggregate data: α capital's income share, υ returns to scale, β the household discount factor, δ the depreciation rate and η the leisure preference. The calibration strategy is as follows.

First, I set υ to imply an average private capital-to-output ratio of 2.3, given the value of α determining the average capital share of income at 0.665. Next, the depreciation rate, δ, is taken so that the model matches the average investment-to-capital ratio at 0:069. These three moments are taken from the U.S. Fixed Asset Tables from 1954 to 2002. The preference parameter, η, is set to imply an average hours worked of one-third. Finally, I set the household discount factor to match an average real interest rate of 4 percent as in Gomme, Ravikumar and Rupert (2011).

All parameters calibrated are listed in Table 1, and the performance of the model relative to the data is shown in Table 2.

Table 2: Calibrated parameters

Parameters	**Value**
Capital share of income: α	0.335
Returns to scale: ν	0.80
Depreciation rate: δ	0.079
Discount factor: β	0.04
Leisure preference: η	2.0
Mean of persistent component of TFP: $\overline{\theta}$	1.38
Variance of temporarly component of TFP: σ_a	0.15
Variance of persistent component of TFP: σ_θ	0.33
Mean of aggregate TFP in non-recessions: z_H	1.00
Mean of aggregate TFP in recessions: z_L	0.98
Probability of a new TFP draw in non-recessions: π_L	0.15
Probability of a new TFP draw in recessions: π_H	0.55

Table 3: Moments: data and model

Targets	**Data**	**Model**
Capital share of income	0.335	0.335
Aggregate K/Y	2.3	2.3
Aggregate I/K	0.079	0.079
Real interest rate	0.04	0.04
Hours worked	0.33	0.33
Micro level mean of i/k	0.122	0.118
Micro level standard deviation of i/k	0.337	0.368
Micro level serial correlation of i/k	0.058	0.007
Micro level mean of TFP shocks in non-recessions	0.000	0.000
Micro level mean of TFP shocks in recessions	-0.166	-0.110
Micro level variance of TFP shocks in non-recessions	0.243	0.234
Micro level variance of TFP shocks in recessions	0.349	0.335

5 Results

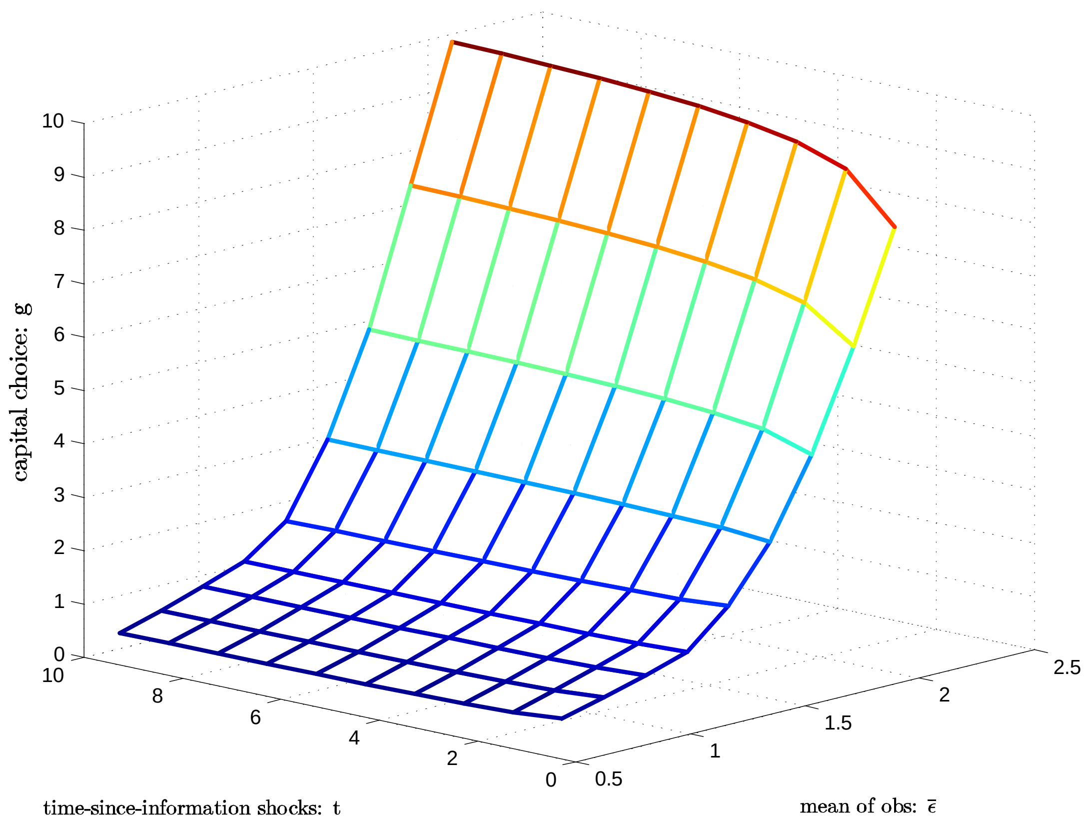
5.1 Steady state

5.1.1 Two-sided capital misallocation

Imperfect information causes misallocation of capital and labor. The pattern of misallocation with imperfect information is distinct from that of financial frictions such as collateral constraints. With imperfect information, the optimal resource allocation can be distorted in two directions: over and under capacity.

If firms have only small number of observations of their productivity, there is a gap between the true value of persistent component of each firm and the mean of observations. When firms are slowly learning that their true value of persistent component is higher than the mean of the entire distribution, capital stock tends to be lower than the efficient level. To reach the efficient level, firms spend time to learn and under capacity persists meanwhile. On the other hand, firms with bottom half level of persistent component gradually scale down and over capacity persists until they reach the efficient level capital stock which is consistent with their true value of productivity. Figure 3 shows capital choices of firms as a function of the mean observations of $\bar{\varepsilon}$ and time-since-reset t, and this figure illustrates the pattern of misallocation—two-sided misallocation. Capital tends to be misallocated among firms that are recently experience the reset of their base component. This misallocation takes form of over capacity for firms with the bottom-half persistent component and under capacity for firms with the top-half one.

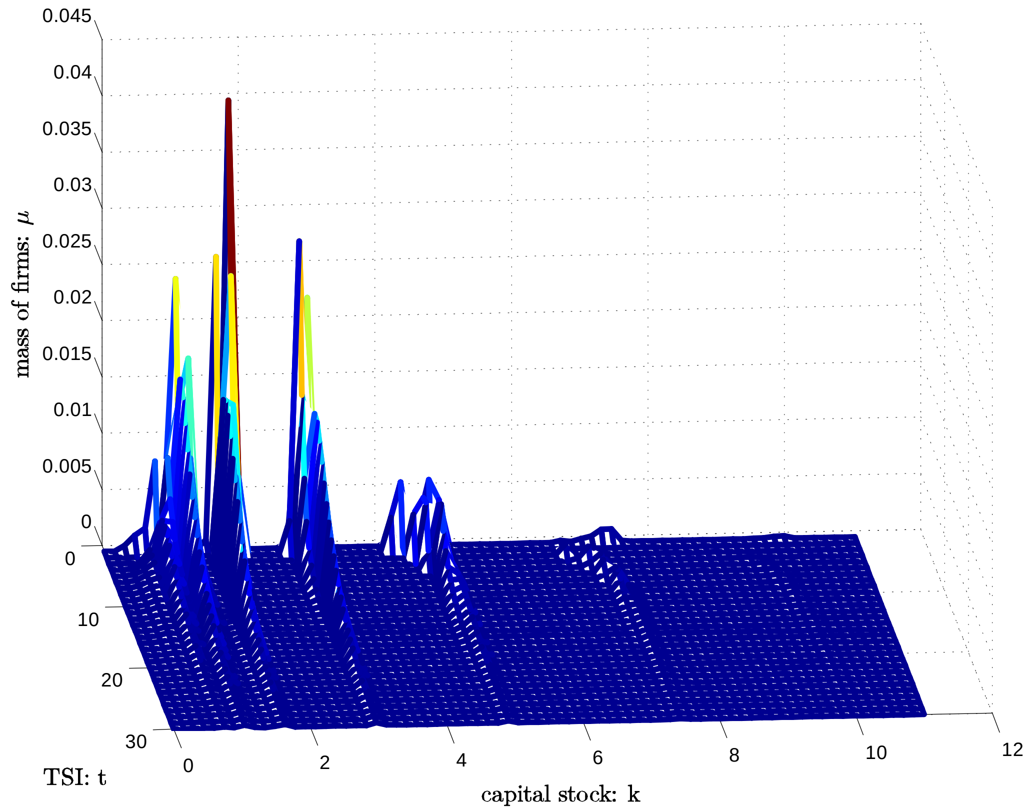
Figure 7: Capital choice



Notes: The mean of observations increases left to right. Time-since-reset shocks increases front to back.

Figure 4 shows the stationary distribution of firms over capital and time-since-reset. The mass of firms is relatively dense in the region of smaller time-since-reset, where capital is more misallocated. In the region of larger time-since-reset, the mass of firm is small, but firms in there are holding capital stock at the efficient level, which is consistent with productivity level. The reset sends firms to the back wall in Figure 4, and therefore, in uncertain times when the reset probability is high, the density of mass of firms near the back wall increases, which leads to a drop in measured aggregate TFP. Once firms experience the reset, they have to restart learning and are slowly crawling towards the front side of the Figure 4. Therefore, capital misallocation persists, and this slow-moving firm distribution plays an important role during recovery time.

Figure 8: Steady state firm distribution

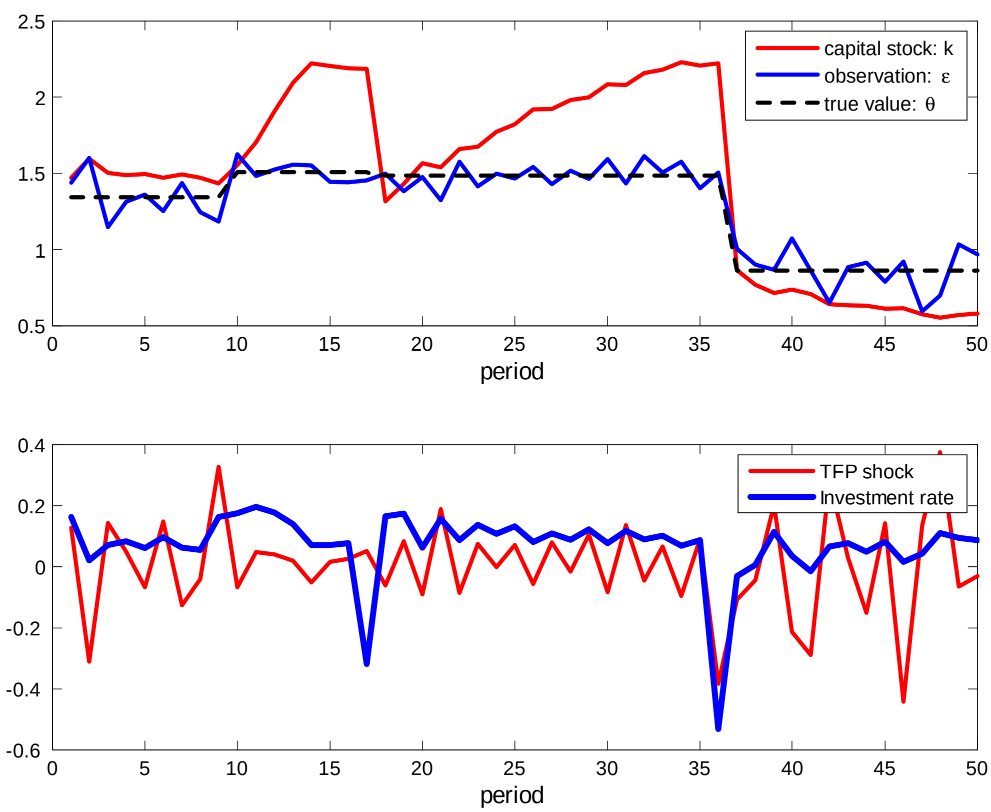


Notes: Capital increases left to right. Time-since-reset increases back to front.

5.1.2 Slow learning and capital accumulation

Figure 5 shows an example of one firm's learning and capital accumulation pattern. In the top panel of the figure, the base component of this firm is reset three times: period 10, 18 and 36. First, the firm loses its initial persistent component and draws a new one in period 10. This new level of productivity turns out to be higher than the last one for this firm, but it learns slowly due to imperfect information. By observing its productivity every period, this firm slowly scales up production capacity by building capital stock. In period 18, this firms draws a new persistent component and loses its anchor for expectation over its own productivity. This new level turns out to be almost the same as the previous one, however the firm scales down first and rebuilds capital stock slowly as it learns. Notice that it experiences a negative investment spike during this period. The second investment spike for this firm happens in period 36 when its third information shock hits. This time, it gets a massive negative shock to its persistent component, but once again, it experiences a negative investment spike and slowly scales down from period 37 and thereafter.

Figure 9: Learning and capital accumulation

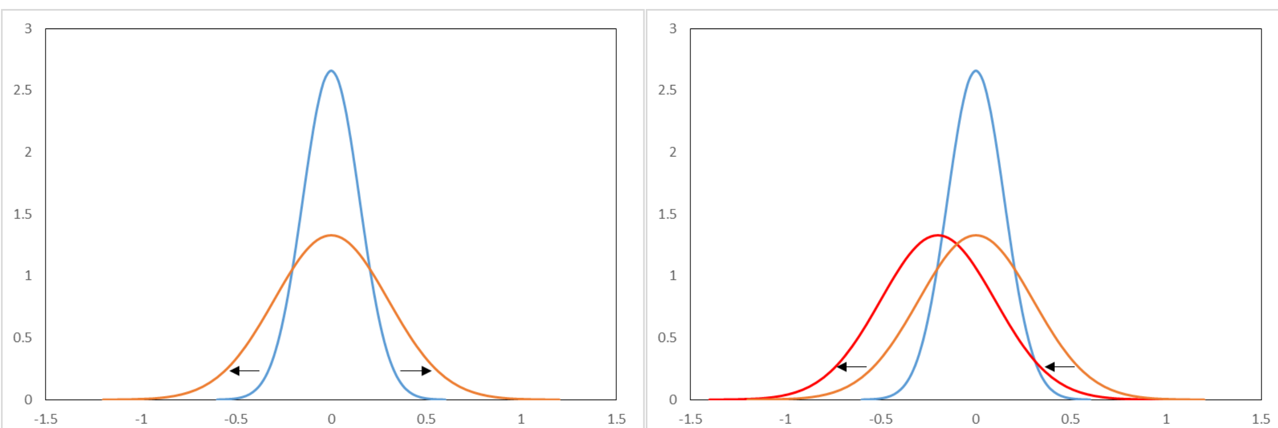


5.2 The Great Recession simulation

In this section, I examine the aggregate behavior of this model in recession. The Great Recession witnessed a fall in the mean as well as a rise in the variance of the distribution of establishment TFP shocks. As explained earlier, this model captures this dynamics at the micro level. Consistent with the data, the Great Recession simulation in this section considers a fall in the mean value of aggregate productivity and a rise in the reset probability of base components. I show that the model can explain the aggregate dynamics of the U.S. economy well, and I study the role of imperfect information in shaping a rapid drop and recovery. From the simulation result, the mechanism of a rapid drop and slow recovery is examined in detail from the perspective of the dynamics of mass of firms—the interaction of how inaction and action regions expand and shrink and how firms move across these regions.

Figure 6 illustrates the combination of two shocks in the Great Recession simulation. The left panel of Figure 6 is the case with only a rise in the reset probability, π. Consistent with the data, the variance of TFP shocks increases, however the mean remains the same. By adding a shock to aggregate productivity z, the mean of the distribution of TFP shocks falls as in the data.

Figure 10: Two series of shocks in the Great Recession simulation



Notes: The left panel illustrates the case with a shock to π (π_L : 0.15$\rightarrow$ π_H : 0.55). The variance increases from 0.234 to 0.335. The right panel illustrates the case with two shocks. With a shock to π (π_L : 0.15$\rightarrow$ π_H : 0.55) and z (z_H : 1.00$\rightarrow$ z_L : 0.98). The mean falls from 0.00 to -0.110.

Table 3 compares the size of the recession between the model and data. The size of the recession is measured by the percentage change in each variable from the peak to trough, which correspond 2007Q4 and 2009Q2, respectively, in the data. First, the recession in this model with the first and second moment shocks is close to what is observed in the data in regards to GDP and investment; each falls by 4.48% and by 14.14%, respectively. While those reductions are 80% and 74% relative to the data, measured TFP in the model overshoots. Notice that the model response to only second moment shocks are not enough to reproduce the size of the 07-09 recession as they merely cause half of the reductions what is observed in the data.

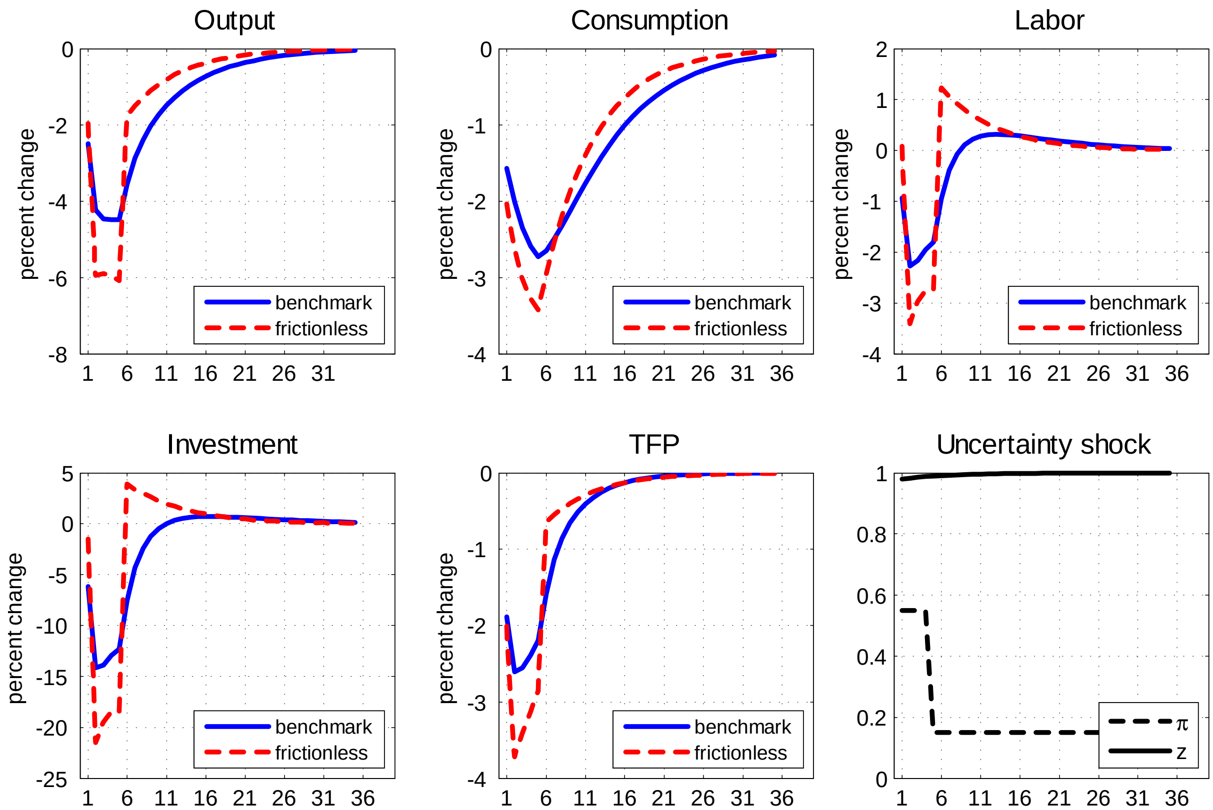
Table 4: Peak-to-trough drops for the Great Recession and model

	GDP	Investment	TFP
data	5.59	18.98	2.18
model (1st moment shock + 2nd moment shock)	4.48	14.14	2.60
model (2nd moment shock)	2.61	8.37	1.39

Notes: The peak-to-trough drops are calculated with log deviations from 07Q4 to 09Q2, detrended using the HP filter with parameter 1600. GDP and investment series are taken from BEA GDP Tables. Measured TFP is a Solow Residual series calculated.

Figure 7 depicts the model economy's response in the Great Recession simulation. Two models are compared: benchmark model with imperfect information and frictionless model without imperfect information. First, imperfect information dampens the impacts of the shocks. Second, imperfect information slows the pace of recovery in aggregates and prevents an overshoot in investment and labor. To gauge the importance of imperfect information in reproducing a rapid drop and slow recovery during the recession, I will decompose the impacts of shocks into two margins: how each type of firms responds to the shocks and how many firms are categorized into each type. In particular, I examine investment dynamics to understand the mechanism of a rapid drop and slow recovery in a model with imperfect information.

Figure 11: Model's responses during the recession



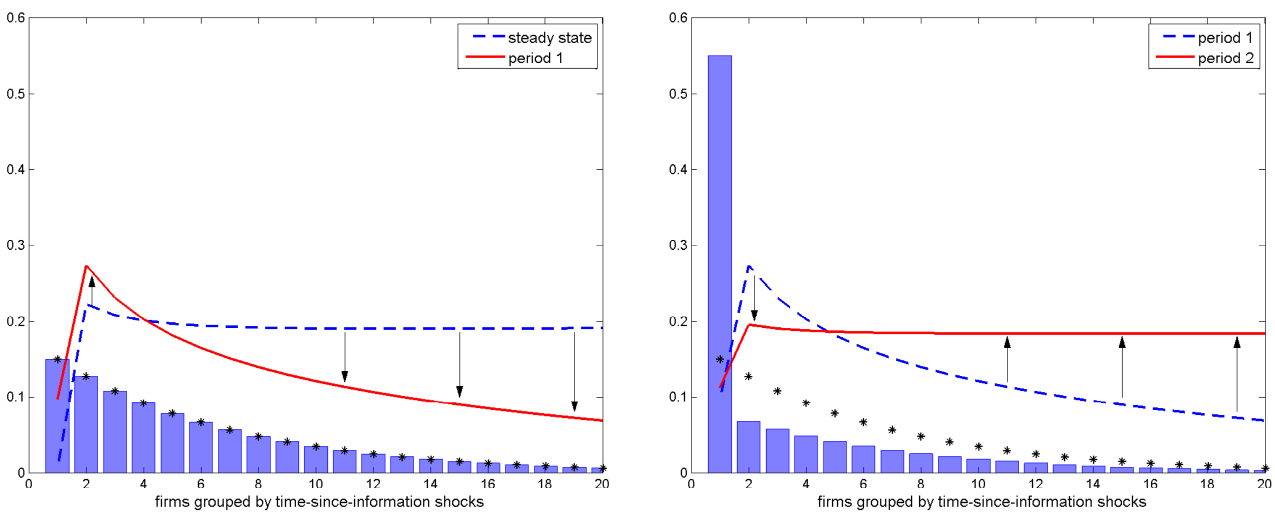
5.2.1 A rapid drop

First, I examine the start of the recession. At the impact of the shock, investment falls by 6%. In the following period, investment falls further by 8%. This two-stage drop in investment represents a rapid contraction of the aggregate economy at the start of recession. To explain this two-stage drop in aggregate investment, Figure 8 illustrates how precautionary effects compound distributional effects.

When firms anticipate the higher reset probability of their base components, they change their target level of capital stock. Firms that believe that their persistent component is higher than the mean reduce their capital stock. On the other hand, firms that believe that they are half bottom increase their capital stock. Given that the distribution of persistent component of productivity is symmetry and the production function has decreasing returns to scale, the net impact is negative. These behaviors apply to firms that have accurate information. For firms that still half way through their learning process, their cautiousness is not much affected by the shock. Therefore, average investment in cohort of firms that have more accurate information falls. In the left panel of Figure 8, with a rise in the reset probability of base components, average investment in each cohort of 5 to 20 falls while that of cohort 1 to 3 slightly rises. This shifts the average investment curve from shown in dashed to bold. Coupled with the steady-state distribution of mass of firms in each cohort, aggregate investment falls.

By contrast, the right panel of Figure 8 highlights the distributional effects in the following period. While precautionary effects are muted, there is a larger inflow of firms into cohort 1 than the pre-recession level. Since the average investment level of cohort 1 is low, the large inflow of firms into this cohort leads to a further drop in aggregate investment.

Figure 12: Adjustment response at the start of the recession

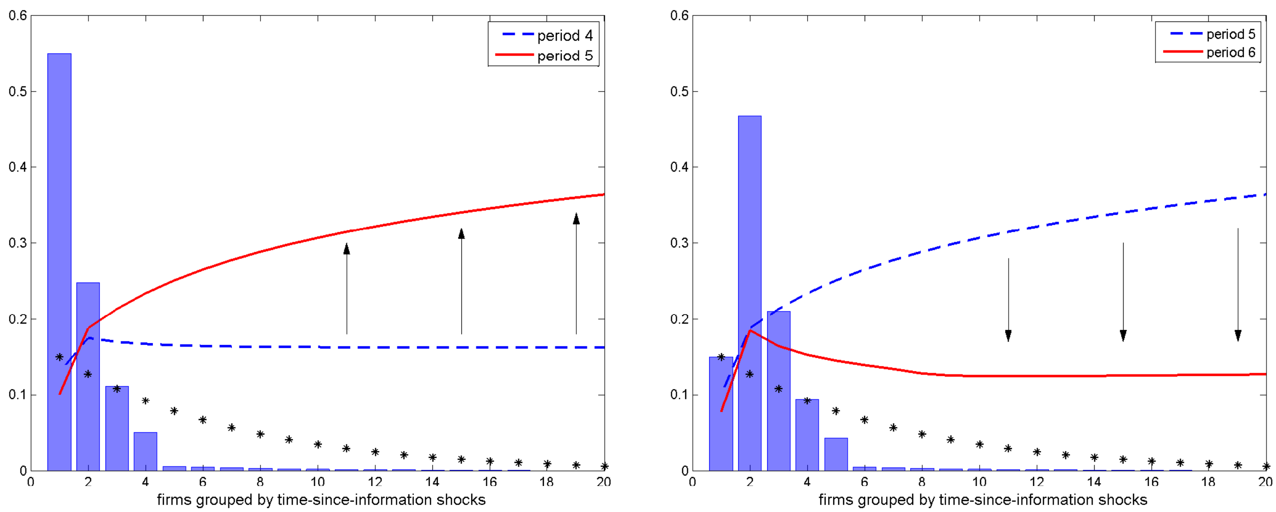


Notes: Bar represents the mass of firms in each cohort that is grouped by the time-since-reset. Higher the number of time-since-reset, more informed firms are about their productivity. Each line represents average investment for each cohort. To see the movement of mass of firms, each dot shows the steady-state distribution.

5.2.2 A slow recovery

In this subsection, I examine how imperfect information eliminates an overshoot of investment. After the shock is turned off, firms expect that they are more likely to maintain their current level of productivity. As before, if firms believe that their persistent component is higher than the mean they increase the scale of production. If firms believe that they are half-bottom they decrease the scale of production. For the same reason in the previous subsection, the pent-up demand for firms with higher productivity shifts the average investment curve from shown in dashed to bold. As in the left panel of Figure 9, this pent-up investment demand is profound in cohort of longer time-since-reset as less accurate information makes firm still cautious.

Figure 13: Adjustment response at the recovery phase



Notes: Bar represents the mass of firms in each cohort that is grouped by the time-since-reset. Higher the number of time-since-reset, more informed firms are about their productivity. Each line represents average investment for each cohort. To see the movement of mass of firms, each dot shows the steady-state distribution.

Pent-up investment demand is stronger for firms with more accurate information. However, when the shock is turned off, the mass of firms in relevant cohorts is much smaller than the pre-recession level. Now the number of firms that have reset of their base components in each period goes back to the pre-recession level. However, many firms had been already hit by shocks and they are still half way through their learning process—cohort of 1 to 4. Therefore, aggregate investment is not pushed up by pent-up demand even after the shock ends.

Imperfect information not only eliminates an overshoot in investment but also slow the pace of recovery afterwards. The right panel of Figure 9 explains how the model economy slowly recovers to its pre-recession level in the following periods. The key mechanism is misallocation. To achieve an efficient level of capital stock, firms need to have accurate information about their productivity. Thus, misallocation of capital and labor is more severe among cohort of smaller time-since-reset. As in the figure, the mass of firms within cohort of 2 and 3 is larger than its steady-state level and that of cohort of 4 and further is smaller than its pre-recession level. As time goes by, the mass of firms in cohort 2 and 3 will gradually fill up the gap the size of mass in cohort 5 and further. Due to a slow-moving distribution of firms because of learning, the negative aggregate effect due to misallocation persists until the economy reach the steady-state firm distribution.

6 Conclusion

This paper explores the aggregate, quantitative implications of imperfect information in shaping business cycles following a shock to micro volatility. In a general equilibrium analysis, I show that the presence of imperfect information at the firm level leads to a prolonged recession. Comparisons between a model with and without imperfect information reveal that a consumption smoothing motive of households does not, on its own, reproduce a rapid drop and slow recovery. The interaction of dynamics of the region of pent-up investment demand and a time-varying firm distribution eliminates an overshoot of investment in aggregate.

Understanding what causes aggregate fluctuations has been one of the central questions in macroeconomics. This paper shows that procyclical aggregate TFP can be decomposed between variations in the mean and variance of firm-level TFP shocks. Quantitative analysis in this paper is micro-founded in a sense that the model captures the firm level TFP shock distribution. However, the relationship between each firm's TFP shock and its characteristics such as size and age is intriguing and unexplored. Getting a better understanding the characteristics of firms that suffer the most during a larger downturn as the Great Recession is indispensable for policy debate; for instance, subsidizing start-ups might not be the same as subsidizing small, but old firms. I leave this to future research.

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Appendix

Figure A1: Hetogenenous uncertainty

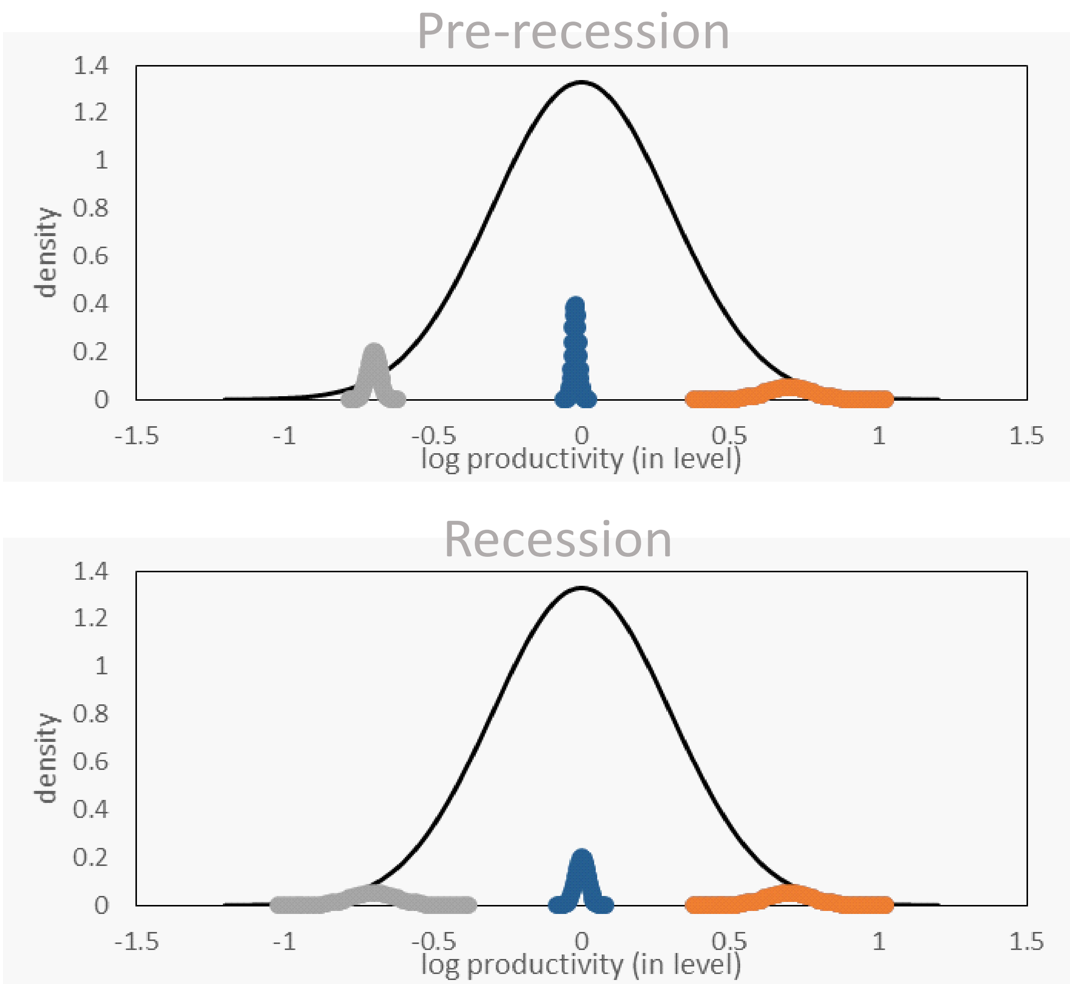

Figure A1 demonstrates heterogeneous uncertainty in a three-firm example. Big line shows the unconditional distribution of idiosyncratic productivity, θ. Small line is the conditional distribution for each firm: grey line represents informed firms, blue line represents well-informed firms, and orange line represents uninformed firms.

The top figure describes pre-recession periods where the population share of uninformed firms is small. On the other hand, the bottom figure represents recession periods where the population share of uninformed firms large.

A key mechanism in this paper is the asymmetric dynamics of population share of each type of firms. In the presence of learning, firms can become uninformed immediately when they are hit by information shocks, however, it takes time for them to become informed. In terms of the distribution of firms, transitions from the top to the bottom figure are immediate at the start of recessions while transitions from the bottom to top figure occur slowly; we have to wait until each uninformed firm learns. The distribution gets its pre-recession shape back after recessions.

Figure A2: Homogenenous uncertainty

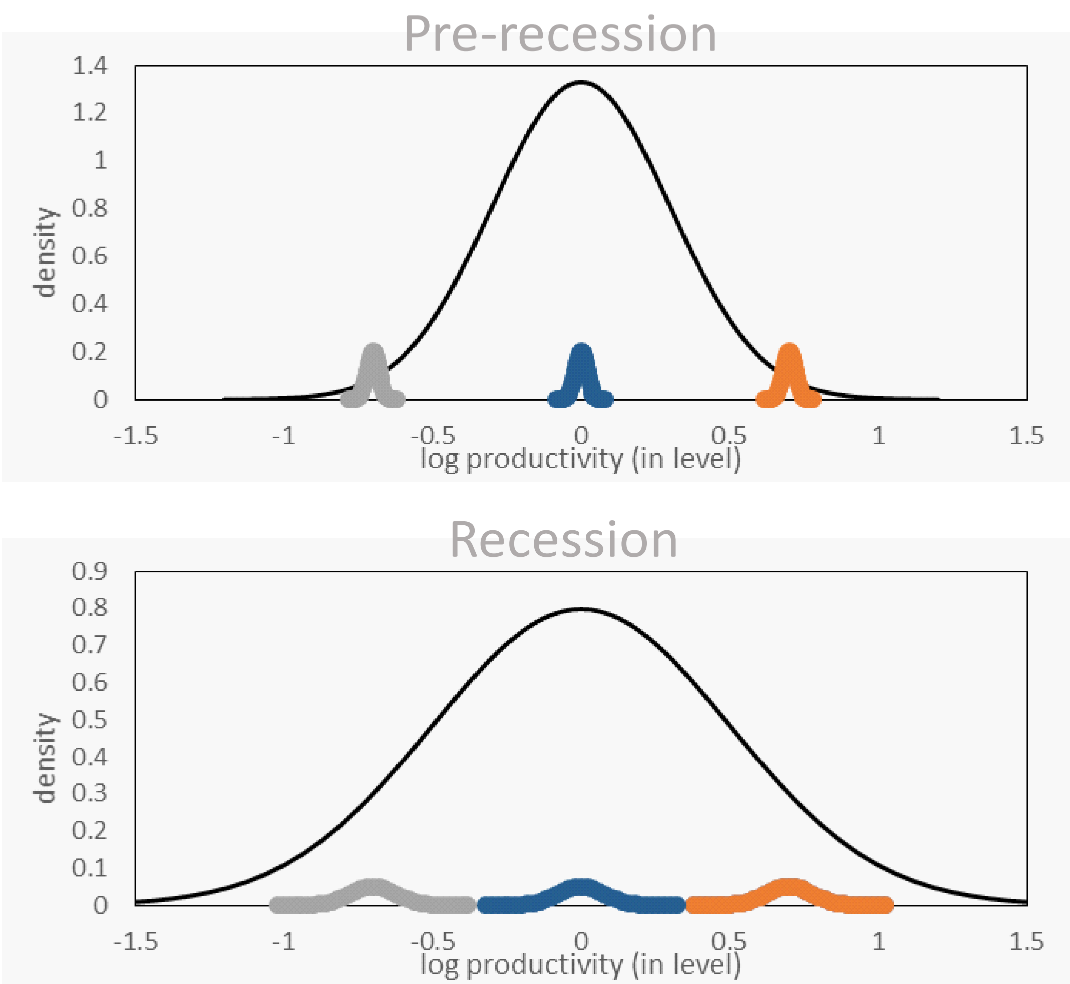

Figure A2 demonstrates homogeneous uncertainty in a three-firm example. Unlike the situation described by Figure A1, transitions from the bottom to top figure are quick in the absence of learning.