Uncertainty, Heterogeneous Beliefs, and Business Cycles: Macro and Micro Evidence

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Abstract

This paper provides empirical evidence both at the aggregate and the micro level to demonstrate that the survey-based forecast dispersion series helps identify a different type of second moment shocks, which affect the distribution of firms' beliefs regardless of whether those beliefs are backed by economic fundamentals. Having jointly identified the "informational disagreement shocks" and the standard uncertainty shocks, innovations that enlarge the forecast dispersion lead to a persistent decline in aggregate investment, employment, and production followed by a slow recovery. Conversely, when the uncertainty is measured by the variability of future firm-specific productivity innovations, the classic "wait and see" effect of uncertainty kicks in such that a quick "rebound-overshoot" ensuing a short-run contraction. Firm-level evidence suggests that those more productive firms increase the investments given larger uncertainty, whereas the investments are cut when they hold more heterogeneous beliefs about future business well-beings. Thus, the heightened uncertainty promotes while rises in the belief heterogeneity hinders the capital reallocation among firms. The results hold with the endogeneity issue corrected with instruments constructed from the USPTO patent data. Identifying the informational second moment shocks implies that a slow recovery does not have to be a result of the combined adverse first moment and second moment shocks that shift the economic fundamentals.

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1 Introduction

What is the impact of time-varying firms' uncertainty about future business conditions on their investment decisions and on the aggregate economy? This paper shows that empirically, the dispersion of business-level forecasts, one of the standard measures of "uncertainty", differs from other commonly used uncertainty proxies for their different aggregate and micro-level implications.[1] I provide novel aggregate and the firm-level evidence to demonstrate that the measure of cross-sectional forecast disagreement helps identify shocks that are distinct from the uncertainty shocks as in Bloom (2009). While the exogenous changes in the variance of firms' future productivity are denoted as uncertainty shocks, such newly identified shocks are labeled, *informational disagreement* shocks, as they affect the distribution of firms' beliefs, even if the distribution of firms' productivity fundamentals is unchanged. Both shocks are considered *second moment* shocks, as they affect the variability of pure beliefs, and the variance of real fundamentals respectively.

Distinguishing the two different types of second moment shocks helps better answer the question on whether or not the uncertainty shocks are a crucial driver of the business cycle fluctuations. In theory, within the framework of micro-level capital and labor adjustment frictions in the form of irreversible investment and non-convex adjustment costs, the "wait and see" channel of uncertainty shocks plays a pivotal role for uncertainty to have a contractionary effect (Bernanke, 1983; Pindyck, 1991; Bloom, 2009; Bloom et al., 2014). Increases in the variance of future demand or productivity can raise the option value of adopting a "wait and see" policy towards investment or hiring. When a significant number of firms pause their capital and labor adjustment actions, it leads to a large economic downturn. However, Bloom et al. (2014) find that the "wait and see" effects are transitory. The aggregate output will be quickly pushed into a rebound mode, and the full recovery is completed within a year. The theoretical predictions of the sign and magnitude of the effects of uncertainty shocks can be mixed. For

[1] Dispersion of private agents' point expectations about future inflation rate, GDP growth rates among others, i.e. the forecast disagreement is considered one of the standard measures of uncertainty about future price stability (Mankiw et al., 2004), or the future aggregate economic conditions (Bloom, 2014).

example, very moderate effects have been found in a model in the absent of the additional market frictions such as the price rigidity (Bundick and Basu, 2014), the credit market friction (Gilchrist et al., 2014), or the search friction (Leduc and Liu, 2015).[2] However, no empirical work has been done to examine the effects of uncertainty shocks over the business cycles using the more direct measure of productivity variability that better corresponds to the definition of uncertainty in the theory papers.[3] Although Bloom (2014) gives a list of various uncertainty measures and argues that they should have very alike effects, Bachmann et al. (2013) finds that the identified impacts of uncertainty shocks largely depend on how we measure the economic uncertainty in the data. In particular, they found that for both Germany and the U.S., when uncertainty is measured by the dispersion of survey-based business forecasts, one of in the list of Bloom (2014), rises in the forecast dispersion lead to a large recession and much slower recovery.

Hence, I provide Vector Autoregression (VAR) evidence to demonstrate that the real-option channel is pronounced if we measure the economic uncertainty in line with the theoretical definition in Bloom et al. (2014), the standard deviation of firm-level productivity shocks. But more importantly, this paper shows that the identified impacts of changes in the survey-based forecast disagreement, do not correspond to the "wait and see" effects highlighted in a model of uncertainty shocks à la Bloom (2009). My joint identifications find that: first, in response to jumps in the uncertainty about future productivity, all major aggregate series experience the "drops and quick rebounds"; second, the shocks that lead to more dispersed beliefs among firms about their own future business conditions, even though there is no change to the *de facto* shape of distribution of productivity fundamentals, affect the economy through a separate channel. Larger forecast disagreement tends to trigger a persistent decline in investment, employment,

[2]Calibration also matters for the results. When a model of standard uncertainty shocks is calibrated to German data, the quantitative importance of the real-option effect is very limited Bachmann and Bayer (2013).

[3]Bloom (2009) measures the economic uncertainty using the stock market volatility though he defines the uncertainty based on the volatility of the Solow residuals, the aggregate demand and productivity factor. It finds uncertainty jumps lead to a recession and a quick rebound of the aggregate economy in a VAR exercise. In Bloom et al. (2014), the uncertainty is defined in the model as the variability of aggregate and idiosyncratic TFP shocks. Baker et al. (2016), however, test the implications of models of uncertainty shocks using a more obscure measure: news frequency counts of key words regarding the economic policy uncertainty, i.e. EPU index.

and production, and is followed by a sluggish recovery. Quantitatively, in the near term of the shocks, changes in the uncertainty about productivity fundamentals may well explain 2 % of the variations in aggregate investment. However, the "wait and see" channel quickly wanes within a year. By contrast, changes to the distribution of firm-level beliefs affect the aggregate investment dynamics all along, until the effect completely dies out after five years. These evidences suggest that an important channel through which the heterogeneous beliefs matter for the aggregate economy is mis-attributed to the role of fundamental uncertainty given the limitation of current realm of theoretical models, which have the sole emphasis on the impacts of changes to variance of economic fundamentals.

In terms of the implementation, I construct the business level forecast disagreement measure based on Philadelphia Fed's Business Outlook Survey (BOS) data following Bachmann et al. (2013). The surveyed manufacturing firms' beliefs about their future business conditions better reflect the actual decision makers' expectations. It thus helps explain why the distribution of firms' beliefs, whether or not they are backed by good or bad fundamentals, could strongly affect their business activities, such as investment. I also consider an alternative measure of belief dispersion using Philadelphia Fed's Survey of Professional Forecasters (SPF) data. Despite that SPF data captures the expectations of institutional forecasters, SPF forecast dispersion still helps identify the second moment shocks that are orthogonal from the changes in the variance of economic fundamentals but still affect forecasters' beliefs dispersion.It shows that the strong contractionary and slow recovery effects of the disagreement shocks are robust, regardless of how we measure the cross-sectional belief difference. Importantly, when a disagreement measure is coupled with the alternative measure of uncertainty in the identification, the news-based Economic Policy Uncertainty (EPU) index, which has been found to have sizable business cycle impacts in Baker et al. (2016), changes in the EPU proxy lost its significant aggregate effects almost entirely. This leads to the conclusion that the disturbances which affect the dispersion of beliefs are largely information-based. I thus call the newly identified second moment shocks as *informational* disagreement shocks.

In addition, using Compustat firm-level data, this paper presents micro-level evidence to identify the separate channels through which uncertainty and disagreement could affect the firm-level investment. Firstly, I disentangled the "wait and see" effect of uncertainty at the firm-level that is consistent with temporary drops and ensuing "rebound and overshoot" of aggregate investment at the macro level. A model of uncertainty shocks in Bloom (2009) predicts that in the short run, the effect of "wait and see" that more firms pause investment during more uncertain periods, dominates the convexity effect, i.e. firms' expected marginal product of capital increases in the variance of productivity uncertainty.[4] In the medium-run, the convexity effect takes the lead, which results in the rebound and even overshoot of aggregate investment.

I provide evidence showing that there is a linear negative association between the firm-level investment and the productivity uncertainty, in supportive of the "wait and see" effect. In addition, the firm-level investment rebound dynamics can be seen through a non-linear effect of uncertainty conditional on firm-level productivity growth rate. Specifically, conditional on a positive growth rate of a firm's productivity, the heightened uncertainty leads the firm to incur greater investment. This *productivity-enhancing* effect implies that the more productive firms will see themselves more productive in anticipation given a larger variance of future productivity draws. The findings on the firm-level rebound motives contributes to the existing literature which only focuses on the linear empirical relationship between the uncertainty and the firm-level investment.[5]

Secondly, the *productivity-dampening* effects of informational disagreement shocks are found at the firm-level, which is consistent with the persistent contractionary effects of disagreement changes at the macro level. Apart from the relatively smaller negative linear effect, conditional on a firm's productivity growth, greater disagreement significantly dampens the firm-level investment. This conditional investment elasticity has the opposite sign different from that of the

[4] This effect is also called Oi-Hartman-Abel effect due to Oi (1962); Hartman (1972); Abel (1983).

[5] For example, Leahy and Whited (1996), and Gilchrist et al. (2014) finds the negatively correlated linear relationship between uncertainty and investment using U.S. firm-level panel data. Using U.K. manufacturing firm level data, Bloom et al. (2007) finds that the linear effect of uncertainty is not statistically significant, but argues for a non-linear term of uncertainty, conditional on the sales growth, as evidence for the "wait-and-see" channel.

non-linear term of the productivity uncertainty. This finding is very important for the following reason. A key shortfall of a model of uncertainty shocks is that the time-varying variance of productivity fundamentals cannot simultaneously generate a sizable recession and a sluggish recovery unless additional adverse aggregate TFP or demand shocks are imposed (Bloom et al., 2014). The productivity-dampening effect of forecast disagreement suggests that the imperfect information that affect the distribution of firms' beliefs can propagate the impacts of uncertainty shocks such that the post-crisis recovery could be very slow.

Clearly, the empirical challenges to distinguish the causal impacts of uncertainty and disagreement on firm-level investments are the reverse causality, and the measurement issue. To approach the first problem, this paper aligns itself with Baker and Bloom (2013) by constructing proxies to capture the exogenous changes to the productivity dispersion and the belief dispersion. I exploit the data of those United States of Patent and Trademark Office (USPTO) patent applications that are originated from non-U.S. residence. Two instrument variables (IV) are constructed to explore the exogenous variations of uncertainty and disagreement respectively: the cross-sector dispersion of non-U.S. patent applications, and the penetration intensity of the information processing technology patents into other sectors. The measurement concern is that belief differences across firms about business conditions are partly reflective of the differences of productivity fundamentals among firms. I follow the rationale of identifications used in Baker and Bloom (2013); Alfaro et al. (2016) by assuming that changes to the IVs can be broken into different types of shocks of interest. In specific, variations in the cross-sector patent applications are primarily associated with shocks to productivity uncertainty, while adopting information processing technology helps firms in the sector to better clarify their understanding of how good their business fundamentals are. Evidence suggests that the cross-sector dispersion of patent applications is positively correlated with the productivity dispersion across firms, while the penetration intensity of the information processing technology patents into other sectors is negatively related to the magnitude of forecast disagreement.

The macro section of this paper is closely related to the findings in Bachmann et al. (2013). This paper differs in the way that the impacts of uncertainty shocks to economic fundamentals and those of informational disagreement shocks are jointly identified. The micro section of this paper joins the literature that examines the linear impacts of uncertainty changes on firm-level decisions such as Leahy and Whited (1996); Bloom et al. (2007); Gilchrist et al. (2014). This paper makes a contribution by documenting the different *non-linear* effects of uncertainty and disagreement shocks, which lead to the distinctive macro implications. In addition, Eisfeldt and Rampini (2006) highlights a puzzling fact that the capital reallocation is procyclical whereas the benefit of the reallocation is countercyclical. This paper, by isolating the between-firm effects of disagreement shocks, provides an explanation that the disagreement shocks could trigger the *informational cost* that prevents more productive firms from accumulating capital in bad times. This paper is also related to Caldara et al. (2016). Both papers aim to differentiate the impacts of two types shocks that are highly correlated. The difference is that this paper assorts to the more traditional VAR and IV frameworks while Caldara et al. (2016) explores the penalty penalty function approach using Structural VAR.

This paper unfolds as followed: Section 2 outline the construction details of the benchmark and alternative measures of productivity uncertainty and the forecast disagreement. Section 3 performs the VAR analyses to provide aggregate evidence for the impacts of shocks to uncertainty and disagreement. Section 4 provides micro-based evidence using panel data and instrument-variable estimations to uncover the causal relationships of uncertainty and disagreement changes on the firm-level investments. Section 5 discusses the consistency between macro and micro evidence. Section 6 gives the concluding remarks.

2 Measurements

Despite the limited consensus on what best measures the economic uncertainty, a range of second moment measures based on time-series volatility and cross-sectional dispersion of key economic variables are considered the closet alternatives (Bloom, 2014). This selection of measures simply reflects the fact that higher volatility of data series means greater difficulty for forecasting with good precision. Commonly used uncertainty measures include the volatility of a range of aggregate economic indicators including stock market price index, GDP growth rate, and Total Factor Productivity (TFP), along with the dispersion of idiosyncratic variables, such as firm-level TFPs and in particular, that of forecasters' point expectations about future aggregate or idiosyncratic conditions. In this paper, I examine the macro and micro impacts of the dispersion of forecasts across firms by comparing and contrasting it with other cross-sectional dispersion-based measures of uncertainty. In addition, I abstract from studying uncertainty measures constructed from the financial data, for example, the implied stock market volatility (VIX) index, as they may partly capture the time-varying changes in the degree of financial stress (Caldara et al., 2016).

Following Bachmann et al. (2013), I construct the forecast dispersion measure (**DIS**) using Philadelphia Fed's Business Outlook Survey (BOS) data. Consistent with Bloom et al. (2014), the uncertainty is measured by the standard deviation of future firm-level log TFP innovations (**UNC**), estimated from the U.S. Compustat Data. To avoid the overuse of terminology, I call the former, "the measure of *disagreement*" and the latter, "the measure of economic *uncertainty*".[6] For the robustness checks, the forecast dispersion index constructed based on the Survey of Professional Forecasters data (**SPF**), is also considered an alternative measure of disagreement. The index of Economic Policy Uncertainty (**EPU**), which counts newspaper references of policy-related uncertainty keywords, is taken as another measure of economic uncertainty. I discuss the data sources and the construction methods for **DIS** and **UNC** below and relegate the readers to Appendix A for additional details on **SPF** and **EPU**.

2.1 Measure of Forecast Disagreement

I construct the forecast disagreement index using the monthly BOS firms' forecast data. Surveyed firms' forecasts captured the difference in beliefs of actual decision makers, which can

[6]Note that both Bachmann et al. (2013) and Caldara et al. (2016) find that empirically, the forecast disagreement can have quite different macro implications as contrasted to other measures of uncertainty, despite they implicitly assume the forecast disagreement is a measure of "uncertainty".

be directly used to examine the economic impacts of changes in firms' expectations.[7]

The BOS survey records the numbers of firms who report an increase, decrease or no change in their beliefs about their future business conditions. I focus on two questions in the survey probing firms' views about the "General Business Conditions" and their expected "New Orders" to be shipped in six months, relative to the survey date. The two survey questions are framed as follows:

- **General Business Conditions**: What is your evaluation of the level of general business activity six months from now versus [CURRENT MONTH]: *Decrease/No Change/Increase*
- **Company Business Indicators**: New Orders. Six months from now versus [CURRENT MONTH]: *Decrease/No Change/Increase*

Based on the fractions of responding firms in month t, with beliefs of increase and decrease in response to the surveyed question, as denoted by F_t^+ and F_t^- respectively, the disagreement index (**DIS**) can be defined below:

$$DIS_t = \sqrt{F_t^+ + F_t^- - (F_t^+ - F_t^-)^2}. \tag{1}$$

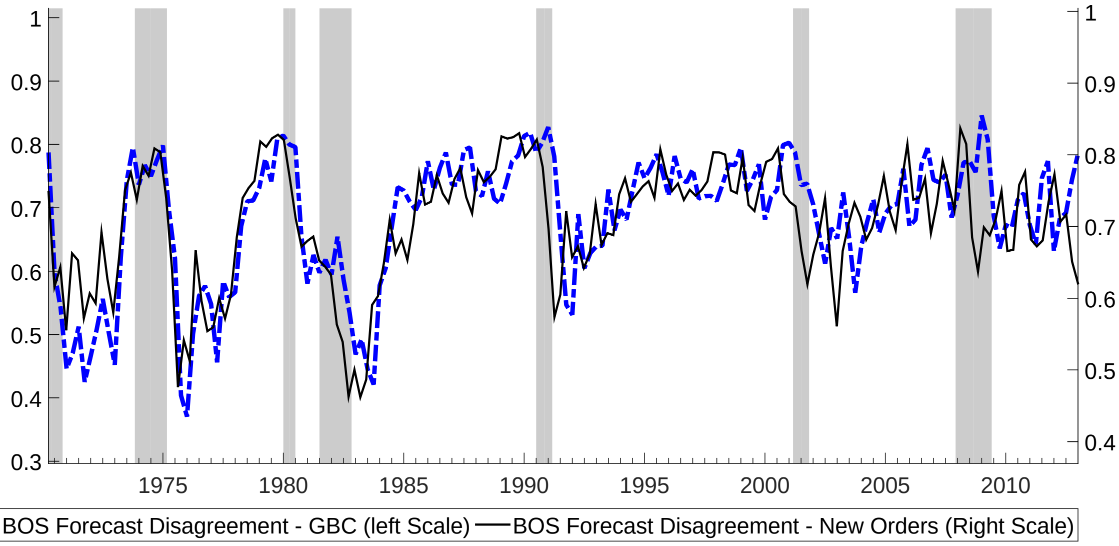
Equation (1) approximately measures the standard deviation of firm-level forecasts. It shows that increases in both fractions (larger F_t^+ and larger F_t^-) at the same time, i.e. more opposed views about future, thus disagreement, are adjusted for changes in the mean forecasts among firms. Mean forecast changes because firms become more optimistic (larger F_t^+ and smaller F_t^-) or more pessimistic (smaller F_t^+ and larger F_t^-). The closer this index is to 1 (when F_t^+ and F_t^- both get closer to 50 %), the greater is the magnitude of cross-sectional disagreement about their own future profitability. The complete optimism or pessimism is characterized by

[7]BOS surveys big manufacturing firms within the Third Federal Reserve District, but the data is found to closely reflect the business outlook at the national level (Nakamura and Trebing, 2008). The third district covers the state of Delaware, the southern half of New Jersey, and the eastern two thirds of Pennsylvania. On average, about 100 to 125 firms responded to the survey each month, out of 250 who received the survey questionnaire (Trebing, 1998).

$DIS_t = 0$ (when F_t^+ or F_t^- equals 1).

I use the BOS survey data from January, 1970 to December, 2013 and then convert the series to quarterly frequency to examine the time series properties of the constructed disagreement index. Figure 1 displays the two disagreement index series over time based on responses to the two selected questions. It suggests that the forecasts about general business conditions and about firm-specific new orders are highly correlated, such that the disagreement series keeps very close track of each other over time.[8] Without loss of generality, I use the disagreement index based on forecast data about the "General Business Conditions" as the benchmark disagreement measure**DIS**.

Figure 1: BOS Forecast Disagreement Indexes: Forecasts of General Business Condition and Forecasts of of New Orders in Six Months



Notes: Sample period: 1970:Q1 - 2013:Q4. The dashed line captures the magnitude of cross-sectional differences in six-month ahead forecasts of "general business condition" and the solid line denotes the forecast differences about "new orders" among manufacturing firms based on Philadelphia Fed Business Outlook Survey data. The disagreement indexes are constructed in line with Bachmann et al. (2013). The shaded bars indicate the NBER-dated recession periods.

[8] Trebing (1998) first finds that firms' responses to the question "general business condition" can be highly correlated with their responses to the question asking for the firm-specific conditions in the future such as shipments, and inventory among others.

2.2 Measure of Economic Uncertainty

The benchmark uncertainty proxy is to capture the cross-sectional dispersion of future firm-specific log productivity innovations, a micro-level measure of the variability of a firm's future productivity. Hence, greater variance in future productivity innovations leads to larger forecast errors of a firm's future business conditions. It can be seen from here that the dispersion of firm-specific *beliefs* about their future fundamentals, forecast disagreement, does not necessarily overlap with the dispersion of firms' actual *draws* of future fundamentals, i.e. real uncertainty.

Following Bloom (2014), idiosyncratic productivity is measured by firm-specific Solow residual (or, firm-specific TFP). The log TFP innovations $e_{i,t}$ are estimated based on the following first order auto-regressive equation about the log productivity $TFP_{i,t}$:

$$TFP_{i,t+1} = \rho_z TFP_{i,t} + \mu_i + \lambda_{t+1} + \sigma_{e,t} e_{i,t+1}. \tag{2}$$

The specification controls for the firm fixed-effect (μ_i: time-invariant cross-firm difference in productivity) and the time fixed-effect (λ_t: cyclical changes in a firm's productivity over time, which are common to all firms). Following Olley and Pakes (1996), firm-level TFPs are estimated based on a Compustat panel of firm-level annual data from 1963 to 2013. The estimation procedure of panel firm-specific TFPs has controlled for the industry fixed-effects and the aggregate effect (yearly time fixed effects). Thus in Equation (2), a period t corresponds to a year. I relegate the readers to Section 4.4 where discusses the sample of firms included in the estimation of the TFP panel.

The standard deviation, $\sigma_{e,t}$ of next year TFP shocks proxies for the uncertainty (**UNC**) regarding the to-be-realized future firm-specific productivity shocks. Uncertainty dated in year t about year $t+1$ is thus given by

$$UNC_t = \sigma_{e,t} \tag{3}$$

Therefore, the more dispersed idiosyncratic TFP shocks known at year t, the larger the forecast error for predicting firm i's productivity of next year, $t+1$. In order to compare and contrast the uncertainty series with the disagreement series without sacrificing the higher frequency of the forecast data, the annual uncertainty series is firstly interpolated into quarterly data.

2.3 Exploratory Analysis

I firstly show the pairwise cross-correlations between the disagreement measures (**DIS** and **SPF**), and the leads and lags of uncertainty measures (**UNC** and **EPU**) using data of quarterly frequency. Following Bloom (2014), the two SPF forecast dispersion series are constructed using data from the year of 1990 going forward when Philadelphia Fed took over the SPF survey project. Table 1 summarizes the results of correlations. In general, proxies for disagreement are positively correlated with the uncertainty measures. This is true regardless of whether the forecast disagreement among firms is about the "General Business Conditions" or about the "New Orders" (**DIS**). The positive correlations also hold when the disagreement is among professional forecasters (**SPF**) regarding the forecasts about either the real GDP or the industrial production in two quarters. In specific, over the short-term horizon of three quarters of leads or lags, the positive co-movements between the disagreement and uncertainty measures are significant with correlations ranging from 0.13 to 0.42. This may well suggest that more uncertain periods are associated with greater forecast disagreement among firms. It is thus important to understand whether or not the belief difference well captures the forecast uncertainty, and if not, how exactly the disagreement and uncertainty would individually or jointly affect the economy, given their tight interactions.

The BOS disagreement measures have the largest correlations with the cross-sectional dispersion of future productivity innovations (**UNC**) for periods when the disagreement lags the uncertainty ($h = 1, 2, 3$). This may imply that the past BOS disagreement indexes tend to indicate larger future productivity uncertainty. Also, we see **UNC** has its largest correlations with **SPF**-based measures when uncertainty lags or when it is contemporaneous with disagreement ($h = -1, 0$). Fluctuations in uncertainty could then be informative about rises in **SPF**-based

Table 1: Correlations Between Proxies of Disagreement and Uncertainty

Forecast	**DIS** (General)		**DIS** (Order)		**SPF** (Real GDP)		**SPF** (IP)	
Lag/Lead (h)	**UNC**	**EPU**	**UNC**	**EPU**	**UNC**	**EPU**	**UNC**	**EPU**
-3	0.230***	0.107	0.115	-0.02	0.270***	0.091	0.207**	0.154
-2	0.243***	0.138*	0.120	-0.01	0.350***	0.171*	0.248**	0.215**
-1	0.271***	0.223***	0.137*	0.090	0.401***	0.330***	0.273***	0.289***
0	0.307***	0.286***	0.163**	0.180**	0.417***	0.300***	0.271***	0.274***
1	0.339***	0.268***	0.187**	0.146*	0.393***	0.239**	0.243**	0.246**
2	0.372***	0.224***	0.213***	0.111	0.351***	0.265	0.190*	0.235**
3	0.400***	0.207***	0.242***	0.105	0.287***	0.197*	0.116	0.165

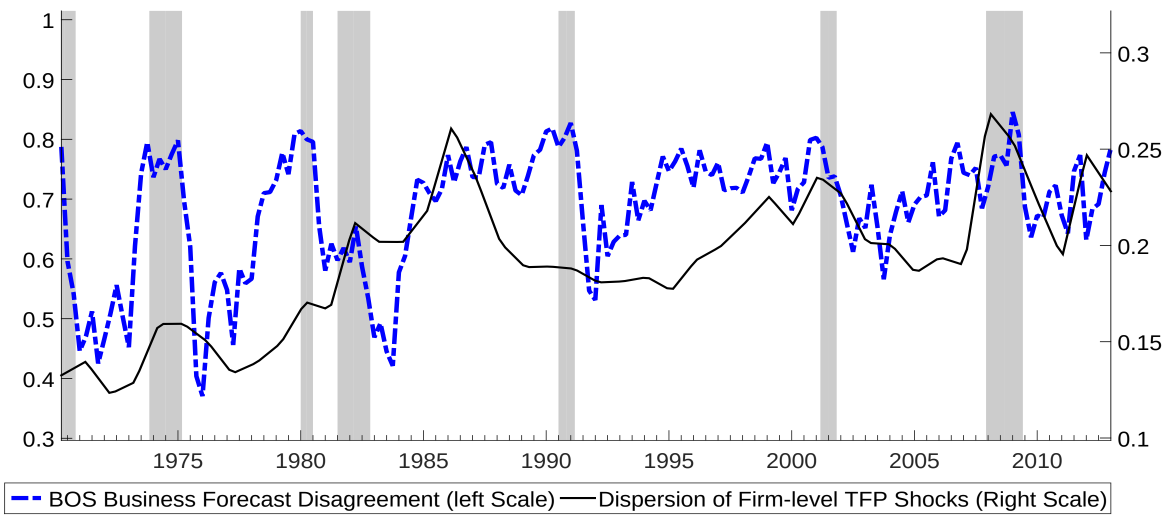
Notes: Numbers reported are the pairwise correlation coefficients between a time series of disagreement measure in quarter t and proxies of uncertainty dated at quarter $t+h$ (**UNC** and **EPU**). h reflects leads and lags of the uncertainty measures. "General" and "Order" respectively refer to the BOS disagreement index (**DIS**) using forecast data about General Business Conditions and about New Order in six months relative to the survey date. Monthly disagreement index and monthly Economic Policy Uncertainty Index **EPU** are converted to quarterly using within-quarter averages. "GDP" and "IP" respectively refers to Survey of Professional Forecasters quarterly forecast dispersion series (**SPF**) regarding forecasts about the Real GDP and about the Industrial Production two quarters ahead. Quarterly data of **UNC** is obtained via linear interpolation of yearly data. Sample period: 1970Q1 - 2013Q4 except that series of **SPF** from 1990Q1-2013Q4 is used. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

forecast disagreement measures. In addition, I find that the **EPU** index tends to be much more correlated with the BOS disagreement indexes based on forecasts about general business conditions, relative to the index based on forecasts about new orders. This suggests that the disagreement about firms' general business conditions are correlated with the fluctuations of policy uncertainty at the aggregate level. Now we move on to check the time series properties of measures of uncertainty and disagreement.

The dashed line in Figure 2 indicates the time-varying BOS firms' disagreement index regarding their forecasts about their future general business conditions. The solid line shows the interpolated quarterly time-variation in cross-sectional productivity uncertainty as estimated from Equation (2). This pair of series has been found to have sizable and positive correlations. As documented by Bachmann et al. (2013) and Bloom (2014), the forecast disagreement and uncertainty series are *counter-cyclical*: jumping before or during a recession and decaying right after a recession. The disagreement tends to quickly jump up and stays constant until further abrupt hikes reach its peak. The peaks quickly turn to huge busts after the recessions.

Conversely, it takes time for the uncertainty to accumulate. For example, during the periods of 1985-1987 and 1995-1999 when uncertainty was climbing, the belief dispersion already stayed quite stable and high. Similarly, when disagreement was undergoing rapid changes, underlying productivity uncertainty was rather sticky during 1982-1983, 1991-1993, and 2004-2006. Also, note that the disagreement series had more bounded variance in the second half of the sample compared to the first half of the time slice. In general, we see the BOS disagreement typically jumps before climbs of uncertainty, except that during the 2008-2009 recession, where very abrupt jumps in uncertainty were followed by rising disagreement.

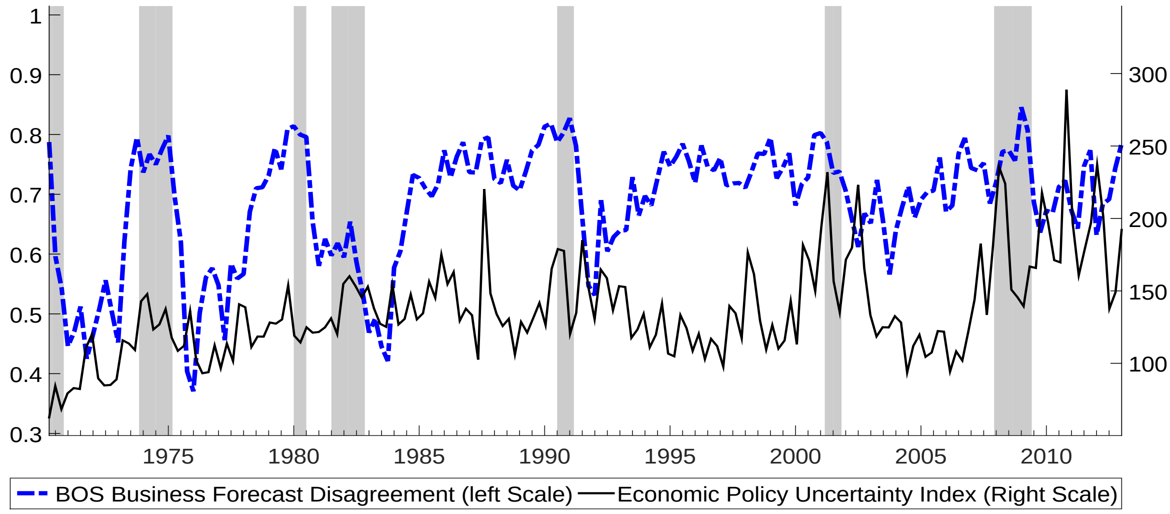
Figure 2: BOS Forecast Disagreement and Dispersion of Firm-level TFP Shocks



Notes: Sample period: 1970:Q1 - 2013:Q4. The dashed line captures the magnitude of cross-sectional difference in six-month ahead forecast of "general business condition" among manufacturing firms based on Philadelphia Fed Business Outlook Survey data. The disagreement index is constructed in line with Bachmann et al. (2013). The solid line depicts the estimate of dispersion of firm-level TFP innovations based on Compustat non-financial firms' data in line with Bloom et al. (2014). The shaded bars indicate the NBER-dated recession periods.

Figure 3 shows that if we are using **EPU** to measure the real uncertainty as denoted by the solid line, the hikes of **EPU** uncertainty are also associated with the recession periods. We see more quick jumps and slumps of the **EPU**, and the second half of the sample has larger variance in **EPU**. Similarly, we see **EPU** jumped before **DIS** picked up for the recession period 2008-2009. Note that **EPU** may capture great spikes, for example, on the Black Monday stock markets crash in 1987, while we see very little changes to the forecast disagreement.

Figure 3: BOS Forecast Disagreement and Economic Policy Uncertainty

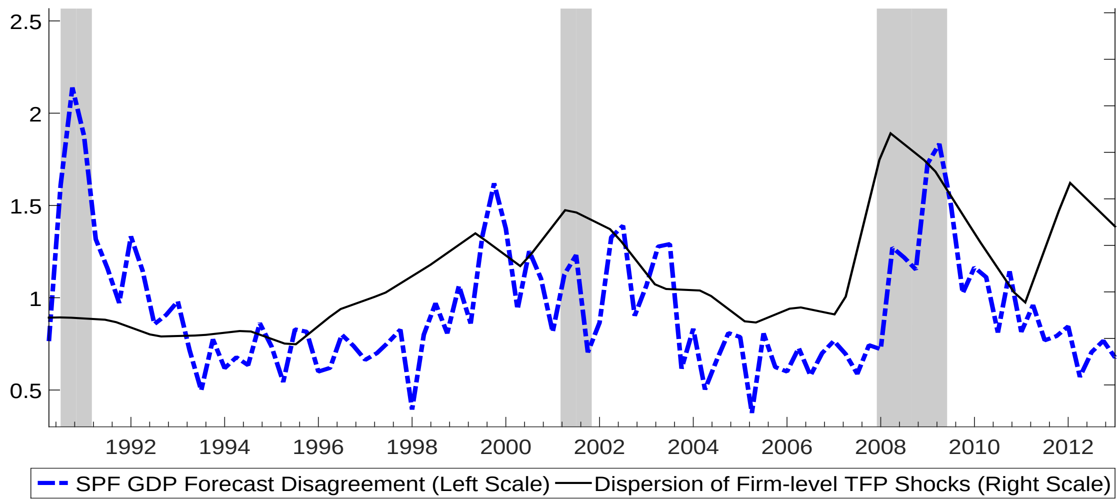


Notes: Sample period: 1970:Q1 - 2013:Q4. The dashed line captures the magnitude of cross-sectional difference in six-month ahead forecast of "general business condition" among manufacturing firms based on Philadelphia Fed Business Outlook Survey data. The disagreement index is constructed in line with Bachmann et al. (2013). The solid line depicts the media-based estimate of economic policy uncertainty based on Baker et al. (2016). The shaded bars indicate the NBER-dated recession periods.

Figures 4 and 5 compare the SPF forecast dispersion (dashed line) measure using the real GDP forecasts with the two uncertainty measures **UNC** and **EPU** respectively (solid line). These figures exhibit that the SPF-based belief dispersion hiked tremendously during the recessions of 1990-1991 and 2008-2009, but less so for the recession of 2000. Importantly, we see that the SPF-based belief dispersion hiked subsequent to the jumps in productivity uncertainty **UNC** or **EPU** during the 2008-2009 Great Recession.

In summary, both the forecast disagreement and the uncertainty are counter-cyclical, and largely maintain the positive synchronicity over time. However, we note that they did suspend synchronizing now and then, and the chronological order of changes may also change for different episodes of time. I proceed to explore the aggregate impacts of the innovations to the disagreement and uncertainty measures, given their close but potentially different empirical impacts.

Figure 4: SPF Forecast Disagreement and Dispersion of Firm-level TFP Shocks



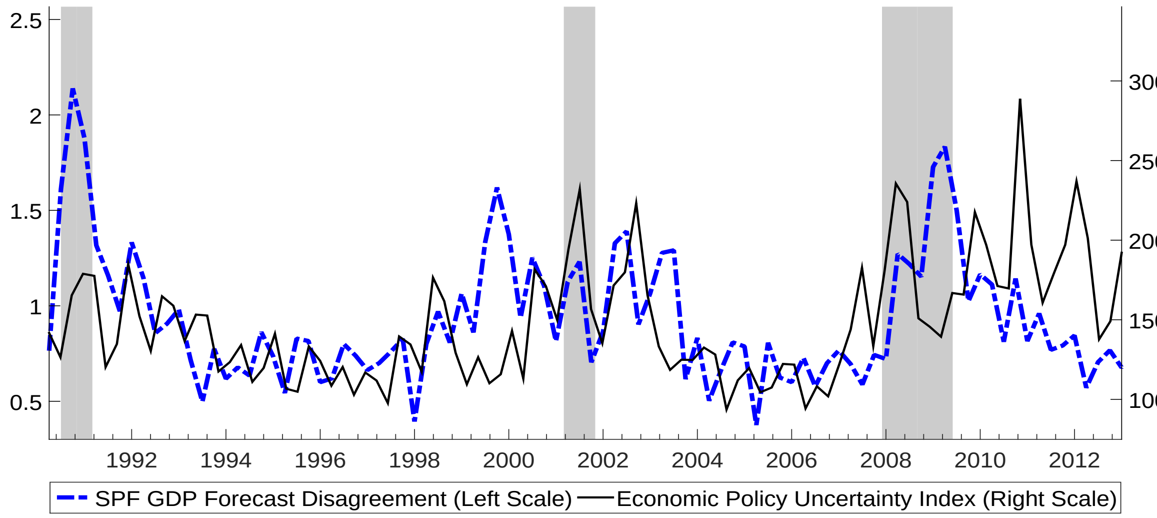
Notes: Sample period: 1990:Q1 - 2013:Q4. The dashed line captures the magnitude of 75 percentile relative to 25 percentile difference in six-month ahead forecast of "Real GDP" among professional forecasters published by Philadelphia Fed Survey of Professional Forecasters (SPF) data. The solid line depicts the estimate of dispersion of firm-level TFP innovations based on Compustat non-financial firms' data in line with Bloom et al. (2014). The shaded bars indicate the NBER-dated recession periods.

3 Aggregate Implications: Macro Evidence

To examine the aggregate effects of productivity uncertainty and the forecast disagreement over business cycles, I employ the standard recursive ordering identification by estimating a range of VAR systems in order to identify and examine the impacts of innovation changes to these second moment measures.

Firstly, I isolate the exogenous changes that directly affect the dispersion of firms' *beliefs* about the future, i.e. the *disagreement shocks* which affect the spread of firms' forecasts, by assuming that the exogenous changes to *real* productivity dispersion, the *uncertainty shocks*, do not affect the forecast dispersion within the same quarter. This benchmark identification shuts down the channel through which disturbances to productivity uncertainty would affect the forecast dispersion on impact (Scheme 1). Specifically, this scheme places the disagreement measure before the uncertainty proxy, as followed by other real macroeconomic variables.

Figure 5: SPF Forecast Disagreement and Economic Policy Uncertainty



Notes: Sample period: 1990:Q1 - 2013:Q4. The dashed line captures the magnitude of 75 percentile relative to 25 percentile difference in six-month ahead forecast of "Real GDP" among professional forecasters published by Philadelphia Fed Survey of Professional Forecasters (SPF) data. The solid line depicts the media-based estimate of economic policy uncertainty based on Baker et al. (2016).The shaded bars indicate the NBER-dated recession periods.

Secondly, I consider specifications that reverse the ordering between the disagreement and uncertainty, so as to disentangle the uncertainty shocks first. This ordering scheme assumes that the shocks that affect the dispersion of productivity fundamentals can immediately drive the belief dispersion this quarter (Scheme 2).

Then, I verify if the impulse responses of other macro variables to the isolated disagreement shocks, using Scheme 1, are quantitatively similar to the impulse responses to the disturbances of disagreement shocks, conditional on the restriction that forecast disagreement can be affected by uncertainty shocks on impact under Scheme 2. Similar comparisons can be performed in order to examine the identified impacts of the uncertainty shocks. Hence, we may conclude whether or not we can identify two different types of shocks, and their different business cycle impacts if any. In particular, it will be interesting to see how the aggregate changes in the forecast dispersion, which are not originated from changes in the variability of real productivity fundamentals, could affect the economy in a different way as compared to the impacts of productivity uncertainty.

3.1 Tri-variate VAR Systems

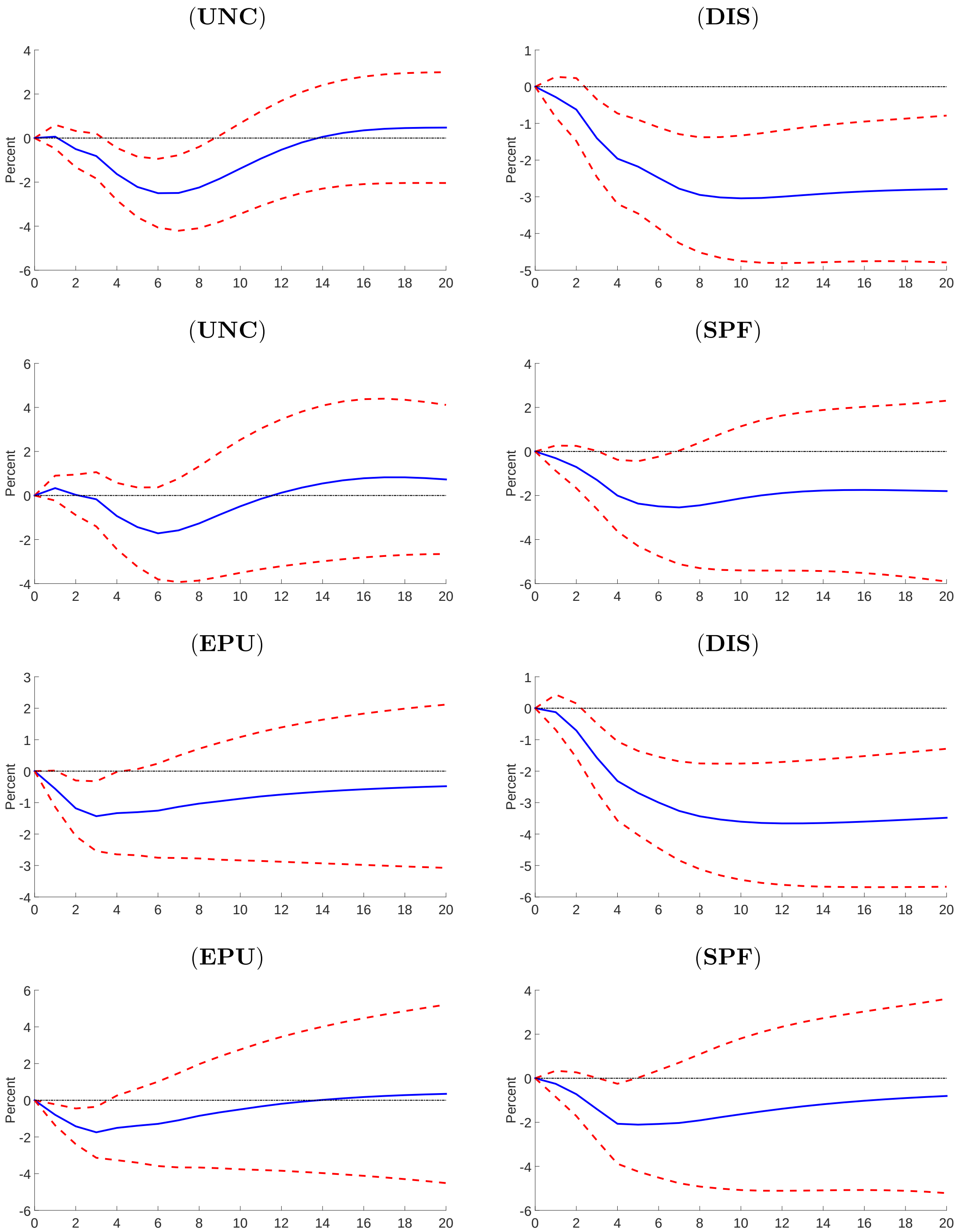
I first show the benchmark results, based on the estimations of a range of trivariate VAR systems, which place various disagreement and uncertainty proxies prior to the U.S. aggregate investment series, as measured by the real gross private domestic investment. I select the aggregate investment series for the following reasons: (1) it is clearly a forward looking variable that is more closely related to the forecasts and uncertainty about future. (2) As documented by Bloom et al. (2014), the uncertainty shocks affect aggregate output primarily though the impacts upon aggregate investment.

I present the estimated impulse responses of aggregate investment to one standard deviation jumps in the innovations to the different measures of uncertainty and disagreement. All variables enter the VARs in log-levels with four quarterly lags included. The sample period covers 1970Q1 up to 2013Q4, except for the system estimated using SPF data, which ranges from 1990Q1 to 2013Q4.

Figure 6 illustrates the impulse responses of aggregate investment, under the identification Scheme 1, where the changes to uncertainty measures are affected by the exogenous shocks that lead to more dispersed forecasts. We first focus on the top two rows when the uncertainty is measured by the dispersion of future TFP shocks, **UNC**. It shows that the aggregate investment drops on impact to the adverse uncertainty shocks imposed in period 1 until bottoming out at 1.5 to 2 % below the pre-shock level in about six quarters. Importantly, we find strong rebound and potentially overshooting expansion, such that in three to four years, the mean prediction about aggregate investment reaches 1 % above the pre-shock level. These "drop-rebound-overshoot" dynamics are consistent with the model-predicted real-option effect of "wait and see" for the uncertainty shocks in Bloom (2009). In addition, the identified effects of uncertainty shocks are robust regardless of how we measure forecast disagreement.

In response to the shocks that trigger greater disagreement among firms assuming that they

Figure 6: IRFs of Aggregate Investment: Uncertainty and Disagreement Shocks
(Trivariate VAR - Ordering: Disagreement, Uncertainty and Investment)

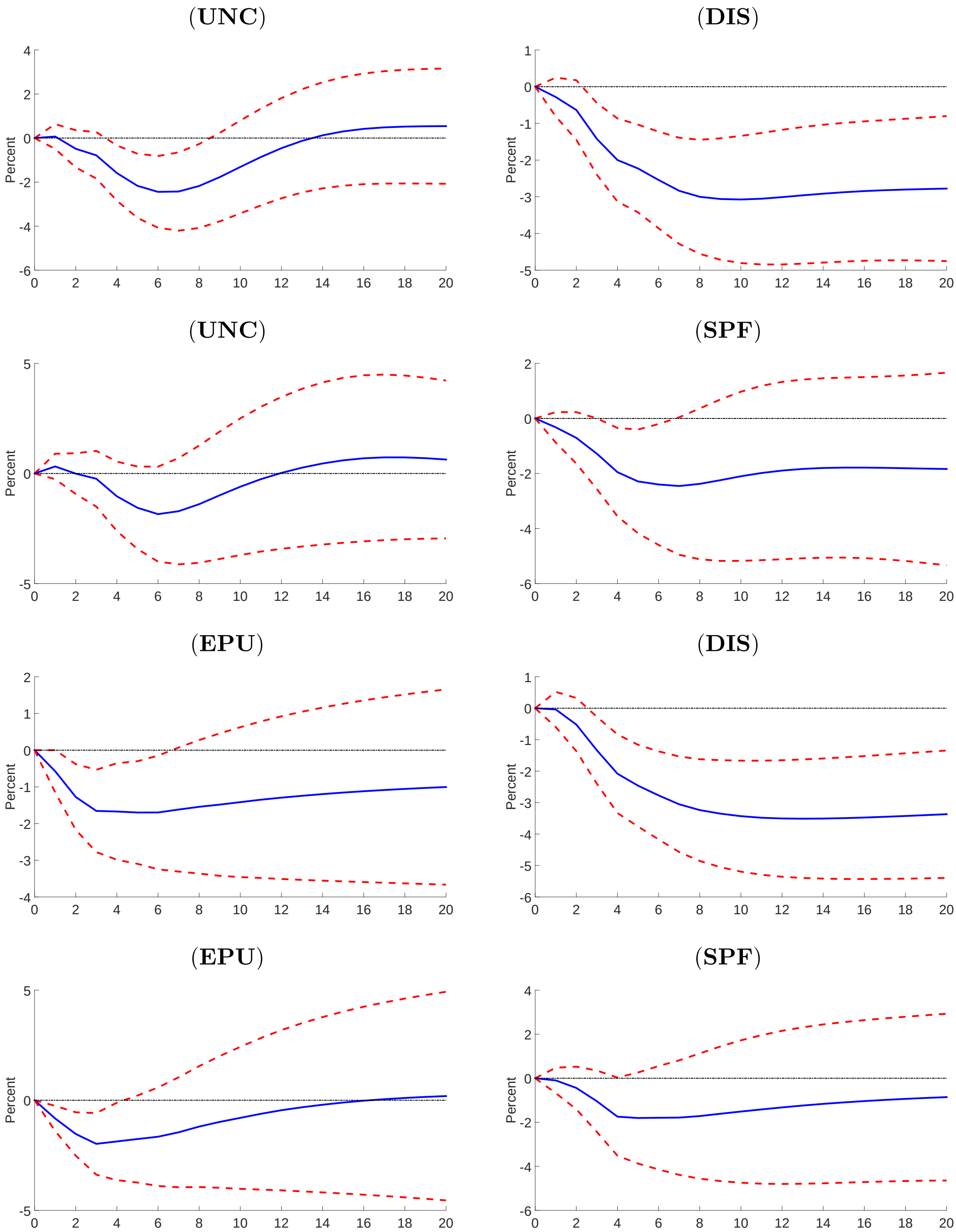


Notes: This figure plots impulse responses of U.S. Real Gross Private Domestic Investment to 1 % increase in disagreement proxies (**DIS** and **SPF**) and uncertainty proxies (**UNC** and **EPU**) based on the estimation of a tri-variate VAR system (all in log levels) with 4 lags using quarterly data; see the text for details. Left column: responses to uncertainty shocks. Right column: responses to disagreement shocks. Each row shows the estimated responses to a particular pair of measures as indicated in the brackets. **DIS** is based on forecast data for "General Business Condition". **SPF** is based on forecast data for Real GDP. Sample period: 1970Q1 - 2013Q4 except for VAR systems involving SPF data: 1990Q1-2013Q4. Area between red dashed lines defines 95 % confidence interval based on 2000 bootstrap simulations not originated from fundamental changes in the real productivity dispersion, the aggregate investment experiences a persistent decline. The drops in aggregate investment reach the bottom with a greater decline of 2 to 3 % below the pre-shock level in about two years after the shock. Importantly, we see no sign of the "rebound-overshoot" path of investment, even five years following the disagreement shocks. This distinctive pattern is robust regardless of whether disagreement is measured using the BOS or SPF forecast data.

Now we move the the bottom two rows of plots when the news frequency-based measure of uncertainty enters the VAR system, **EPU**. We see that the aggregate investment can still achieve a maximal drop of 3 % with no sign for a recovery in response to increases in BOS disagreement, **DIS**. When using **SPF** to proxy for the disagreement, the magnitude of drops can be smaller and the post-shock recovery path of investment dynamics to disagreement shocks is estimated with large standard errors. Regarding the impacts of uncertainty shocks, we also get poorly estimated impulse responses of aggregate investment to jumps in **EPU**. Intuitively, the reason why the drop and rebound dynamics due to uncertainty shocks is missing here could be due to the fact that the **EPU** captures more of the public *attention* towards uncertain policies. It is less of a measure of the firms' real productivity variance so as to initiate impacts in consistent with predictions of a model of uncertainty shocks. To account for the large standard errors, it could be that as **EPU** counts crisis and uncertainty related news, it already conditions itself on the changes that directly affect private agents' beliefs. Therefore, once disagreement shocks are firstly isolated, the orthogonalized changes in **EPU** would no longer have significant aggregate effects. Also, since the SPF-based dispersion measure does not necessarily reflect the firms' forecast differences, and the estimation window is shorter, it's not surprising to obtain larger standard errors.

Figure 7 shows the estimated impulse responses of aggregate investment, when Scheme 2 of identification is imposed. The uncertainty shocks are isolated first when the exogenous changes to disagreement do not alter the distribution of real productivity fundamentals across firms on impact. We found almost exact drops, quick rebound and overshoot of aggregate investment in response to the enlarged uncertainty shocks with respect to both the magnitude and the

Figure 7: IRFs of Aggregate Investment: Uncertainty and Disagreement Shocks
(Trivariate VAR - Reversed Ordering: Uncertainty, Disagreement and Investment)



Notes: This figure plots impulse responses of U.S. Real Gross Private Domestic Investment to 1 % increase in disagreement proxies (**DIS** and **SPF**) and uncertainty proxies (**UNC** and **EPU**) based on the estimation of a tri-variate VAR system (all in log levels) with 4 lags using quarterly data; see the text for details. Left column: responses to uncertainty shocks. Right column: responses to disagreement shocks. Each row shows the estimated responses to a particular pair of measures as indicated in the brackets. **DIS** is based on forecast data for "General Business Condition". **SPF** is based on forecast data for Real GDP. Sample period: 1970Q1 - 2013Q4 except for VAR systems involving SPF data: 1990Q1-2013Q4. Area between red dashed lines defines 95 % confidence interval based on 2000 bootstrap simulations timing of the investment dynamics. This is also true for the responses of investment to the disagreement shocks, that is, a persistent decline and very slow recovery. In addition, we found greater standard errors associated with estimations using **EPU** and **SPF**.

Table 2 summarizes the forecast error variance decomposition of aggregate investment at different forecast horizons, based on the estimation of the trivariate VAR systems under the identification of Scheme 1 ordering. For the near term of one quarter, innovations in **UNC** explain about 2 % of the variance of aggregate investment, while changes in the disagreement measure, **DIS** explain less than 1 % of variance in investment, a smaller magnitude of effects on impact. However, in three years, innovations of disagreement proxies of either **DIS** or **SPF** could explain around 30 % to 40 % of the variance, whereas changes in **UNC** explain at most 15 %. In about five years, more than half of the variance in investment can be explained by the dynamics of forecast dispersion. Rather, the fraction of the variance in the aggregate investment, which can be explained by the dispersion of productivity fundamentals, decays to roughly 15 % at most. In addition, when the uncertainty is measured by **EPU** and the VAR estimation is coupled with SPF, we could still see a dominant fraction of aggregate investment dynamics explained by the time-varying forecast disagreement.

3.2 Larger VAR Systems

I further show that with a larger VAR system, the macro impacts of disagreement shocks and uncertainty shocks are robust and different. In particular, by augmenting the ordering scheme considered in Bloom (2009) with aggregate investment and disagreement measure, I estimate a 10-variable VAR system under the Scheme 1 ordering: log(S&P 500 stock market index) , log(disagreement measure), log(uncertainty measure), Federal Funds Rate , log(average hourly earnings in manufacturing), log(consumer price index), weekly average hours in manufacturing, log(non-farm payroll employment), log(real gross private domestic investment), and log(industrial production). Such a benchmark identification aims to isolate shocks to the belief dispersion, which are not originated from the changes in the variance of productivity funda-

Table 2: Aggregate Investment: Forecast Variance Due to Innovations to Disagreement and Uncertainty (Trivariate VARs)

VAR System	Horizon:	One Quarter	One Year	Three Years	Five Years
(1)	**UNC**	2.22	11.32	14.39	11.56
	DIS	0.70	10.53	38.83	51.00
(2)	**EPU**	2.28	7.42	6.36	4.99
	DIS	0.10	10.68	42.19	55.82
(3)	**UNC**	0.54	4.80	7.52	15.38
	SPF	3.30	21.18	57.77	58.41
(4)	**EPU**	7.10	11.97	5.57	4.03
	SPF	4.61	16.55	27.67	30.11

Notes: Each cell number in a row denotes the fraction (in percent) of the total forecast error variance of log aggregate investment due to innovations to either uncertainty proxy (**UNC** or **EPU**) or to the disagreement proxy (**DIS** or **SPF**) given a particular VAR system estimation. Column 1 specifies the four trivariate VAR systems estimated using different combinations of uncertainty and disagreement measures all with disagreement ordered before the uncertainty proxy: Scheme 1 Ordering; see text for details on specification of these VARs. Sample period: 1970Q1 - 2013Q4 except for those systems that involve series of **SPF**, which has data ranging from 1990Q1-2013Q4.

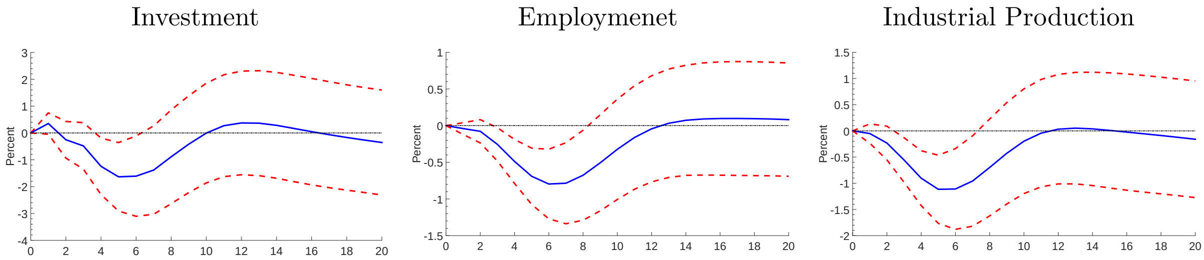
mentals. Similarly, I consider the case when the disagreement and uncertainty measures are flipped in the Scheme 2 ordering.

Rows (I) and (II) in Figure 8 display the impulse responses of aggregate investment, nonfarm payroll employment, industrial production in logs to 1 % increases in the innovations of **UNC** and **DIS** respectively in period 1. Firstly, we still see the drop-rebound-overshoot pattern for the impulse responses of aggregate investment to increases in uncertainty shocks. The drop-rebound dynamics are also seen for the employment and industrial production, though limited overshoots are found for the response of industrial production. In addition, the aggregate investment now bottoms at 1% below the pre-shock level around five quarters after the shocks, a smaller impact compared to the effect of uncertainty shocks identified for a trivariate system. Conversely, in response to jumps in disagreement shocks, the aggregate investment, employment, and industrial production all undergo a persistent decline until reaching the bottom beyond two years. Despite larger standard errors are found to be associated with these impulse responses from three years onward after the disagreement shocks, we see no sign for quick rebounds, let alone the overshoots. Rather, it takes about more than five years for the investment, employment and production to fully return to the pre-shock levels subsequent to the disagreement shocks.

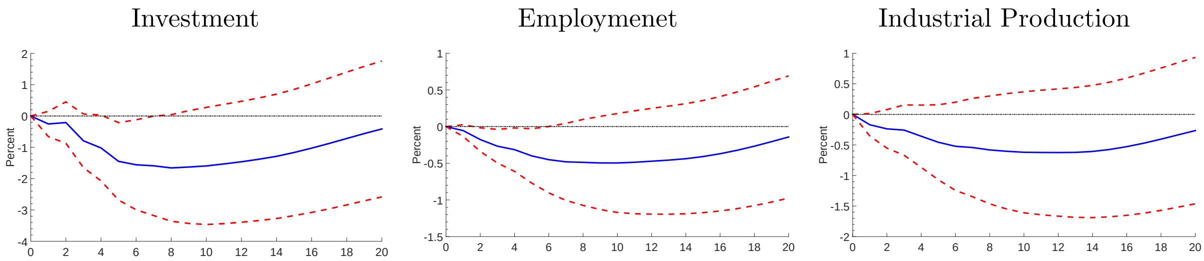
Rows (III) and (IV) plot the impulse responses of the three aggregate variables in a system when the uncertainty is measured by **EPU** and the disagreement is measured by **DIS**. Although we found the drop-rebound-overshoot dynamics of these series in response to increases in the **EPU**-based uncertainty measure, these impulse response paths are estimated very imprecisely. The empirical effects of the **EPU**-based uncertainty shocks seem trivial for the employment and the industrial production, despite investment drops on impact by less than 1 %. These findings contrast the results found in Baker et al. (2016) in which rises in the **EPU** index exhibit significant impacts that a contraction and a slow recovery are followed after the shocks. Here, according to Row (IV), it is the increases in the disagreement measure that drive major macroeconomic series to drop and to stay low without an ensuing rebound. Therefore, it's intrigue to understand why the documented strong effects of **EPU** are absent and why the disagreement shocks have stronger contraction effects. Note again that the **EPU** is not a direct measure of the future productivity variance but a proxy for the intensity of public attention paid to the crisis or ongoing events. Changes in **EPU** could be the reflected reactions to the shocks that affect the dispersion of private agents' beliefs. Therefore, in absent of the forecast disagreement series in systems highlighted in Baker et al. (2016), changes in **EPU** could depress the economy by picking up the channel of the disagreement shocks, through which the economy is affected.

Under the reversed ordering of disagreement and uncertainty measures, Figure 9 demonstrates that our findings are robust such that rises in uncertainty have a short-run recessionary effect, which is followed by a quick rebound of expansion. Differently, the effects of disagreement shocks can have more persistently dampening effects. The declining takes for a duration of up to two or three years following the shocks. Table 3 shows the forecast error variance decomposition of aggregate investment and industrial production at horizons up to five years,

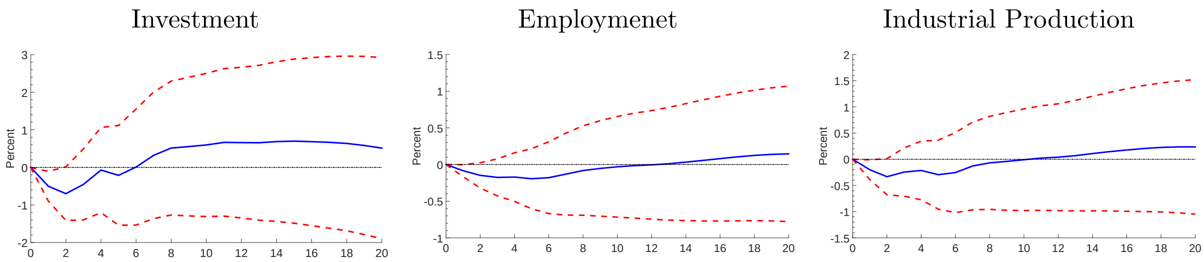
Figure 8: Aggregate Implications: Uncertainty and Disagreement Shocks
[Disagreement Index (**DIS**) Ordered Before Uncertainty)]



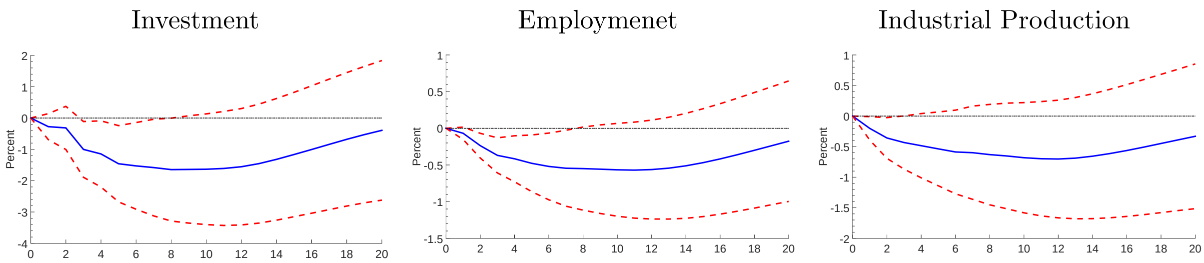
(I) Responses to an Uncertainty Shock (**DIS-UNC**)



(II) Responses to an Disagreement Shock (**DIS-UNC**)



(III) Responses to an Uncertainty Shock (**DIS-EPU**)



(IV) Responses to an Disagreement Shock (**DIS-EPU**)

Notes: This figure plots impulse responses of U.S. real private domestic investment (first column), non-farm payroll employment (second column), and industrial production (third column) to 1 % increase uncertainty (**UNC** or **EPU**) and disagreement proxies (**DIS**), obtained from estimation of a ten-variable system of VAR with Scheme 1 Cholesky recursive ordering; see details in text. The frequency of data is quarterly and the VARs are estimated with 4 lags. The sample covers 1970Q1 to 2013Q4. Area between red dashed lines defines 95 % confidence interval based on 2000 bootstrap simulations.

based on the estimations of the larger VAR systems with Scheme 1 ordering. It shows that at three-years up to five-years, changes in the disagreement measure over time can account for up to 15 % of the variance in aggregate investment and approximately 8% to 14 % of the variance in production. By contrast, less than 5 % of the variances in investment and production can be explained by variations in the uncertainty about productivity fundamentals or by the **EPU** variations over time.

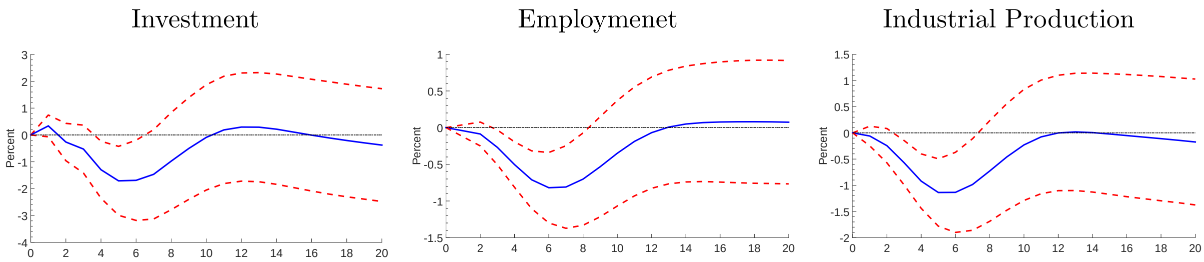
Table 3: Aggregate Investment and Industrial Production: Forecast Variance Due to Innovations to Disagreement and Uncertainty (Large VAR Systems)

VAR System	Horizon:	One Quarter	One Year	Three Years	Five Years
Aggregate Investment					
(1)	**UNC**	0.10	2.92	3.13	2.99
	DIS	2.58	8.21	13.45	13.11
(2)	**EPU**	1.39	0.90	0.57	1.00
	DIS	0.33	8.63	15.68	15.03
Industrial Production					
(1)	**UNC**	0.22	4.82	3.64	3.05
	DIS	3.90	7.22	7.56	7.76
(2)	**EPU**	0.51	0.26	0.24	0.33
	DIS	2.46	9.09	13.44	13.93

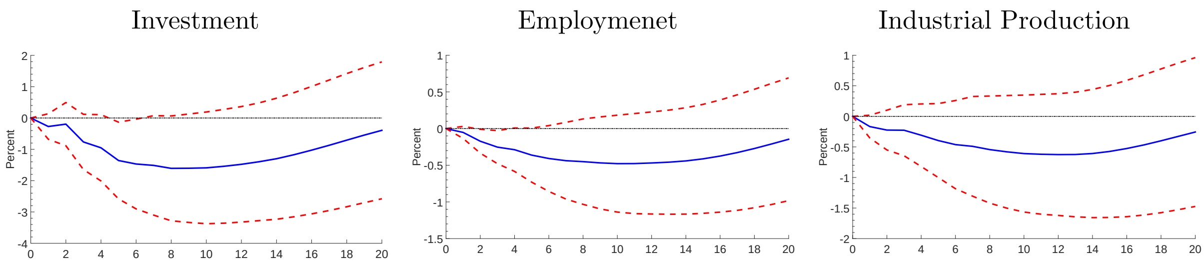
Notes: Each cell number in a row denotes the fraction (in percent) of the total forecast error variance of log aggregate investment due to innovations to either uncertainty proxy (**UNC** or **EPU**) and to the disagreement proxy (**DIS**) for a particular VAR system estimated. Column 1 refers to the large VAR systems estimated using either pair of proxies **DIS** and **UNC**, i.e. system (1), or **DIS** and **EPU**, i.e. system (2). Disagreement measure is ordered before the uncertainty proxy under Scheme 1 Ordering; see text for details on specification of these VARs. Sample period: 1970Q1 - 2013Q4.

When the forecast disagreement is measured by the SPF-based forecast dispersion index, the estimated impulse responses are associated with very large standard errors such that neither the impacts of uncertainty nor those of disagreement shocks can be well-identified. Figures 12 and 13 in Appendix B show that regardless of the ordering scheme, the estimation of a large VAR system with **SPF** included introduces too much noises. Therefore, the effects of uncertainty and disagreement shocks are no longer statistically distinguishable from zero. These results could be partly due to the fact that the SPF data does not capture the firms' own views. In

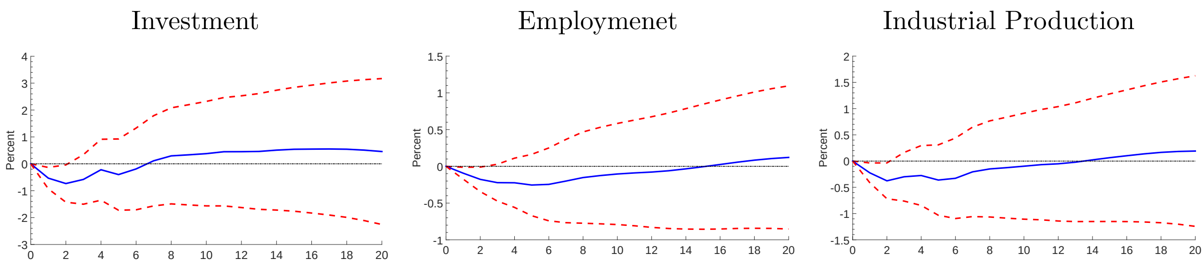
Figure 9: Aggregate Implications: Uncertainty and Disagreement Shocks
[Uncertainty Measure Ordered Before Disagreement Index (**DIS**)]



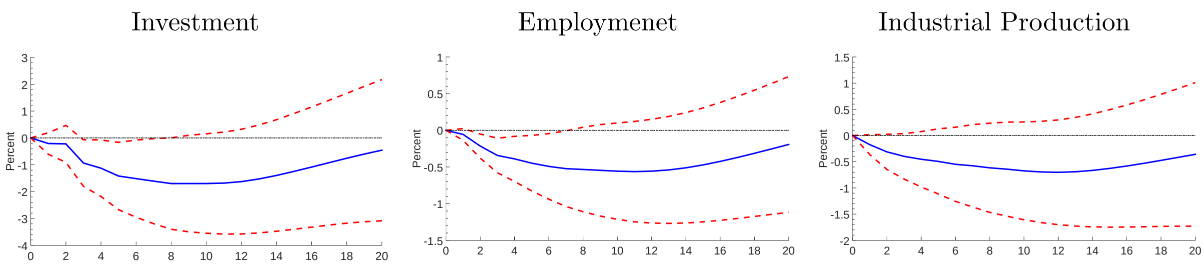
(I) Responses to an Uncertainty Shock (**UNC-DIS**)



(II) Responses to an Disagreement Shock (**UNC-DIS**)



(III) Responses to an Uncertainty Shock (**EPU-DIS**)



(IV) Responses to an Disagreement Shock (**EPU-DIS**)

Notes: This figure plots impulse responses of U.S. real private domestic investment (first column), non-farm payroll employment (second column), and industrial production (third column) to 1 % increase uncertainty (**UNC** or **EPU**)and disagreement proxies (**DIS**), obtained from estimation of a ten-variable system of VAR with Scheme 2 Cholesky recursive ordering; see details in text. The frequency of data is quarterly and the VARs are estimated with 4 lags. The sample covers 1970Q1 to 2013Q4. Area between red dashed lines defines 95 % confidence interval based on 2000 bootstrap simulations.

addition, a much smaller sample size from 1990 onward with ten-endogenous variables in the system are responsible for not being able to deliver the results for the robustness checks.

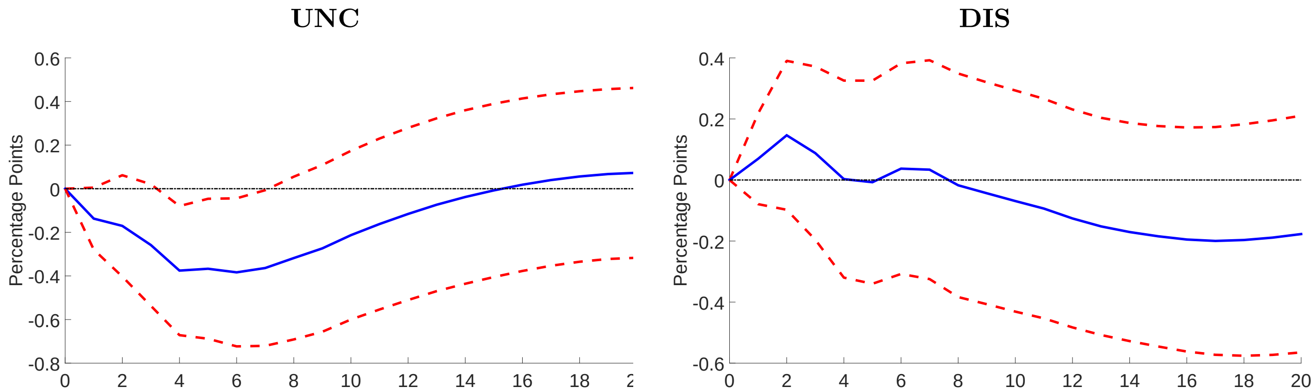
Based on the results from a range of VAR estimations, I may conclude that the survey-based disagreement index and the dispersion of future firm-level productivity fundamentals have identified two separate channels, through which the economy are affected by two different types of second moment shocks. However, one concern with this argument is that the policy, for example, the monetary authority's policy practices, may endogenously react differently to movements in the disagreement and uncertainty measures, which then leads to different aggregate impacts.

Figure 10 shows the impulse responses of Federal Funds Rate to innovation increases in uncertainty **UNC** and disagreement **DIS** measures. It shows that the monetary policy rate is adjusted to counteract the adverse impacts of real uncertainty shocks. On impact, the lower rate could have reduced the extent of contractions caused by the jumps in productivity uncertainty. In the medium run, the return of rate also attenuate the overshoots of economy that can be triggered by the enlarged uncertainty shocks. Such smoothing effects of monetary policy, however, does not announce the non-existence of the "drops-rebound-overshoot" effects of real uncertainty shocks. Rather, it simply argues for the impacts of uncertainty shocks as the contraction effects due to uncertainty jumps could be otherwise larger in absent of the adjustments of the policy rate. Therefore, the channel through which the productivity uncertainty shocks can affect the economy is robust. On the other hand, the monetary policy does not react to the changes in the dispersion of firm-level forecasts, which further explains why the economy may suffer from a persistent decline and slower recovery per the enlarged disagreement shocks. Hence, such evidence does not support the argument that the active management of monetary policy is the cause for the different aggregate effects. Hence, it is safe to conclude that there exist two types of *second moment* shocks.

Last but not least, I propose that the disagreement shocks are related to the information diffusion among firms. I call these shocks the "informational disagreement shocks" for the following reasons. First, these shocks, by construction, affect the firms' belief dispersion, which

Figure 10: IRFs of Federal Funds Rate: Uncertainty and Disagreement Shocks

[Disagreement Index (**DIS**) Ordered Before Uncertainty)]



NOTES: This figure plots impulse responses of U.S. Federal Funds Rate to 1 % increases to uncertainty (**UNC**) or disagreement proxy (**DIS**), obtained from estimation of a ten-variable system of VAR with Scheme 1 Cholesky recursive ordering; see details in text. The frequency of data is quarterly and the VARs are estimated with 4 lags. The sample covers 1970Q1 to 2013Q4. Area between red dashed lines defines 95 % confidence interval based on 2000 bootstrap simulations.

are orthogonal to changes to the spread of productivity fundamentals, i.e. "real uncertainty shocks". Second, we see that by including the forecast disagreement series, the significant effects associated with the Economic Policy Uncertainty Index, which counts the number of news reference intensity, are largely muted. By contrast, the "drops-rebound-overshoot" effects of real uncertainty shocks are robust as long as the empirical measure of uncertainty corresponds to the equivalent definition of future productivity variance as in Bloom (2009); Bloom et al. (2014). Now, we proceed to provide additional micro-level evidence that lends further credence to these arguments.

4 Firm-level Investment: Micro Evidence

In this section, I give additional micro evidence to illustrate how the firm-level investment is differently affected by the changes in measures of the disagreement and the uncertainty. The aggregate investment is found to be mostly affected by the uncertainty shocks compared to the other parts of the total output (Bloom et al., 2014). I thus specifically examine how the productivity uncertainty and the forecast disagreement affect the firm-level physical capital investment.

4.1 Within-firm Effects

As the firm-level capital and investment series are annual data in the Compustat sample, in the following, a period t thus corresponds to a year. I consider a specification of firm-level investment equation for firm i in year t as:

$$\log[I/K]_{i,t} = \alpha_1 \log DIS^F_{t-1} + \alpha_2 \log UNC_{t-1} + \eta_i + \theta \log MPK_{i,t} + \epsilon_{i,t} \tag{4}$$

Different from other specifications such as Leahy and Whited (1996) and Gilchrist et al. (2014), Equation (4) incorporates the lagged forecast disagreement DIS^F_{t-1} and the lagged productivity uncertainty UNC_{t-1}. Note that uncertainty dated in $t-1$ measures the dispersion of firm-level TFP shocks realized in year t. To ensure the timing consistency between measures, I use a notation DIS^F_{t-1} (differed from DIS_t in Section 3) to capture the forecast disagreement *about* year t business conditions, a forward looking measure, rather than the disagreement of forecasts *surveyed* in year t. Given that the monthly BOS survey forecasts have a six-month forecast horizon, the dispersion of forecasts about year t is then the average of 12 monthly disagreement measures using forecasts surveyed from July in year $t-1$ up to June in year t. The robustness of results using disagreement measures by the survey dates or by the forecast-relevant dates are discussed in a later section. Similarly, I stick to the benchmark BOS measure of forecast disagreement regarding firms' forecasts about the "General Business Conditions" (**DIS**). The productivity uncertainty is again measured by the dispersion of future firm-level TFP shocks (**UNC**).

$[I/K]_{i,t}$ denotes the firm-level investment rate, which is measured by a firm's investment-capital ratio in year t. η_i denotes the firm fixed-effect. $MPK_{i,t}$ captures the marginal product of capital, a measure of future investment opportunities (Gilchrist et al., 2014). I consider a range of $MPK_{i,t}$ proxies including $[Y/K]_{i,t}$ (current sales-to-capital ratio, our baseline measure), $[\pi/K]_{i,t}$ (current operating income-to-capital ratio) following Gilchrist and Himmelberg (1999), and the cash flow - capital ratio $[CF/K]_{i,t}$.[9] See details on the definitions of these empirical proxies in Appendix D.

In addition, note that the regression equation (4) does not accommodate a time fixed effect given the presence of the time-varying second moment measures DIS^F_{t-1} and UNC_{t-1}. The coefficients, α_1 and α_2, capture the signs and the magnitudes of *linear* associations between the two measures of second moments and the firm-level investment rate, the estimates of *within-firm* effects. Including the lagged uncertainty and forecast disagreement dated in $t-1$ is to explore their causal impacts. Having both the disagreement and uncertainty measures in the equation helps disentangle the partial impacts of changes to the belief dispersion once the differences in productivity fundamentals across firms are controlled. While the theories of real-option effects suggest $\alpha_2 < 0$, it is an empirical question regarding the sign and the size of α_1 holding other covariates fixed.

4.2 Between-firm Effects

While previous works were largely devoted to uncover the *within-firm* estimates of the uncertainty impacts on the firm-level investment, I also consider whether the capital reallocation *between* firms is affected by the uncertainty changes. In addition, I compare and contrast the impacts of uncertainty and disagreement measures on capital reallocation. Doing this helps further examine the mechanism that may explain the presence and the absence of the rebound dynamics of aggregate investment found at the macro level due to changes in productivity uncertainty and forecast disagreement respectively.

By the prediction of real-option effects of uncertainty, the more productive firms are outside

[9] Little consensus has been established on how we interpret why firm's investment significantly responds to cash flow changes. Here I simply treat it as an alternative measure of MPK. Fazzari et al. (1988) argue that the cash flow reflects the financial constraint of the firm. Gilchrist and Himmelberg (1999) find it also a measure of expected marginal product of capital, or a measure related to future demand and profitability growth (Bond et al., 2004).

the inaction region of "wait-and-see" and are actively adjusting their capital stock (Bloom, 2009). Ex-ante, as the variance of future idiosyncratic productivity increases, these "active" firms see themselves more productive in expectation due to the convexity effect, and thus invest more. Ex-post, realized productivity dispersion enlarges, which pushes a mass of firms beyond the investment threshold. The aggregated increases in investments among the more productive firms lead to the rebound of aggregate investment. The heightened uncertainty thus promotes a fast accumulation of capital among the more productive firms, and quick capital retirement for the less productive firms ex-post. From the perspective of resource reallocation, capital is increasingly reallocated from the less productive to the more productive firms in response to rises in the productivity uncertainty.

Hence, to identify the rebound motive at the micro-level, I look into the *non-linear* effect of uncertainty on the impact of a firm's productivity shocks upon its investment. Similarly, I also consider the effect of disagreement on firm's investment response to the productivity shocks. In the following, I estimate an augmented investment equation of the form:

$$\begin{aligned}\log[I/K]_{i,t} =& \alpha_1 \log DIS^F_{t-1} + \alpha_2 \log UNC_{t-1} + \eta_i + \theta \log MPK_{i,t} \\ &+ \beta_1 \log DIS^F_{t-1} \times \Delta PROD_{i,t} + \beta_2 \log UNC_{t-1} \times \Delta PROD_{i,t} + \beta_3 \Delta PROD_{i,t} + \epsilon_{i,t}.\end{aligned} \tag{5}$$

In spirit of Bloom et al. (2007), I include two interaction terms of firm i's productivity growth $\Delta PROD_{i,t}$ with the uncertainty and with the disagreement. Equation (5) incorporates the additional partial effects of interests: how a firm with good productivity draws makes its investment decisions upon disagreement changes β_1 and uncertainty changes β_2. The presence of aggregate investment rebound dynamics suggests $\beta_2 > 0$. In order to see if the capital reallocation channel is crucial to explain whether a quick rebound of aggregate investment is missing, we thus hypothesize that the capital reallocation given rises in disagreement is limited such that $\beta_1 \leq 0$. I consider two measures of firm i's productivity $PROD_{i,t}$: firm-specific TFP in log, $TFP_{i,t}$, and the logged labor productivity (sales to employment ratio), $\log[y/N]_{i,t}$.

Again, the firm-level TFPs are estimated from the Compustat sample following the approach of Olley and Pakes (1996).

4.3 Endogeneity: Instruments using Patent Data

I continue to address the possible endogeneity concern in the specifications of Equations (4) and (5) in order to better identify the causal impacts of real uncertainty shocks and informational disagreement shocks on the firm-level investments. The differences of firms' forecasts about their future business conditions in year t, DIS^F_{t-1}, could have well reflected the fundamental differences in productivity across firms in year t, UNC_{t-1}. In addition, the heterogeneous and noisy information distributed among firms could also help shape each firm's own belief about how productive the firm is. Therefore, including the crude measure of forecast disagreement injects a measurement error as absorbed by the regression residuals, which are correlated with the other important covariate variable, the productivity uncertainty. Such measurement issue potentially triggers the endogeneity concern.

I approach this endogeneity problem by using instrument variable (IV) estimations. The IV exclusion restriction requires that the instruments should be correlated with the productivity uncertainty or the forecast disagreement but with no correlations with the shocks to the firm-level investments. I thus exploit the utility patent application data collected by the USPTO covering years of 1964-2012. I use patent applications data rather than the grants data to construct the instrument variables.[10]

The empirical proxies of uncertainty and disagreement that are subject to endogeneity issue are both cross-sectional measures. The patent applications are categorized by USPTO into the sectors according to the 2002 North American Industry Classification System (NAICS). I thus explore the cross-sector variations over time regarding the patent applications. [11] In addition,

[10]For example, Shea (1999) and Christiansen (2008) etc. use patent applications data instead of the patent grants data for the reasons that the patent applications are better measures of intensity of innovations. Also, the patent grants are the endogenous actions taken by the U.S. patent office.

[11]USPTO categorizes utility patents into 30 categories with 26 unique categories, and 4 categories as combinations or roll-ups of the 26 unique categories. These categories are at the 3 or 4 digits level.

given that the U.S. firm-level investments can be related to the R&D efforts taken within the U.S., I focus on the patent applications originated from the non-U.S. residence only. [12]

Firstly, I compute the cross-sector standard deviations of the number of foreign patent applications associated with a NAICS code relative to the total number of foreign patent applications. For a list of NAICS sectors used for computing the IVs, see the table in Appendix C. I use the year-over-year difference of this standard deviation series, a flow measure of patent dispersion as the baseline instrument for the productivity uncertainty. For robustness checks, I also consider the max-min sector difference in the relative ratio of patent applications. The underlying assumption is that the foreign patent applications filed with different sectors in the U.S. will translate into fundamental differences in productivity across sectors within the U.S.. I will show that the dispersion of productivity across sectors can pick up the productivity differences among firms.

Secondly, to construct an instrument variable that is correlated with pure belief heterogeneity, I exploit the following rationale. If a sector is associated with increasing number of patents that are associated with the information processing technology, then such a sector is more likely to manage its idiosyncratic informational noise that obscures itself from well perceiving its own business fundamentals. In the following, I illustrate how I can compute an index so as to capture the penetration intensity of the information processing patents (IPP) into other sectors.

In specific, I consider the following patent categories marked by a NAICS code in the bracket as the patents associated with the information processing technology. They are the Communications Equipment (3342, the baseline) and the Computer and Peripheral Equipment (3341). Further, in order to measure the penetration intensity of these IPP, I utilize the difference of two conventions used by USPTO for counting the patent numbers, i.e. *Whole Counts* (WC) and *Fractional Counts* (FC). According to the WC convention, when an IPP is also matched to a non-IPP NAICS category. the very patent is then counted once in each of the

[12]The origin of a patent, foreign or U.S., is determined by the residence of the first-named inventor at the time of patent application.

matched NAICS categories. However, the FC convention divides each patent equally between the matched NAICS categories. Given that the WC number is no less than the FC number, their difference in patent counts within the category of information processing patent suggests how many patents filed for application are associated with sectors other than the information processing category itself.

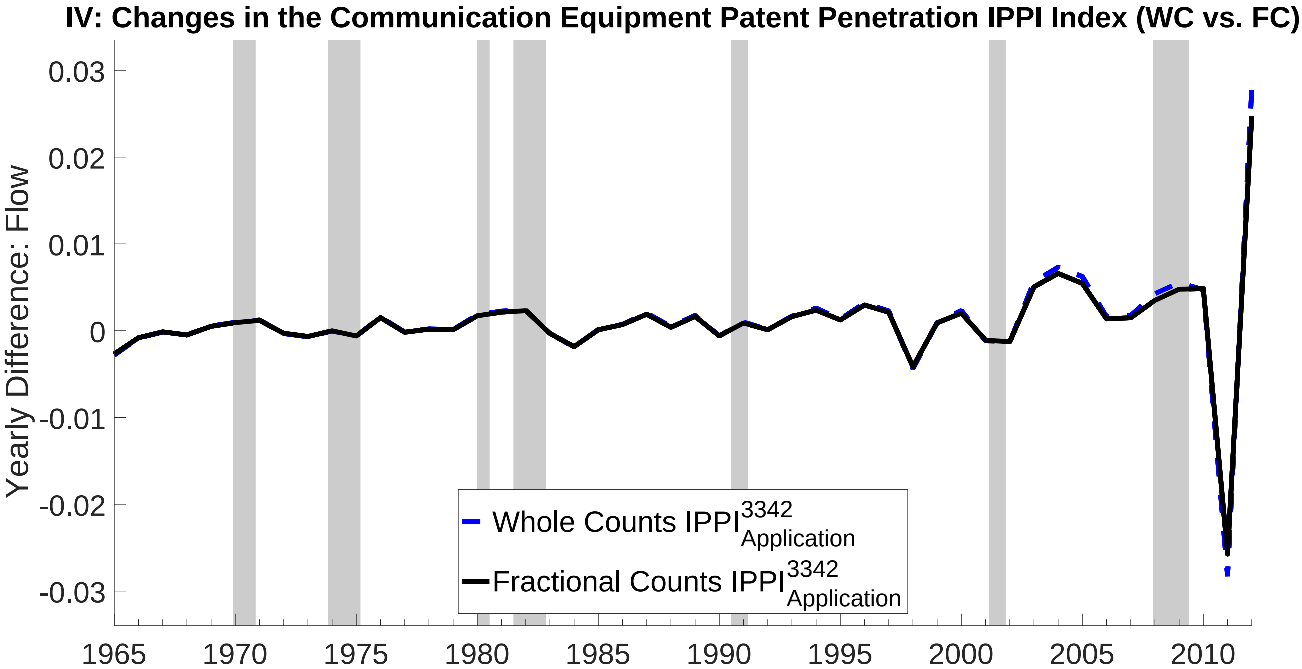
For example, suppose a new patent of telecommunication technology filed for application in year 2000 is categorized into three categories: Communications Equipment (3342), Primary Metal (331), and Miscellaneous Manufacturing (339). This adds the WC number of 3342 with number 1, and adds the FC numbers of 3342, 331, and 339 with only $\frac{1}{3}$. If this invention is otherwise categorized with 3342 and 331 only, the WC number of 3342 still adds 1 but the FC numbers of 3342 and 331 will be $\frac{1}{2}$. Therefore, such a difference between the two conventions of counting an IPP reflects how much more this patent can be associated with other sectors. Therefore, $\frac{2}{3}$ in the former scenario apparently means a greater penetration intensity than $\frac{1}{2}$ in the latter case.[13] I give the IPP penetration index $IPPI_t$ of the form:

$$IPPI_t = \frac{Num^{WC}_{IPP\ Code,t} - Num^{FC}_{IPP\ Code,t}}{Num^{FC}_{Non-IPP\ code,t}} \tag{6}$$

$IPPI_t$ takes in an information processing patent code (either 3342 or 3341) in year t, and computes the difference of number counts of WC and FC. This count difference is then normalized by the total number of FC counts of *non-IPP* patents. In Figure 11, I show that neither FC or WC counts of non-IPP patents in the denominator will affect our baseline measure of $IPPI_t$. Hence, the flow measure of this index, the yearly difference, is taken as the baseline IV for the disagreement measure. I hypothesize that higher $IPPI_t$ is negatively associated with the magnitude of forecast disagreement across firms.

[13] Note that neither the WC nor FC reporting convention affects the relative ratio of the patent applications for a sector over the total number. Hence this convention difference does not apply to how we construct the IV for the measure of productivity uncertainty.

Figure 11: Instrument Variables for the Disagreement Measure



Notes: Sample period: 1964 - 2012. The shaded bars indicate the NBER-dated recession periods.

4.4 Sample and the Descriptive Statistics

Annual data from Compustat covering years from 1970 to 2012 are used to estimate the specified empirical relationships. A firm is identified by its Global Company Key (GVKEY). I restrict the sample to the non-financial firms by removing the firm-year observations with the Standard Industry Classification (SIC) codes ranging between 6000 and 6999. I further exclude those regulated utility firms (SIC codes 4900 to 4999), the public administration agencies (SIC codes 9100 to 9729), and the non-US headquartered incorporations. In addition, a firm is dropped if it did not continuously operate at least for three years. Those remaining firms are further restricted to have greater than zero total asset, at least one employee, and the positive capital stock which is measured by the net total property, plant and equipment. To further address the concerns with the sample outliers, I remove the firm-year observations with sales-to-capital ratio, the baseline MPK measure that is greater than the two standard deviations of the sample average of the ratio. This cutoff point corresponds to a 98.5 % of the distribution of sales-to-capital ratio. Then I have the following summary statistics:

Table 4: Summary statistics of Sample Firm Characteristics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
$[I/K]_{i,t}$	0.31	0.37	0	16.19	89799
$[Y/K]_{i,t}$	8.72	9.99	0.03	78.49	89799
$[\pi/K]_{i,t}$	0.83	1.38	-32.43	54.97	89799
$[CF/K]_{i,t}$	0.21	1.79	-305.62	65.18	89798
$TFP_{i,t}$	-0.32	0.41	-4.88	3.36	89799

In the sample, on average, we have approximately 2000 firms each year. As we don't have very good reasons to pin down the bounds for these operating measures of a firm, I will consider a different sample of firms with tighter constraints simply for the robustness checks of the regression results.

4.5 Results

4.5.1 OLS Estimates

Table 5 summarizes the key results regarding the within-firm and the between-firm effects based on Ordinary Least Squares (OLS) estimations. All columns have controlled for the firm fixed-effects. Column (1) suggests that a 10% increase in the productivity uncertainty about next year is associated with 3.4 % drops in the firm-level investment rate. This coefficient is statistically significant at 1 % level. Column (2) finds that the dispersion of firms' forecasts about next year's business well-beings also exhibits a significantly negative association with the firm-level investment rate. Further, as shown in Column (3), when both the lagged productivity uncertainty and the disagreement measure are included, we still see a statistically significant association between the measure of forecast disagreement and the firm's investment rate, though the magnitude of correlation shrinks to a half compared to Column (2). This can be explained by the fact that the productivity differences across firms are positively correlated with the belief differences about fundamentals across firms. The disagreement measure can pick up the negative association between the uncertainty and the firm-level investment in Column (2), when the bias of omitted variable kicks in and leads to the over-estimation of the partial effects of the disagreement. It shows that the sign and the magnitude regarding the association between uncertainty and the firm-level investment are quite robust, which is consistent with the prediction of the real-option effect of the uncertainty about economic fundamentals, i.e. the "wait and see" effect (Bloom, 2009).

Table 5: OLS Estimates: Uncertainty, Disagreement, and Firm-level Investment

	(1)	(2)	(3)	(4)	(5)	(6)
$\log[Y/K]_{i,t}$	0.865***	0.879***	0.864***	0.775***	0.788***	0.775***
	(0.014)	(0.013)	(0.014)	(0.015)	(0.013)	(0.014)
$\log UNC_{t-1}$	-0.337***		-0.296***	-0.312***		-0.270***
	(0.024)		(0.021)	(0.026)		(0.026)
$\log DIS^F_{t-1}$		-0.246***	-0.139***		-0.239***	-0.143***
		(0.023)	(0.025)		(0.021)	(0.023)
$\log UNC_{t-1} \times \Delta TFP_{i,t}$				0.189***		0.186***
				(0.063)		(0.071)
$\log DIS^F_{t-1} \times \Delta TFP_{i,t}$					0.205**	0.056
					(0.090)	(0.118)
$\Delta TFP_{i,t}$				-0.147	-0.355***	-0.134
				(0.092)	(0.035)	(0.083)
$TFP_{i,t}$				0.657***	0.659***	0.656***
				(0.022)	(0.024)	(0.025)
$[\Delta TFP_{i,t}]^2$				0.101***	0.099***	0.100***
				(0.011)	(0.012)	(0.011)
$R^2(Within)$	0.240	0.237	0.241	0.281	0.278	0.282
No. Obs.	79839	79839	79839	79839	79839	79839

Notes: Sample: annual data from 1970 - 2012. Dependent Variable: yearly firm-level investment-capital ratio in log $\log[I/K]_{i,t}$. Measure of Uncertainty: UNC_{t-1}, dispersion of year t TFP shocks in log. Measure of Disagreement: DIS^F_{t-1}, annualized dispersion index of six-month ahead forecasts of the "General Business Conditions" among manufacturing firms, which incorporates all the forecasts regarding firms business conditions in year t; see text for details. Firm-level fixed effects are included for all specifications (not reported). Estimations are done through OLS. Bootstrapped Standard Errors are in parentheses based on 100 repetitions and are clustered at the firm level. Significance levels: 10% *, 5% **, 1% ***

Columns (4)-(6) show the estimation results regarding the between-firm effects of the productivity uncertainty and the disagreement measure in line with the specified Equation (5). The estimations also control for the level and the squared growth of our baseline productivity measure, $TFP_{i,t}$, which turn out to be significant and help improve the goodness of fit. However, the results are robust regardless of whether or not these covariates are included. Column (4) reveals that rises in the variability of future productivity are consistently associated with drops in the firm-level investments. More importantly, the regression results highlight a "productivity-enhancing" effect of changes in the uncertainty. It suggests that the firms with faster productivity growth are associated with even greater firm-level investment rates, conditional on the enlarged uncertainty. This statistically positive coefficient of the interaction term between the uncertainty and the productivity growth implies that the rebound dynamics of the aggregate investment per the higher uncertainty exists at the firm-level. Column (5) suggests that omitting the measure of uncertainty, the linear term and the interaction term regarding the forecast disagreement still pick up the potentially linear and non-linear effects of productivity uncertainty respectively, given the positive correlations of the two second moment measures. Similarly, controlling for both the measures of uncertainty and disagreement, Column (6) finds robust linear and non-linear associations between the uncertainty and the firm-level investment, along with a linear association between disagreement and investment with a nearly halved magnitude. However, we no longer see a significant and positive correlation between the firm-level investment and interaction term of disagreement and productivity growth. This may well suggest that a potentially negative non-linear association could exist and offset the positive correlation, or simply an absence of rebound motive at all in case of pure belief changes. Clearly the OLS results are sensitive to the measurements and the correlations of uncertainty and disagreement. Hence, we will better disentangle the effects of changes to the real uncertainty and the informational disagreement with the help of Instrument Variable estimations. IV estimations will deal with the endogeneity concern more carefully.

4.5.2 IV Estimates: Within-firm Results

I display the results of IV estimations regarding the within-firm effects in Table 6. The upper panel shows the causal impacts of changes to uncertainty and disagreement on the firm-level investments. The lower two panels summarize the first stage regression statistics regarding the validity of our instruments choices.

We firstly focus on the first-stage results by looking at the lower two panels. Column (1) takes the Column (3) results from OLS estimations in Table 5 to aid the comparisons. In Column (2) of the IV results, the productivity uncertainty about the year t and the dispersion of forecasts regarding the year t business conditions are instrumented by the lagged changes in the dispersion of patent applications across sectors $\Delta[PatentAppDisp]_{t-1}$, and the lagged changes in the penetration intensity of information processing patents, i.e. the communication equipment patents, into other sectors $\Delta IPPI_{t-1}$. The instruments are expressed in yearly differences of flow measures. We see that the more dispersed patent applications across sectors translates into the more dispersed productivities across firms. Such evidence is consistent with literature using patent applications to measure the technological progress (Shea, 1999; Christiansen, 2008). We also see that the enlarged dispersion of patent applications across sectors are positively associated with more heterogeneous forecasts about firms' own business conditions among firms. Since the firms' forecasts are reflective of their productivity fundamentals, R&D's contributions to technological advancement in the sector help shape firms' beliefs about their own business well-beings. Focusing on the $IPPI$ index, we find that when the information processing patents are associated within more sectors, firms' differences in forecasts are mitigated. This lends credence to our hypothesis that a firm with the information processing technology is better equipped to erase the perception noises that affect the firm's confidence about its own business. However, contemporaneously, the association between the productivity uncertainty, and changes in the penetration intensity of communication equipment into other sectors are negative. The two F-statistics suggest that the impacts of underlying real uncertainty shocks and the informational disagreement shocks are well absorbed by the measures of productivity uncertainty and forecast disagreement across firms.

A concern with using contemporaneous IVs is that there are lagged effects of R&D on the productivity progress (Christiansen, 2008). I test the robustness of first stage regression results by using additional lags and lags in the far back of the patent application dispersion across sectors and of the IPPI indexes. In Column (3) of the IV results, both the one-year and two-year lags of the cross-sector dispersion of patent applications raise the cross-firm differences in the productivity as well as the belief heterogeneity among firms. In addition, we see that the larger the penetrations of information processing patents into other sectors in the past, the smaller the belief heterogeneity is. Interestingly, as differed from Column (2), the association between the productivity uncertainty and the $\Delta IPPI_{t-1}$ is no longer significant, and $\Delta IPPI_{t-2}$ picks up a positive sign. In Column (4), when instrumented with sixth and seventh lags of $\Delta[PatentAppDisp]$ and $\Delta IPPI$, we found that the cross-sector dispersion of patent applications and the penetration of information processing patents into other sectors always raise the fundamental differences of productivities across firms. Higher $\Delta IPPI$, however, consistently shrinks the forecast dispersion. Based on the F-statistics, we are convinced that these instruments have strong joint predictive power on the measures of uncertainty and forecast disagreement.

Turning to the second stage results in the upper panel, across the IV results Columns (2)-(4), we see that using different sets of instruments trivially affects the estimates of the linear impacts of uncertainty and disagreement shocks on the firm-level investments. However, Compared to Column (4), Column (3) gives smaller standard errors associated with the causal impact of disagreement shocks. Its p-value of Hansen J statistic 0.121 suggests that there is no over-identification at the 10 % level. Specifically, we see that a 10 % increase in real uncertainty causes around 10 % drops in the firm-level investment holding informational disagreement changes fixed. While holding the fundamental differences across firms fixed, 10 % increase in the pure informational disagreement shrinks the firm-level investment by 5.8 %.

We see that both estimates of the linear impacts of uncertainty and disagreement shocks are larger than those with OLS estimations in Column (1) in absolute magnitude. This is due to the endogeneity issue triggered by the measurement error. Changes in informational disagreement shocks could also shift productivity uncertainty while real uncertainty shocks may affect the belief heterogeneity across firms. Therefore, the simple OLS estimation may give the underestimation bias. Also, it shows that both uncertainty and informational disagreement shocks lead to cuts in the firm-level investments. However, the linear effects of the latter are roughly 50 % weaker.[14] This finding is consistent with our macro evidence that on impact, jumps in the uncertainty knocks down the investment much harder than the informational disagreement shocks.

4.5.3 IV Estimates: Between-firm Results

Table 7 presents the between-firm effects of productivity uncertainty and informational disagreement based on the IV estimations. The IV results in Column (2) are obtained from estimations using $\Delta[PatentAppDisp]_{t-1}$, $\Delta IPPI_{t-1}$, and their direct interactions with the productivity growth $\Delta TFP_{i,t}$ as the set of IVs to jointly instrument for lagged uncertainty, lagged disagreement, and their non-linear term conditional on $\Delta TFP_{i,t}$. The IV results in Column (3) take additional IVs $\Delta[PatentAppDisp]_{t-2}$, $\Delta IPPI_{t-2}$, and their direct interactions with the productivity growth $\Delta TFP_{i,t}$ into the IV set in Column (2). For now, I call these IV identification as IV Scheme 1. The F statistics in both columns suggest that in the first stage, these instruments are significantly correlated with the endogenous variables of uncertainty and disagreement.

Column (1) lists the exact OLS results from Column (6) in Table 5. Compared to the OLS results, Column (2) again finds that the IV estimates of the linear effects of uncertainty and disagreement shocks are stronger and the effect of disagreement is significantly smaller than that of uncertainty. With respect to the non-linear effects, the productivity-enhancing effect of uncertainty shocks is robust for the sign and its magnitude, which are significant at the 1% level. Importantly, we find the sign of the interaction term of TFP growth and disagreement is negative though insignificant. This finding suggests that potentially, there could a *productivity-dampening* effect for greater informational disagreement shocks. At least, the pro-capital reallocation of uncertainty channel is not seen here in the case of changes to

[14]However, note that the findings here are not directly comparable to other empirical works that use micro-level data to uncover the negative associations between the uncertainty and the firm-level investment. Those panel regression evidences typically construct the uncertainty measures from firms' stock-market returns (Leahy and Whited, 1996; Bloom et al., 2007). However, as Caldara et al. (2016) shows, these uncertainty measures are highly correlated with firms' financial distress conditions, which do not necessarily correspond to the uncertainty about future productivity or demand in a theory paper such as Bloom et al. (2014).

Table 6: Instrument Variable Estimates: Within-firm Effects

	OLS Est.(1)	IV Est. (2)	IV Est. (3)	IV Est. (4)
$\log[Y/K]_{i,t}$	0.864***	0.792***	0.792***	0.744***
	(0.014)	(0.020)	(0.021)	(0.033)
$\log UNC_{t-1}$	-0.296***	-1.154***	-1.011***	-1.108**
	(0.021)	(0.159)	(0.172)	(0.467)
$\log DIS^F_{t-1}$	-0.139***	-0.498**	-0.581***	-0.739
	(0.025)	(0.249)	(0.194)	(0.767)
No. Obs	79839	72452	65036	38861
Hansen J P-val	N/A	N/A	0.121	0.000
		IV First Stage: $\log UNC_{t-1}$		
$\Delta[Patent\ App\ Disp]_{t-1}$		12.300***	11.336***	
$\Delta[Patent\ App\ Disp]_{t-2}$			2.574***	
$\Delta[Patent\ App\ Disp]_{t-6}$				19.090***
$\Delta[Patent\ App\ Disp]_{t-7}$				10.295***
$\Delta IPPI_{t-1}$		-0.534***	-0.085	
$\Delta IPPI_{t-2}$			0.740***	
$\Delta IPPI_{t-6}$				9.805***
$\Delta IPPI_{t-7}$				3.829***
Instrument F Stat.		1187.873	997.562	3483.510
		IV First Stage: $\log DIS^F_{t-1}$		
$\Delta[Patent\ App\ Disp]_{t-1}$		16.685***	15.554***	
$\Delta[Patent\ App\ Disp]_{t-2}$			7.909***	
$\Delta[Patent\ App\ Disp]_{t-6}$				29.180***
$\Delta[Patent\ App\ Disp]_{t-7}$				8.445***
$\Delta IPPI_{t-1}$		-3.719***	-5.708***	
$\Delta IPPI_{t-2}$			-4.498***	
$\Delta IPPI_{t-6}$				-12.355***
$\Delta IPPI_{t-7}$				-11.933***
Instrument F Stat.		1221.334	596.193	3084.772

Notes: Sample: 1970 - 2012. Dependent Variable: yearly firm-level investment-capital ratio in log $\log[I/K]_{i,t}$. $[Patent\ App\ Disp]_t$, cross-NAICS sector dispersion of year t applications of utility patents from non-U.S. residence. $IPPI_t$, measure of the penetration intensity of information processing patents into other sectors; see details in text. First stage regressions put stacked data with aggregate regressors for all firms. Firm fixed-effects, and $\log[Y/K]_{i,t}$ are controlled (not reported). Bootstrapped S.E. are in the parentheses from 100 repetitions and are clustered at the firm level. S.E.s for the first stage regressions are not reported. Significance levels: 15% +, 10% *, 5% **, 1% ***

the informational disagreement. Also, the magnitude differences between the OLS and IV estimations are again indicative of the underlying endogeneity concern.

In Column (3), with no sign of over-identifying suggested by a Hansen J statistic P-value of 0.891, similar estimates of the linear and the non-linear effects of uncertainty and disagreement shocks are obtained. The negative impact of informational disagreement shocks are still smaller than that of uncertainty shocks. Also, the productivity-enhancing effect of uncertainty is still statistically significant at 1 % level. Differently, the productivity-dampening effect of disagreement shocks is significant at 1% level. The latter effect implies that if firms that disagree more about their future business conditions because of non-fundamental changes to their beliefs, those more productive firms with greater productivity growth will further cut back their investments. It exhibits that, as the firm-level investment responds to the changes to firm-specific productivity shocks, large investment spikes that are otherwise taken by firms with greater productivity draws, are knocked down when firms disagree more about their future business conditions, even if their fundamental productivity distribution is not changed. This effect is distinctively different from the rebound of investment actions taken by the more productive firms in response to the heightened uncertainty.

In Column (4), I follow an identification approach suggested by Wooldridge (2010) (IV Scheme 2): regressing $\log UNC_{t-1}$ and $\log DIS^F_{t-1}$ respectively on $\Delta[PatentAppDisp]_{t-1}$ and $\Delta IPPI_{t-1}$ along with other controls to obtain their fitted values first. The fitted values of uncertainty and disagreement are interacted with TFP growth. I take these two interactions to substitute out the two interactions of the TFP growth with $\Delta[PatentAppDisp]_{t-1}$ and $\Delta IPPI_{t-1}$. Along with the linear IVs $\Delta[PatentAppDisp]_{t-1}$, $\Delta IPPI_{t-1}$, the new interaction IVs enter the IV set. Column (5) estimation also uses the fitted values of uncertainty and disagreement obtained from regressions on both one-year and two-year lags: $\Delta[PatentAppDisp]_{t-1}$, $\Delta IPPI_{t-1}$, $\Delta[PatentAppDisp]_{t-2}$ and $\Delta IPPI_{t-2}$. Then the fitted values are interacted with the TFP growth. Doing this helps resolve some of the potential multicolinearity problem in the first stage regressions if the direct interactions are used.

The results in Columns (4) and (5) show that little has changed with respects to the coefficients' signs and statistical powers compared to results in Column (2) and (3). However, we have obtained smaller standard errors associated with point estimates under IV Scheme 2. The linear impacts of uncertainty and disagreement shocks are still found to be robust regardless of which IV scheme is used. However, we see that the point estimates of coefficients of the two non-linear terms under Scheme 2 are relatively smaller compared to IV Scheme 1 estimates. Therefore, we regard Column (3) IV results about non-linear effects of uncertainty and disagreement shocks as some upper and lower bounds of the between-firm effects.

Hence, the between-firm results suggest that there are two separate channels through which the informational disagreement shocks, and the real uncertainty shocks are affecting the firm-level investments. The productivity-enhancing effect of uncertainty changes are contributing to the aggregate investment rebound. However, the productivity-dampening effect of disagreement changes not only suggests that the capital reallocation activity is hindered, but announces the absence of aggregate investment rebound. This effect can be responsible for leading the aggregate economy to a persistent decline until the effects are bottoming out.

4.5.4 Robustness Checks

I further examine the robustness of the identified linear and non-linear effects of uncertainty and disagreement shocks on the firm-level investments by running a range of tests.

Timing of the Forecast Disagreement. Our baseline measure of the forecast disagreement DIS^F_{t-1} in this section is constructed using forecasts data about firms' to-be-realized business conditions in year t. Doing this is to make the horizon of forward-looking consistent with that of uncertainty UNC_{t-1}, which is the dispersion of productivity shocks to-be-realized in year t. We thus investigate if using the measure of disagreement DIS_{t-1}, which averages the forecasts disagreement index **DIS** over the 12 survey months in its calender year $t-1$, may affect the causal relationships between the firm-level investments and the disagreement shocks. The definition of DIS_{t-1} considered here is consistent with our benchmark measure of disagreement in Section 3. Table 8 summarizes the results.

Columns (1) and (2) present the IV estimations of the within-firm and between-firm effects

Table 7: Instrument Variable Estimates: Between-firm Effects

	(1)	(2)	(3)	(4)	(5)
		IV Scheme 1		IV Scheme 2	
$\log[Y/K]_{i,t}$	0.775***	0.726***	0.729***	0.726***	0.730***
	(0.014)	(0.019)	(0.019)	(0.015)	(0.020)
$\log UNC_{t-1}$	-0.270***	-0.906***	-0.711***	-0.903***	-0.682***
	(0.026)	(0.138)	(0.141)	(0.131)	(0.128)
$\log DIS^F_{t-1}$	-0.143***	-0.357+	-0.446**	-0.357*	-0.464**
	(0.023)	(0.233)	(0.207)	(0.205)	(0.189)
$\log UNC_{t-1} \times \Delta TFP_{i,t}$	0.186***	1.517***	3.260***	1.362***	1.718***
	(0.071)	(0.141)	(0.151)	(0.188)	(0.167)
$\log DIS^F_{t-1} \times \Delta TFP_{i,t}$	0.056	-1.665	-3.993***	-1.671**	-2.163***
	(0.118)	(1.287)	(0.833)	(0.731)	(0.643)
$\Delta TFP_{i,t}$	-0.134+	1.175***	2.842***	0.946***	1.267***
	(0.083)	(0.398)	(0.220)	(0.044)	(0.042)
No. Obs.	79839	72452	65036	72452	65036
Hansen J P-val	N/A	N/A	0.891	N/A	0.599
1st Stage F Stat. (UNC)		599.344	504.151	587.864	652.980
1st Stage F Stat. (DIS)		606.976	301.450	606.257	398.956
1st Stage F Stat. ($UNC \times \Delta TFP$)		48.275	20.763	38.662	37.341
1st Stage F Stat. ($DIS \times \Delta TFP$)		43.036	25.294	37.553	41.240

Notes: Sample: 1970 - 2012. Dependent Variable: yearly firm-level investment-capital ratio in log $\log[I/K]_{i,t}$. Measure of Uncertainty: UNC_{t-1}, dispersion of year t TFP shocks in log. Measure of Disagreement: DIS^F_{t-1}, annualized dispersion index of six-month ahead forecasts of the "General Business Conditions" among manufacturing firms, which incorporates all the forecasts regarding firms business conditions in year t; see text for details. Firm-level fixed effects are included for all specifications (not reported). All columns have controlled the level and the squared growth of $TFP_{i,t}$ (not reported). IV Column (1): $[Patent\ App\ Disp]_{t-1}$, $IPPI_{t-1}$, and all their interactions with $\Delta TFP_{i,t}$ as IVs. IV Column (2): $[Patent\ App\ Disp]_{t-1}$, $[Patent\ App\ Disp]_{t-2}$, $IPPI_{t-1}$, $IPPI_{t-2}$ and all their interactions with $\Delta TFP_{i,t}$ as IVs. IV Column (3): $[Patent\ App\ Disp]_{t-1}$, $IPPI_{t-1}$, and the interactions of $\Delta TFP_{i,t}$ with the fitted values of $\log UNC_{t-1}$ and $\log DIS^F_{t-1}$, which are estimated from regressing each of the second moment measures in $t-1$ on the lagged patent dispersion, and the lagged $IPPI$ index. IV Column (4): $[Patent\ App\ Disp]_{t-1}$, $[Patent\ App\ Disp]_{t-2}$, $IPPI_{t-1}$, $IPPI_{t-2}$, and the interactions of $\Delta TFP_{i,t}$ with the fitted values of $\log UNC_{t-1}$ and $\log DIS^F_{t-1}$, which are estimated from regressing each of the second moment measures in $t-1$ on the two lags of patent dispersion, and those of $IPPI$ index. Bootstrapped S.E. are in the parentheses from 100 repetitions and are clustered at the firm level. Significance levels: 15% +, 10% *, 5% **, 1% ***

under IV Scheme 1. We see that the signs and the magnitudes of linear and non-linear effects of uncertainty and disagreement shocks are close to the results in Columns (2) andd (3) from Table 7. Again, including the second lags of IVs in Column (2) helps locate smaller standard errors and the Hansen statistic suggests no over-identification. Columns (3) and (4) give the IV estimation results under IV scheme 2. It reveals that the negative impacts of uncertainty and disagreement shocks along with their productivity-enhancing and productivity-dampening effects are found to be robust and significant even if we have a different measure of disagreement. This result suggests that no matter how we date the forecast disagreement proxy, our IV strategy is good enough to capture the underlying informational shocks that shift the spread of beliefs even if distribution of productivity fundamentals is unchanged. Again, we see that the IV scheme 1 gives larger magnitude of non-linear effects, which consistently serve as the upper and lower bounds of our point estimates.

More Restricted Sample. Another concern is whether or not the extreme values of the firms' operating metrics are driving the key results. I thus restrict the firm sample to test for the robustness of results. Our reference Compustat sample is inGilchrist et al. (2014), which matches the Compustat data with the Center for Research in Security Prices (CRSP) data. With the outliers filtered, they use a sample with the following firm profiles: investment rate bounded by 1 from above; sales to capital ratio is bounded from above by 15; operating income to capital ratio bounded by -0.5 and 2.5. I further impose the cash flow-over-capital bounds -12.5 and 12.5. I present the IV estimation results in Table 9 based on the restricted sample with truncated bounds of metrics.

Firstly, the linear coefficients of uncertainty and disagreement shocks are negative. The negative impacts of disagreement shocks are significant at the 5% level if the two-year lags of changes in the cross-sector patents dispersion and the IPPI index are included as IVs under either IV Scheme 1 or 2. Also, the linear negative effects of disagreement shocks on the firm-level investments are about the half of the effects per the changes to uncertainty. In terms of the non-linear effects, IV scheme 1 still yields larger absolute values of the point estimates. Across all columns of Table 9, the estimated productivity-enhancing of uncertainty shocks, and

Table 8: IV Estimates: Survey Dates vs. Forecasts Relevant Dates

	(1)	(2)	(3)	(4)
	IV Scheme 1		IV Scheme 2	
$\log[Y/K]_{i,t}$	0.731***	0.731***	0.731***	0.730***
	(0.018)	(0.019)	(0.016)	(0.021)
$\log UNC_{t-1}$	-0.848***	-0.691***	-0.851***	-0.700***
	(0.154)	(0.153)	(0.155)	(0.147)
$\log DIS_{t-1}$	-0.518+	-0.577**	-0.510+	-0.563***
	(0.329)	(0.240)	(0.320)	(0.188)
$\log UNC_{t-1} \times \Delta TFP_{i,t}$	2.033***	2.318***	1.176***	1.465***
	(0.143)	(0.129)	(0.149)	(0.154)
$\log DIS_{t-1} \times \Delta TFP_{i,t}$	-2.520+	-2.933***	-0.965*	-1.598***
	(1.712)	(0.703)	(0.570)	(0.581)
$\Delta TFP_{i,t}$	1.611***	1.852***	0.925***	1.097***
	(0.480)	(0.186)	(0.042)	(0.053)
No. Obs.	72452	65036	72452	65036
Hansen J P-val	N/A	0.871	N/A	0.996
1st Stage F Stat. (UNC)	599.344	504.151	587.360	653.320
1st Stage F Stat. (DIS)	434.464	259.831	434.340	341.248
1st Stage F Stat. ($UNC \times \Delta TFP$)	48.275	20.763	56.033	36.516
1st Stage F Stat. ($DIS \times \Delta TFP$)	35.828	20.336	64.572	46.166

Notes: Sample: 1970 - 2012. Dependent Variable: yearly firm-level investment-capital ratio in log $\log[I/K]_{i,t}$. Measure of Uncertainty: UNC_{t-1}, dispersion of year t TFP shocks in log. Measure of Disagreement: DIS_{t-1}, annualized dispersion index of six-month ahead forecasts of the "General Business Conditions" among manufacturing firms, which incorporates all the forecasts surveyed in year $t-1$; see text for details. Firm-level fixed effects are included for all specifications (not reported). All columns have controlled the level and the squared growth of $TFP_{i,t}$ (not reported). Column (1): $[Patent\ App\ Disp]_{t-1}$, $IPPI_{t-1}$, and the interactions of $\Delta TFP_{i,t}$ with them as IVs. Column (2): $[Patent\ App\ Disp]_{t-1}$, $[Patent\ App\ Disp]_{t-2}$, $IPPI_{t-1}$, $IPPI_{t-2}$ and all the interactions with $\Delta TFP_{i,t}$ as IVs. Column (3): $[Patent\ App\ Disp]_{t-1}$, $IPPI_{t-1}$, and the interactions of $\Delta TFP_{i,t}$ with the fitted values of $\log UNC_{t-1}$ and $\log DIS_{t-1}$, which are estimated from regressing each of the second moment measures in $t-1$ on the lagged patent dispersion, and the lagged $IPPI$ index. Column (4): $[Patent\ App\ Disp]_{t-1}$, $[Patent\ App\ Disp]_{t-2}$, $IPPI_{t-1}$, $IPPI_{t-2}$, and the interactions of $\Delta TFP_{i,t}$ with the fitted values of $\log UNC_{t-1}$ and $\log DIS^F_{t-1}$, which are estimated from regressing each of the second moment measures in $t-1$ on the two lags of patent dispersion, and those of $IPPI$ index. Bootstrapped S.E. are in the parentheses from 100 repetitions and are clustered at the firm level. Significance levels: 15% +, 10% *, 5% **, 1% ***

the productivity dampening effects of disagreement shocks are found to be larger among these firms with less extreme operating metrics. Therefore, including the firms with extreme values of operation in our baseline estimations gives a more conservative estimates of the impacts of uncertainty and disagreement conditional on the firms' productivity growth.

Alternative Measures of $MPK_{i,t}$. Table 10 shows that our main findings are robust when the marginal product of capital is proxied by the cash flow over capital ratio and the operating income over capital ratio instead. Regardless of which one of the two MPK measures is used, for a given specification, the point estimates are little changed. In Columns (1) and (2), the negative impacts of disagreement shocks again are about half the effects of uncertainty shocks. The non-linear effects are also in the range of our estimates given sales to capital ratio $\log[Y/K]_{i,t}$ is used instead. However, as shown in Columns (3) and (4), when both the one-year and two-year lags of the two patent proxies and their interactions with the TFP growth are added in the IV set under IV Scheme 1, the null hypothesis that there is no over-identification using this set of IV is rejected at 1 % significance level. Also, the F statistics for the first stage regressions regarding the the interaction terms are halved compared to F statistics reported in Columns (1) and (2). That may explain why we see some peculiar findings in Columns (3) and (4): the productivity-enhancing and the productivity-dampening effects are overly large and the linear impact of uncertainty shocks is found no larger than that of disagreement shocks. Suspecting that the extreme values in $[CF/K]_{i,t}$ and $[\pi/K]_{i,t}$ may potentially drive these results, I further apply the same IV estimations to the more restricted sample with no extreme performance outliers. The results based on the restricted sample are summarized in Columns (5) and (6). It shows that the magnitudes of non-linear effects are both shrunk. In addition, the sizes of the linear impacts of disagreement shocks relative to those of changes to uncertainty are much closer to our results in Table 9 based on the restricted sample. Though Column (5) is still subject to the over-identification problem, Column (6) has a Hansen P-value greater than 10 %. In sum, in terms of the sign and the magnitudes of linear and non-linear effects of uncertainty and disagreement shocks, using other measures of MPK does not alter the key results of this paper.

Table 9: IV Estimates: More Restricted Sample

	(1)	(2)	(3)	(4)
	IV Scheme 1		IV Scheme 2	
$\log[Y/K]_{i,t}$	0.695***	0.708***	0.695***	0.707***
	(0.021)	(0.023)	(0.019)	(0.020)
$\log UNC_{t-1}$	-0.988***	-0.653***	-0.958***	-0.653***
	(0.144)	(0.156)	(0.130)	(0.156)
$\log DIS^F_{t-1}$	-0.116	-0.336**	-0.138	-0.340**
	(0.216)	(0.165)	(0.208)	(0.159)
$\log UNC_{t-1} \times \Delta TFP_{i,t}$	5.907***	3.019***	2.481***	2.679***
	(0.276)	(0.184)	(0.177)	(0.133)
$\log DIS^F_{t-1} \times \Delta TFP_{i,t}$	-7.954***	-3.643***	-3.071***	-3.143***
	(1.920)	(1.108)	(0.711)	(0.540)
$\Delta TFP_{i,t}$	5.285***	2.599***	2.049***	2.286***
	(0.283)	(0.176)	(0.038)	(0.041)
No. Obs.	60954	55207	60954	55207
Hansen J P-val	N/A	0.437	N/A	0.231
1st Stage F Stat. (UNC)	415.879	321.118	408.932	415.699
1st Stage F Stat. (DIS)	565.507	273.305	568.057	359.290
1st Stage F Stat. ($UNC \times \Delta TFP$)	69.729	30.739	56.031	38.662
1st Stage F Stat. ($DIS \times \Delta TFP$)	74.579	49.186	70.939	69.639

Notes: Sample: 1970 - 2012. Estimations are based on a restricted sample; see text for details. Dependent Variable: yearly firm-level investment-capital ratio in log $\log[I/K]_{i,t}$. Measure of Uncertainty: UNC_{t-1}, dispersion of year t TFP shocks in log. Measure of Disagreement: DIS^F_{t-1}, annualized dispersion index of six-month ahead forecasts of the "General Business Conditions" among manufacturing firms, which incorporates all the forecasts surveyed in year $t-1$; see text for details. Firm-level fixed effects are included for all specifications (not reported). All columns have controlled the level and the squared growth of $TFP_{i,t}$ (not reported). Column (1): $[Patent\ App\ Disp]_{t-1}$, $IPPI_{t-1}$, and all their interactions with $\Delta TFP_{i,t}$ as IVs. Column (2): $[Patent\ App\ Disp]_{t-1}$, $[Patent\ App\ Disp]_{t-2}$, $IPPI_{t-1}$, $IPPI_{t-2}$ and all their interactions with $\Delta TFP_{i,t}$ as IVs. Column (3): $[Patent\ App\ Disp]_{t-1}$, $IPPI_{t-1}$, and the interactions of $\Delta TFP_{i,t}$ with the fitted values of $\log UNC_{t-1}$ and $\log DIS^F_{t-1}$, which are estimated from regressing each of the second moment measures in $t-1$ on the lagged patent dispersion, and the lagged $IPPI$ index. Column (4): $[Patent\ App\ Disp]_{t-1}$, $[Patent\ App\ Disp]_{t-2}$, $IPPI_{t-1}$, $IPPI_{t-2}$, and the interactions of $\Delta TFP_{i,t}$ with the fitted values of $\log UNC_{t-1}$ and $\log DIS^F_{t-1}$, which are estimated from regressing each of the second moment measures in $t-1$ on the two lags of patent dispersion, and those of $IPPI$ index. Bootstrapped S.E. are in the parentheses from 100 repetitions and are clustered at the firm level. Significance levels: 15% +, 10% *, 5% **, 1% ***

Table 10: IV Estimates: Measures of MPK

	(1)	(2)	(3)	(4)	(5)	(6)
	IV Scheme 1		IV Scheme 1		IV Scheme 1	
	(One Lag)		(Two Lags)		(Restricted Sample)	
$\log UNC_{t-1}$	-0.667***	-0.750***	-0.285*	-0.427***	-0.399***	-0.574***
	(0.158)	(0.145)	(0.159)	(0.158)	(0.148)	(0.130)
$\log DIS^F_{t-1}$	-0.243	-0.355+	-0.433**	-0.499**	-0.403**	-0.462**
	(0.227)	(0.220)	(0.193)	(0.208)	(0.202)	(0.213)
$\log UNC_{t-1} \times \Delta TFP_{i,t}$	2.348***	2.499***	4.685***	4.391***	4.314***	3.943***
	(0.171)	(0.199)	(0.150)	(0.159)	(0.204)	(0.192)
$\log DIS^F_{t-1} \times \Delta TFP_{i,t}$	-3.320**	-3.623**	-6.366***	-6.073***	-5.597***	-4.933***
	(1.489)	(1.621)	(1.026)	(0.907)	(1.145)	(1.165)
$\Delta TFP_{i,t}$	1.776***	1.894***	4.042***	3.731***	3.793***	3.505***
	(0.466)	(0.498)	(0.273)	(0.256)	(0.173)	(0.194)
$\log[CF/K]_{i,t}$	10.338**		19.433***		90.972***	
	(4.538)		(6.468)		(13.068)	
$\log[\pi/K]_{i,t}$		6.800***		7.401***		21.055***
		(0.742)		(0.772)		(0.875)
No. Obs.	72452	72452	65036	65036	55207	55207
Hansen J P-val	N/A	N/A	0.000	0.004	0.011	0.104
F Stat. (UNC)	579.866	579.964	548.517	525.677	307.348	323.339
F Stat. (DIS)	605.905	606.005	295.755	297.179	269.223	271.760
F Stat. ($UNC \times \Delta TFP$)	48.037	48.861	20.639	21.096	30.797	31.071
F Stat. ($DIS \times \Delta TFP$)	42.903	43.455	25.152	25.609	49.201	49.510

Notes: Sample: annual data from 1970 - 2012. Dependent Variable: yearly firm-level investment-capital ratio in log $\log[I/K]_{i,t}$. Measure of Uncertainty: UNC_{t-1}, dispersion of year t TFP shocks in log. Measure of Disagreement: DIS^F_{t-1}, annualized dispersion index of six-month ahead forecasts of the "General Business Conditions" among manufacturing firms, which incorporates all the forecasts regarding firms business conditions in year t; see text for details. Columns (1) and (2): $[\textit{Patent App Disp}]_{t-1}$, $IPPI_{t-1}$, and all their interactions with $\Delta TFP_{i,t}$ as IVs. Columns (3) and (4): $[\textit{Patent App Disp}]_{t-1}$, $[\textit{Patent App Disp}]_{t-2}$, $IPPI_{t-1}$, $IPPI_{t-2}$ and all their interactions with $\Delta TFP_{i,t}$ as IVs. Columns (5) and (6): same IV specifications as Columns (3) and (4) but with a restricted sample; see text for details. Firm fixed-effects are included for all specifications (not reported). Bootstrapped Standard Errors are in parentheses based on 100 repetitions and are clustered at the firm level. Significance levels: 10% *, 5% **, 1% ***

Alternative Measures of Instrument Variables. Our baseline instrument variable for the productivity uncertainty is the yearly changes in the dispersion of utility patent applications across the NAICS sectors, as measured by the cross-sector standard deviation. I examine the robustness of results by taking the difference of largest patent application ratio of a NAICS sector and the smallest ratio associated with another sector as the alternative IV for uncertainty. Columns (1) in Table 11 presents estimation results using the two lags of patent proxies under IV scheme 1. While we find both the negative linear effects of uncertainty shocks and its productivity-enhancing effects. The linear effect of disagreement changes have shown an opposite sign and its non-linear effects, despite negative, are significant only at 10 % level. These results are coupled with a bad overidentification test result. An explanation of this finding is that the measure of max-min sector difference of patent applications could have different correlation relationships with the IPPI index. This could slightly alter the first stage regression results, which lead to a different set of estimated coefficients. I experiment by dropping the second year lag of this max-min sector difference of patent applications in the first stage and leave other IVs untouched. In Column (2), I present the new IV estimation results. Now the linear and non-linear effects of uncertainty and disagreement shocks are more aligned with our baseline results. However, note that the magnitudes of coefficients for the interaction terms are overly large. This is due to the fact that the max-min sector difference in patent applications is not denominated in the same metrics of a standard deviation measure. The results are robust.

Holding the baseline IV for the productivity uncertainty unchanged, we now recompute the IPPI index taking the Computer and Peripheral Equipment (NACIS code 3341) as the information processing technology category. Using one-year lag, and both one-year and the two-year lags of patent proxies under IV scheme 1, Columns (3) and (4) both find a negative though insignificant impacts of disagreement shocks, and a strong linear effects of uncertainty. The signs and the magnitudes suggesting the presence of the productivity-enhancing effects of uncertainty shocks, and the productivity-dampening effects of disagreement shocks appear to be robust too.

Alternative Measure of Productivity. I continue examining the estimation results

Table 11: IV Estimates: Other Instrument Variables Measures

	(1)	(2)	(3)	(4)
	IV Scheme 1		IV Scheme 1	
	Max-Min Sector Diff. of Patent App Ratios		IPP: Computer and Peripheral Equipment (NAICS 3341)	
	(Two Lags)	(Drop 2nd Lag)	(One Lags)	(Two Lags)
$\log[Y/K]_{i,t}$	0.750***	0.750***	0.722***	0.717***
	(0.018)	(0.018)	(0.018)	(0.020)
$\log UNC_{t-1}$	-0.646***	-0.503***	-1.022***	-0.956***
	(0.138)	(0.182)	(0.153)	(0.131)
$\log DIS^F_{t-1}$	0.514*	-0.076	-0.240	-0.207
	(0.306)	(0.591)	(0.217)	(0.209)
$\log UNC_{t-1} \times \Delta TFP_{i,t}$	0.666***	4.835***	2.972***	2.289***
	(0.161)	(0.235)	(0.144)	(0.136)
$\log DIS^F_{t-1} \times \Delta TFP_{i,t}$	-1.247*	-8.895***	-3.936***	-2.775***
	(0.732)	(1.116)	(1.459)	(0.783)
$\Delta TFP_{i,t}$	0.086	3.357***	2.477***	1.880***
	(0.179)	(0.225)	(0.439)	(0.242)
No. Obs.	65036.000	65036.000	72452.000	65036.000
Hansen J P-val	0.002	0.103	N/A	0.696
F Stat. (UNC)	464.694	604.516	573.843	613.869
F Stat. (DIS)	317.096	214.700	343.781	176.357
F Stat. ($UNC \times \Delta TFP$)	42.101	45.293	47.323	19.939
F Stat. ($DIS \times \Delta TFP$)	27.763	24.267	39.563	27.559

Notes: Sample: 1970 - 2012. Dependent Variable: yearly firm-level investment-capital ratio in log $\log[I/K]_{i,t}$. Measure of Uncertainty: UNC_{t-1}, dispersion of year t TFP shocks in log. Measure of Disagreement: DIS^F_{t-1}, annualized dispersion index of six-month ahead forecasts of the "General Business Conditions" among manufacturing firms, which incorporates all the forecasts regarding firms business conditions in year t; see text for details. Firm-level fixed effects are included for all specifications (not reported). All columns have controlled the level and the squared growth of $TFP_{i,t}$ (not reported). Column (1): $[\textit{Patent App Disp}]_{t-1}$, $IPPI_{t-1}$, and the interactions of $\Delta TFP_{i,t}$ with them as IVs. Column (2): $[\textit{Patent App Disp}]_{t-1}$, $IPPI_{t-1}$, $IPPI_{t-2}$ and all the interactions with them as IVs. Column (3): $[\textit{Patent App Disp}]_{t-1}$, $IPPI_{t-1}$, and the interactions of $\Delta TFP_{i,t}$ with them as IVs. Column (4): $[\textit{Patent App Disp}]_{t-1}$, $[\textit{Patent App Disp}]_{t-2}$, $IPPI_{t-1}$, $IPPI_{t-2}$ and the interactions of $\Delta TFP_{i,t}$ with them as IVs. Bootstrapped S.E. are in the parentheses from 100 repetitions and are clustered at the firm level. Significance levels: 15% +, 10% *, 5% **, 1% ***

when firm i's productivity is measured by the log labor productivity (sales over employment). Similarly, in Table 12, Column (1) takes one-year lag of IV sets while Column (2) have both one-year and two-year lags of IV sets for estimations under IV Scheme 1. Columns (3) and (4) run both estimations under IV Scheme 2. All columns include the level and the squared change of labor productivity as additional controls per their significance.

Across columns, we find that the linear effects of disagreement shocks are consistently smaller than those negative effects of uncertainty shocks. The productivity-enhancing effect of uncertainty and the productivity-dampening effect of disagreement are both present except for Column (1). Nevertheless, these coefficients are found to be associated with larger standard errors as compared to our baseline results using firms' TFP growths. Two explanations can be offered here: first, the poor point estimates can be a result of the higher multicolinearity between sales-over-capital ratio, and the labor productivity measures. Secondly, the sales per labor is also endogenous in the sense that the firm-level investment from the left hand side is correlated with the right hand side labor productivity. Instrumenting for the uncertainty and the disagreement only while treating labor productivity as exogenous may introduce additional estimation bias and mitigates the statistical power. Thirdly, as similarly noted by Alfaro et al. (2016), the employment data in Compustat may contain measurement errors. This can also affect the estimation precision in our test here. However, qualitatively, we have very similar results when changes in the labor productivity replaces the TFP growth of a firm.

5 Discussions

The micro-level evidence exhibits that the changes to the productivity uncertainty trigger the "wait and see" effect, which is consistent to the predictions of a model of uncertainty shocks. In addition, we find the productivity-enhancing effect of uncertainty such that the more productive firms would increase investments when the productivity shocks become more variable in the future. This serves as the micro-foundation for a quick rebound and a possible overshoot of investments at the aggregate level. Conversely, a linear negative impact of informational

Table 12: IV Estimates: Labor Productivity

	(1)	(2)	(3)	(4)
	IV Scheme 1		IV Scheme 2	
$\log[Y/K]_{i,t}$	0.771***	0.851***	0.794***	0.860***
	(0.048)	(0.028)	(0.055)	(0.043)
$\log UNC_{t-1}$	-1.462***	-0.577**	-1.338***	-0.598*
	(0.429)	(0.232)	(0.473)	(0.345)
$\log DIS^F_{t-1}$	-1.425*	-0.495	-1.062	-0.319
	(0.827)	(0.466)	(0.979)	(0.695)
$\log UNC_{t-1} \times \Delta \log[Y/L]_{i,t}$	-0.140	0.610*	2.419***	2.594***
	(0.603)	(0.332)	(0.646)	(0.532)
$\log DIS^F_{t-1} \times \Delta \log[Y/L]_{i,t}$	2.463	-0.401	-2.061	-3.613*
	(2.672)	(1.399)	(2.359)	(1.930)
$\Delta \log[Y/L]_{i,t}$	0.419*	0.595***	2.598***	2.364***
	(0.218)	(0.078)	(0.177)	(0.137)
$\log[Y/L]_{i,t}$	3.373***	1.787***	3.123***	1.756**
	(1.016)	(0.488)	(1.113)	(0.755)
$(\Delta \log[Y/L]_{i,t})^2$	-0.137***	-0.079***	-0.129***	-0.079***
	(0.038)	(0.018)	(0.041)	(0.028)
No. Obs.	72452	65036	72452	6503
Hansen J P-val	N/A	0.043	N/A	0.101
1st Stage F Stat. (UNC)	526.802	610.764	543.161	827.893
1st Stage F Stat. (DIS)	473.689	214.184	473.173	295.157
1st Stage F Stat. ($UNC \times \Delta TFP$)	171.536	91.436	312.127	205.503
1st Stage F Stat. ($DIS \times \Delta TFP$)	147.442	114.116	170.475	155.220

Notes: Sample: 1970 - 2012. Dependent Variable: yearly firm-level investment-capital ratio in log $\log[I/K]_{i,t}$. Measure of Uncertainty: UNC_{t-1}, dispersion of year t TFP shocks in log. Measure of Disagreement: DIS^F_{t-1}, annualized dispersion index of six-month ahead forecasts of the "General Business Conditions" among manufacturing firms, which incorporates all the forecasts regarding firms business conditions in year t; see text for details. Firm-level fixed effects are included for all specifications (not reported). Column (1): $[Patent\ App\ Disp]_{t-1}$, $IPPI_{t-1}$, and all their interactions with $\Delta \log[Y/L]_{i,t}$ as IVs. Column (2): $[Patent\ App\ Disp]_{t-1}$, $[Patent\ App\ Disp]_{t-2}$, $IPPI_{t-1}$, $IPPI_{t-2}$ and all their interactions with $\Delta \log[Y/L]_{i,t}$ as IVs. Column (3): $[Patent\ App\ Disp]_{t-1}$, $IPPI_{t-1}$, and the interactions of $\Delta \log[Y/L]_{i,t}$ with the fitted values of $\log UNC_{t-1}$ and $\log DIS^F_{t-1}$, which are estimated from regressing each of the second moment measures in $t-1$ on the lagged patent dispersion, and the lagged $IPPI$ index. Column (4): $[Patent\ App\ Disp]_{t-1}$, $[Patent\ App\ Disp]_{t-2}$, $IPPI_{t-1}$, $IPPI_{t-2}$, and the interactions of $\Delta \log[Y/L]_{i,t}$ with the fitted values of $\log UNC_{t-1}$ and $\log DIS_{t-1}$, which are estimated from regressing each of the second moment measures in $t-1$ on the two lags of patent dispersion, and those of $IPPI$ index. Bootstrapped S.E. are in the parentheses from 100 repetitions and are clustered at the firm level. Significance levels: 10% *, 5% **, 1% ***

disagreement changes, conditional on no changes to the dispersion of productivity fundamentals has been found. The magnitude of this linear effect, however, is less pronounced than the "wait-and-see" effect associated with uncertainty changes. More importantly, the positive coefficient associated with the non-linear term of productivity growth and the disagreement measure, i.e. the productivity-dampening effect of disagreement shocks, suggests that the forecast disagreement helps identify a different type of second moment shocks that can affect firm-level investments through a distinctive channel.

Hence, both at the aggregate level and the firm level, we found that innovations to the firms' forecast disagreement can affect aggregate dynamics and the firm-level investment in a different way, as compared to the impacts of productivity uncertainty shocks. The defining feature that distinguishes the impulse responses of macroeconomic aggregates to the uncertainty shocks from those to the informational disagreement shocks, is whether or not there is a quick rebound and overshoot after the adverse second moment shocks. At the firm level, whether the elasticity of the firm-level investment conditional on the productivity growth with respect to the changes to second moment shocks is positive or negative, helps identify if disturbances originate from changes to the spread of real economic fundamentals, or from changes to the dispersion of heterogeneous beliefs. The implications drawn from the micro-level evidence is that while jumps in productivity uncertainty can promote capital reallocation in the following years after the shocks, more dispersed beliefs can obstruct the reallocation.

Importantly, we see that the macro and micro-based evidence are consistent with each other. Aggregate rebounds and overshoots of aggregate investment after jumps in uncertainty shocks could be the consequences of the collection of larger investments taken by those more productive and active firms. On the contrary, when belief changes are not backed by good or bad economic fundamentals, innovations that increase the dispersion of the firms' heterogeneous beliefs about future business conditions could increasingly dampen the size of investment spikes taken by more productive firms. As a result, in absent of the rebound and micro-level reallocation dynamics, we could see a much slower recovery of aggregate investment along with other major aggregate variables.

6 Conclusion

This paper provides empirical evidence both at the aggregate level and the firm level to demonstrate that survey-based forecast dispersion identifies a different type of second moment shocks that affect the firm-level belief dispersion, which are not backed by good or bad economic fundamentals. Such pure informational disagreement shocks differ from the canonical uncertainty shocks that directly affect the variance of real economic fundamentals for their very different macro and micro implications.

Using the firm-level forecasts dispersion to measure the disagreement, macro series such as aggregate investment, employment, and industrial production, all experience a persistent decline followed by a slow recovery in response to greater disagreement shocks. Conversely, when the uncertainty is measured by the cross-sectional dispersion of future firm-specific productivity innovations that well corresponds to the theoretical concept of productivity uncertainty in a model of uncertainty shocks, the "wait and see" effect as marked by "drops-rebound-overshoot" of macro aggregates is robust, following jumps in the productivity uncertainty.

At the micro-level, conditional on being more productive and away from the "wait-and-see" threshold, firm producers tend to invest more as larger variance of future productivity increases the expected marginal product of capital. Such findings confirm the dynamism at the firm-level, which aggregates up to a macroeconomic rebound. However, by triggering the informational confusion about future business conditions, innovations that lead to greater disagreement among firms dampen the size of investment spikes among more productive firms, which results in a shrinking capital reallocation market, a persistent economic downturn, and a weak recovery.

By identifying the impacts of the informational disagreement shocks, this paper finds that the dispersion of firms' heterogeneous beliefs is not a direct measure of the fundamental uncertainty, i.e. the variance of future productivity as stipulated in a model of uncertainty shocks. Hence, identifying the informational second moment shocks suggests that a slow recovery does not have to be a result of the combined adverse first moment and second moment shocks that shift the economic fundamentals.

A Appendix

A Alternative Measures of Disagreement and Uncertainty

Index of Economic Policy Uncertainty (**EPU**): based on the frequency of newspaper references to policy-related economic uncertainty, the index has been found to spike near tight presidential elections, Gulf Wars I and II, the 9/11 attacks, the failure of Lehman Brothers, the 2011 debt-ceiling dispute and other major battles over fiscal policy. See details in Baker et al. (2016).

Dispersion of Forecasts Measures Based on Philadelphia Fed's Survey of Professional Forecasters data (**SPF**): the survey is conducted quarterly among professional forecasters regarding their forecasts about major macroeconomic variables of the U.S. for the quarter of survey, and up to one year or two years ahead. The survey started in 1968 and the Federal Reserve Bank of Philadelphia took over the collection from the National Bureau of Economic Research, and maintained the survey since 1990. It has been claimed that measurement issues can be severe fore the data before 1990 and I use the data from 1990Q1 up to 2013Q4 in line with Bloom (2014).

Cross-sectional forecast dispersion measures the degree of disagreement among the expectations of different forecasters. I use the forecast dispersion index published by Philadelphia Fed's regarding forecasts about the U.S. real GDP and the industrial production. The exact measure of dispersion is taken as the difference between the 75th percentile and the 25th percentile (the interquartile range) of the point forecasts surveyed. To aid the comparisons with the BOS survey-based forecast disagreement which is constructed based on six month ahead forecast data, I consider two quarters ahead SPF forecast dispersion measure as benchmark SPF measure.

B IRFs Based on Large VAR system Estimations Using SPF-based Disagreement Measures

See Figures of 12 and 13 for details.

C A List of NAICS Sectors Used For Computing IVs

Table 13: USPTO NAICS Industry Classifications Profile

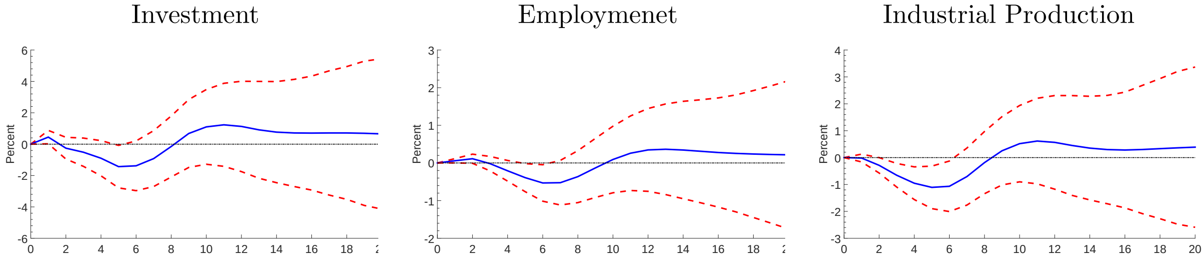
NAICS Code	Classification Title
311	Food
312	Beverage and Tobacco Products
313-316	Textiles, Apparel and Leather
321	Wood Products
322,323	Paper, Printing and support activities
325 (3251-3259)	Chemicals
326	Plastics and Rubber Products
327	Nonmetallic Mineral Products
331	Primary Metal
332	Fabricated Metal Products
333	Machinery
334 (3341-3346)	Computer and Electronic Products
335	Electrical Equipment, Appliances, and Components
336 (3361-3369)	Transportation Equipment
337	Furniture and Related Products
339 (3391-3399)	Miscellaneous Manufacturing

D Measures of Operation Ratios For the Empirical Investment Equations

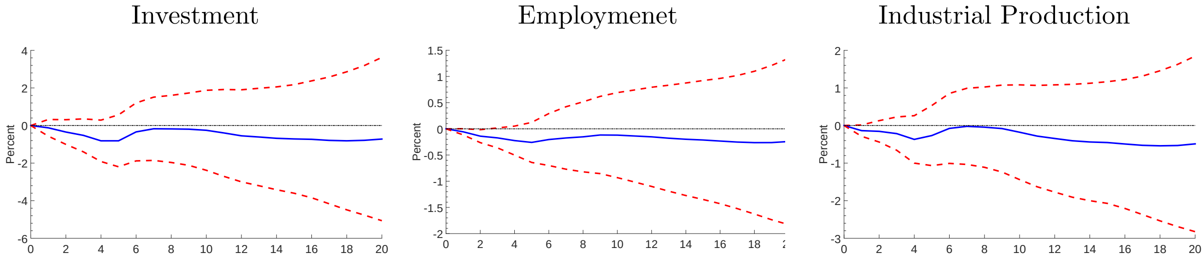
Firm-level data of annual frequency is used in the firm-level investment equation estimations. I stick to the Compustat fiscal year definitions so that a firm's operation is considered in year $t-1$ data entry if this firm has its end of the fiscal year from January through May of calendar year t otherwise in year t. The definitions of empirical measures are listed below:

1. $[I/K]_{i,t}$: investment-capital ratio, Capital Expenditures in year t divided by Property, Plant and Equipment - Total (Net) in year $t-1$.

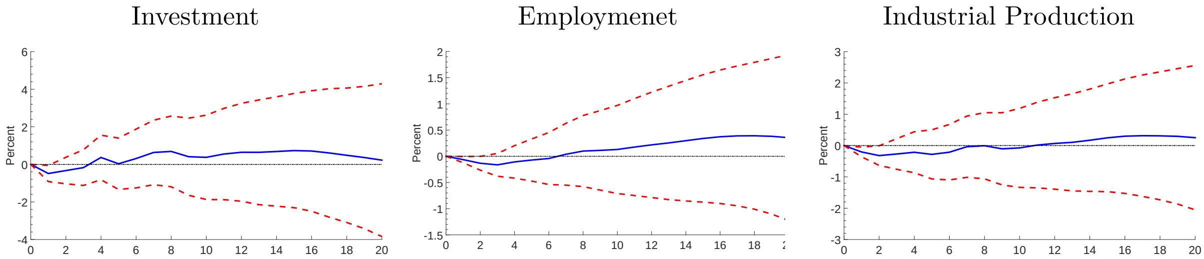
Figure 12: Aggregate Implications: Uncertainty and Disagreement Shocks
[Disagreement Index (**SPF**) Ordered Before Uncertainty)]



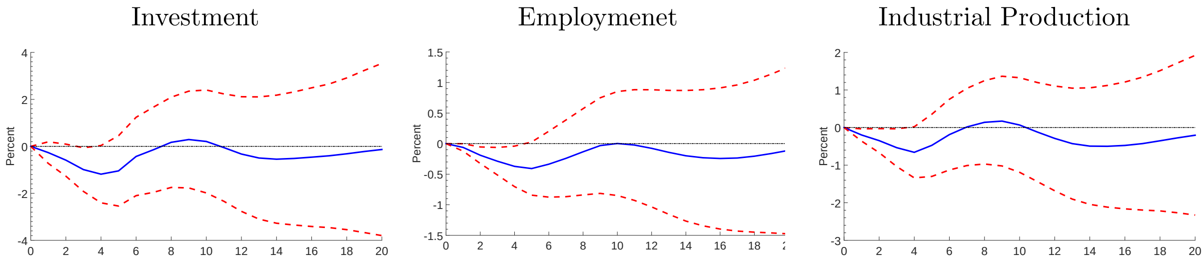
(I) Responses to an Uncertainty Shock (**SPF-UNC**)



(II) Responses to an Disagreement Shock (**SPF-UNC**)



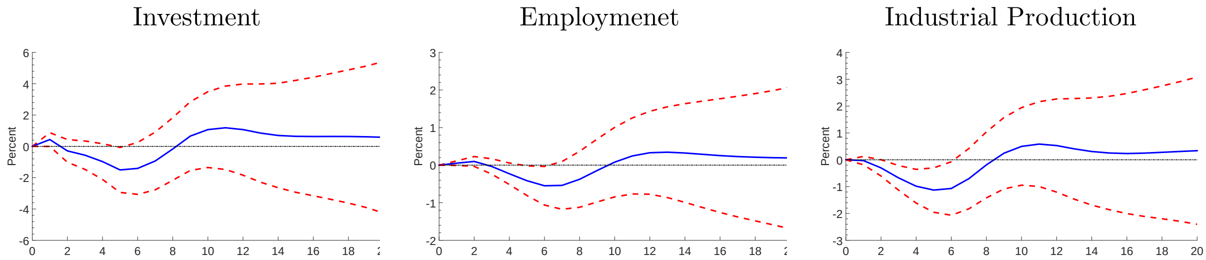
(III) Responses to an Uncertainty Shock (**SPF-EPU**)



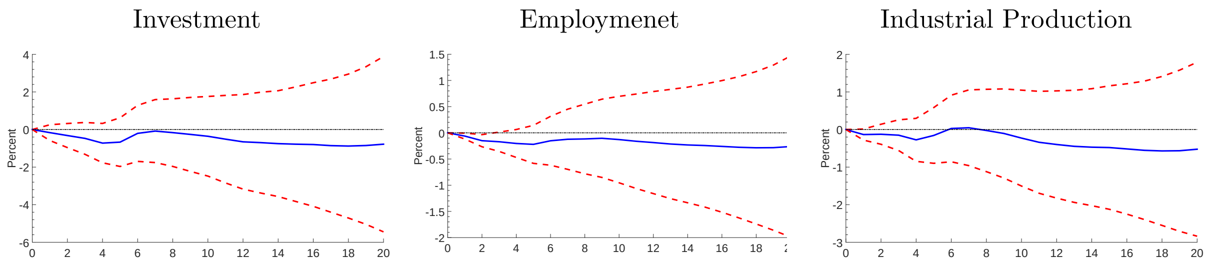
(IV) Responses to an Disagreement Shock (**SPF-EPU**)

NOTES: This figure plots impulse responses of U.S. real private domestic investment (first column), non-farm payroll employment (second column), and industrial production (third column) to 1 % increase uncertainty (**UNC** or **EPU**)and disagreement proxies (**SPF**), obtained from estimation of a ten-variable system of VAR with Scheme 1 Cholesky recursive ordering; see details in text. The frequency of data is quarterly and the VARs are estimated with 4 lags. The sample covers 1990Q1 to 2013Q4. Area between red dashed lines defines 95 % confidence interval based on 2000 bootstrap simulations.

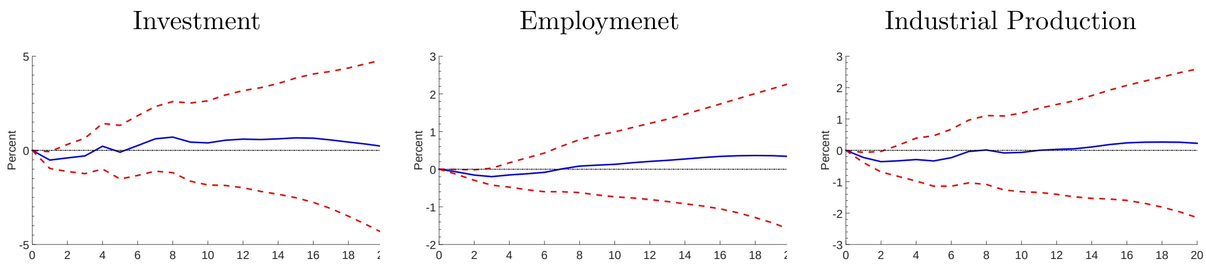
Figure 13: Aggregate Implications: Uncertainty and Disagreement Shocks
[Uncertainty Measure Ordered Before Disagreement Index (**SPF**)]



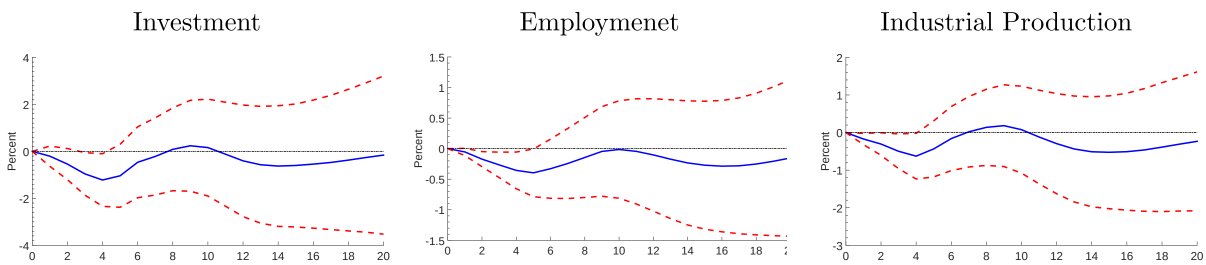
(I) Responses to an Uncertainty Shock (**UNC-SPF**)



(II) Responses to an Disagreement Shock (**UNC-SPF**)



(III) Responses to an Uncertainty Shock (**EPU-SPF**)



(IV) Responses to an Disagreement Shock (**EPU-SPF**)

NOTES: This figure plots impulse responses of U.S. real private domestic investment (first column), non-farm payroll employment (second column), and industrial production (third column) to 1 % increase uncertainty (**UNC** or **EPU**)and disagreement proxies (**SPF**), obtained from estimation of a ten-variable system of VAR with Scheme 2 Cholesky recursive ordering; see details in text. The frequency of data is quarterly and the VARs are estimated with 4 lags. The sample covers 1990Q1 to 2013Q4. Area between red dashed lines defines 95 % confidence interval based on 2000 bootstrap simulations.

2. $[Y/K]_{i,t}$: current sales-to-capital ratio, Sales/Turnover (Net) in year t divided by Property, Plant and Equipment - Total (Net) in year $t-1$.

3. $[\pi/K]_{i,t}$: current operating income-to-capital ratio, Operating Income Before Depreciation in year t divided by Property, Plant and Equipment - Total (Net) in year $t-1$.

4. $[CF/K]_{i,t}$: cash flow-capital ratio, Income Before Extraordinary Items - Adjusted for Common Stock Equivalents in year t divided by Property, Plant and Equipment - Total (Net) in year $t-1$.

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