MEASURING MICRO AND MACRO UNCERTAINTY

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ABSTRACT

This dissertation aims at building alternative measures of economic uncertainty from micro data. The resulting panel measurements enable investigations of real uncertainty effects at the individual, firm, industry, and macro level. Two uncertainty models are introduced to demonstrate additional channels through which uncertainty poses impacts on economic activities.

In the first chapter, I propose a novel firm-level uncertainty measure based on the latent conditional volatility of forecast errors. By applying this measure to I/B/E/S database, I track 1,916 U.S. public companies' uncertainties for over 34 years. The firm-level measurements are then aggregated into a macro uncertainty index and the implications at the macro- and micro-level are compared. At the macro level, VAR results indicate a strong "granular origin" of real uncertainty effects from large firms in addition to the classical short-lived "drop and rebound" effect. At the firm level, panel regression results confirm the negative impact of macro uncertainty on firm investment and reveal a composite effect of idiosyncratic uncertainty that depends on investment horizon, firm profitability and magnitude of shock (Empirical results are also shown in Chapter 2).

The second chapter introduces two uncertainty models that show channels other than "real option" and "risk aversion & risk premia" in contemporary literature. The first model is based on Lucas Island Model and Capital Asset Pricing Model (CAPM). It tries to understand the uncertainty effects from the perspective of inefficient expectation

and the resulting underproduction problem. The second model inherits New-Keynesian assumptions and features a competition mechanism. It emphasizes the real loss from unexpected supply and demand shocks. Both models include idiosyncratic and macro uncertainty as separate factors and predict a generally negative impact of macro uncertainty versus a composite effect of idiosyncratic uncertainty.

The third chapter is coauthored with Xuguang Sheng and as a standalone paper, it is accepted by the International Journal of Forecasting for publication. In this chapter, we propose a new measure of macroeconomic uncertainty that incorporates rich information set from U.S. SPF density forecasts. Our measure has two key advantages over traditional measures: (i) it reflects the subjective perceptions of market participants; (ii) it is an *ex-ante* measure that does not require the knowledge of realized outcomes. We study the features of this measure of macroeconomic uncertainty and explore its impact on real economic activities within the U.S. as well as its spillover effects on BRIC countries.

The Appendix discusses the methodology used in Chapter 3.

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CHAPTER 1

MEASURING FIRM UNCERTAINTY

1.1 Introduction

Recent trade wars, as well as partial breakdowns of trade partnerships (for example the U.S. leaving The Trans-Pacific Partnership (TPP), Brexit) inject a tremendous amount of uncertainty in the economic environment. International Monetary Fund (IMF) director Christine Lagarde publicly expressed her concerns about trade conflicts that might hurt the current "sweet spot" of international growth. Meanwhile, United States Secretary of the Treasury Steven Mnuchin showed full support for tariffs and believed such policies would reestablish a reciprocal and fair trade system. [1] While the U.S. stock market had a strong performance in 2018, there was a major downturn in the rest of the world and this divergence recently hit 14 years high. Major disagreements following economic policy shocks send a strong signal of an uncertain future. However, economists, as well as policymakers, seem to be uncertain about how to respond to the elevated world uncertainty.

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[1] Achleitner, Paul et al. "The Remaking of Global Finance", World Economic Forum on CNBC, January 25, 2018.

Despite efforts that have been put into building uncertainty indeces, current measures are still far from perfect. An example would be the decreasing sensitivity of VIX to new waves of U.S. tariffs (since the large VIX spike following the U.S. "global safeguard tariffs" on solar panels) with an increasing media coverage on such events. [2] In addition, VIX has long been criticized for containing volatilities directly from trading (See Fema (1965)). Other uncertainty measures face challenges too. Qualitative measures such as Economic Policy Uncertainty (EPU) (see Baker, Bloom, and Davis (2016)) lack innovative statistics to effectively summarize qualitative data. Disagreement depends too much on prior beliefs (see Zarnowitz and Lambros (1987), Lahiri and Sheng (2010), Krüger, Fabian and Nolte, Ingmar (2016)). Any cross-sectional variance measure of companies' earnings, productivity, etc.,(see Bloom et al. (2016)) contains predictable components that are not uncertain. Methods such as the variance of density forecast and entropy to a large extent are limited by the availability of compatible data (see Liu and Sheng (2018) and Istrefi and Mouabbi (2017). Besides, uncertainty measures are mainly constructed at the macro level. There are very few micro uncertainty indices that capture firm-level information in this regard. To address this gap, I propose a new firm-level uncertainty measure that has the following merits: (1) It is closely linked with uncertainty by its definition; (2) It is largely independent with respect to first-moment shocks and contains only second-moment dynamics; (3) The measure can be used on data covering a large number of firms for a long history with a quarterly frequency; (4) It might be easily extended to forecast horizons up to 10-year ahead with current data.

Existing measures basically capture two aspects of uncertainty: subjective uncertainty, which reflects a human emotion, or objective uncertainty, which concerns the stochastic factor of a data generating process (DGP) (see Jaynes (1957)). The measure proposed in this chapter focuses on the objective side of uncertainty and defines un-

[2] VIX is a measure of the implied volatility in U.S. stock market based on S&P 500 index options. It is maintained and published by the Chicago Board Options Exchange (CBOE).

certainty as the conditional volatility of an unpredictable event. Such a volatility is a composite result of stochastic factors in both the economic phenomena and their corresponding human forecasting activities. In addition, it should not be confused with the volatility of the event itself since predictable volatilities are not "uncertain" (see Jurado et al. (2015)). In other words, I emphasize volatilities associated with unpredictable factors that lead to real economic problems.

The measure is therefore formalized as

$$e_{i,t} = Y_{i,t} - E(Y_{i,t}|I_{t-1}), \quad e_{i,t} \sim \mathcal{N}(\mu_t,\, \sigma^2_{i,t}), \tag{1.1}$$

where i is the micro-level entity, $e_{i,t}$ is the forecast error for event $Y_{i,t}$ that can be measured continuously, and $E(Y_{i,t}|I_{t-1})$ is the foreseeable component of $Y_{i,t}$ under information set I_{t-1}. Assuming $e_{i,t}$ follows a certain parametric distribution (such as Gaussian in the notation) with time varying mean μ_t and variance $\sigma^2_{i,t}$, then $\sigma^2_{i,t}$ captures the volatility of the unpredictable factor and thus measures uncertainty. Removing the predictable component $E(Y_{i,t}|I_{t-1})$ is essential for getting a clean uncertainty measure. Jurado et al. (2015) use model-based predictions as a proxy. Alternatively, Sheng and Thevenot (2012) use real professional forecasts. I adopt the latter method due to difficulties in designing individual prediction models for a large number of firms. In addition, real forecasts from analysts are consistent estimates of true values and are also robust to structural breaks. Banko and Brill (2001) show that the performance of a simple prediction tends to converge with that of a complicated model once they are given with enough data, so the challenges in specify the correct model as well as the heterogeneous prior beliefs among forecasters might be largely mitigated by using a rich cross-sectional sample.

Since $\sigma^2_{i,t}$ is unobserved, econometric models are needed for the estimation. I choose Stochastic Volatility model over Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model for the desired independence between first- and second-moment shocks, which returns uncertainty dynamics beyond the observed first-moment movements. I focus on firm-earning as the key variable that generates important firm-level consequences when it is uncertain. Also, a strict data selecting process featuring a machine learning approach is used on the Institutional Brokers' Estimate System (I/B/E/S) database to capture the largest sample while maintaining high-quality estimations.

The firm-level uncertainty measure leads to a series of new research directions. First, it breaks down macro uncertainty effects at the firm level and enables studies on macro drivers of uncertainties associated with heterogeneous firms. By matching individual firm's uncertainty dynamics with a series of macro volatilities in the U.S., I find that GDP and financial volatilities are the two major contributors to firm uncertainties with direct effects. The effect of policy uncertainty is also significant, yet shows ambiguous directions. Exchange rate volatility seems to have much stronger impacts on larger firms. Oil price volatility, on the other hand, leads to a countercyclical pattern of uncertainty dynamics for many firms. All 5 macro volatilities combined explain 44% firm-uncertainty variations. A similar study can also be seen in Barro et al. (2017). In contrast to their work, I focus on a larger set of macro drivers and adopt a novel empirical method.

Second, earlier uncertainty indices are usually constructed on macro-level data, which contains little micro-level information. An apparent drawback is their inability to show uncertainty effects in the granular view. However, aggregating micro-level data is not an easy task. Standard methods such as mean or median completely lose their power when facing significant size effects. By studying the size distribution of firms in my I/B/E/S sample and the scale effect embedded in Earning Per Share (EPS) values, I use a unique weighting scheme to build micro-founded macro uncertainty indices at industrial levels and the country level. The real effect of macro uncertainty is tested in a 7 variable VAR framework and results are in line with the "drop and rebound" theory in Bloom (2009). More importantly, Gabaix (2011) points out that first moment shocks associated with large companies generate non-trivial effects on the entire economy. To test a similar effect for the second moment, I aggregate two uncertainty series associated with the largest 100 U.S. companies as well as smaller firms. I discover that the common uncertainty surrounding large companies alone is capable of generating real economic impacts seen after economy-wide uncertainty shocks. Smaller firms, despite their non-trivial earning and size shares in the U.S. economy, give insignificant results.

Third, literature has been mainly focusing on macro uncertainty impacts, but to some extent overlooking micro effects following idiosyncratic uncertainty shocks. Campbell et al. (2001), Bachmann et al. (2013) and Bijapur (2015) are some of the very few papers that addresses both. I conduct a decomposition on my firm-level measurements to separate out firm-specific (idiosyncratic) uncertainty series that are orthogonal to macro uncertainty shocks. Both macro and idiosyncratic components of uncertainty are studied in panel models. Regression results suggest that while both types of uncertainty have negative impacts on firm investment, the effect of macro uncertainty is stronger. In contrast, idiosyncratic uncertainty shows a composite effect: First, it changes firms' term structure of investment from short-term to long-term and such a change is largely linked to increased spendings on developing new products; second, the direction of its impacts depends on firms' profitabilities: firms with high excess returns benefit from increasing idiosyncratic uncertainty while firms with low returns suffer; third, its average effect on investment shows a convex path: the negative effect diminishes and possibly turns positive as idiosyncratic uncertainty continuously goes up.

This chapter has several contributions to the growing uncertainty literature. It proposes a new and reliable uncertainty measure at the firm level. It proposes a new micro-founded macro uncertainty index that tracks the U.S. market. It bridges the gap between macro and micro empirical studies on the real impacts of uncertainty. It unveils a composite effect of firm-specific (idiosyncratic) uncertainty.

The chapter is arranged as follows: Section 1.2 introduces the firm-level uncertainty measure, its application on I/B/E/S database, and its macro-drivers; Section 1.3 proposes a micro-founded macro uncertainty index and the granular origin of macro-uncertainty impacts; Section 1.4 shows the uncertainty decomposition and firm-specific uncertainty effects; Section 1.5 concludes.

1.2 Measuring Firm Level Uncertainty

1.2.1 Data

I/B/E/S, the Institutional Brokers' Estimate System, is a database created and maintained by Thomson Reuters. It is a historical earnings estimate database containing analysts' estimates for more than 20 forecast measures. Detailed history is delivered monthly and contains data collected by Thomson Reuters up to the Thursday before the third Friday of every month. The estimate used in this chapter is at the quarterly frequency. However, since not all companies have the same fiscal year end, the standard quarter end may not apply to many companies. Hence, I map fiscal quarters to calendar quarters as closely as possible for all firms. The actual value of firm's earning measure takes 30-40 days to arrive. For this reason, forecast circles do not exactly match targeted periods. For each company, forecast circle starts from the activation date of last period actuals and end at the next activation date.[3] Analysts are asked to make forecasts for as close as current quarter and as far as 10 fiscal years ahead. The one-quarter ahead forecast is, therefore, nowcast and is the only forecast horizon concerned in this research. Estimates associated with longer horizons are left for future researches. Due to the short forecast horizon, the resulting measurement is for short-term uncertainty. Analysts are allowed to make multiple estimates for the same target during each forecast cycle and their information updates are therefore documented in the data. There are rare cases where

[3]The activation date is the date that actual values for the last period become active in the I/B/E/S database

analysts still update forecasts after the actual value is announced but before it becomes active in the system[4]. Those forecasts are removed due to potential "cheating". Figure 1.1 illustrates the timeline of forecast activities. The I/B/E/S detail dataset records forecast information for 60,000 companies worldwide. In this research, I focus on U.S. firms.

The variable of my main interest is the firms' Earning Per Share (EPS). Despite variables such as Return on Assets (ROA) or Return on Equity (ROE) that allow more straightforward cross-sectional comparisons, EPS has the single longest forecast history and also the richest cross-sectional observations essential for an extensive empirical study.[5] The raw data for the EPS 1 quarter nowcast contains more than 3 million EPS estimates provided by 18,992 financial analysts for 16,724 U.S. firms. However, there are some concerns regarding this sample: (1) EPS values change with stock split thus the raw estimates are inconsistent through time. I/B/E/S provides split-adjusted values so estimates regarding the same firm are based on a consistent scale; (2) EPS is not a perfect indicator of firms' comparative profitability as those values are individually scaled by firms' outstanding shares. This issue is carefully examined in section 1.3.

Other firm-level variables used in this study are acquired from the Compustat database. Sources for macroeconomic variables and financial series are Federal Reserve Bank of St. Louis and Yahoo Finance.

1.2.2 Model and Estimation

The time-varying volatility of forecast errors $\sigma^2_{i,t}$ is unobserved, so I have to rely on econometrics model for its estimation. GARCH is frequently used for such a task. However, GARCH family models assume a serial correlation between the first and second

[4]It takes Thomson Reuters up to a week to update actual values in their system so analysts could potentially make "forecasts" based on actual values.

[5]While other variable estimates start after 2000, EPS estimates go back to 1982. The Firm Level Uncertainty series extracted form EPS estimates is, therefore, much longer than competing measures in the literature.

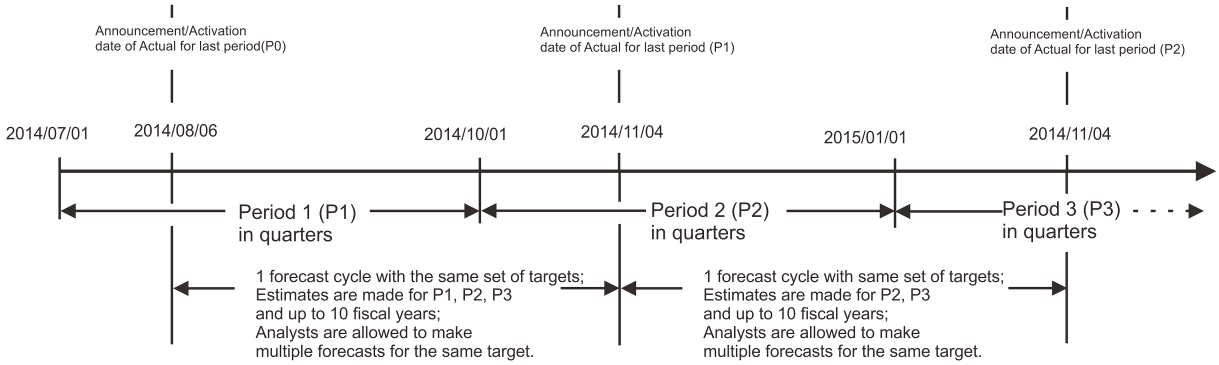

Figure 1.1: The Timeline of EPS Estimates and Actuals Announcements

moment and a deterministic path for the second-moment dynamics, both of which make the estimation results strongly correlated with first-moment shocks. Stochastic volatility models, on the other hand, are free of both assumptions and thus return second-moment dynamics beyond first-moment movements. Although the advantage of SV model over GARCH has been discussed in many papers (see Jacquier et al. (2002), Kim et al. (1998) etc.), the computational difficulty in its estimation makes it underused. (See Kastner et al. (2014)).

The forecast error associated with certain economic target at time t with horizon h is defined as

$$e_{h,t} = Y_{t+h} - E(Y_{t+h}|I_t), \tag{1.2}$$

where $E(Y_{t+h}|I_t)$ is the conditional forecasts on current information I_t. In order to obtain a quality unpredictable component $e_{h,t}$, it is essential to make conditional forecast $E(Y_{t+h}|I_t)$ as good as possible. Jurado et al. (2015) use model-based predictions to proxy $E(Y_{t+h}|I_t)$ due to the lack of forecast data for variables of concern. Here, I use consensus forecasts from financial analysts in the I/B/E/S database for best predictions in the market. Assuming the forecast error is Gaussian $e_{h,t} \sim \mathcal{N}(\mu_{h,t}, \sigma^2_{h,t})$,[6] and the log-variance

[6]The Gaussian distribution for the forecast error is based on the Central Limit Theorem. As the forecast error is considered to be the composite of a large number of minor influences (including influences associated with both economy phenomena and human forecast activities), the distribution of the composite results tends to approach the Gaussian.

process $\sigma_{h,t}$ has an $AR(1)$ autoregressive behavior:

$$\log \sigma_{h,t}^2 = \mu_h + \phi_h(\log \sigma_{h,t-1}^2 - \mu_h) + \eta_h \epsilon, \tag{1.3}$$

where ϵ is white noise. Also assuming the initial value $\log \sigma_{h,0}^2$ is drawn from $\mu_h + \frac{\eta_h}{\sqrt{1-\phi_h^2}}\epsilon$, the parameter space left for estimating is $\theta = (\mu_h, \phi_h, \eta_h)$. For each $\mathbf{Y}_h = (Y_{1+h}, Y_{2+h}, ..., Y_{t+h})$, the values of interest $(\sigma_{h,1}^2, \sigma_{h,2}^2, ...\sigma_{h,t}^2)$ are recursively and stochastically determined by θ via Metropolis-Hasting sampling.

The parameters are all estimated by Markov Chain Monte Carlo (MCMC). The prior distribution for μ_h is Gaussian. The prior for ϕ_h could be quite influential so I choose uninformative beta prior due to the lack of reference in the literature. The prior for η_h is uninformative Gamma distribution. As Bayesian estimation returns entire distributions of parameters instead of point estimates, I use median values of their respective posterior distributions as final parameter values. Therefore, $\sigma_{h,t}$ is the latent time-varying uncertainty associated with economic target $Y_{h,t}$ backed out from forecast errors series $(e_{h,1}, e_{h,2}, ...e_{h,t}, ...)$.

1.2.3 Properties of Firm Level Uncertainty (FLU)

The estimation is conducted on one quarter ahead EPS estimates at the quarterly frequency. In order to obtain the best prediction for each forecast target, the following efforts are made: (1) Since analysts are allowed to make multiple forecasts for the same target, only the latest estimate of each analyst associated with certain target are used to reflect their best information set; (2) For each target, I check the number of forecast contributors and keep only those targets that have forecasts from a minimum of 3 different analysts; (3) For each forecast target, the consensus (mean) forecast is used to proxy the best estimate in the market. The corresponding forecast errors are computed together with the actual EPS values from I/B/E/S vintage; (4) A quality estimation result requires a relatively long forecast series. I set the threshold at 40 quarters so only firms that have at least 40 continuous estimates and also satisfy criterion (2) are kept for the model fitting; (5) If a forecast series contains several segments of 40 (or more) continuous estimates with gaps in-between, segments are fitted separately to reflect structure breaks.[7] For my I/B/E/S sample, a total of $1,916$ U.S. firms survive this selection process. The requirement for 10 year continuous estimates disqualifies many of the smaller or short-lived firms. In addition, the I/B/E/S sample only contains publicly traded firms so the size bias is one limitation in the measure. [8] In addition, the potential smoothness due to earnings management might also contribute to some of the smoothness in the forecast errors.

In addition, there are three concerns with the feasibility of such an estimation method that require extra attention. First, the forecast error series cannot be autocorrelated. Otherwise, at least part of these errors should be predictable. To solve this issue, I use the $AR(1)$ model to detect autocorrelation in each forecast error series. About 45% of the forecast error series show significant autocorrelation at 10% level. For those series, stochastic volatility model fits on the corresponding $AR(1)$ residuals instead of the original series. Second, first-moment correlations due to the "herd behavior" among analysts in response to large common exogenous shocks partially translate into correlations at the second-moment, which could lead to over-estimated uncertainty at the firm level. I remove the time-varying common error prior to SV model fitting to mitigate such

[7] Case studies suggest that most of the forecast breakpoints are caused by shocking events that likely generate structural breaks of a company's volatility series. Those shocking events include merging, economic crisis or initiating bankruptcy.

[8] It is possible to include more firms by lowering the 40 continuous estimates at some cost of estimation quality.

a effect. [9] [10] Finally, as I/B/E/S dataset covers a relatively long period, EPS values might change dramatically following large changes to stock prices. The dataset has been adjusted for the stock split, but inflation and fast growth could lead to a non-trivial scale effect on forecast errors. In other words, large forecast errors could be attributed to larger EPS values but not higher uncertainty. The distribution of all actual EPS series and the distribution of all EPS estimate have thin tails with 99% of values within the range [-4,10]. I remove observations within 1 percentile on both sides to make the sample free of extreme values. In addition, I run a correlation test between forecast errors and actual EPS which returns a low value, 0.004. A similar bivariate regression shows a negligible R^2 value. Both test results imply a trivial scale effect in my measure.[11]

The final fitting results return an unbalanced panel that contains uncertainty measurements for 1,916 U.S. firms. For the rest of the chapter, I call them Firm Level Uncertainty (or FLU, or $\sigma_{i,t}$). Figure 1.2 shows FLU for some well-known U.S. companies. The uncertainty surrounding Apple is very sensitive to new lines of product announcements and former CEO Jobs' death. Amazon's uncertainty rises substantially in recent years due to the very fast expanding and the Whole Foods deal. Starbucks, on the other hand, experiences high uncertainty when it was forced to close more than 300 stores during the 07-09 recession. In addition, its uncertainty is also closely linked to the business expan-

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[9] I use the market average forecast error $\mu_{m,t}$ as the distribution mean μ_t in equation (1.1), or equivalently $e_{i,t} = \mu_{m,t} + \epsilon_{i,t}$, where $\mu_{m,t}$ is obtained by collapsing individual forecast errors sequentially along the dimension of analysts with pegged firm i and time t then along the dimension of firms with pegged t. This method is not perfect as excess forecast errors are not orthogonal to $\mu_{m,t}$ (Campbell et al. (2001)). However, this drawback has limited effects on the result and likely disappears after aggregation.

[10] The main purpose of such a demean process is to further reduce the influence of first-moment dynamics on uncertainty estimations at the firm level.

[11] For a more strict robustness check, I run the following regression

$$\sigma^2_{i,t} = a_i + EPS_{i,t} + \xi_{i,t} \tag{1.4}$$

at the firm level and use $a_{i,t} + \xi_{i,t}$ as the scale-free uncertainty measure. This measure returns very similar results at both macro and micro level. Graphs based on $\xi_{i,t}$ might be provided upon request.

sion in China. Bank of America' uncertainty is extremely sensitive to financial crises and recessions; Major Mergers and acquisitions trigger large uncertainty spikes in general.

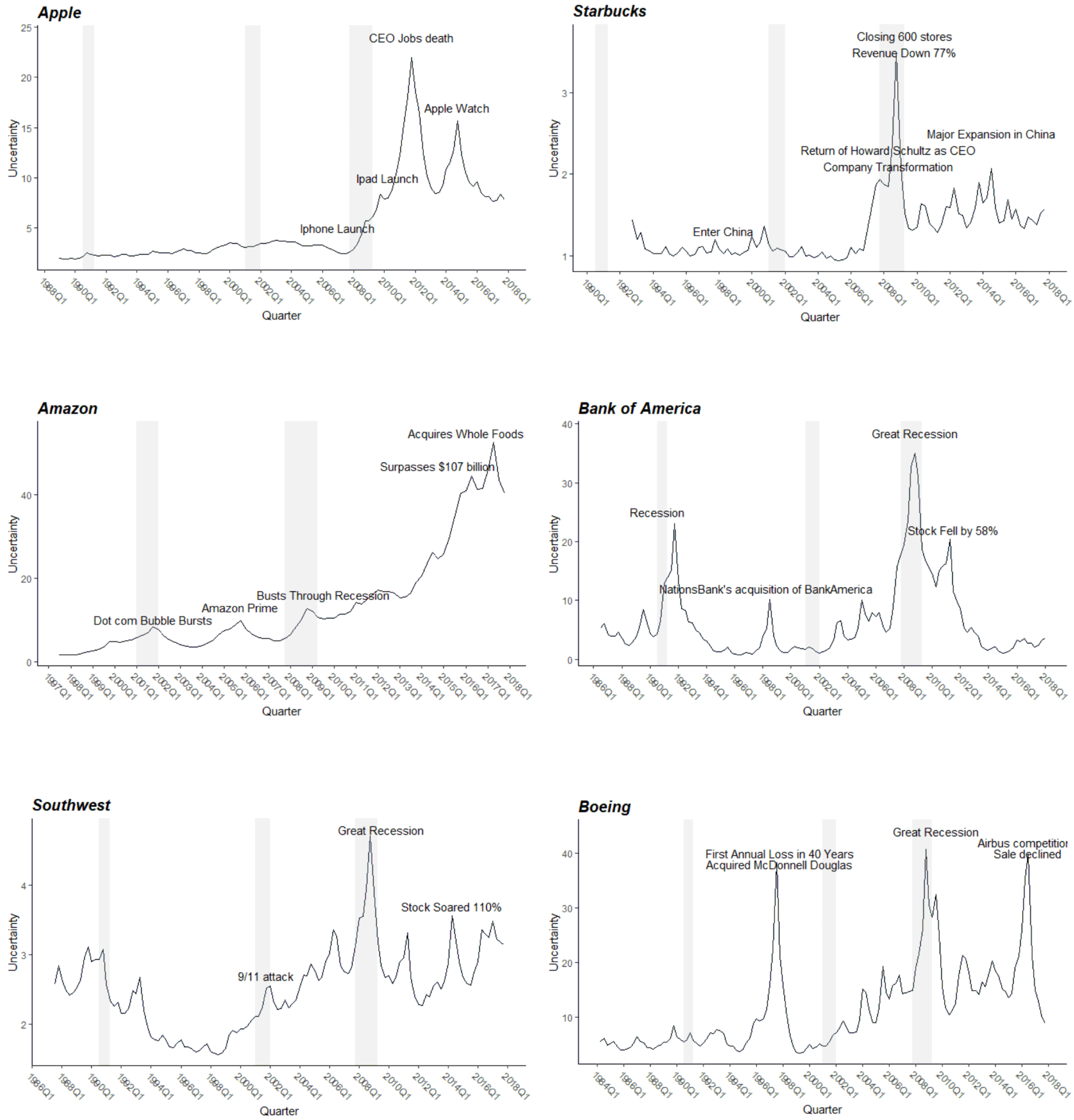

Figure 1.2: Uncertainties of Some Well-known U.S. Companies (FLU)

1.2.4 What Drives Firm Level Uncertainty?

The FLU captures latent second-moment shocks that indirectly drag firms away from the consensus path. Analysts observe these consequences, but they might not see the cause. While macroeconomic or political shocks such as trade wars or coups lead to a noisy economic environment that interferes with firms' business planning, idiosyncratic shocks such as manager turnovers or incidents also hurt firms' performance. Designing proper strategies to counter the negative effect of uncertainty requires a good understanding of drivers behind those phenomena. In this section, I focus on macro drivers of firm uncertainties by examining the link between FLU and second-moment dynamics of 5 major macroeconomic variables. The firm-specific idiosyncratic uncertainty effects are covered in section 1.4.

The set of U.S. macro variables includes Real GDP, Oil price, Exchange rate, Economic policy, and Stock price.[12] [13] These macro variables cover different aspects of the U.S. economy and are considered to have general impacts on the majority of firms. Data for GDP, oil price and exchange rate are first-moment measurements so I apply stochastic volatility models to their detrended log-series to derive their implied volatilities. I choose not to use realized volatility due to the strong backward-looking nature of such a method and the low frequency of macro data.[14] EPU and VIX, on the other hand, are natural second-moment measures and are used without treatments. Figure 1.3 illustrates the dynamics of volatilities associated with these 5 macro series. They respond

[12]The exchange rate is a weighted average of the foreign exchange value of the U.S. dollar against the currencies of a broad group of major U.S. trading partners. The stock price refers to S&P 500 index and its volatility is proxied by VIX. The economic policy refers to EPU proposed by Baker et al. (2016).

[13]Data for real GDP, Exchange rate are acquired from St. Louis FRED. VIX data is acquired from the CBOE website. EPU is downloaded from the Economic Policy Uncertainty Index website.

[14]Using realized volatilities of these macro variables returns lagged peak points corresponding to shocking events.

similarly to large economic and political shocks but display distinct persistence, timing, and magnitude upon small or medium shocks.

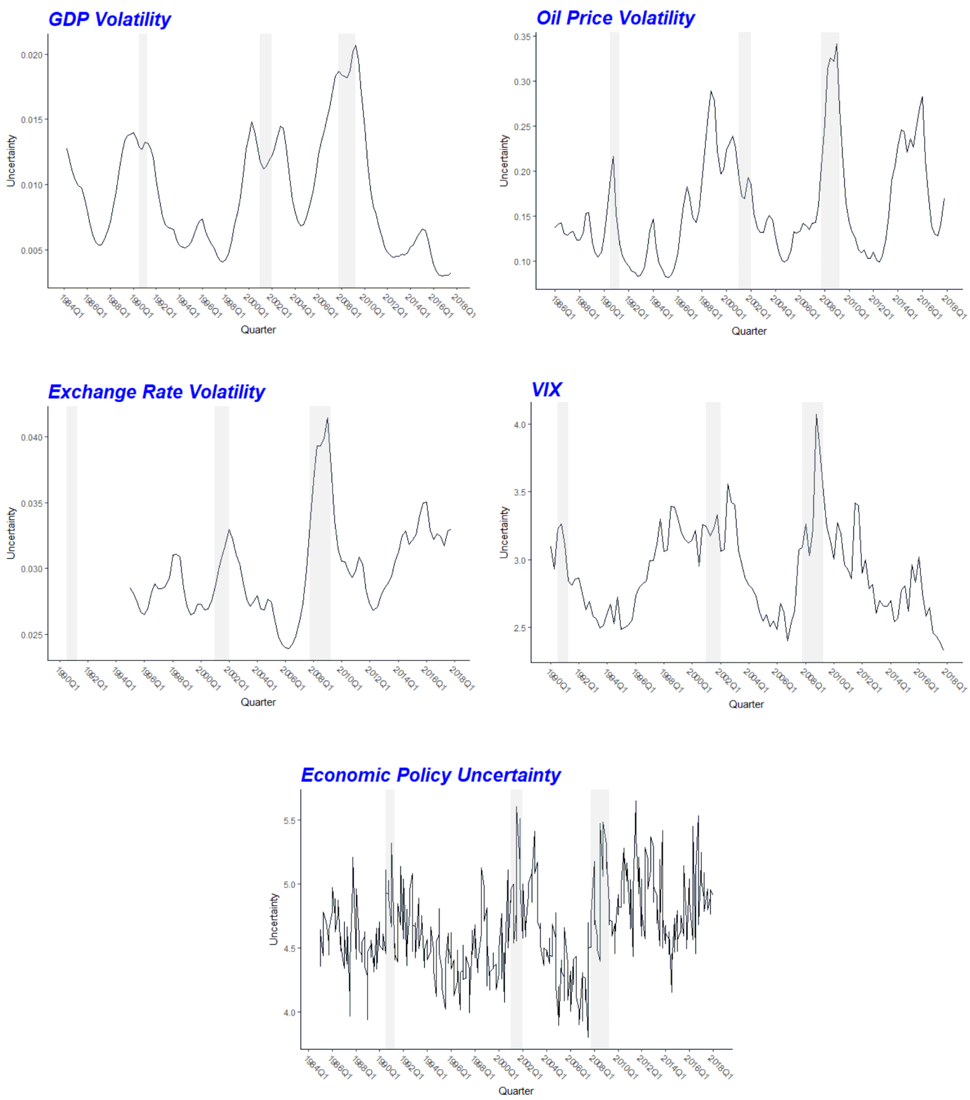

Figure 1.3: Volatilities of Macro Variables

Volatilities for GDP, Oil price and Exchange rate are computed by fitting stochastic volatility models on their detrended log-series. EPU and VIX are log-series. Data for real GDP, Exchange rate are acquired from St. Louis FRED. VIX data is acquired from the CBOE website. EPU is downloaded from the Economic Policy Uncertainty Index website.

Volatility series associated with those macro variables might already be well studied. However, the firm-level breakdown of those macro influences is missing from the literature. To see how individual firms respond following macro uncertainty shocks, I start with regressions:

$$\sigma_{i,t}^2 = c_i + \boldsymbol{\beta}_{i,c}\boldsymbol{X}_t + \zeta_i \quad \text{for each i,} \tag{1.5}$$

where $\sigma_{i,t}^2$ is FLU; $\boldsymbol{X}_t$ is the vector of macroeconomic volatilities including GDP volatility, Oil price volatility, Exchange rate volatility, Economic policy uncertainty, and VIX; ζ_i is the disturbance with firm-specific variance. Regression is conducted at the firm level so each firm has its own regression results. Since most of the companies in my sample are not large enough to generate visible impacts on the entire economy but vulnerable to fluctuations in the market, those regression results provide information regarding the causality.

In Table 1.1 upper panel, I report three statistics obtained from $\boldsymbol{\beta}_{i,c}$ and p_i values from $1,865$ individual firm regressions:[15] (1) Response rate: the share of firms that respond to certain macro volatilities at 10% significant level ($p_i \leq 0.1$); (2) Positive: the share of firms that have significant and positive response ($p_i \leq 0.1$ and $b_i \geq 0$); (3) Negative: the share of significant but negative responses ($p_i \leq 0.1$ and $b_i < 0$). Among 5 macro volatilities, policy uncertainty, GDP volatility and oil volatility have a slightly higher response rate which implies potentially more universal impacts. In addition, depending on the type of macro drivers, firm uncertainties could present both pro-cyclical and counter-cyclical patterns. Although stock market volatility shows a slightly lower response rate, it has a quite large positive share which implies a direct effect of the financial market volatility on firms. Meanwhile, firms' responses to oil price uncertainty show a counter-cyclical pattern, which is not surprising considering that unstable oil price would encourage more domestic oil production which not only benefits many companies

[15] The sample size shrinks slightly as a result of merging with other databases.

but stabilizes oil price expectation. The effect of policy uncertainty is a mixed bag: while some firms' uncertainties rise after an unspecified policy uncertainty shocks some other firms fall. The nearly equal split in the data implies biases in any policy changes. GDP volatility displays the most dominating negative effect on firms' earning stability. The exchange rate volatility turns out to be less influential in this micro setup. However, as we see in the next section, its macro-level effects are much stronger.

Table 1.1: Macro Drivers of Firm-Level Uncertainty

Statistics	Politics	Stock Market	GDP	Oil Price	Exchange rate
Response Rate	0.55	0.37	0.51	0.51	0.37
Positive	0.28	0.31	0.43	0.12	0.23
Negative	0.26	0.06	0.07	0.38	0.14
Mean R^2			0.44		
Change of R^2	0.09	0.14	0.18	0.09	0.13

Note: Results are based on β and p values from 1,865 individual regressions. Numbers show the share of firms have p values smaller than 0.1, the share of positive β conditional on $p \leq 0$, and the share of negative β.

Note: Mean R^2 is the mean of $1,865$ regression results. Change of R^2 is the percentage change of mean R^2 after removing one of 5 variables in regressions.

In the lower panel, I report the mean R^2 of all $1,865$ regressions and the percentage change of mean R^2 after excluding 1 of 5 macro volatility. Nearly half of FLU variations might be explained by the aggregate effect of these 5 macro volatilities. In addition, GDP and stock market volatilities contribute most to firms' uncertainty fluctuations.

1.3 Constructing Macro Uncertainty Index

1.3.1 Estimating the Weighting Scheme

The reason for constructing a micro-founded macro uncertainty measure is three-fold: (1) Policymakers might be interested in macro uncertainty since their policy goals are usually at the macro scale; (2) Existing macro uncertainty measures are usually built on macro variables such as GDP, inflation, stock market indices, which contain little micro-level information; (3) An effective measure of idiosyncratic uncertainty requires removing the macro component. Otherwise, researchers might not be able to distinguish idiosyncratic uncertainty shocks from macro ones, and thus unable to study their respective economic effects. A further discussion of such an issue is provided in section 4.

Two challenges are unavoidable while aggregating the microdata: the panel is unbalanced and the weights need to be specific. Liu and Sheng (2018) study the panel composition issues in the SPF dataset and show that changes of panel composition substantially drive estimation results. Unfortunately, both firms and forecasters in I/B/E/S database varies from time to time. To mitigate such issues, I limit the uncertainty episodes to periods that have enough overlapping firms as well as sufficient participating forecasters. The remaining sample has an average of 50% shared companies. A proper weighting scheme for FLU is also needed. A standard approach would be to use equal weights on all firms. However, weights are usually quite influential in aggregating results. On one hand, the size-effect matters, or more specifically, in the granular view shocks to large firms have non-trivial real impacts on the entire economy, and such effects are not found among small firms (see Gabaix (2011)). On the other hand, EPS value contains built-in scale as the number of outstanding shares that requires proper controls prior to aggregating.

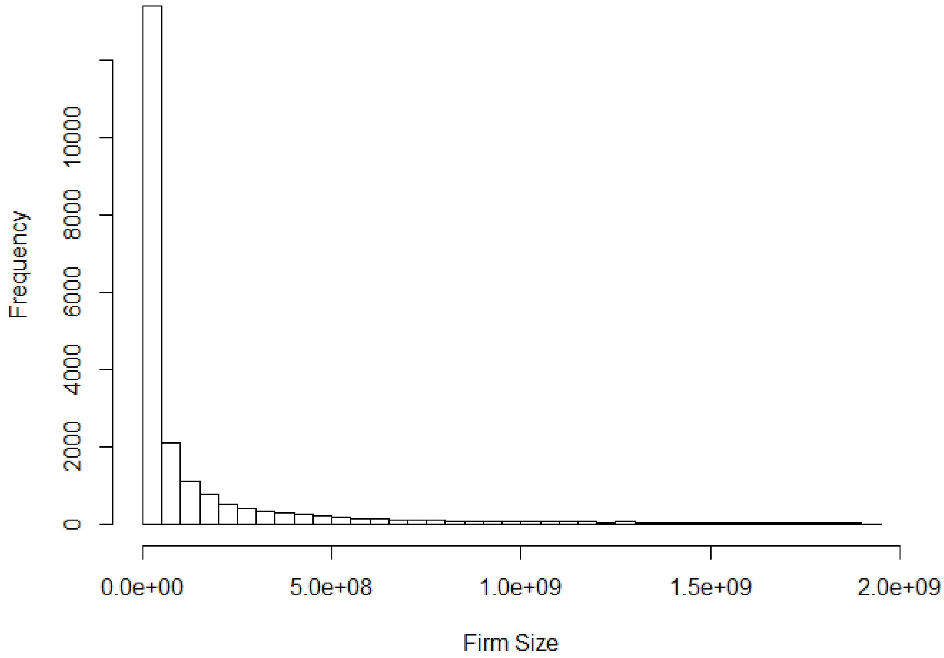

Figure 1.4: The Distribution of Firm Size

The firm size is proxied by market capitalization. Using company earnings renders similar results.

The size distribution of firms in my I/B/E/S sample follows a power-law as shown in Figure 1.4.[16] This result is consistent with Axtell(2001) who uses the Census data to show a Zipf law distribution of firm size. With a fat-tailed distribution, sample mean and median are not good measures for characterizing the distribution. I start my calculation with a macro target that consists of individual firm earnings. Supposing that the process of EPS within arbitrary short time interval t follows Brownian motion with μ_t and $\sigma_{i,t}$, which

[16]The size is proxied by firms' market capitalization. For robustness check, I also use company total earnings as size for the distribution plot and the results are similar. Additional variables are from Compustat database.

are firm and time specific. [17] The stochastic volatility model returns the latent volatility $\sigma_{i,t}$ associated with the unpredictable component in EPS. However, policymaker's concern is about the uncertainty of the overall economy, so they are interested in the volatility of unpredictable total earning M_t, which is the sum of all individual firm earnings. The variance associated with the total earning growth $\frac{\Delta M_t}{|M_t|}$ is broken down into the weighted average of individual $\sigma_{i,t}$ with weights determined by $w_{i,t} = (\frac{n_{i,t}}{|\sum_{\mathbf{i}} s_{i,t}n_{i,t}|})^2$, where $s_{i,t}$ is EPS and $n_{i,t}$ is the outstanding shares traded in the market. The derivation is shown as follows:

$$\Delta s_i = \sigma_{i,t}\epsilon_i \tag{1.6}$$

$$M_t = \sum_{\mathbf{i}} s_{i,t}n_{i,t} \tag{1.7}$$

$$\frac{\Delta M_t}{|M_t|} = \frac{1}{|M_t|}\sum_{\mathbf{i}} \Delta s_{i,t}n_{i,t} = \sum_{\mathbf{i}} \sigma_{i,t}\frac{n_{i,t}}{|\sum_{\mathbf{i}} s_{i,t}n_{i,t}|}\epsilon_i \tag{1.8}$$

Taking variance on both sides we get

$$\sigma^2_{M,t} = \sum_{\mathbf{i}} \sigma^2_{i,t}\Big(\frac{n_{i,t}}{|\sum_{\mathbf{i}} s_{i,t}n_{i,t}|}\Big)^2 \tag{1.9}$$

The above equations show that in the extreme case where all firms have identical size and volatility, the market volatility decays according to $\frac{1}{s_t\sqrt{N}}$ where N is the number of all firms. As N goes to infinity, market volatility converges to 0 with probability 1. However, if the size distribution of firms is fat-tailed and the individual volatility is specific, then the contribution of firm uncertainties is a combination of both factors, and the market volatility would not converge to 0 as N goes to infinity. Using the weights in equation (1.9), I aggregate Firm Level Uncertainty at the industrial level, as shown in Figure 1.5.

[17] Using Brownian motion for EPS process omits predictable movements in EPS series as well as correlations among different firms. However, the process is consistent with my processed I/B/E/S forecast error sample which has controls for both.

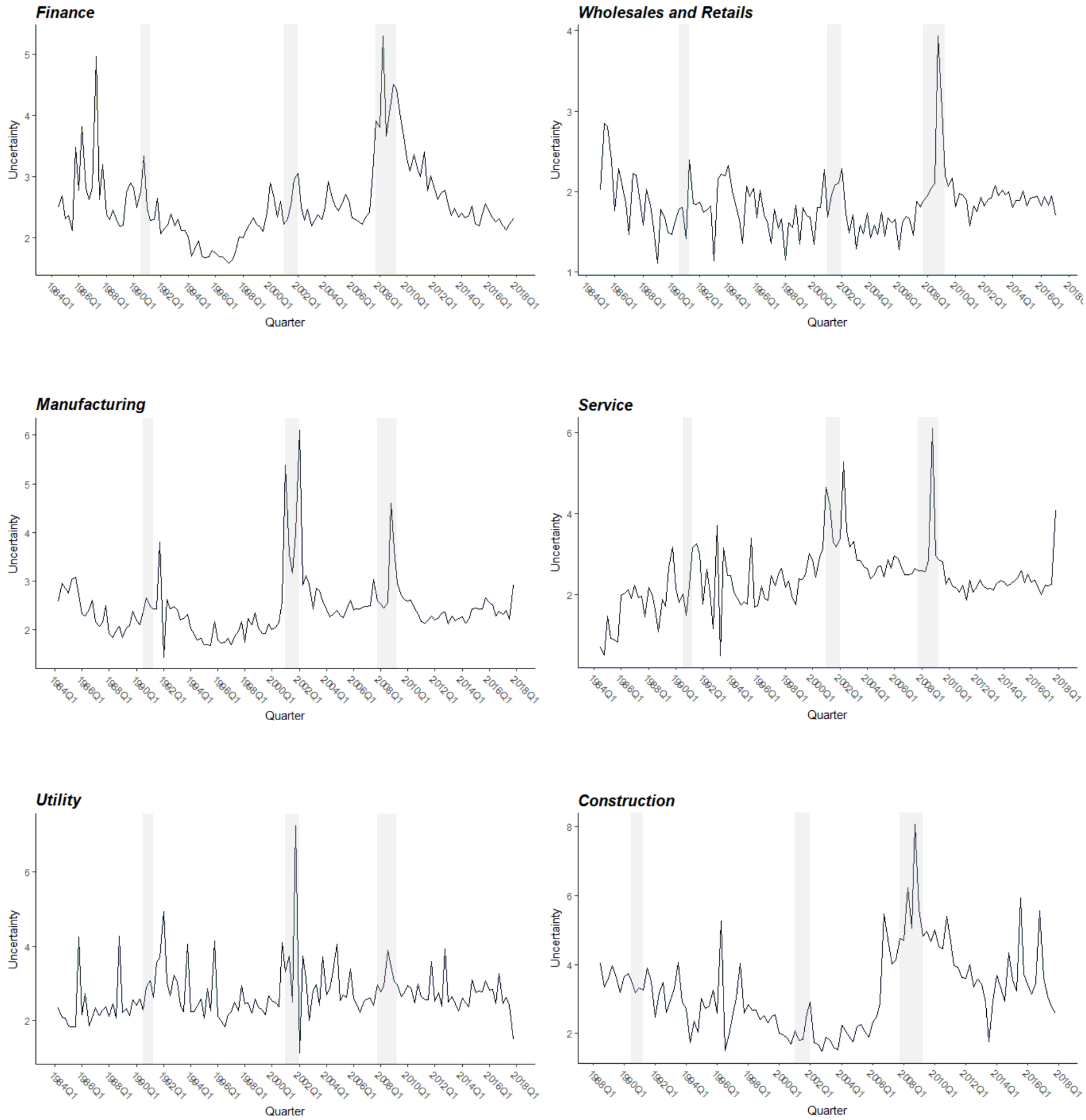

Figure 1.5: Industrial Level Uncertainties

I focus on two special shocking events to examine uncertainty effects across industries: 2007-09 Great Recession started with the collapse of investment banks then spread out to the whole economy. Its universal impacts are seen in 4 major industries – finance, retails, manufacturing, as well as construction housing which produces durable goods. The origin of this crisis is clearly shown as the financial sector leads other industries in uncertainty spikes during the recession. By comparison, the recession surrounding 9/11 terrorist attacks and the following Iraq War causes the highest uncertainty spike in manufacturing and utility sectors. The magnitude and timing of those uncertainty spikes imply that uncertainty shocks of different origins have uneven impacts across industries and cause distinct persistence and magnitude.

Figure 1.6 shows the 1 quarter ahead short-term Macro Uncertainty index (or MU, or $\sigma_{M,t}$) based on the total earning growth associated with $1,865$ U.S. firms using the weighting scheme produced in equation (9). [18] [19] This index captures the common uncertainty dynamics in FLU, and appears to be sensitive to recessions, financial crises, wars, terrorist attacks, and presidential elections. Three recession episodes post 1984 are marked with large uncertainty spikes. The 2007-09 recession shows especially high uncertainty compared to other periods. In addition, Gulf War I, 9/11, Iraq War, and recent terrorist attacks all trigger high levels of uncertainty. The great moderation in the 90s shows the lowest uncertainty level of the entire observed period. Moreover, the level of uncertainty after the great moderation (2001Q2 as cutoff) becomes significantly higher even without those large spikes surrounding 2009.[20]

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[18] The utility sector is excluded from the aggregation due to its noisy pattern. Also, the full sample returns a similar macro uncertainty dynamics.

[19] As a robustness check, I repeat this experiment with GARCH(1,1) model and the results are qualitatively similar. However, the SV model returns more precise responses to large shocking events.

[20] The elevated uncertainty level post 2001Q2 is confirmed with a one-side t-test at 1% level. Peak points surrounding the 2007-09 recession are excluded.

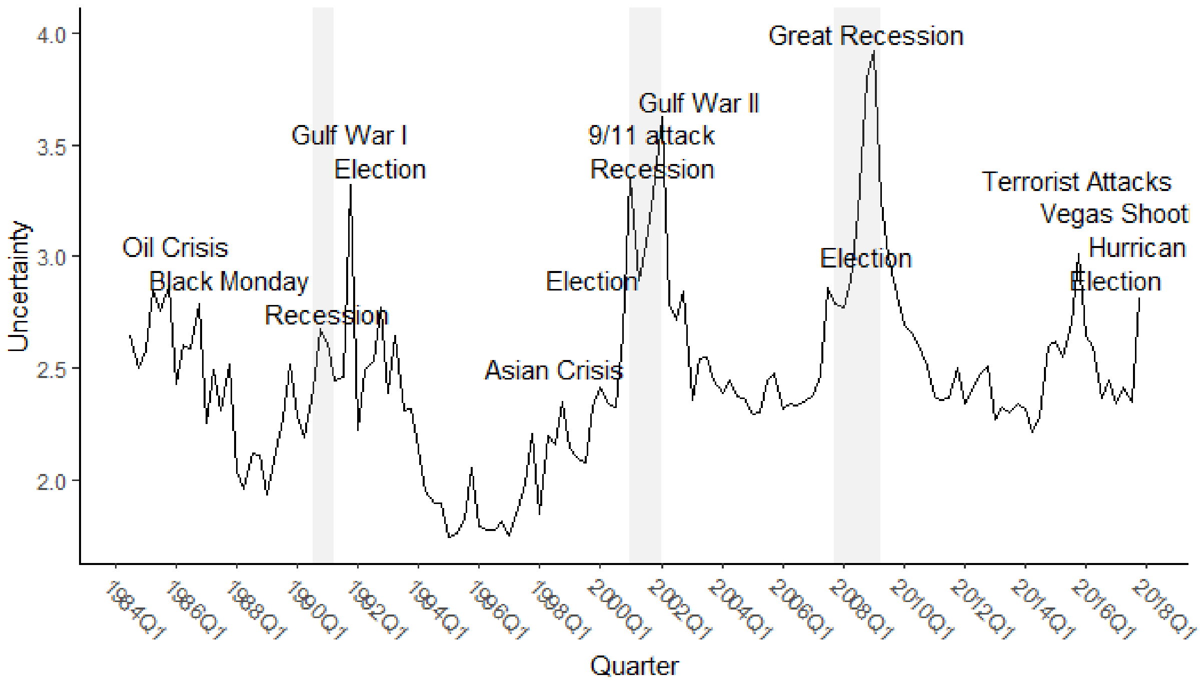

Figure 1.6: Macro Uncertainty Index (MU)

1.3.2 Comparison with Other Uncertainty Measures

Firm-Level Measures

My comparison starts with uncertainty measures in the literature that are conducted at the firm level. Although firm-level measures are uncommon, we have alternative measures such as Barrero et al. (2017) that use firm-level implied volatilities; Hassan et al. (2017) which experiments with text analysis on earning conference call memos. In addition, forecaster disagreement, which has been popular in the macro context, might also be applied to firm-level data such as I/B/E/S.

Disagreement: The forecast disagreement is defined as the standard deviation of cross-sectional forecasts associated with a target. It is an ex-ante uncertainty measure that can be tracked in real time. Although FLU is an ex-post measure, the link between these two could be tight – a highly unpredictable economic environment would produce noisy signals that lead to diversified opinions on the future. If this hypothesis is valid then we should expect a high correlation between these two measures. Disagreements are computed from the same I/B/E/S sample, and I focus on forecast targets with a minimum of 3 contributors. Again, only the last forecast associated with each target and each analyst is used. At the firm level, the correlation is 0.6. If both measures are compared after aggregation, the correlation rises to 0.9. The high correlation shows a close empirical link between these two. Hence, forecast disagreement contains key information regarding the unpredictability of the underlying process.

Firm General Risks: Uncertainty measures based on qualitative studies have drawn increasing attention in recent years. Baker et al. (2016) have extended their EPU measure to 22 regions and the EPU has become a standard index to monitor uncertainties around the world. Hassan et al. (2017) extend this methodology with a more sophisticated text scanning algorithm and apply it to company quarterly earning conference call memos to build up firm risk indices in regard to political risks, non-political risks, and general risks. My comparison only focuses on Firm General Risks (FGR) because drivers of firm earning uncertainty in FLU are not limited to politics alone. At the firm level, the correlation between FLU and FGR is weak, around 0.13. However, if I compare both measures at the macro scale,[21] the correlation jumps up to 0.5.[22] To see the reason, I compare two measures side by side with the same set of companies. I discover that the

[21] I use the weighted average of FLU and the cross-sectional mean of FGR following Hassan et al. (2017).

[22] The major disagreement between these two measures are found prior to 2003. FGR shows no spike for the 2001 recession and the Iraq war periods while my measure shows large spikes. If both measures are compared post-2003, the correlation at the macro level further increases to 0.71.

low firm-level correlation is largely due to the much higher volatilities in FGR as shown in Figure 1.7. However, much of those micro level volatilities seem to cancel out after aggregation which leaves a similar macro level dynamics.

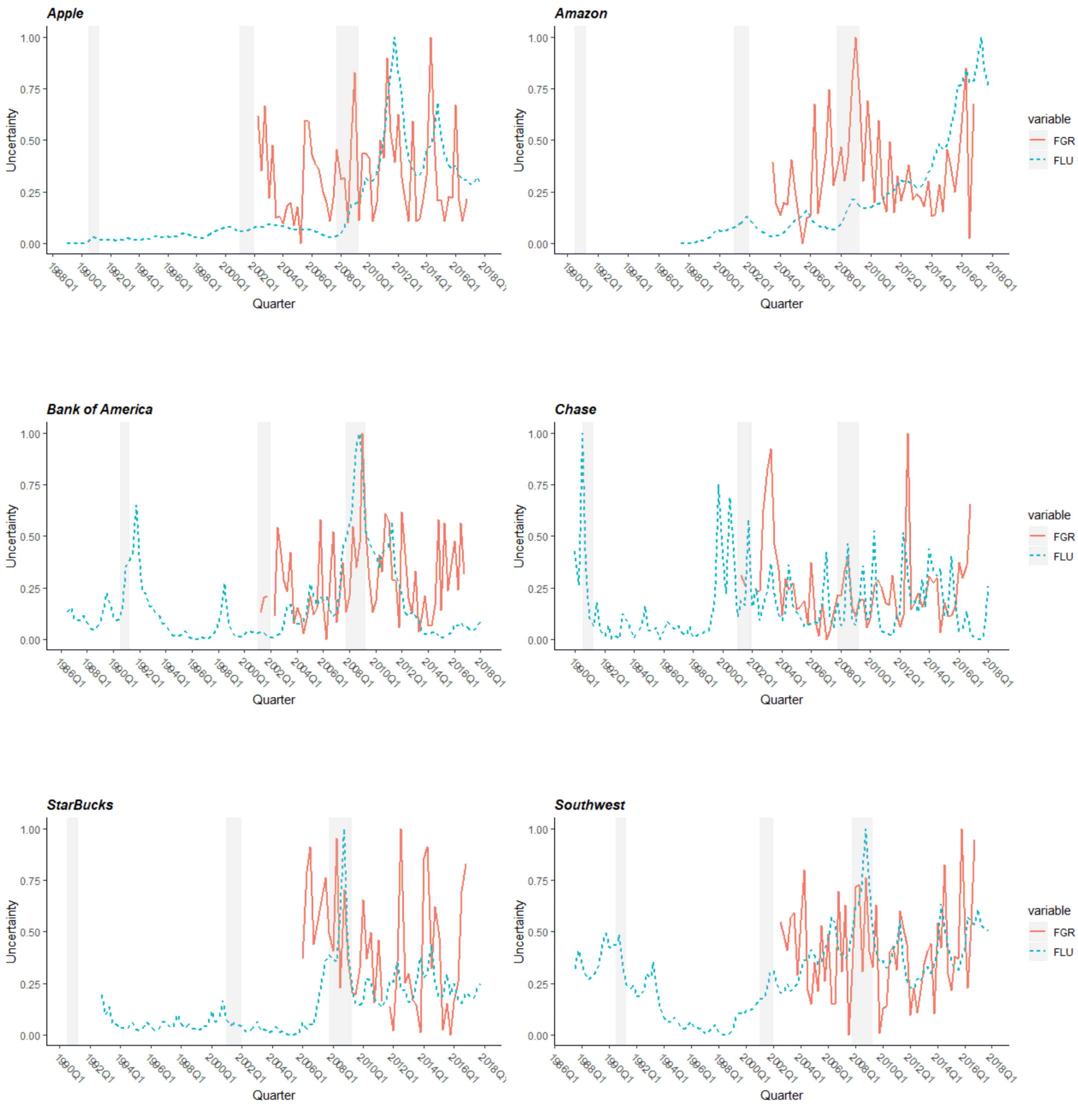

Figure 1.7: Firm-Level Comparisons with Firm General Risks (FGR)

FGR refers to Firm General Risk proposed by Hassan et al. (2017); FLU refers to my measurements.

The dynamics of these three uncertainty measures at the macro level are shown in Figure 1.8. While the weighted disagreement and MU follow closely with each other, mean FGR displays higher overall volatility. However, major shocking events can be identified in all three measures and the pattern shows a high similarity between 2004 and 2015. The major disagreement can be seen as the unidentified plummets during the 2001 recession in FGR. The main advantage of FLU is its much longer history. It is also worth noting that FLU captures the 1 quarter ahead short-term uncertainty, but FGR does not have a clear term specification. Barrero et al. (2017) argue that the term structure is a non-trivial factor of uncertainty impacts, which might also explain the low correlation between these two measures at the firm level.

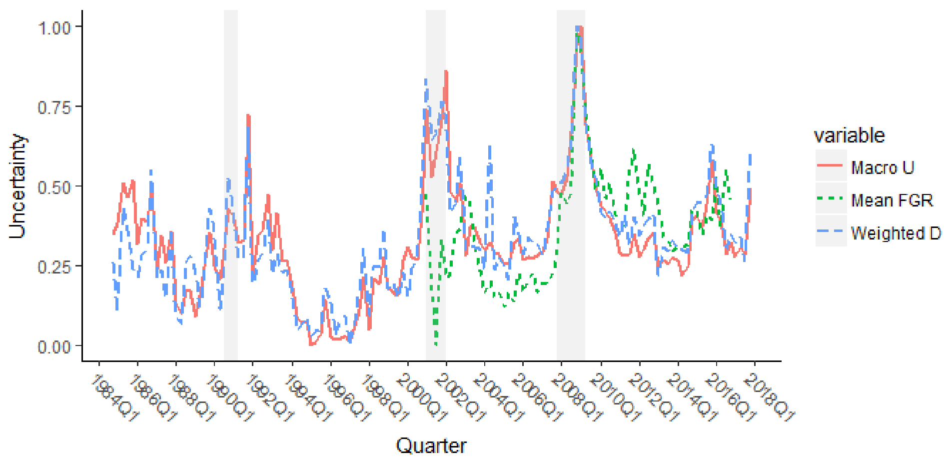

Figure 1.8: Comparison of Firm Uncertainty Measures

Mean FGR is the cross-sectional mean value of firm general risks in Hassan et al. (2017). Weighted Disagreement uses the same weighting scheme in equation (9).

Macro Measures

For the economy-wide uncertainty measures, I include three macro uncertainty measures that are frequently used to monitor the U.S. market: (1) VIX, often referred to as "investor fear gauge", is the implied volatility based on S&P 500 index options; (2) EPU, a well-known economic policy uncertainty index constructed from newspaper (See Baker et al. (2016)); (3) JLN, a macro uncertainty measure based on second-moment co-movements among a large number of macro variables. (see Jurado et al. (2015)). Table 1.2 shows the correlation between my Macro Uncertainty index (MU) and the above three popular measures.[23] MU is highly correlated with all three measures with the highest correlation with JLN. This is expected as EPU and VIX only capture the political and financial side of U.S. economy, while JLN incorporates many U.S. macro variables and thus is considered a more all-around measure. Hence, the scope of JLN has a better match with MU because drivers behinds unexpected firm earning changes are likely linked to a wide variety of factors instead of political or financial factors alone. The exact movements of all four macro uncertainty indexes are shown in Figure 1.9.

[23]I use the 3 months ahead uncertainty index in Jurado et al. (2015) to match the forecast horizon in my I/B/E/S sample. It is labeled as JLN.

Table 1.2: Macro-Uncertainty Correlations

	MU	EPU	VIX	JLN	GDP Vol	Oil Vol	Exchange Vol
MU	1.00						
EPU	0.52	1.00					
VIX	0.56	0.57	1.00				
JLN	0.82	0.33	0.54	1.00			
GDP Vol	0.66	0.06	0.41	0.78	1.00		
Oil Vol	0.44	0.11	0.49	0.55	0.40	1.00	
Exchange Vol	0.63	0.45	0.54	0.65	0.40	0.66	1.00

Note: The measures include the VIX in Bloom (2009), the EPU in Baker et al.(2016), the JLN index in Jurado et al. (2015), and Macro Uncertainty introduced in this paper. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

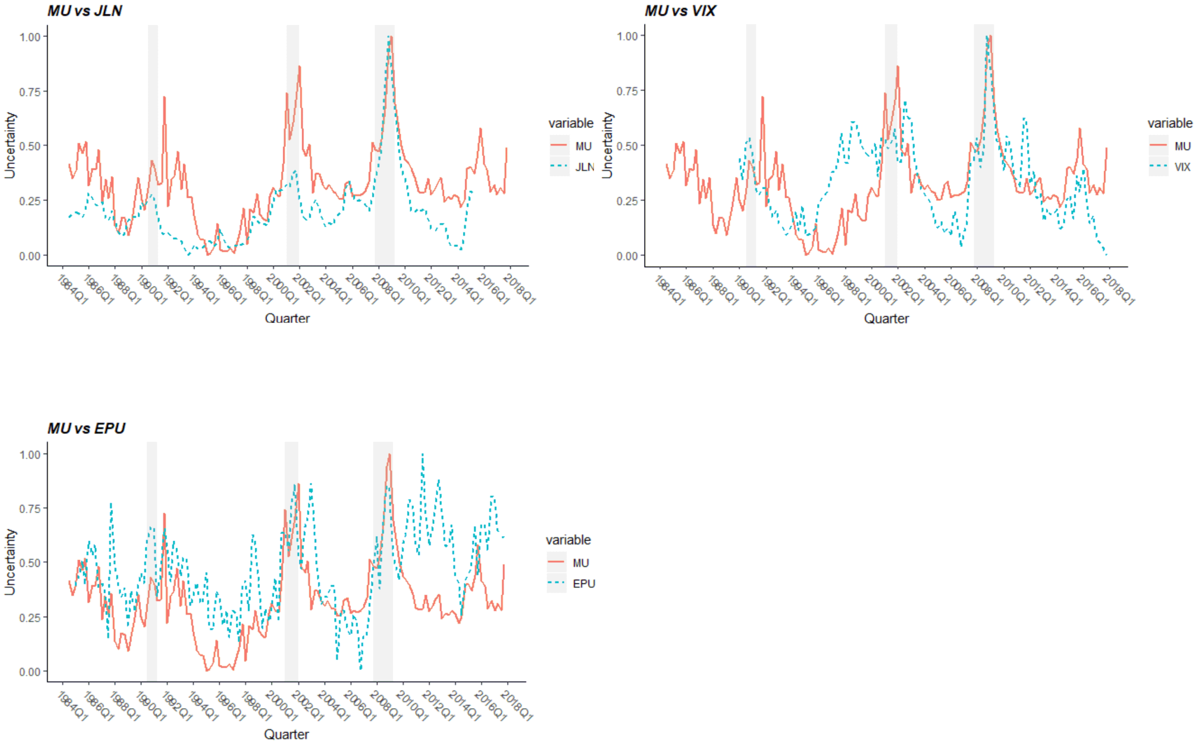

Figure 1.9: Comparison of Macro Uncertainty Measures

EPU refers to Economic Policy Uncertainty (Baker et al. (2016)); VIX is the uncertainty index provided by CBOE; JLN refers to the macro uncertainty index in Jurado et al. (2015).

It is also interesting to see the correlation between MU and the volatility associated with a specific macro variable. These correlations are also reported in Table 1.2. MU captures a good portion of volatilities associated with GDP, oil price, and exchange rate surprises with its highest correlation with GDP and lowest with oil price. Exchange rate, despite getting a relatively low response rate in section 2.4, is highly correlated with MU. The improvement is largely due to the distinct weighting scheme used for aggregating firm-level data. MU puts heavier weights on larger firms which are more vulnerable to unstable exchange rates due to their extensive international businesses. By comparison, the response rate in Table 1.1 puts equal weights on all firms alike, so the strong effect of the exchange rate volatility on large firms are diluted by smaller firms who have less or no international businesses. The low correlation with oil price volatility at the macro level could be attributed to three facts: 1. Top U.S. companies are largely technology or finance oriented whose businesses are not tightly linked to fossil fuel; 2. Increasing volatility in oil price has diversified impacts on firms of different industries and many of these firm-level effects cancel out after aggregation; 3. In general, oil price pass through has fallen over time as firms become less fossil fuel dependent. To see the total effect of 5 macro volatilities, I run a regression of $\sigma_{M,t}$ on these 5 series and get $R^2 = 0.7$ – above two third of MU dynamics can be explained by volatilities associated with these 5 macro variables. [24]

1.3.3 The Macro Impact of Uncertainty

Mainstream theories suggest a negative real impact of macroeconomic uncertainty, and such a claim is largely supported by empirical evidence. The major disagreement is whether the initial drop of investment and employment is followed by a strong rebound. Bloom (2009) gives theoretical insights on rebounds post uncertainty shocks. However, such a view is to some extent challenged by Jurado et al. (2015) and their VAR results show a persistent drop in investment and employment with no significant rebound.

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[24] I exclude JLN duo to the fact that JLN contains common uncertainty dynamics in many macro variables.

Following the literature, I include Macro Uncertainty in a 7 variable VAR framework in the following order: [25] [26]

$$\begin{bmatrix} \text{log(S\&P 500 Index)} \\ \text{Uncertainty (MU)} \\ \text{log(Wage)} \\ \text{Federal Funds Rate} \\ \text{log(CPI)} \\ \text{Unemployment Rate} \\ \text{log(Industrial Production)} \end{bmatrix}$$

Impulse response functions for both industrial production and unemployment are shown in Figure 1.10 with 90% confident bands. A one standard deviation shock to macro uncertainty is accompanied by a 0.55% industrial production drop and a 0.12 increase in unemployment rate roughly 6 months post the shock. A significant rebound for industrial production is observed after 1 year, but a similar rebound is not clear for unemployment. This result is consistent with Bloom (2009).

[25] All macro data are downloaded from St.Louis FRED or Yahoo Finance. All variables in level are rescaled with their log-values. Variables shown non-stationary due to time trend are detrended by HP filter. Cholesky decomposition is used to identify shocks through ordering.

[26] The variable order follows Bloom (2007). In general, the main VAR results are robust to different ordering including moving unemployment and industrial production to the front.

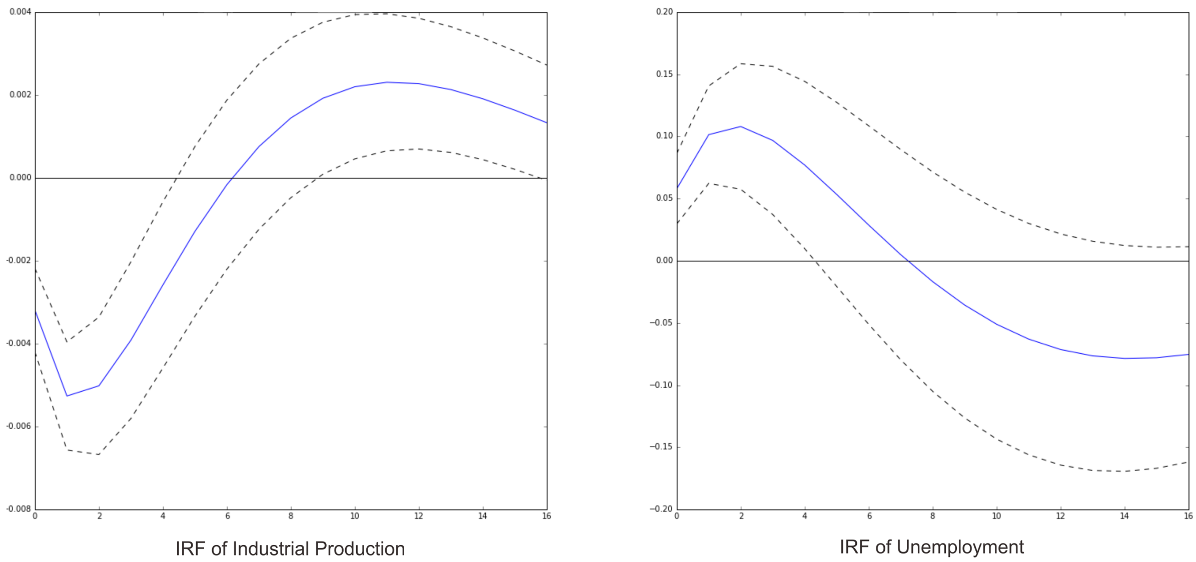

Figure 1.10: Responses of Industrial Production and Unemployment to Macro Uncertainty (MU) shocks (90% Confidence Interval)

1.3.4 The Granular Origin of Uncertainty

An uncertainty index built on macro variables is impossible to test for the “granular origin”. By exploiting my FLU measure, I build two additional uncertainty series for the largest 100 U.S. firms and the remaining smaller firms (using the same weighting scheme). The average number of firms at each forecast period is 906 but the top 100 companies on average account for 51.8% market share. Nevertheless, smaller firms have a non-trivial market share in my granular test (around 50%). Figure 1.11 illustrates these two series alongside MU. Not only is the uncertainty of smaller firms higher than that of large firms, but their volatility is also higher. The former result is consistent with Stanley et al. (1996), and the latter implies a potential negative relationship between firm size and the volatility of firm uncertainty.

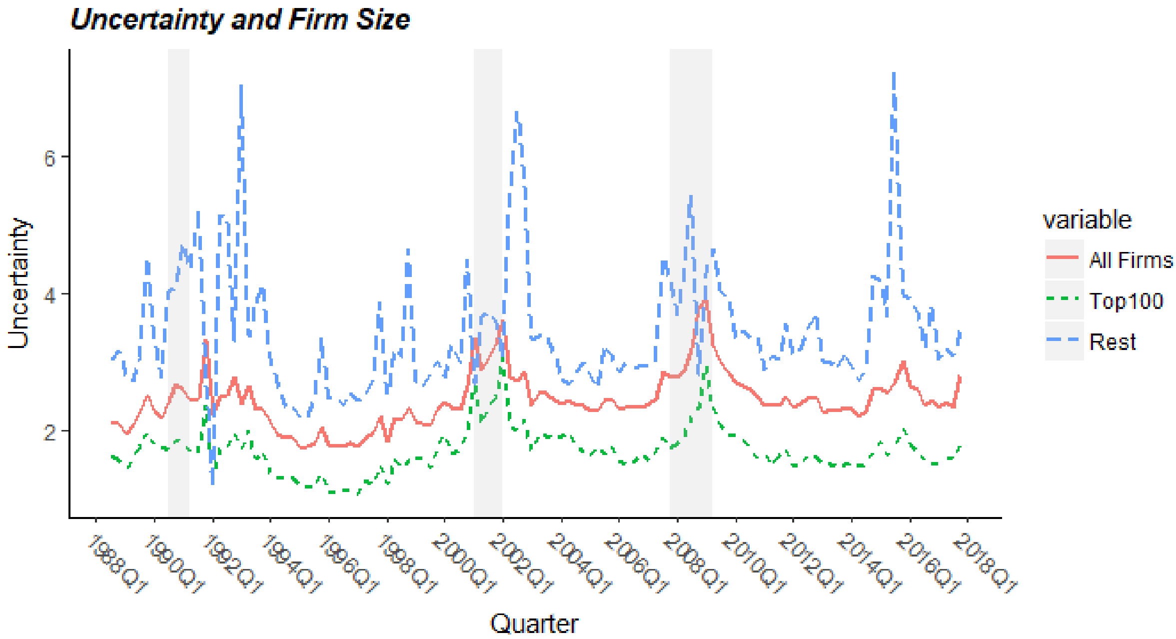

Figure 1.11: Uncertainty and Firm Size

If the macro-level uncertainty effects have a granular origin, then we should expect a non-trivial real impact of uncertainty shocks exclusive to large companies. The two series associated with the top 100 firms and smaller firms are again included in the VAR framework for an empirical test. Impulse response functions are reported in Figure 1.13 and Figure 1.14. Results confirm the granular origin of macro uncertainty effects from large firms. The IRFs for top 100 firms are very similar to those from the whole sample with slightly wider confident bands. In addition, the negative impacts of MU on industrial production and employment are statistically significant at 1% level. By comparison, the

IRFs for smaller firms show insignificant results for both variables. Also, the magnitude of impacts is smaller for both cases. Figure 1.12 illustrates the pairwise difference between Figure 1.13 and Figure 1.14 and the result is statistically significant at 1%. Despite smaller firms having a non-trivial share in the economy and a higher uncertainty level on average, real macroeconomic effects are generated by uncertainty shocks associated with large companies. It is worth noting that in Gabaix (2011), all effects are proposed for first-moment shocks. Here, a similar "granular origin" is found in firms' second-moment dynamics.

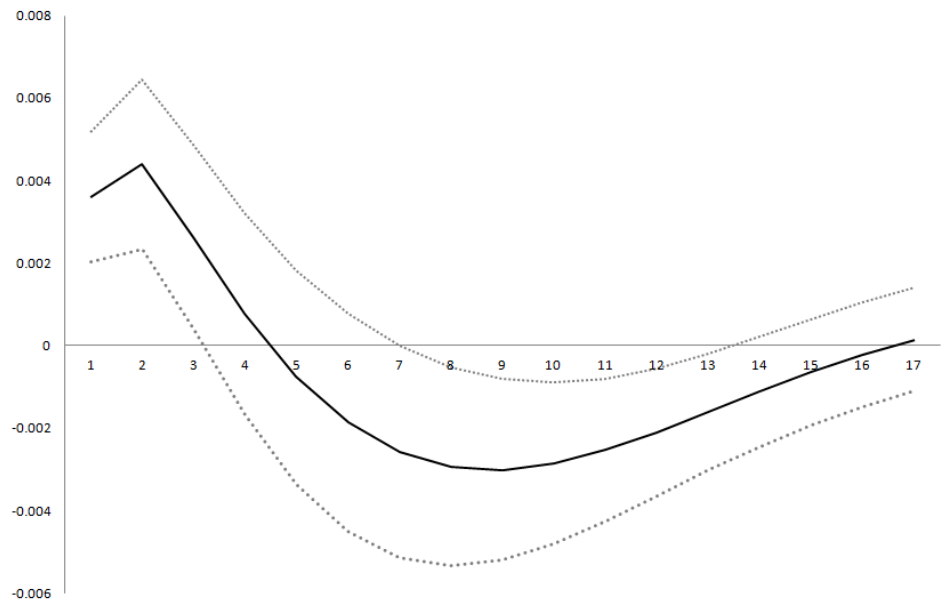

Figure 1.12: Difference in IRFs between Top 100 Firms and the Rest (90% Confidence Interval)

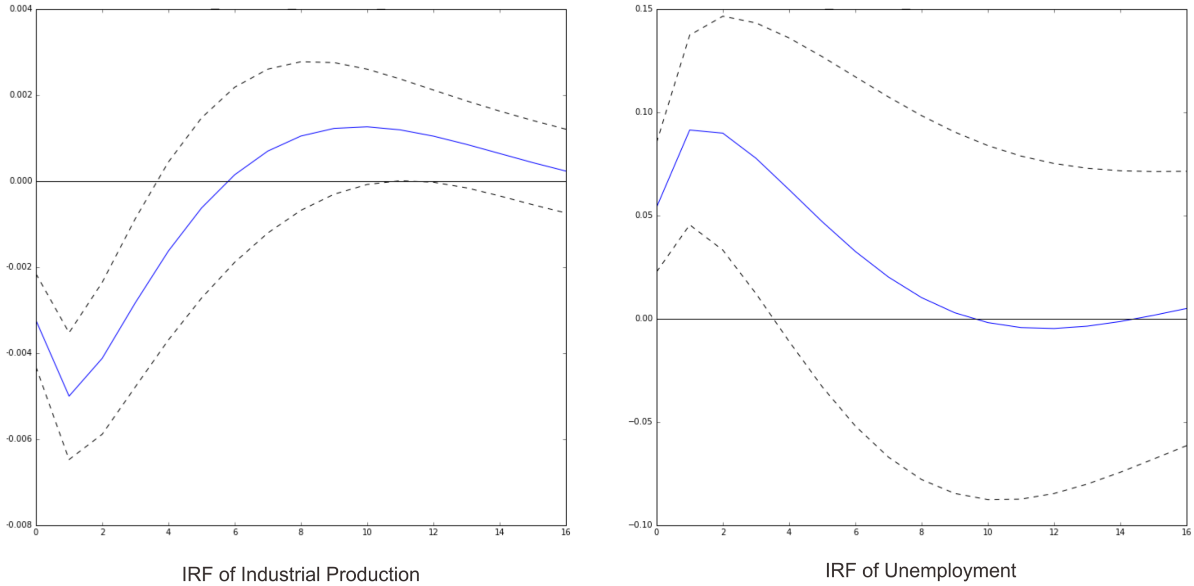

Figure 1.13: Responses of Industrial Production and Unemployment to 100 Largest U.S. Firms' Common Uncertainty Shocks (90% Confidence Interval)

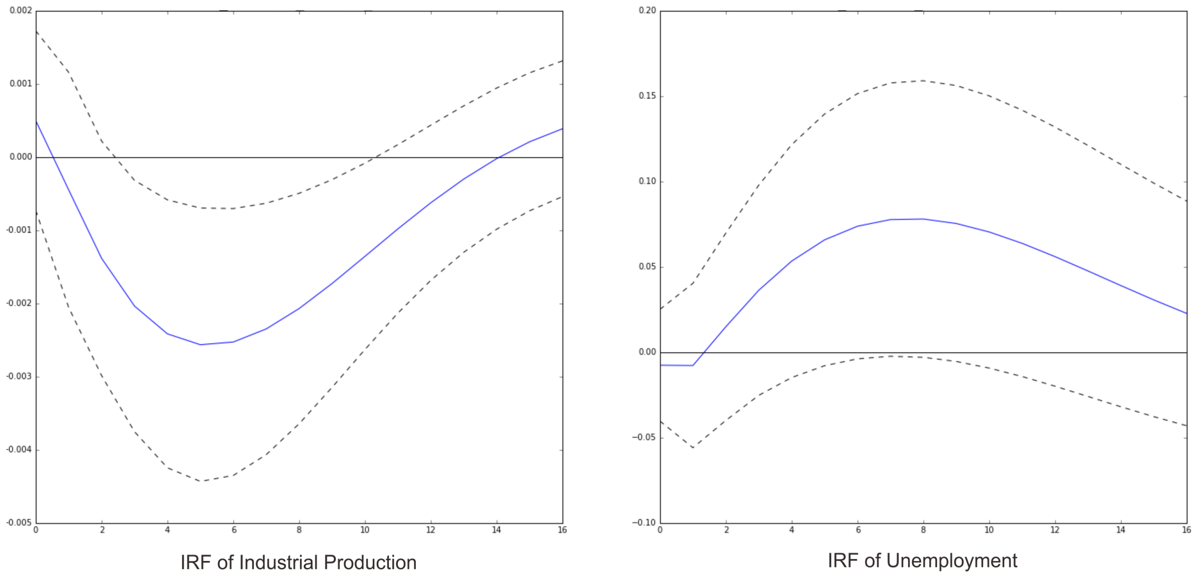

Figure 1.14: Responses of Industrial Production and Unemployment to Shocks on the Common Uncertainty Excluding TOP 100 (90% Confidence Interval)

The VAR analysis for macro impacts of uncertainty has been extensively used in the literature. However, the micro-level uncertainty effect is to some extent overlooked due to the lack of firm-level measures. In the next section, I shift my attention to firm-level uncertainty effects by focusing on microdata.

1.4 The Impact of Firm-Specific Uncertainty

1.4.1 Decomposing Firm Level Uncertainty

In section 1.2.4, I provide empirical evidences that FLU contains non-trivial share of macro volatilities not specific to individual firms. Consequently, using FLU directly in a micro setup would not separate out effects of idiosyncratic uncertainty from macro ones. [27] I might, therefore, overlook important dynamics exclusive to each component of firm-level uncertainty by looking at their composite values. Moreover, while macro uncertainty is usually exogenous to smaller producers, idiosyncratic uncertainties are tied to day-to-day business operations so managers need to see the separate dynamics of idiosyncratic uncertainty if they want to examine the effectiveness of their business strategies. Hence, I decompose FLU into macro and idiosyncratic uncertainty and include both components in micro-level regressions.

A volatility decomposition based on Capital Assets Pricing Model (CAPM) in Campbell et al. (2001) provides some guidance for such a task. Their decomposition starts with regressions on the first moment shocks,

$$e_{i,t} = \widetilde{\beta}_{i,c} e_{c,t} + \eta_{i,t} \tag{1.10}$$

[27] The issue arises in any micro-level uncertainty measures that do not identify the sources of all observed uncertainty shocks.

Taking variance on both sides, we get

$$Var(e_{i,t}) = \widetilde{\beta}_{i,c}^2 Var(e_{c,t}) + Var(\eta_{i,t}) \tag{1.11}$$

or using different notations:

$$\sigma_{i,T}^2 = \widetilde{\beta}_{i,c}^2 \sigma_{c,T}^2 + \widetilde{\nu}_{i,T}, \qquad t \in T \tag{1.12}$$

where $e_{i,t}$ is the first-moment shock, $\sigma_{i,T}$ is the realized volatility of $e_{i,t}$, $\sigma_{c,T}^2$ is the common or macro volatility, and $\widetilde{\nu}_{i,T}$ is a candidate of idiosyncratic uncertainty.

The main drawback of this decomposition is that it only controls for the first-moment dependency between $e_{i,t}$ and $\eta_{i,t}$, so $\widetilde{\beta}_{i,c}$ would not return orthogonality between $\sigma_{i,T}^2$ and $\widetilde{\nu}_{i,T}$.[28] Ignoring such an issue would lead to a statistically inconsistent measure of idiosyncratic uncertainty. I have shown in section 1.2 that the first-moment correlation is controlled by fitting SV models on excess forecast errors (over market average) instead of original forecast error series. Here, the second-moment correlation is further controlled by decomposing $\sigma_{i,t}$ in the following regressions:

$$\sigma_{i,t}^2 = c_i + \beta_{i,c}\sigma_{c,t}^2 + \nu_{i,t} \text{ for each i,} \tag{1.13}$$

where $\sigma_{i,t}^2$ is FLU; c_i is the firm specific intercept that controls for level effects; $\sigma_{c,t}^2$ is market common uncertainty proxied by MU; $\nu_{i,t}$ is the disturbance with firm-specific variance. The resulting $\psi_{i,t} = c_i + \nu_{i,t}$ is the proposed firm Idiosyncratic Uncertainty

[28]To make my point clear, imaging two random variables A and B with A distributed as (μ_A, σ_A) and B distributed as (μ_B, σ_B), where σ_A and σ_B are also stochastic. There is a nested joint distribution between σ_A and σ_B which has a high correlation value Π. The correlation between random variables A and B might not be immediately clear. However, a Monte Carlo simulation of 1000 samples for 1000 rounds returns no correlation value between A and B bigger than 0.1 with second moment high correlation Π bigger than 0.8. Hence, independence in the first-moment shocks would not automatically give independence for the second moment.

(or IU, or $\psi_{i,t}$) that are orthogonal to macro volatilities at both first ($\mu_{m,t}$) and second moments (MU).[29] It is worth noting that $\beta_{i,c}$ from regression (1.13) is different from $\widetilde{\beta}^2_{i,c}$ from equation (1.12) since $\beta_{i,c}$ is estimated with all second-moment variables but $\widetilde{\beta}_{i,c}$ is estimated with all first-moment shocks. Consequently, only $\beta_{i,c}$ returns desired second-moment independence between $\nu_{i,t}$ and $\sigma^2_{c,t}$. Based on equation (1.13), $1,865$ firm-level regressions are estimated to extract out corresponding Idiosyncratic Uncertainty series $\psi_{i,t}$ for each firm.

Figure 1.15 illustrates the weighted average of Idiosyncratic Uncertainty ($\psi_{i,t}$) together with MU. This series should not be confused with MU because it captures an average firm's IU dynamics that are orthogonal to MU. Despite the high similarity of both series, I observe several changes of comparative positions. Macro Uncertainty is generally higher in the 80s, but Idiosyncratic Uncertainty starts to outgrow MU in the early 90s and its dominance lasts for the entire great moderation. The gap again disappears prior to the 2007-09 recession and both series closely follow each other thereafter.

To see the macro impact of IU, I put the weighted average of IU in the same VAR model. Figure 1.16 illustrates the IRFs of industrial production and unemployment to shocks on IU. Similar to earlier results, IU generates a drop and rebound for industrial production, but only a drop in employment. While the dynamics is again significant and quite similar, the effect for both cases are now $20-30\%$ smaller. This finding is in line with Ozturk and Sheng (2017), who discover a smaller real effect of country-specific uncertainties comparing to the global uncertainty.

1.4.2 Uncertainty Effects at the Firm Level

Reasons why firms decide to change their tangible investments or financial portfolios when facing rising uncertainties are diversified. VAR analysis draws a broad picture

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[29] An apparent drawback of equation (13) is that $\nu_{i,t}$ necessary goes below 0 thus $\psi_{i,t} \geq 0$ is not guaranteed. Such a problem is trivial as I only concern relative variations of idiosyncratic uncertainty rather than absolute variations.

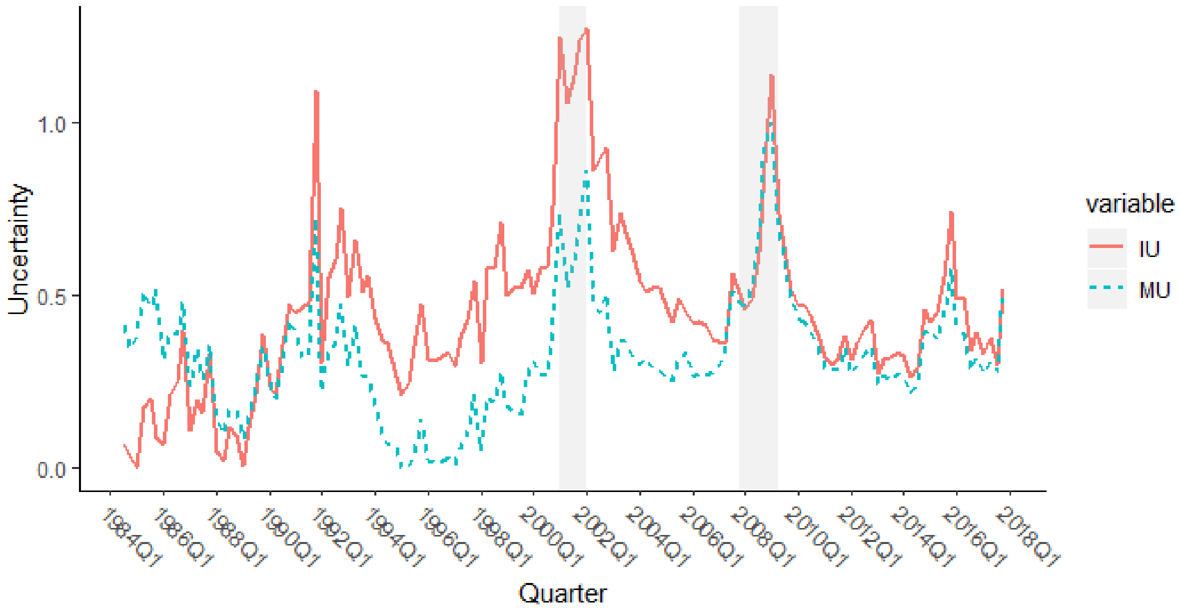

Figure 1.15: The Weighted Average of Firm Idiosyncratic Uncertainty

IU: Weighted average of idiosyncratic uncertainties; MU: Macro Uncertainty Index

of firms' reactions following uncertainty shocks, but it is unable to separate out the effect associated with each component of uncertainty and break down their effects at the firm level. For individual firms, both macro and idiosyncratic uncertainty are equally important, and their effects could be quite different. In this section, I include both macro and idiosyncratic uncertainties in panel regressions to determine their impacts on firms' investing behaviors with a focus on the term structure of investments.

Dependent variables include short-term investment, long-term investment, and R&D. Short-term investment refers to investments that are intended to be converted into cash

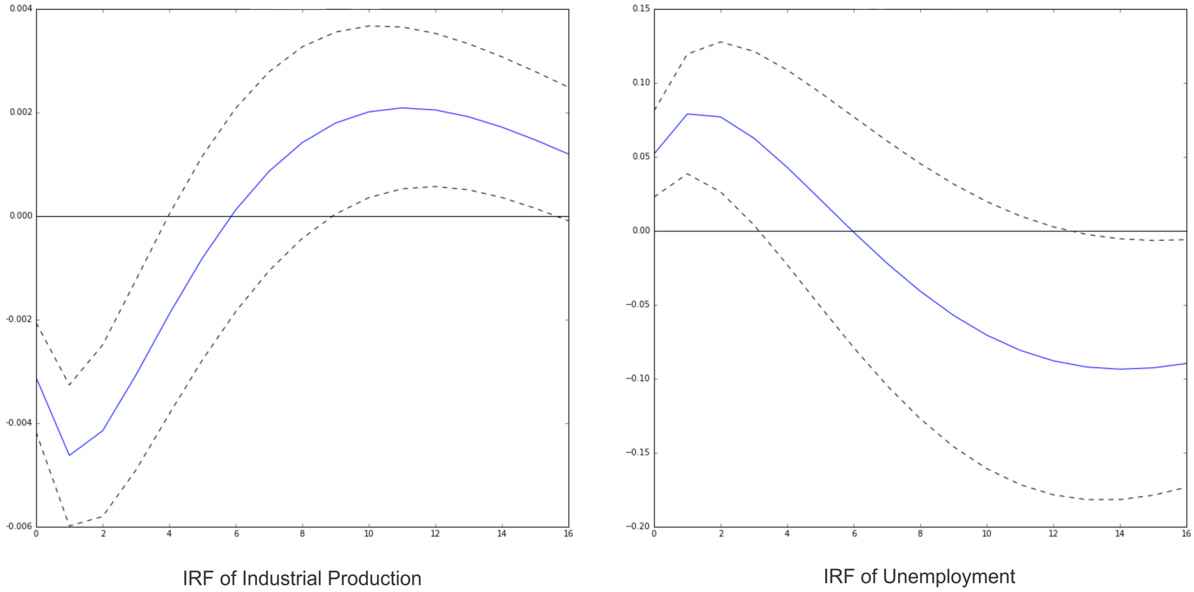

Figure 1.16: Responses of Industrial Production and Unemployment to Average Idiosyncratic Uncertainty (IU) Shocks (90% Confidence Interval)

within a relatively short period of time, usually within 1 year. Long-term investment has a horizon longer than a year. R&D is companies' expenses on new product developments and usually considered long-term as well. Control variables include the standard first moment controls: Tobin's Q, the ratio of current cash flows to total assets (CFA), sales growth (S), and also variables that reflect companies' ability to borrow: leverage (L) and current ratio (CR).[30] Since the scales of different variables are quite distinct, I take logarithm of all level measurements to show their sensitivities to uncertainty shocks. Ratio measures maintain the original format. Also, it is important to keep in mind that the uncertainty measure is applied to forecasts with a relatively short horizon which only matches the short-term investment in the Compustat data. The exact specification is as

[30]Tobin's Q is defined as $\frac{Market\ value}{Total\ assets}$; Current cash flow is the cash flow from operating activities; Current ratio is defined as $\frac{Current\ asset}{Current\ liability}$; Following Barrero et al. (2017), leverage is defined as $\frac{Assets}{Assets-(LT\ Debt-ST\ Debt)}$.

follows:

$$
\begin{aligned}
log(Y_{i,t}) = \alpha + \beta_1 log(MU_t) + \beta_2 log(IU_{i,t}) + \beta_3 Q_{i,t} \\
+ \beta_4 CFA_{i,t} + \beta_5 log(L_{i,t}) + \beta_6 CR_{i,t} + \beta_7 log(S_{i,t}) + u_i + \epsilon_{i,t},
\end{aligned}
\quad (1.14)
$$

where Y is one of the three dependent variables; MU is the macro uncertainty measure in section 3.1; IU is the idiosyncratic uncertainty measure in section 4.1; u_i is panel random effects. I use the random effect model due to the small sample size compared to the firm population. For details see Green and Tukey (1960).[31] MU and IU are orthogonal by construction thus are free of collinearity. Main regression results are shown in Table 1.3.

[31] All regressions are also tested with fixed effect model and all key results maintain.

Table 1.3: Micro Impacts of Uncertainties on Investment and R&D

	(1)	(2)	(3)	(4)	(5)
$Y_{i,t}$	log ST Invest	log LT Invest	log R & D	log ST Invest	log ST Invest
Frequency	Quarter	Quarter	Quarter	Quarter	Quarter
log IU	-0.06***	0.03**	0.04***	-0.20***	-0.06***
log MU	-0.81***	-0.00	-0.15***	-0.76***	-0.81***
Tobin's Q	0.03**	-0.05***	-0.02***	0.02*	0.03**
Cash F/Asset	0.01	-0.00	-0.03***	0.01	0.01
log Leverage	-0.36***	0.09*	0.11***	-0.38***	-0.36***
Current Ratio	0.15***	-0.03***	-0.02***	0.15***	0.15***
log Sales	0.40***	0.53***	0.55***	0.39***	0.40***
log IU x High R				0.14***	
High R				-0.40***	
$(\log \text{IU})^2$					0.01*
Obs	11,491	13,046	9,336	11,491	11,491
R^2	0.26	0.33	0.46	0.27	0.27

Panel (1) shows uncertainty effects on short-term investment. Both macro and idiosyncratic uncertainties have significant negative impacts and the effect is stronger for macro uncertainty. These results are consistent with my previous VAR analysis where average IU brings about 20-30% less real impacts than MU. To my knowledge this is the first time economic effects of uncertainty are tested at both the macro and micro level with a consistent uncertainty measure.

Panel (2) displays results of long-term investment. In this case, the effect of macro uncertainty becomes less significant which suggests a decreasing influence of short-term macro uncertainty on firms' long run plans. However, a rise in IU significantly increases firms' long-term investments. Together with previous finding, I conclude that firms shift investments from short-term to long-term following a positive idiosyncratic uncertainty shock. The reason behind such a term structure change might be better understood by looking at results in panel (3).

Panel (3) gives uncertainty effects on R&D expenses for new product development. MU drags down market sentiment and makes companies hesitant to develop new products due to concerns of shrinking aggregate demand under economy-wide uncertainty. However, if the uncertainty shock is idiosyncratic, it is likely caused by local supply or demand issues rather than an unstable market condition. Hence, increasing investment on new product and new technology seems to be a reasonable response to reduce volatilities associated with local factors. Regression results are in line with this story. I observe a negative effect of macro uncertainty and a positive effect of idiosyncratic uncertainty on R&D. Since developing new products takes time and effort, R&D usually accounts for a big portion of firms' long-term investments. Hence, results in panel (2) are closely linked to those in panel (3).

Control variables such as Tobin's Q, leverage, and current ratio also show significant impacts on a company's term structure of investments. Sales growth, on the other hand, is positively associated with both short-term and long-term investments. Signs of these variables are in line with the literature.

To see whether these empirical results for idiosyncratic uncertainty are robust, I use the first principal component of 5 macro volatilities in section 1.2.4 as an alternative measure of macro uncertainty. All results are nearly identical (Table 1.4).

Table 1.4: Micro Impacts of Uncertainties on Investment and R&D (Alternative Macro Uncertainty Measure)

	(1)	(2)	(3)	(4)	(5)
$Y_{i,t}$	log ST Invest	log LT Invest	log R & D	log ST Invest	log ST Invest
Frequency	Quarter	Quarter	Quarter	Quarter	Quarter
log IU	-0.04***	0.03**	0.04***	-0.20***	-0.05**
Macro PC1	-0.07***	0.00	-0.01***	-0.07***	-0.08***
Tobin's Q	0.03**	-0.05***	-0.02***	0.02**	-0.01
Cash F/Asset	0.012	-0.00	-0.03**	0.01	0.04
log Leverage	-0.36***	0.08*	0.01***	-0.39***	-0.34***
Current Ratio	0.15***	-0.03***	-0.02***	0.15***	0.13***
log Sales	0.39***	0.53***	0.54***	0.38***	0.24***
log IU x High R				0.15***	
High R				-0.38***	
$(\log \text{IU})^2$					0.01
Obs	11,214	12,726	9,081	11,214	11,214
R^2	0.26	0.33	0.46	0.27	0.25

1.5 Concluding Remarks

Unlike policymakers, company managers emphasize the local specific effect of macro uncertainty, or uncertainties with an idiosyncratic origin. A credible uncertainty measure at the firm level is essential for researchers. However, existing measures focus on macro variables and thus contain little micro-level information. To fill this gap, I propose a firm-level uncertainty measure based on the latent conditional volatility of forecast errors and apply it to the I/B/E/S database. The resulting Firm Level Uncertainty (FLU) panel dataset opens up a wide variety of research directions.

To understand the macro drivers of firm-level uncertainties, I regress FLU on volatilities associated with stock market, economic policy, real GDP, oil price, and exchange rate, I discover that an average of 44% of firm-uncertainty variations are driven by these 5 macro variables. Financial and GDP uncertainty have generally large direct impacts. Policy uncertainty turns out to be significant with an equal split between positive and negative effects. In addition, oil price volatility leads to countercyclical responses from many firms. Exchange rate volatility has a much stronger impact on large firms which have extensive international businesses.

The firm-level uncertainties are informative, but a macro-level uncertainty index is also needed to monitor the market. By carefully examining the size distribution of firms in my I/B/E/S sample, I build a specific weighting scheme to aggregate FLU into a Macro Uncertainty index MU. MU appears to be sensitive to economic recessions, financial crises, presidential elections, wars, and terrorist attacks. Both FLU and MU are carefully compared with other measures in the literature. At a macro scale, MU has good correlations with popular uncertainty indices such as VIX and EPU. At the firm level, FLU is closely linked with forecast disagreement but only weakly correlated with Firm General Risk in Hassan et al. (2017). Nevertheless, FLU covers a much longer history while has a reasonable overall volatility.

The macro effect of uncertainty is tested using VAR models. Both industrial production and employment show contemporaneous drops following a macro uncertainty shock, but fully recover and rebound a year later. Moreover, FLU enables a study on the granular origin of macro uncertainty effects. I discover that the common uncertainty among the top 100 U.S. firms are enough to generate economy-wide consequences. The micro level breakdown of uncertainty effects is studied in panel models. Results show that both macro and idiosyncratic uncertainty have significant negative impacts on short-term investment but the effect of macro uncertainty is much stronger. Similar results are also seen in VAR analysis using only macrodata. In comparison, idiosyncratic uncertainty changes firms' term structure of investments by shifting investment from short-term to long-term. One reason behind such a change is found to be increased spending on new product development when firms face only idiosyncratic uncertainty.

CHAPTER 2

TWO ECONOMIC MODELS OF UNCERTAINTY

2.1 Introduction

Contemporary economic uncertainty models mainly focus on two channels: the "wait and see" attitude towards uncertain future that defers current investments; High borrowing costs and weak demands associated with high-risk premia and precautionary savings during uncertain periods. However, these two channels might not explain all uncertainty phenomena in an economy. Moreover, models based on these two mechanisms usually do not separate out effects exclusive to the macro and idiosyncratic component. In this chapter, I propose two additional models that incorporate both types of uncertainty and explain their economic effects through alternative channels. The first model built on the Lucas Island Model (see Lucas (1973)) and Capital Asset Pricing Model (see Sharpe and Sharpe (1970)). This model tries to explain uncertainty effects from the perspective of inefficient expectation and the resulting underproduction problem. It also demonstrates a mechanism similar to "Growth Options" theory in Bar-Ilan and Strange (1996) for idiosyncratic uncertainty. The second model looks at the real loss caused by unexpected demand and supply shocks, as well as the market share loss due to competition. Despite the different channels, both models predict a negative impact of macro uncertainty and a composite effect of idiosyncratic one. Model predictions are generally consistent with my empirical findings and the literature.

2.2 Uncertainty Models in the Literature

Theories concerning the real impact of uncertainty shocks mainly focus on two channels, both of which predict a negative effect (see Bloom (2014)). The first channel is referred to as "real options" theory. Bernanke (1983) argues that investors face a continuously varying set of investing options and would prefer to wait if they feel uncertain about the outcome. In other words, uncertainty increases the value of new information which makes "wait" a more compelling option although it could be costly. A similar idea is also explored in Bloom (2009) using a structural framework with a time-varying second moment and mixed labor-capital adjustment costs. While the "real option" theory works well for irreversible projects, it might not be the appropriate model for easily reversible projects or projects that cannot wait.

A more universal effect of uncertainty is related to the risk aversion and risk premia. On one hand, a strong sense of risk aversion during uncertain times causes increased precautionary savings and weak overall demand. Under sticky prices, those extra savings cannot be converted to new investments. On the other hand, uncertainty raises the risk premia due to a high probability of default, which makes financing projects more expensive. These two channels become foundations of many economic uncertainty models. Works include Hansen et al. (1999), Bansal and Yaron (2004), and Basu and Bundick (2017) among many other. However, most of these models do not separate the effects of idiosyncratic and macro uncertainty. More importantly, they are not sufficient to explain all economic phenomena associated with uncertainty. One reason that has been overlooked in the literature is that uncertainty takes on many interpretations so its real impacts to large extent depend on its underlying notion.

In this chapter, I introduce two uncertainty models and both incorporate idiosyncratic and macro components as separate factors in determining firm performance. The first model is based on Lucas Island Model and Capital Asset Pricing Model (CAPM) and incorporates the discrete "jump to zero" condition similar to McDonald and Siegel (1986) that bring needed asymmetric to uncertainty effects. The model shows the underproduction problem caused by inefficient expectations during uncertain time. [1] The original Lucas model is used to explain the Phillips curve under imperfect information. However, part of its mechanism might be translated into investment decisions under uncertainty.

The second model adopts many New-Keynesian assumptions such as the demand-driven economy, slow adjustment of supply following demand change etc. It emphasizes the real loss from unexpected supply and demand shocks in an uncertain environment. In addition, this model features a competition mechanism not often seen in the uncertainty literature. In a competitive economy, companies who operate with higher idiosyncratic uncertainty would experience slow growth due to loss of market share. On the other hand, competition benefits an uncertain economy by reducing the opportunity loss because the risk from central planning is dispersed by a large number of autonomous producers.

2.3 An Inefficient Expectation Model of Uncertainty

2.3.1 Model

The model starts with firm's investment function (2.1) in a competitive economy. Firms are all small in size so their idiosyncratic uncertainty shocks have little macro-scale impact. Different from the Lucas model, I focus on investment return R and assume excess returns $(R_{i,t} - \beta_i R_{M,t})$ as the "engine" of new investments. I also assume a truncated condition similar to the discrete jump to zero market value of a project in McDonald and

[1]It is worth noting that information asymmetry, as the foundation of Lucas Model, also plays a key role in both "real option" and "risk premia" theories. The economic effect of uncertainty can, therefore, be better understood by combining all these channels.

Siegel (1986). With perfect information, firms respond positively to their excess profit margins.

$$y_{i,t} = \begin{cases} \alpha \exp(R_{i,t} - \beta_i R_{M,t}) & \text{if } \ R_{i,t} \geq 0 \\ 0 & \text{if } \ R_{i,t} < 0 \end{cases} \tag{2.1}$$

An exponential function is used to avoid negative investment when firm's return goes below market level. It also captures the "excitement" of small producers when facing large profit margins. Without loss of generality, I assume that the market return $R_{M,t}$ is strictly positive. β_i measures a firm's exposure to "swings" in the market condition and its value is exogenous. Lastly, I assume that firms temporarily halt production in current period if they observe negative returns. With perfect information, uncertainty plays no role. Firms observe market facts and make investment decisions accordingly.

The key mechanism of the Lucas model comes from the uncertainty caused by imperfect information. Firms might observe their own current investment return $R_{i,t}$, but they do not observe the current market average return $R_{M,t}$. Considering that macro data on market returns usually take more than one quarter to arrive, such an assumption is quite reasonable even without assuming producers are located on isolated islands. Following Lucas' logic, firms understand that their expectations would deviate from the real value with an error, or

$$R^e_{M,t} = R_{M,t} - \epsilon_{M,t}, \quad \epsilon_{M,t} \sim \mathcal{N}(0,\, \sigma^2_{M,t}) \ , \tag{2.2}$$

where $R^e_{M,t}$ is the expected market average return; $\sigma_{M,t}$ is the market macro uncertainty that captures the predictability of the market. Based on CAPM, I assume that individual values deviate from the "effective" market average by a random amount, or

$$R_{i,t} = \beta_i R_{M,t} + \epsilon_{i,t}, \quad \epsilon_{i,t} \sim \mathcal{N}(0,\, \sigma^2_{i,t}) \ , \tag{2.3}$$

where $\epsilon_{i,t}$ is the excess return of firm i; $\sigma_{i,t}$ measures the idiosyncratic uncertainty that exclusive to firm i. By model construction, $E(\epsilon_{M,t}\epsilon_{i,t}) = 0$ and $E(\sigma_{M,t}\sigma_{i,t}) = 0$.

Firms observe the difference between $R_{i,t}$ and $\beta_i R^e_{M,t}$, which is a composite errors $\epsilon_{i,t} + \beta_i \epsilon_{M,t}$. They also understand that only $\epsilon_{i,t}$ should be considered to determine the quantity of new investment but is unobserved. Under rational expectations, they would use regression model

$$\epsilon_{i,t-n} = \theta_i(\epsilon_{i,t-n} + \beta_i \epsilon_{M,t-n}) + u_{i,t-n}, \quad (n = 1, 2, 3...) \tag{2.4}$$

on historical data to determine the proportion of ϵ_i. Hence, we have an empirical approximation of $\theta_i = \frac{\sigma_i^2}{\sigma_i^2+\beta_i^2\sigma_M^2}$, where σ_i and σ_M are historical averages of idiosyncratic and macro uncertainty. Therefore, the conditional expectation of firm i's excess return is

$$E(\epsilon_{i,t}|I_{t-1}, R_{i,t}) = \frac{\sigma_i^2}{\sigma_i^2 + \beta_i^2\sigma_M^2}(R_{i,t} - \beta_i R^e_{M,t}) \ . \tag{2.5}$$

Substitute into equation (2.1), we get the conditional investment function of firm i under imperfect information:

$$y_{i,t} = \begin{cases} \alpha \exp(\frac{\sigma_i^2}{\sigma_i^2+\beta_i^2\sigma_M^2}(R_{i,t} - \beta_i R^e_{M,t})) & \text{if} \quad R_{i,t} \geq 0 \\ 0 & \text{if} \quad R_{i,t} < 0 \ , \end{cases} \tag{2.6}$$

where $\frac{\sigma_i^2}{\sigma_i^2+\beta_i^2\sigma_M^2}$ measures the sensitivity of firms in response to observed excess returns. Equation (20) shows the conditional investment on an observed gap $(R_{i,t} - \beta_i R^e_{M,t})$. For the unconditional case, I consider random variable $R_{i,t} \sim \mathcal{N}(R_{M,t}, \sigma_{i,t}^2)$ and $(R_i - \beta_i R^e_M) \sim \mathcal{N}(0, \ \sigma_i^2 + \beta_i^2\sigma_M^2)$ so

$$E(y_{i,t}) = \alpha P(R_{i,t} \geq 0) E\Big(\exp\big(\frac{\sigma_i^2(R_{i,t} - \beta_i R^e_{M,t})}{\sigma_i^2 + \beta_i^2\sigma_M^2}\big) \big| R_{i,t} \geq 0 \Big) \ , \tag{2.7}$$

where $P(R_{i,t} \geq 0)$ is the probability of $R_{i,t} \geq 0$. By assuming $\sigma_{i,t}$ equal to the historical average σ_i, $P(R_{i,t} \geq 0) = \displaystyle\int_0^{\infty} \frac{1}{\sqrt{2\pi\sigma_i^2}} e^{\frac{-(R_{i,t}-\beta_i R_{M,t})^2}{2\sigma_{i,t}^2}} dR_{i,t}$. [2] To understand the effects of σ_i and σ_M on expected investment $E(y_{i,t})$, I need to get the locus of $\frac{\partial E(y_{i,t})}{\partial \sigma_M}$ and $\frac{\partial E(y_{i,t})}{\partial \sigma_i}$.

2.3.2 Simulations

Partial effects of σ_M

An analytical solution to equation (2.7) is not immediate due to the complexity in the joint distribution between $R_{i,t}$ and $R_{i,t}-\beta_i R^e_{M,t}$. However, it is easy to obtain a numeric solution through simulations. The parameter is set according to following rules: (1) The initial value of idiosyncratic uncertainty σ_i is much larger than that of market uncertainty σ_M; (2) The market average return R_M is set to be a constant 10%; (3) The initial value of σ_i is equal to R_M so the "jump to zero" event has noticeable impacts on firms' average investments but not overwhelming. Figure 2.1 illustrates the simulation result based on varying σ_M with a fixed σ_i and corresponding $E(y_i)$ of 1 million iterations at each σ_M value. There is a clear negative trend between macro uncertainty and the firm's expected investment when σ_M increases from 0.05 to 0.30. A further rise in σ_M results in a flatter curve but no turning point is observed. The intuition is that a rise in macro uncertainty σ_M would decrease firms' sensitivity (θ_i) to observed excess returns and discourage firm's investment on average. In other words, observed excess returns become less credible if the macroeconomy is very noisy so firms hesitate to react to the data. However, the same insensitivity also applies to negative excess returns, which would encourage firms to invest more. What leaves the total effect asymmetric and being unconditional negative is the truncated area associated with $R_{i,t} < 0$. As such jumps occur with a higher probability when $R_i - \beta_i R^e_M < 0$ and the total probability of its occurrence is non-trivial (around 32% with $\sigma_i = R_M$), it generates imbalanced negative impacts on investments. Consequently,

[2]With a strictly positive $R_{M,t}$, $E(y_{i,t})$ is negatively related to $\sigma_{i,t}$. Here for simplicity I assume $\sigma_{i,t}$ equals historical average σ_i.

with a truncated production function, an increase in macro uncertainty would discourage investments on average for all firms, and therefore hurt the entire economy.

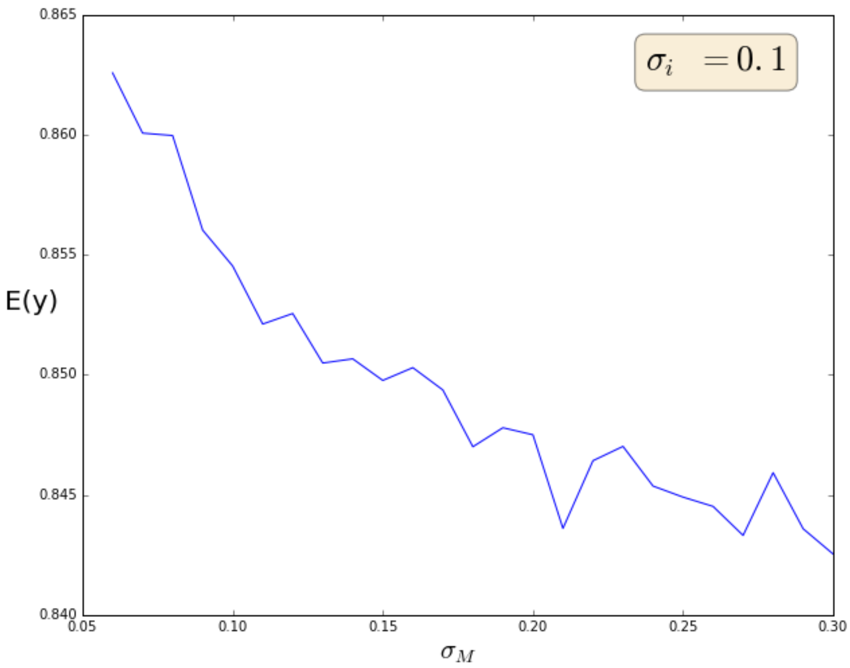

Figure 2.1: Simulation Result: Macro Uncertainty and Investment

This figure illustrates the relationship between y and σ_M in equation (2.7). By keeping σ_i constant, I simulate 10000 y at each σ_M value and plot only the conditional mean of y ($E(y|\sigma_M)$).

Partial effects of σ_i

From equation (2.7), we see that an increase in σ_i raises firms' sensitivity to excess returns and pushes its expected value, conditional on positive and negative excess returns, further away from the center point. As a result, a rise of σ_i would only impose positive impacts on $E(y_i)$ conditional on $R_{i,t} - \beta_i R^e_{M,t} \geq 0$ and negative impacts conditional on $R_{i,t} - \beta_i R^e_{M,t} < 0$. The question is which effect dominates? The simulation result in Figure 2.2 shows that when σ_i rises from 0.1 to 0.25, there is a downward trend between σ_i and $E(y_i)$. However, further increasing σ_i from 0.25 to 0.35 unveils a turning point and the effect of σ_i eventually turns positive. The reason for such a convex path again comes down to the truncated area in the investment function. If σ_i is low, firms are unlikely to observe large excess return and thus unlikely to benefit big from higher sensitivity. Consequently, the negative impact of "jump to 0" dominates the positive effect from the increased sensitivity to positive excess returns. However, while the negative effect from a large σ_i value is bounded at 0, its positive effects are unbounded so further increasing σ_i would eventually make the positive impact overshadow the negative impact. To illustrate my point, separate graphs for simulation points associated with only positive and negative draws of $(R_{i,t} - \beta_i R^e_{M,t})$ are shown in Figure 2.3. Idiosyncratic uncertainty positively affects firms' investments without a bound conditional on positive excess returns, but affects investments negatively with the lower bound 0 conditional on negative excess returns. Since firms have equal probability of facing negative and positive excess returns according to $(R_i - \beta_i R^e_M) \sim \mathcal{N}(0,\ \sigma_i^2 + \beta_i^2 \sigma_M^2)$, their combined effects have to follow a convex path. This mechanism is also known as "growth option" in Bar-Ilan and Strange (1996), who argue that uncertainty might positively affect investments if the potential prize of success is big. For this model, rising idiosyncratic uncertainty would increase the prize for getting a large positive draw without bound. However, the loss of getting an unlucky negative draw has a lower bound at 0.

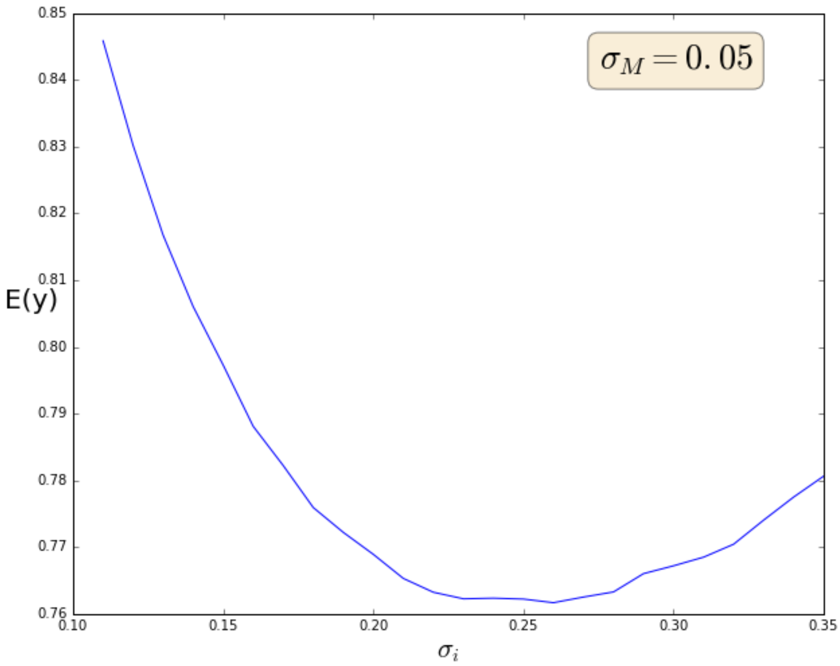

Figure 2.2: Simulation Result: Idiosyncratic Uncertainty and Investment

This figure illustrates the relationship between y and σ_i in equation (2.7). By keeping σ_M constant, I simulate 10000 y at each σ_i value and plot only the conditional mean of y $(E(y|\sigma_i))$.

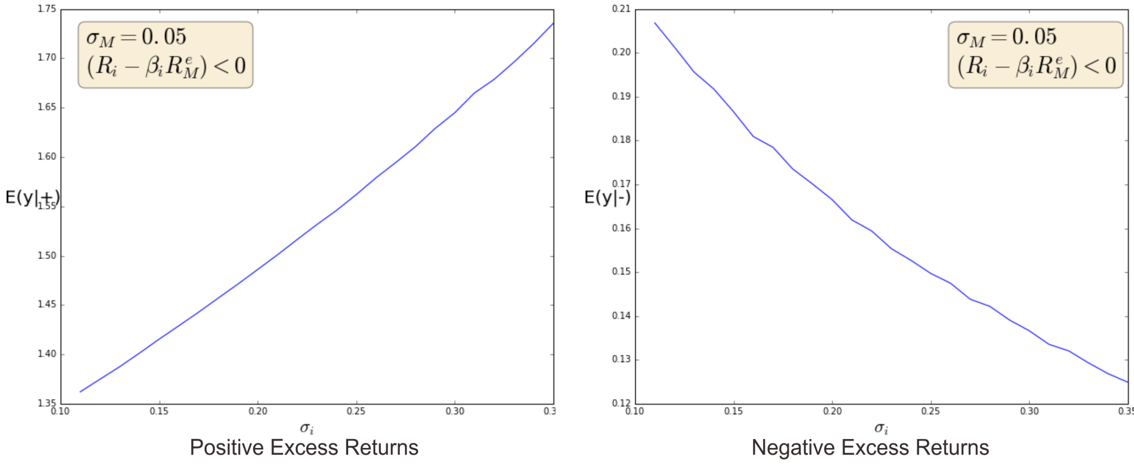

Figure 2.3: Simulation Result: Idiosyncratic Uncertainty and Investment (Separated by the Sign of Excess Return)

I divide all simulation points in Figure 2.2 into two groups based on the sign of $(R_i - \beta_i R_M^e)$, then plot the conditional mean of y $(E(y|\sigma_i))$ for each group similar to Figure 2.2.

Empirical Support

Empirically, I have already shown some support for above model predictions. The negative impact of macro uncertainty are captured in both VAR analyses and panel regression. For the composite effects of idiosyncratic uncertainty, Figure 1.2 illustrate fast-growing (high-profitability) companies such as Apple and Amazon both show increasing idiosyncratic uncertainty. However, an average company would not have such a wide swing in investment returns so the effect of idiosyncratic uncertainty is negative on average as shown in Table 1.3 column (1). In addition, to see whether the direction of idiosyncratic uncertainty effects depends on the sign of excess return, I include a dummy variable that takes the value of 1 if a firm's return is higher than the market average at t and interact it with IU in the panel model. Results are shown in Table 1.3 panel (4). The significant positive sign on the interaction term confirms the positive effect of IU on short-term investment for firms with higher than market return. To capture the convex path between IU and firm investment, I also include the squared value of IU to test the effect. Results are shown in Table 1.3 panel (5). The significant positive sign on IU^2 together with the significant negative sign on IU largely supports my hypothesis.

To sum up, this model predicts a negative impact of macro uncertainty for all firms. Idiosyncratic uncertainty, on the other hand, has negative impacts under normal conditions but could turn positive when its value is high enough. Such a convex path for firm investment is due to the unbounded gain and bounded loss from increasing idiosyncratic uncertainty. All model predictions manage to find empirical support in the data.

2.4 An Alternative Competition Model of Uncertainty

2.4.1 Model

Modern production features extensive use of planning and contracting prior to manufacture, which is largely attributed to the increasing complexity of production chains. "Contract economy" allows producers, wholesalers and retailers to allocate their resources and managing their portfolio for maximum efficiency and profits, but it also brings amplified risks upon unexpected economic or political shocks through partial irreversibility or high adjustment cost. Financial innovations disperse these risks and provide cushions for producers, but they might reinforce damages following large shocks via high leverage and transmission effects.

One source of economic uncertainty is productivity shock that occurs on the production side. Such shocks include technology innovation, managers' turnover, factor supply issues etc. The effect of productivity shocks is usually local and firm-specific, thus they are considered idiosyncratic uncertainty. The other source of economic uncertainty is unexpected changes of business condition, which is largely a result of preference shift, policy instability, or market sentiment changes on the demand side. While productivity shocks occur sporadically among a large number of producers, factors that affect business condition might hit the economy at the macroscale. For this reason, market condition shocks are seen as macro uncertainty.

This model adopts New-Keynesian assumptions. To capture the stickiness of the production process and the demand-driven economy, I assume products take two stages to produce. In the first stage, producers study the market and contract quantities for both inputs and outputs. In the second stage, producers produce and sell products in the markets and make contracts for the next period. Any adjustments in the second stage are considered to be extremely costly thus not feasible. I also assume homogeneous products in the market, which is essential to keep the model simple.

The market condition evolves as a geometric random walk:[3] [4]

$$\log M_{t+1} = \log M_t + \sigma_M \epsilon \tag{2.8}$$

, where σ_M measures the uncertainty of market condition (or macro uncertainty). ϵ is white noise.

On the supply side, the production function is a one-factor Cobb Douglas:

$$S_t = A_t K_t^{\alpha} \tag{2.9}$$

or

$$\log S_t = \log A_t + \alpha \log K_t \tag{2.10}$$

, where K is productive factor and A is productivity (or technology). Similar to the market condition, I assume that the dynamic of productivity A also follow geometric

[3]By assuming a geometric random walk, the size effect on market growth is mitigated.

[4]The geometric random walk for market condition implies an exogenous demand. We will see later that factor and good prices are normalized to be none influential. This apparent drawback becomes less important by assuming a homogeneous product in the market which is likely to be necessities, so the demand process is driven by exogenous factors such as population growth, seasonal change, or general preference shift.

random walk: [5]

$$\log A_{t+1} = \log A_t + \sigma_S \epsilon \tag{2.11}$$

,where σ_S is productivity uncertainty [6]

Macro Model with One-side Tail Loss

In the macro setup, I consider the aggregate action of all producers. Under rationality, producers' best quantity estimate for next period demand giving equation (2.8) is:

$$S^e_{t+1,t} = E(M_{t+1}) = M_t e^{E(\sigma\epsilon)} = M_t e^0 = M_t \tag{2.12}$$

, where $S^e_{t+1,t}$ is the quantity estimates for $t+1$ at t. The contracted quantity of input K^c_t to produce $S^e_{t+1,t}$ giving current productivity A_t is therefore

$$\log K^c_t = \frac{1}{\alpha}(\log S^e_{t+1,t} - \log A_t) \tag{2.13}$$

Plug (2.12) and (2.13) in (2.10), the actual quantity produced at $t+1$ is

$$\log S_{t+1} = \sigma_S \epsilon + \log M_t \tag{2.14}$$

Note that uncertainty kicks in as an unexpected productivity shock. Plug in equation (2.8), the unforeseen demand surplus (or supply deficit) at $t+1$ is therefore

$$W_{t+1} = \log M_{t+1} - \log S_{t+1} = \sigma_M \epsilon - \sigma_S \epsilon \tag{2.15}$$

---

[5] Similar to my previous argument, I assume that technology progress is independent of technology size. Otherwise, under-developed countries might never catch up with developed ones.

[6] It is not idiosyncratic uncertainty yet as I haven't defined the scope of this model.

Taking variance on both side, total market uncertainty decomposes into market condition uncertainty and productivity uncertainty.[7]

$$Var(W) = Var(\sigma_M \epsilon) + Var(\sigma_S \epsilon) = \sigma_M^2 + \sigma_S^2 \tag{2.16}$$

Equation (2.15) shows the unforeseeable supply deficit. Equation (2.16) shows irreducible market uncertainty under rational expectation. [8] If I normalize good and factor prices to 1 and assume that all producers make profit rate r when their products are sold in the market, but suffer a depreciation rate d when their products are not sold, [9] the profit function for the economy at $t+1$ is:

$$R_{t+1} = \begin{cases} r \log M_{t+1} - r|W_{t+1}|, \text{ if } W_{t+1} \geq 0 \\ r \log M_{t+1} - d|W_{t+1}|, \text{ if } W_{t+1} < 0 \end{cases} \tag{2.17}$$

As shown in the equation (2.17), the damage of uncertainty is done through the negative tail effect $d|W_{t+1}|$. Such a effect is one-sided and occurs when market demand M_{t+1} falls short of actual supply S_{t+1}. If there is a demand surplus, the producer would not be able to take advantage of the unexpected demand surge due to high adjustment costs and the long production time, and thus regret an opportunity loss $r|W_{t+1}|$. Consequently, there is always a penalty for uncertainty, one way or the other. High market volatility is not desirable because the probability of getting a large negative value of W_{t+1} increases as $Var(W_{t+1})$ increases. If the market is free of uncertainty by removing all stochastic elements in our equations, producers would consistently make a profit of $r \log \bar{M}$. Uncer-

[7]By model construction, productivity shocks are independent of demand shocks.

[8]With irrational producers, equation (2.16) need to include another element demonstrating the variance of irrational increase or decrease of production, which raises the value of $Var(W)$.

[9]Imaging that producer get too optimistic and overproduce for the market, the excess supply might only be sold with heavy discount.

tainty drives the economy away from optimal path and results in real losses. The macro setup, however, does not show separate effects associated with σ_M^2 and σ_S^2.

Many empirical studies have shown that the macroeconomic impact is mainly driven by macro uncertainty but not idiosyncratic ones. (See Ozturk and Sheng (2017), Bijapur (2015) among many other). Such a phenomenon could be interpreted in this mode as a relatively small value of productivity uncertainty σ_S. There are two reasons for it: 1. For a large number of small firms, sporadic innovations offset each other and leave the aggregate effects at the macro level trivial; 2. For a small number of large producers, idiosyncratic shocks are naturally small (see Stanley et al. (1996) and also recall figure 1.11). For simplicity, I assume the market has two different firm size "small" and "large", the total market volatility breaks down to

$$Var(W) = \sigma_M^2 + \alpha \frac{\sigma_{s,i}^2}{N_i} + (1-\alpha)\frac{\sigma_{s,j}^2}{N_j} \tag{2.18}$$

,where α is total market share of small firms with uniform productivity volatility $\sigma_{s,i}^2$ and number N_i. Similarly, large firms have uniform productivity volatility $\sigma_{s,j}^2$ and number N_j. Also, $N_i >> N_j$ and $\sigma_{s,i} >> \sigma_{s,j}$. In a extreme case where $N_i \to +\infty$ and $\sigma_{s,j}^2 \to 0$, $Var(W) \to \sigma_M^2$ with probability 1. This convergence implies that uncertainty effects observed at the macro level to large extent originates from market condition changes or macro uncertainty shocks, but not necessarily from the aggregate effect of idiosyncratic productivity shocks.

Micro Model with Two-side Tail Loss

In the micro setting, I focus on individual (small) producers and allow them to compete for market share. Firms produce for their local markets as a fraction of the whole market. Thus the market share of firm i is

$$D_{i,t} = M_t^{\eta_{i,t}} \tag{2.19}$$

or

$$\log D_{i,t} = \eta_{i,t} \log M_t \tag{2.20}$$

, where $\eta_{i,t}$ is some measure of market share for firm i at t. [10] Also $\eta_{i,t} \in [0, 1]$ and $M_t > 1$.

Ceteris paribus, the demand surplus of firm i at $t + 1$ is

$$w_{i,t+1} = \eta_{i,t}\sigma_M\epsilon - \sigma_{s,i}\epsilon \tag{2.21}$$

,and the demand surplus of all other firms (but i) is

$$w_{\mathbf{i}',t+1} = (1 - \eta_{i,t})\sigma_M\epsilon - \sum_{j\neq i}\sigma_{s,j}\epsilon \tag{2.22}$$

,where $\sigma_{s,i}\epsilon$ and $\sigma_{s,j}\epsilon$ are the productivity uncertainty specific to firm i and firm j; $\eta_{i,t}$ is the dynamic market share of firm i that evolves with firm's relative performance; $\mathbf{i}'$ stands for all firms but i.

In the previous macro setting, $W_{t+1} < 0$ has one-sided real negative impact on firms' profitability when market demand falls short of supply so producers cannot get rid of their excess products without a loss d. The loss associated with $W_{t+1} \geq 0$ is only considered opportunity loss. However in a competitive economy, real negative impact of $w_{i,t+1}$ are two-sided. When $w_{i,t+1} > 0$, which means local demand exceeds local supply by $w_{i,t+1}$, producer i would lose market share by $\dfrac{\min(w_{i,t}, -w_{\mathbf{i}',t})}{\log M_t}$ to its competitors if the

[10]The market share is determined by many factors, including but not limited to, producers' capacities, marketing expenditures and reputations. Here I assume these parameters to be exogenous, but the model can be extended by writing $\eta_{i,t}$ as a function of those factors.

rest of the market have excess products $|w_{\mathbf{i}',t+1}| < 0$ at $t+1$. Apparently, this would only happen if $w_{i,t+1}$ and $w_{\mathbf{i}',t+1}$ have opposite signs. The dynamics of firm i's market share is therefore:

$$\eta_{i,t+1} = \begin{cases} \eta_{i,t} - \dfrac{\min(w_{i,t}, -w_{\mathbf{i}',t})}{\log M_t} & \text{if } sgn(w_{i,t}) = -sgn(w_{\mathbf{i}',t}) \\ \eta_{i,t} & \text{if } sgn(w_{i,t}) = \ \ sgn(w_{\mathbf{i}',t}) \end{cases} \tag{2.23}$$

By symmetry, this equation also hold when firm i seizes market shares from its competitors ($w_{i,t} \leq 0$ and $w_{\mathbf{i}',t} > 0$). The expected loss (gain) from losing (seizing) market share is $r\min(w_{i,t}, -w_{i',t})$. [11] It worth noting that despite firms face two-side tail loss in this micro setup, the real loss from making excess products ($w_{\mathbf{i}',t+1} < 0$) is reduced since firms are now possible to sell their excess products to external markets where supply deficits occur. This implies that the economy as a whole benefits from competition as it pushes the economy to its potential. The profit function for small producer i in a competitive economy when redistribution of market share occurs ($w_{i,t-1}$ and $w_{i',t-1}$ have opposite signs) is:

$$R_{i,t} = \begin{cases} r\Big(\eta_{i,t-1} - \dfrac{\min(w_{i,t-1}, -w_{\mathbf{i}',t-1})}{\log M_{t-1}}\Big)\log M_t - rw_{i,t} & \text{if } w_{i,t} \geq 0 \\ r\Big(\eta_{i,t-1} - \dfrac{\min(w_{i,t-1}, -w_{\mathbf{i}',t-1})}{\log M_{t-1}}\Big)\log M_t - d\max(|w_{i,t}| - |w_{\mathbf{i}',t}|, 0) & \text{if } w_{i,t} < 0 \end{cases} \tag{2.24}$$

If there is no market share redistribution ($w_{i,t-1}$ and $w_{i',t-1}$ have same signs), the profit

[11] The real loss is $r\dfrac{\min(w_{i,t}, -w_{\mathbf{i}',t})\log M_{t+1}}{\log M_t}$.

function is the same as the one in the macro setup:

$$R_{i,t} = \begin{cases} r\eta_{i,t}\log M_t - r|w_{i,t}| & \text{if } w_{i,t} \geq 0 \\ r\eta_{i,t}\log M_t - d|w_{i,t}| & \text{if } w_{i,t} < 0 \end{cases} \tag{2.25}$$

By comparing equation (2.24) to equation (2.17), we see that in this competition setup the profit dynamics of firm i depends on the relative performance of its competitors $\mathbf{i'}$ at t and $t-1$. The tail loss from $w_{i,t} \geq 0$ is shown in the model as the market share loss $r\left(\dfrac{\min(w_{i,t-1}, -w_{\mathbf{i'},t-1})}{\log M_{t-1}}\right)\log M_t$ in addition to the opportunity loss $rw_{i,t}$. However, the tail loss from $w_{i,t} < 0$ is reduced because over produced products might find their way in external markets.

Intuitively, if firm i constantly overproduces, it is capable of seizing competitors' market shares whenever they under-produce, but lose d when excess product can not be sold. In extreme case where other producers constantly hit the target and no external demand ever happens for firm i, then firm i would continuously lose capital from depreciation of unsold products. On the other hand, extreme volatility of other producers would benefit firm i since firm i could quickly seize market share whenever other firms under-produce but loses product value d just like everyone else when other firms overproduce. Hence, relative high idiosyncratic uncertainty would hurt firm investment returns through two-side tail loss and markets share redistribute toward firms with relative low uncertainty. In the next section, I provide a numeric proof for this model and show dynamics of capital accumulation under the composite effect of macro and idiosyncratic uncertainty.

2.4.2 Simulation: Two-Firm Model with Competition

In the simulation, I allow two firms of different idiosyncratic uncertainty to compete in an uncertain market. I present dynamics of three variables: 1. the capital of the high-uncertainty firm; 2. the capital of the low-uncertainty firm; 3. the market share of the high-uncertainty firm. To make the simulation more robust, I allow firms to borrow at interest rate π if their capital reserves fall short of required amount $K^c_{i,t}$ to produce for the expected demand in the next period. Formally, the dynamic of capital reserve for firm i follows:

$$K_{i,t+1} = K_{i,t} + R_{i,t} - \pi(\max(K^c_{i,t} - K_{i,t}, 0)) \tag{2.26}$$

However, firms go out of business whenever their capital reserve hit below 0 ($K_{i,t} < 0$). If this happens, its competitor picks up all its market share. Based on the model mechanism, we should expect two things to happen: 1. macro uncertainty has generally negative impacts on firm capital accumulation; 2. The high-uncertainty firm has slower capital accumulation due to two-side tail loss; In addition, two things that are not obvious in the model need a numeric solution: 1. the dynamics of market share for the high-uncertainty firm; 2. the partial effect of macro uncertainty between the high-uncertainty firm and the low-uncertainty firm.

The simulation starts with two companies who jointly have enough capitals to produce for the entire market. They also have an equal market share at the beginning. However, the productivity of one firm has volatility $\sigma_{s,h}$ double that of the other $\sigma_{s,l}$. The market volatility (macro uncertainty) σ_M are set at low, medium and high for each round of simulation. The interest rate π is set to equal to profit rate r so firms do not make money from the part of production financed. However, by doing so firms avoid losing market shares. The depreciation rate d is set to be a much higher value than profit rate r, which is common for both goods and factors markets. 300 steps are iterated to see the evolution of both firms' capital reserves and their markets shares. For each σ_M setting, simulation is run for 1000 times and I report their mean values for illustration. Table 2.1 shows values of parameters used in the simulation. The simulation results are shown in graph 2.4. [12] When the macro uncertainty σ_M is low, both firms grow steadily during the entire period. However, the capital reserve of the low-uncertainty firm reaches around 200 at the peak comparing to that of high-uncertainty firm only reaches 150. The market share, however, has insignificant changes so neither firm is capable of consistently seizing market from its competitor and making additional profits. This result is expected as the high-uncertainty firm suffers tail loss associated with supply surplus more often than the low-uncertainty firm, while market redistribution does not play a role due to a relatively low variation on the composite shock w_i. The results from medium σ_M are similar. However, both firms reach significantly lower capital level for the peak point. The market share, on the other hand, still change insignificantly. We can see that there is an initial downward trend for the high uncertainty firm but a few consecutive positive productivity shocks help it regain the loss. Both results imply that the redistribution of market share due to competition is less likely to happen if the market condition is stable. If I further increase σ_M, the two-side tail loss starts to kick in. We see that the low uncertainty firm grows at a much lower rate while the high uncertainty firm starts to lose money. More importantly, the market share of high uncertainty firm shrinks consistently as competition goes on and dropped 10% at 300 steps. This redistribution effect put additional pressure on the high-uncertainty firm' investment return.

[12] The first row shows the dynamic of low-uncertainty firm capital reserve (Equation 2.26) with different σ_M setting. The second row illustrates the dynamic of high-uncertainty firm capital reserve with different σ_M setting. The third row displays the dynamic of the high-uncertainty firm market share (Equation 2.23) with different σ_M setting. All results are based on the mean values of 10000 rounds of iterations. Each iteration simulates 300 steps ($t = 1, ..., 300$).

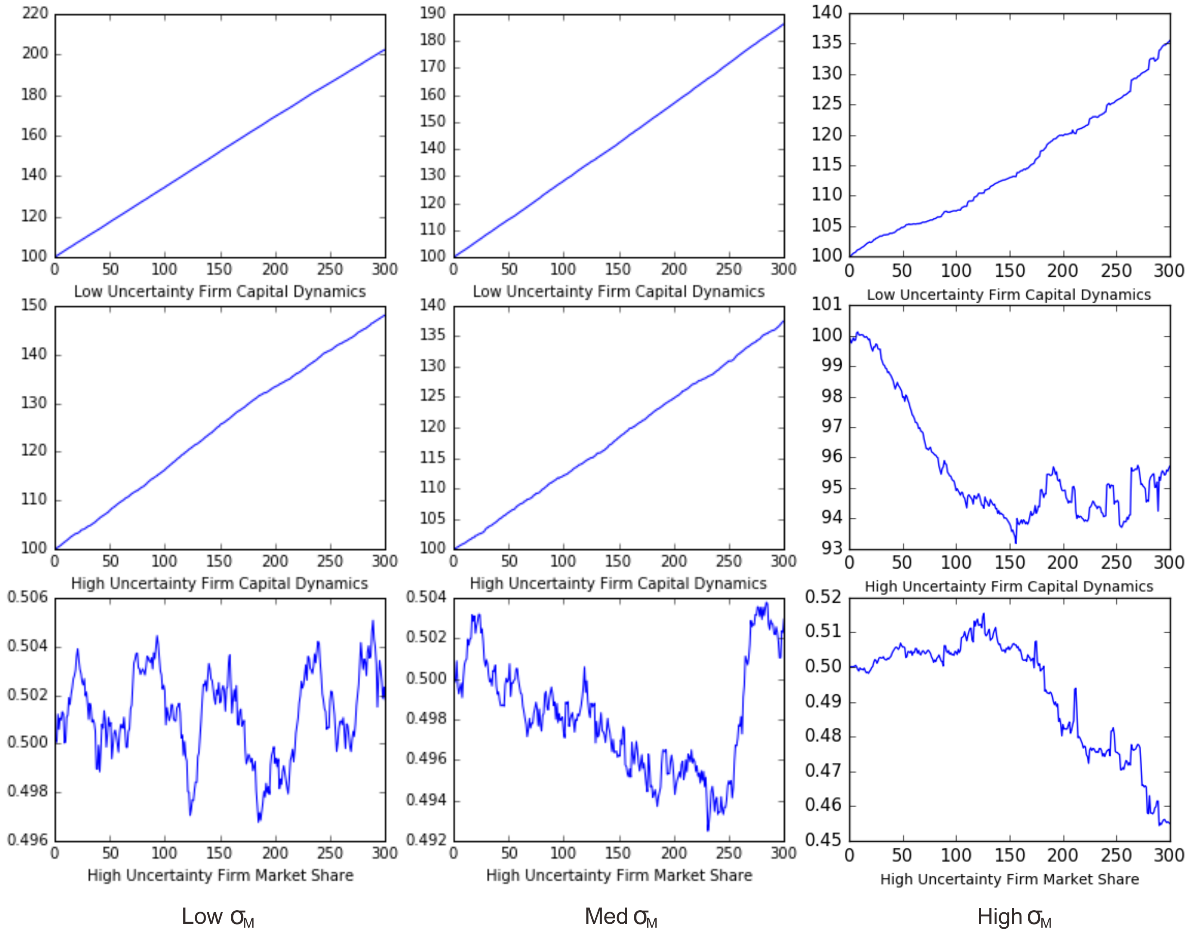

Figure 2.4: Model Simulation Results

The first row shows the dynamic of low-uncertainty firm capital reserve (Equation 2.26) with different σ_M setting. The second row illustrates the dynamic of high-uncertainty firm capital reserve with different σ_M setting. The third row displays the dynamic of the high-uncertainty firm market share (Equation 2.23) with different σ_M setting. All results are based on the mean values of 10000 rounds of iterations. Each iteration simulates 300 steps ($t = 1, ..., 300$).

Table 2.1: Hyperparameters in the Simulation

Parameter	Value	Rationale
r	0.01	Profit rate. The production cycle is assumed weekly.
π	0.01	Interest rate. Set to be equal to r
d	0.5	Depreciation rate.
$\sigma_{s,l}$	1	Productivity uncertainty of low-uncertainty firm l
$\sigma_{s,h}$	2	Productivity uncertainty of high-uncertain firm h
Low σ_M	1	Market/Common uncertainty at low setting
Med σ_M	2	Market/Common uncertainty at medium setting
High σ_M	4	Market/Common uncertainty at high setting
$K_{l,0}$	100	The initial capital reserve of low-uncertainty firm
$K_{h,0}$	100	The initial capital reserve of high-uncertainty firm
$\eta_{l,0}$	0.5	The initial market share of low-uncertainty firm
$\eta_{h,0}$	0.5	The initial market share of high-uncertainty firm

To sum up, the simulation results provide 3 implications: 1. Macro uncertainty and idiosyncratic generally have negative impacts on firm investment and profitability; 2. The negative partial effect of macro uncertainty is stronger for firms with higher idiosyncratic uncertainty, which is attributed to two-side tail losses from overproducing and losing market share; 3. Following the second implication, firms with relative low idiosyncratic uncertainty might consistently capture market share from its competitors and grow bigger. However, the model does not imply whether or not firm size could in return affect firm uncertainty. The model prediction is consistent with my empirical finding in section 1.3.4 that large firms has a lower uncertainty on average. (See figure 1.11)

2.5 Concluding Remarks

Uncertainty appears to drag down investments through channels other than "real options" or "risk primia & risk aversion". This chapter presents two additional channels that why uncertainty matters to the real economy. These channels are mainly explained in two theoretical models, but they also get support from empirical studies. I focus on separate impacts from idiosyncratic and macro uncertainty, and examine the problem at the micro- and macro-level.

The first model is based on Lucas Island Model and CAPM. This model tries to understand real uncertainty effects through inefficient expectations duo to an uncertain environment. This model predicts that macro uncertainty has a generally negative impact on firm investment. The effect of idiosyncratic uncertainty, on the other hand, depends on firm profitability and the magnitude of shock. High-return firms benefit from increasing idiosyncratic uncertainty while low-return firms suffer. On average, the relationship between idiosyncratic uncertainty and firm investment follows a convex path – the negative effect diminishes and eventually turns positive as the magnitude of idiosyncratic uncertainty goes up. Both model predictions find strong empirical support in the data.

The second model inherits some New-Keynesian assumptions. I separate out idiosyncratic uncertainty from macro one and shows their relations with the demand and supply side of a economy. The negative uncertainty effects are shown as the real loss following unexpected first moment shocks as well as the market share shrinkage due to relatively high idiosyncratic uncertainty. The macro setup has only one-side tail losses which occur when firms over-produce. The micro setup demonstrates two-side tail losses by including a competition mechanism. The model predicts that both macro and idiosyncratic uncertainty have negative impact on firm investment. However, the partial effect of macro uncertainty is stronger for firms with high idiosyncratic uncertainty due to the disadvantages of high-uncertainty firms in competing for market share. This finding helps understand the inverse relationship between idiosyncratic uncertainty and firm size in the data.

CHAPTER 3

MEASURING MACROECONOMIC UNCERTAINTY WITH DENSITY FORECASTS

3.1 Measuring Macroeconomic Uncertainty

3.1.1 Subjective Uncertainty and its Origin

A primary challenge to the uncertainty literature is the inability to directly observe uncertainty. The proxies of uncertainty vary from study to study. In finance, model-based uncertainty is measured as price movements of volatile financial instruments such as stocks or options, which are assumed to be tightly linked to economic uncertainty, e.g. Black and Scholes (1973) and Engle (1982). In communication and information theory, entropy is an interchangeable notion with uncertainty because information can reduce uncertainty during communication, e.g. Kullback and Leibler (1951). In politics, uncertainty is measured based on the frequency of uncertainty-related linguistic expressions used in mass media, e.g. Baker et al. (2016). In macroeconomics, forecast error-based uncertainty measures have been proposed by Jurado et al. (2015) and Rossi and Sekhposyan (2015).

The contrasting approaches in those studies signify a potential inconsistency in the underlying notion of uncertainty. Similar to the philosophical differences in probability theory as discussed in Jaynes (1957), uncertainty is multifaceted. Uncertainty may be objective or subjective. Objective uncertainty originates from the underlying structure of events which in nature generates outcomes in a stochastic manner, and in principle, can always be partially observed by examining post-event outcomes. In consequence, such type of uncertainty is not reducible by additional information.[1] Since observing objective uncertainty requires the knowledge of event realizations, it is also known as ex-post or post-event uncertainty. Notable examples of ex-post uncertainty include Jurado et al. (2015), Jo and Sekkel (2017) and Ozturk and Sheng (2017). All papers define uncertainty in predicting a single variable as the volatility of its forecast error and measure macro uncertainty as the common component of variable-specific uncertainty. They differ in that Jurado et al. (2015) generate forecasts based on statistical models, while the other two use expert forecasts directly. Despite these differences, they require the knowledge of realized values and provide ex-post measures of uncertainty.[2]

In contrast, subjective uncertainty regards uncertainty as a type of human feeling caused by limited information or stochastic factors. This notion is exactly the core idea of subjective school of probability theory, which regards probability as merely a formal expression of human ignorance. Since subjective uncertainty exists only if the realizations of events are not yet known, it is also called ex-ante or pre-event uncertainty. Broadly speaking, there are three categories of ex-ante uncertainty in the literature. The first category uses option implied volatility in the stock market, e.g. Bloom (2009). Option prices reflect market participant perceptions of expected volatility in underlying securities. The accuracy of implied volatility as an uncertainty measure, to a large extent, depends on the

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[1] A good example would be the classical dice problem. The outcome of tossing a fair dice follows a predetermined and unchanging structure. However, even if players fully understand such a structure, they are still incapable of correctly predicting every toss and no additional information could potentially reduce such uncertainty. In fact, this is exactly the classical notion of "Knightian Risk" or simply "the game of chance".

[2] Istrefi and Mouabbi (2017) propose an ex post measure of interest rate uncertainty that accounts for both disagreement among forecasters and the perceived variability of future aggregate shocks.

volatility of underlying securities estimated by models such as Black and Scholes (1973). The movement in the implied volatility is often driven by non-fundamental factors, such as risk premia. The second category is disagreement across forecasters with the underlying assumption that this inter-personal dispersion is a good proxy for the intra-personal uncertainty. As aptly pointed out by Lahiri and Sheng (2010), disagreement only captures one component of uncertainty and misses the other component - the volatility of aggregate shocks. Furthermore, heterogeneity among forecasters, rather than uncertainty, might be the main source of disagreement. The third common measure of uncertainty is policy uncertainty proposed by Baker et al. (2016) that count the frequency of uncertainty-related keywords in major newspapers. This measure has been criticized for its excess volatility and low persistence by Jurado et al. (2015), among others.

In this chapter we focus on subjective uncertainty and study how economic agents “contemplate” the state of the economy. Recall that subjective uncertainty arises when agents have limited information about the true state. In order to formalize agents’ complete understanding of an uncertain event, probability expression is a natural choice. The virtue of probability forecasts is that they contain not only perceived outcomes, but also an associated likelihood. Taking advantage of the unique dataset on density forecasts of output growth, we propose a new measure of macro uncertainty as the common component in forecaster-specific uncertainty. We emphasize two features of this definition. (i) Our uncertainty measure incorporates a rich information set and captures perceived uncertainty for economic agents. As such, it does not have to be tightly linked with fluctuations in the volatility of realized outcomes. (ii) It is an ex-ante measure of macro uncertainty that does not require the knowledge of realized outcomes and thus can be tracked in real time.

3.1.2 Data Description and Parametric Fitting on Probability Forecasts

Our dataset comes from the Survey of Professional Forecasters (SPF), originally maintained by American Statistical Association and taken over by Philadelphia Fed in 1990Q2. Besides the long history of point forecasts for many macro variables, the SPF also contains probability forecasts that record experts' predictions for GDP and inflation. We use forecasts for the annual-average over annual-average percent change in real GDP, available since 1981Q3. Although the survey also offers probability forecasts for inflation, we focus on the probability distribution in real GDP only, because the uncertainty literature emphasizes the origin of uncertainty from real economic activities.[3] At each quarter, experts give their probability forecasts for both current and next year output growth in the form of histograms. One of the challenges in analyzing this dataset is that the survey structures experience many rounds of changes involving the number of bins and the range for each bin. These structural changes unavoidably cause inconsistency in uncertainty estimates over a long period of time. Regarding the information set, survey questionnaires are sent out at the end of the first month of each quarter. Therefore, experts are aware of the BEA's advanced release of real GDP for the previous quarter.

After filtering out all missing values, we are left with 4639 observations. Each observation contains a distribution of an analyst's forecasts for the "current year" and "next year" real GDP growth and thus we have a total of 9278 probability forecasts. Some forecasts have rounding issues in that the sum of probabilities does not equal 1 due to apparent typos. We fix the rounding problems by proper scaling and no observation is removed from the data.[4] The probability distributions in the SPF take the form of histograms.

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[3]Note that inflation forecast uncertainty alone has been studied extensively in the literature; see Giordani and Söderlind (2003), among others.

[4]We repeat our analysis by deleting those observations with rounding issues and the uncertainty estimates remain the same. This is not unexpected, since almost all of the rounding errors are very small, less than 1 percentage point.

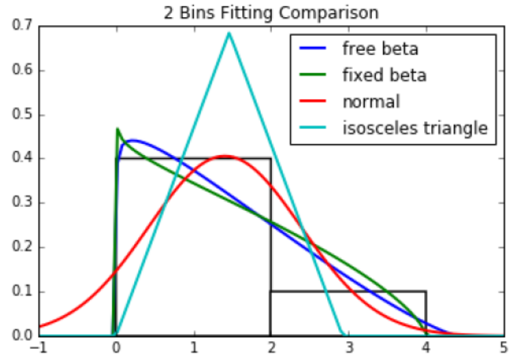
Several problems arise with such a format and prevent us from using these histograms directly for uncertainty estimation. First of all, the histogram has open intervals at both ends, implying that their support covers the entire real number space. It is unlikely for professional forecasters to assign probabilities to infinite positive/negative values. To close open intervals for more reasonable fitting results, we use either the minimum and maximum historical values or simply close them with associated bin size, depending on the support variation associated with the survey periods. Second, the histogram provides no information regarding the distribution within each bin. For each probability forecast, we generate separate samples from uniform distributions with supports equal to the range of each bin and set the sample sizes proportional to the probabilities assigned to each bin. Then we combine these samples together to represent one probability forecast. The generated histogram from the combined sample looks exactly like the bar plots of the original probability forecast. We fit parametric distributions to the combined sample and estimate the parameters by the maximum likelihood method.[5] Engelberg et al. (2009) use both non-parametric and parametric methods to analyze SPF density data. They conclude that only a limited relationship between point forecast and density forecast can be drawn using parametric method alone. Moreover, many of the non-parametric methods are designed for measuring the distribution spread so higher moments might not be available by using them. In contrast, the parametric method allows consistent measures and easy access to higher moments.

The choice of parametric distributions is critical for studies using SPF density forecasts. However, the literature has no standard methodology. While Giordani and Söderlind (2003) use normal distributions to fit the data, Engelberg et al. (2009) and Clements (2014) adopt a mixed strategy that fits generalized beta distributions to obser-

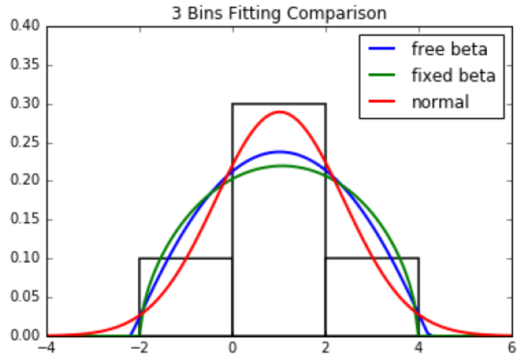
[5] The estimation method used in this chapter is different from all previous studies where the minimum distance estimation is used. The advantage of using the maximum likelihood method is that it yields consistent and most efficient estimates.

vations with more than two bins and triangle distributions to the rest. Karaca (2015) experiments with a mixture of constrained and unconstrained beta distribution. Clements and Galvao (2017) fit normal distributions to observations with more than two bins and triangle distributions to the rest. Without clear guidance, we conduct the experiment with four different distribution settings on a subsample of 2456 probability forecasts from 1992Q1 to 2009Q2. These settings include: (i) normal distribution, e.g. Giordani and Söderlind (2003), (ii) generalized beta distribution with no parameter constraint, (iii) generalized beta distribution with supports determined by individual forecast values, and (iv) combination of generalized beta and triangle distributions, e.g. Engelberg et al. (2009). Figure 3.1 illustrates all four fittings on a small sample. Due to its high flexibility and closed support, the third setting performs very well in mimicking asymmetric and irregular empirical distributions in the data. For observations that show symmetry, the fitting results from the third setting are almost identical to the first setting of normal distributions. We further evaluate all four settings based on their performance in terms of goodness of fit, consistency with point forecasts, forecast accuracy and variance consistency. Not surprisingly, the third setting gives the best fitting results.[6] Therefore, we fit the generalized beta distribution with support individually determined by the end points of each probability forecast to all histograms, and calculate the variance of the fitted distribution as expert i's uncertainty at period t, denoted by U_{it}.

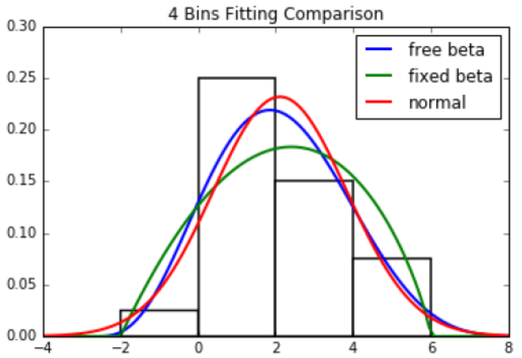
[6]The details regarding this experiment are left in the appendix.



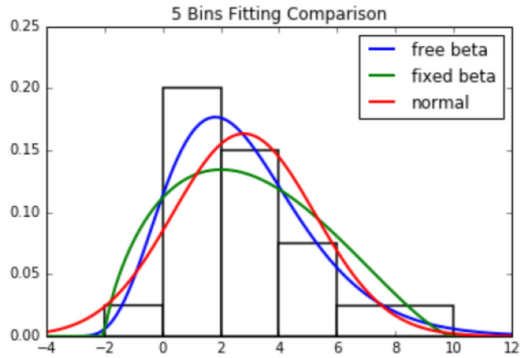
(a) Probability Forecast with 2 Bins



(b) Probability Forecast with 3 Bins



(c) Probability Forecast with 4 Bins



(d) Probability Forecast with 5 Bins

Figure 3.1: Parametric Fitting on Histograms using Different Distributions

3.1.3 Constructing the Macro Uncertainty Index

To construct the time series of macro uncertainty index, we have to deal with four complications in the survey. (1) Seasonality: Forecast horizons change from 8- to 1-quarter ahead and consequently, macro uncertainty becomes lower at shorter horizons. (2) Structural changes: The survey experiences multiple structure breaks due to changes in survey format and maintainer, e.g. when the Philadelphia Fed took over the survey in 1990Q2. (3) Panel composition: There are substantial gaps in the panel of forecasts, reflecting non-responses by existing participants, and the frequent entry and exit of some participants. Figure 3.2 plots forecaster identification number against the survey periods they participated. To control for changes in panel composition, probability forecasts at individual levels are required. This is the main reason why we do not use aggregate probability distributions in this study. (4) Measurement errors: The values in 1985Q1 and 1986Q1 suffer from the “wrong target asked” issue so they are replaced by predicted values. The values in 1990Q2 are also replaced by predicted values because the questionnaires were not sent in time during the transition. The imputation method will be stated in details later. We include two dummy variables to control for three different survey structures and one dummy to separate two survey maintainers. To address the changes in panel composition, we first remove all forecasters who participated only once during the entire survey period and then include a fixed effect for each forecaster.[7] Specifically, we run the following regression:

$$U_{it} = \sum_{k=1}^{K} \beta_k S_k + \gamma P + \sum_{i=1}^{I-1} \delta_i F_i + \epsilon_{it}, \tag{3.1}$$

where S are dummy variables controlling for different survey structures, P is the dummy for the change in survey maintainers, and F is a series of dummies for individual forecasters. The resulting residual $\hat{\epsilon}_{it}$ is the adjusted uncertainty measure controlling for changes in survey structure, survey maintainer and panel composition. Furthermore, we apply X13 to $\hat{\epsilon}_{it}$ to remove any remaining seasonality and obtain perceived uncertainty at individual levels.[8] Finally, we construct our macro uncertainty index as the cross-sectional median of individual uncertainty values.[9] We do so for both current and next year, representing

[7]We conduct the analysis based on a subsample study on forecasters having provided at least 8 forecasts and our uncertainty estimates remain the same after removing these additional infrequent forecasters.

[8]We also experiment with seasonal dummies and obtain very similar uncertainty estimates.

[9]The index calculated using the cross-sectional mean is very similar to that using the median. For brevity, we report the results using the median only.

the short- and medium-term uncertainty.[10] For easy comparison, we normalize the index between 0 and 1. We emphasize two features of these definitions: (i) our measure reflects the common variation in their uncertainty perceived by professional forecasters and does not have to be tightly linked with fluctuations in the volatility of realized outcomes; (ii) it is a real-time measure that does not require the knowledge of realized outcomes.[11]

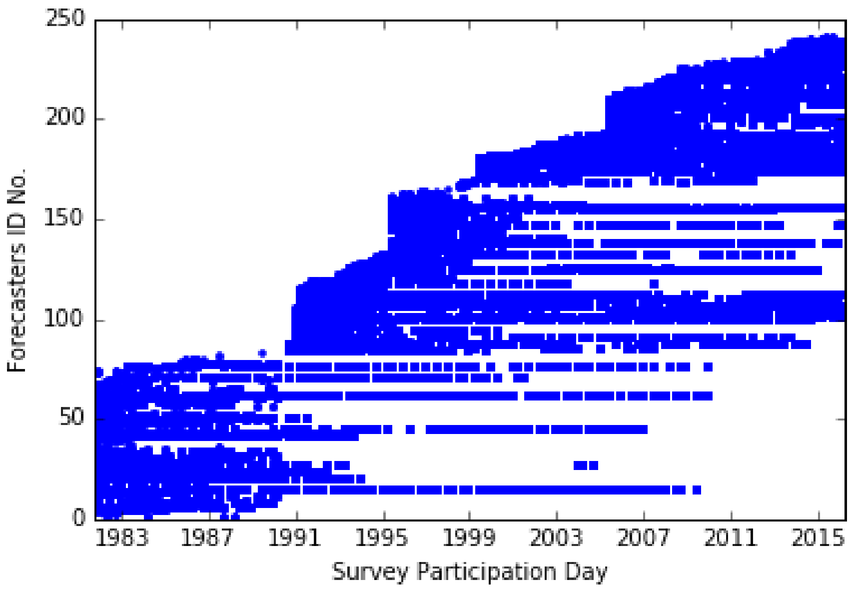


Figure 3.2: Panel Composition in the U.S. SPF

Figure 3.3 plots short-term uncertainty at one-year ahead and medium-term uncertainty at two-year ahead. Short-term uncertainty experiences many spikes during recessions, wars and presidential elections, and the largest one occurs during the 2007-09 recession. Except for two big spikes, the short-term uncertainty is less volatile after 1992, implying that real economic variables such as real GDP become more consistent and pre-

[10]The erroneous values at 1985Q1, 1986Q1 and 1990Q1 are replaced by the predicted values from fitting a time trend on the group of forecasts that share the same targets as those erroneous values.

[11]A long-standing issue in the literature is about the relationship between uncertainty and disagreement. Notice that our macro uncertainty measure is the weighted average of individual uncertainties, which has already incorporated disagreement as one component, a result established by Lahiri and Sheng (2010).

dictable in 1990s and 2000s than 1980s. The spike in 2004 is associated with events such as presidential election and Iraq war, which is not well documented in other uncertainty indexes. When taking a closer look at the original density forecast data in 2004Q1 and Q2, we find that the density forecasts are much more dispersed than those in run-of-the-mill periods. The macro uncertainty at the medium term is on average higher than its counterpart at the short term and has two largest spikes during the crude oil collapse and post Iraq war periods. The correlation between short- and medium-term uncertainty is about 0.47 during our sample period. We explore what may drive uncertainty over these different time horizons. Consistent with Barrero et al. (2017), we find that oil price volatility and currency volatility are particularly important for short-term uncertainty, while EPU and oil price volatility affect medium-term uncertainty.[12]

Table 3.1 shows the correlation between our macro uncertainty and other uncertainty measures. Those measures include the VIX in Bloom (2009), the EPU by Baker et al. (2016), the JLN index in Jurado et al. (2015), forecast disagreement computed from the same dataset, and the OS uncertainty in Ozturk and Sheng (2017). To ease comparison, all monthly uncertainty measures are converted to quarterly values by using the quarterly average. Our macro uncertainty index is weakly correlated with all other measures. Specifically, the low correlation with disagreement (0.25) suggests that this inter-personal dispersion might not be a good proxy for macro uncertainty, since disagreement could increase due to the heterogeneity among forecasters rather than high uncertainty.[13] The low correlations with both JLN and OS uncertainty indexes reflect the key differences with these measures: our measure captures the perceived uncertainty

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[12]The correlations of short-term macro uncertainty are 0.59 with oil price volatility, 0.46 with currency volatility and 0.17 with EPU. In contrast, the correlations of medium-term macro uncertainty are 0.10 with oil price volatility, -0.04 with currency volatility and 0.11 with EPU.

[13]Using surveys of professional forecasters from the Bank of England, the U.S. and the European Central Bank, respectively, Boreo et al. (2008), Rich and Tracy (2010) and Abel et al. (2016) find little support for the use of disagreement as a proxy for uncertainty.

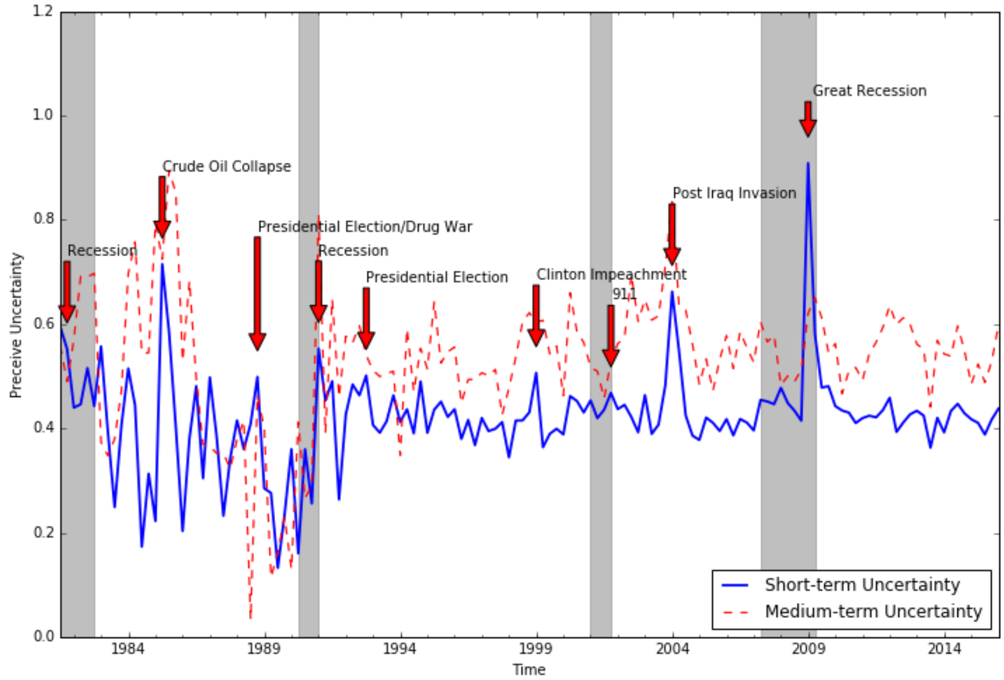

Figure 3.3: Short- and Medium-term Macro Uncertainty

by market participants but does not have to be tightly associated with the volatility of realizations; in contrast, both JLN and OS require the knowledge of realized values and give ex-post measures of uncertainty.[14] The low correlations with the VIX and EPU can be explained by different targets of these measures. Our measure captures economy-wide uncertainty, while the VIX most likely reflects uncertainty in the stock market and EPU emphasizes the policy aspect of uncertainty.[15] To summarize, our uncertainty estimates display independent variations from other leading uncertainty proxies, suggesting that

[14]We find further supporting evidence by comparing our measure with the objective measure of GDP volatility, estimated by fitting the GARCH model to real GDP (in logged values). Both measures show a large spike during the 2007-09 crisis. But often, the ex post GDP volatility moves in a different direction with the ex ante macro uncertainty. This result again highlights the conceptual difference between objective, ex post uncertainty and subjective, ex ante uncertainty.

[15]The VIX is highly and negatively correlated (-0.49) with the market return based on S&P 500 index. In contrast, the correlation between our measure and the market return is very low (-0.03).

much of their variation is not driven by perceived macro uncertainty.

Table 3.1: Correlation Among Uncertainty Measures

	DIS	VIX	EPU	JLN	OS
Macro Uncertainty	0.25***	0.27***	0.17*	0.30***	0.19*
DIS		0.25**	0.02	0.53***	0.42***
VIX			0.52***	0.66***	0.61***
EPU				0.31***	0.22***
JLN					0.82***

Note: The measures include the VIX in Bloom (2009), the EPU in Baker et al. (2016), the JLN index in Jurado et al. (2015), forecast disagreement computed from the same dataset, the OS uncertainty in Ozturk and Sheng (2017), and Macro Uncertainty introduced in this paper. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Figure 3.4 compares our macro uncertainty with other uncertainty measures from the literature. All uncertainty measures are countercyclical. The VIX and EPU indexes experience many spikes during both recessions and non-recessionary episodes. In contrast, the JLN, OS and our index reach their peaks during most of the recessionary episodes and remain low during expansions.[16]

[16]Note that the half-life of our uncertainty measure is estimated to be about 0.57. The corresponding half-life estimates are 1.51 for EPU, 2.31 for VIX, 7.45 for JLN and 9.77 for OS uncertainty index. Clearly, our uncertainty measure shows the lowest persistence, compared to the other measures.

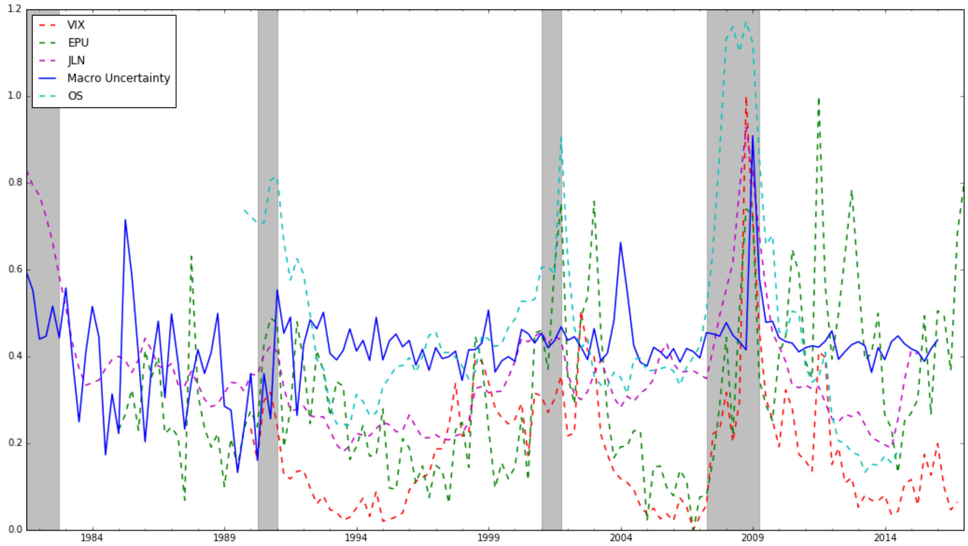

Figure 3.4: Comparison of Alternative Uncertainty Measures

3.2 The Impact of Macro Uncertainty

3.2.1 U.S. Evidence

The impact of uncertainty shocks on real economic activities has been given some theoretical insights by Bernanke (1983) and Bloom (2009). There are also abundant empirical supports such as Romer (1990) and Jurado et al. (2015), among others. Almost all studies find a negative effect of uncertainty shocks on real economic activities, but the persistence of these shocks varies. For instance, Bloom (2009) finds that, using the VIX index, both employment and production show rebounds six months after the initial drop following the uncertainty shock. However, Jurado (2015) show that uncertainty shocks lead to large and persistent responses in real activity without overshooting.

To ease comparison with the results in the literature, we adopt a similar VAR framework including seven variables in the following order:

$$\begin{bmatrix} \text{log(S\&P 500 Index)} \\ \text{Uncertainty} \\ \text{log(Wage)} \\ \text{Federal Funds Rate} \\ \text{log(CPI)} \\ \text{Unemployment Rate} \\ \text{log(Industrial Production)} \end{bmatrix}$$

All monthly data are converted to quarterly to match our macro uncertainty index. Following Bloom (2009), we detrend all series using HP filter with smoothing parameter λ as 1600.[17] Rather than define the uncertainty shocks using dummy variables, we use the detrended uncertainty series directly to allow the variation of macro uncertainty to fully interact with macro variables.

Figure 3.5 illustrates the impulse response function of industrial production and unemployment rate to an one standard deviation uncertainty shock. Industrial production falls about 0.25% immediately after an uncertainty shock and recovers slowly afterwards. After five quarters industrial production recovers and rebounds slightly but insignificantly, unlike the strong rebound shown by other measures.[18] Following the uncertainty shock, the unemployment rate increases by about 0.05 percentage points immediately, recovers and rebounds insignificantly after ten quarters.

[17]The results with all original series are qualitatively similar to those with the detrended series.

[18]After the initial decline for about two quarters, industrial production rebounds quickly following the VIX or EPU uncertainty shock. For the other two measures, we also observe strong rebounds in industrial production: in two years following the JLN and three years following the OS uncertainty shock. For brevity, these graphs are not reported here.

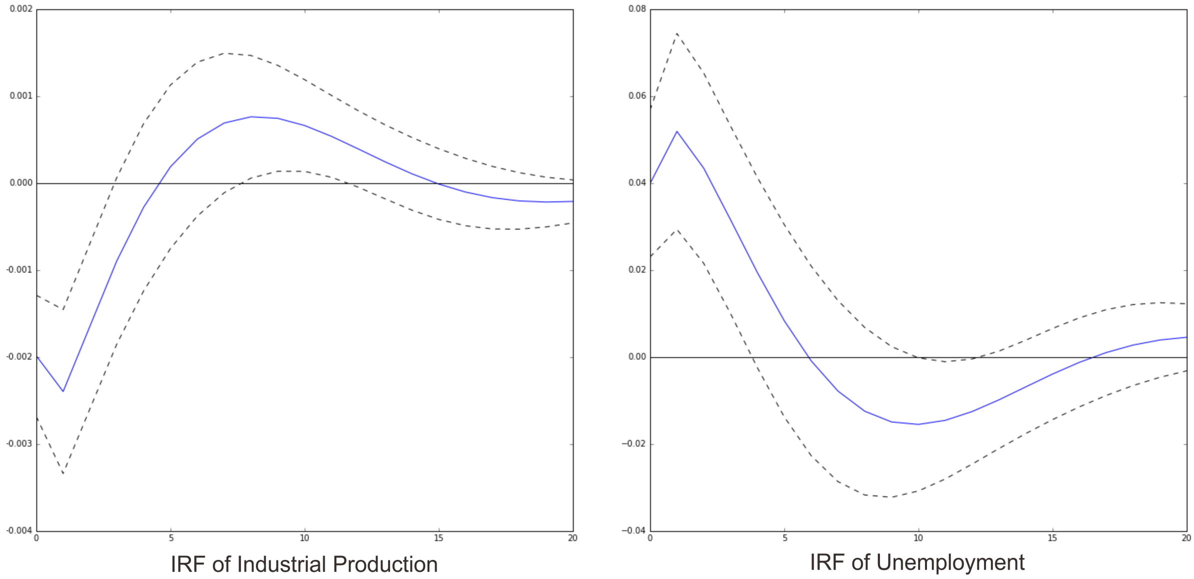

Figure 3.5: Response of Industrial Production and Unemployment to Macro Uncertainty (64% Confidence Interval)

3.2.2 Evidence from BRIC Countries

As the superpower in the world, the U.S. has the world's largest GDP (based on exchange rate) that accounts for roughly 22% of global output. The size of the economy makes it among the top two countries in terms of exports, imports and foreign direct investment. Due to its large share in global real economic activities and its interconnectedness, both supply and demand shocks in the U.S. generate tremendous shockwaves to global consumers and producers. Furthermore, changes in U.S. monetary policy and fluctuations in its financial market can easily transmit to the rest of the world through U.S. dollar denominated assets. A recent review on the role of U.S. in the global economy is given by Kose et al. (2017) in which they document that the U.S. originated economic shocks have significant global spillovers through trade, monetary policy and financial market.

Although uncertainty shocks might have larger effects on emerging market than advanced economies, there have been only a few studies on the former. Choi (2017) explores the spillover effect of U.S. uncertainty to emerging market economies. Carriere-Swallow and Cespedes (2013) find that emerging economies suffer deeper and more prolonged impacts from uncertainty shocks. In this section, we focus on the transmission of the U.S. macro uncertainty to BRIC countries due to their interconnectedness to global markets and vulnerability to uncertainty shocks. The acronym BRIC refers to the countries of Brazil, Russia, India and China, which are all deemed to be at a similar stage of newly advanced economic development. Despite the similarity, each country is unique in its economic development and relation with the U.S. In particular, China has grown to the second largest economy in the world and the U.S. and China have become the largest trading partners on earth. India has been growing consistently in the past decade and its relationship with U.S. has been intimate both economically and politically. In contrast, Russia and Brazil are trapped in economic turmoil in recent years, but nevertheless, are still closely related to U.S. economy via different channels. For China, large trade volume with U.S. ensures a major trade channel, but its relatively closed financial market partially shuts off the financial credit channel. For India and Brazil, due to their tight link with U.S. in both real and financial sectors, the channels are most likely a combination of both.

The effects of U.S. uncertainty shocks on BRIC real economies are again studied under the VAR framework. The variables include stock market index, short-term interest rate, CPI and real GDP.[19] In order to control for BRIC countries' domestic uncertainty, we also include their own policy uncertainty measures downloaded from Economic Policy

[19]The stock market indexes are Shanghai Composite Index for China, Bovespa for Brazil, MICEX for Russia and SENSEX for India. These series are obtained from Bloomberg.

Uncertainty website.[20] All other macro variables are obtained from the IMF. Due to data limitations, we only have a complete set of variables since 2002 for China, 1995 for Brazil, 1997 for Russia, and 2003 for India. All series are again detrended by the HP filter. The variables in the VAR are ordered as follows:

$$\begin{bmatrix} \text{log(Stock Market Index)} \\ \text{log(BRIC EPU)} \\ \text{U.S Uncertainty} \\ \text{Interest Rate} \\ \text{log(CPI)} \\ \text{log(Real GDP)} \end{bmatrix}$$

We estimate separate VAR models for each and report the country-specific response of real GDP to U.S. uncertainty shock. Figure 3.6 shows that both China and Russia's real GDP drop immediately after U.S. uncertainty shocks and the recovering pattern is similar to that of U.S. For example, one standard deviation of U.S. uncertainty shock results in an immediate decline in Chinese real GDP by about 0.2%. However, both countries have less significant rebound comparing to U.S. As for China, there is a small, second round dip three years after the shock. Following U.S. uncertainty shocks, Brazil's real GDP shows a quick, insignificant rebound after the initial dip, but drops and recovers similarly as other countries. For India, however, we do not see any significant impact. One important caveat is in order. The insignificant impacts on Brazil and India might be due to relatively short time series. To increase the number of observations, we apply panel VAR to the pooled dataset for all BRIC countries and report the impulse response function in Figure 3.7. After controlling for country-specific uncertainty, real GDP on

[20] Choi and Shim (2017) find much smaller effect of policy uncertainty shocks than financial uncertainty shocks on BRIC countries. In a different exercise, we use realized stock price volatility as a control for BRIC countries' own uncertainty. Both country-specific and panel VAR results are similar to those using the policy uncertainty.

average displays an immediate drop following U.S. uncertainty shock and then recovers after 4 quarters. Both the magnitude and recovery time are similar to the U.S. domestic case we have seen earlier, highlighting the significant spillover effect of U.S. uncertainty to emerging market economies.[21]

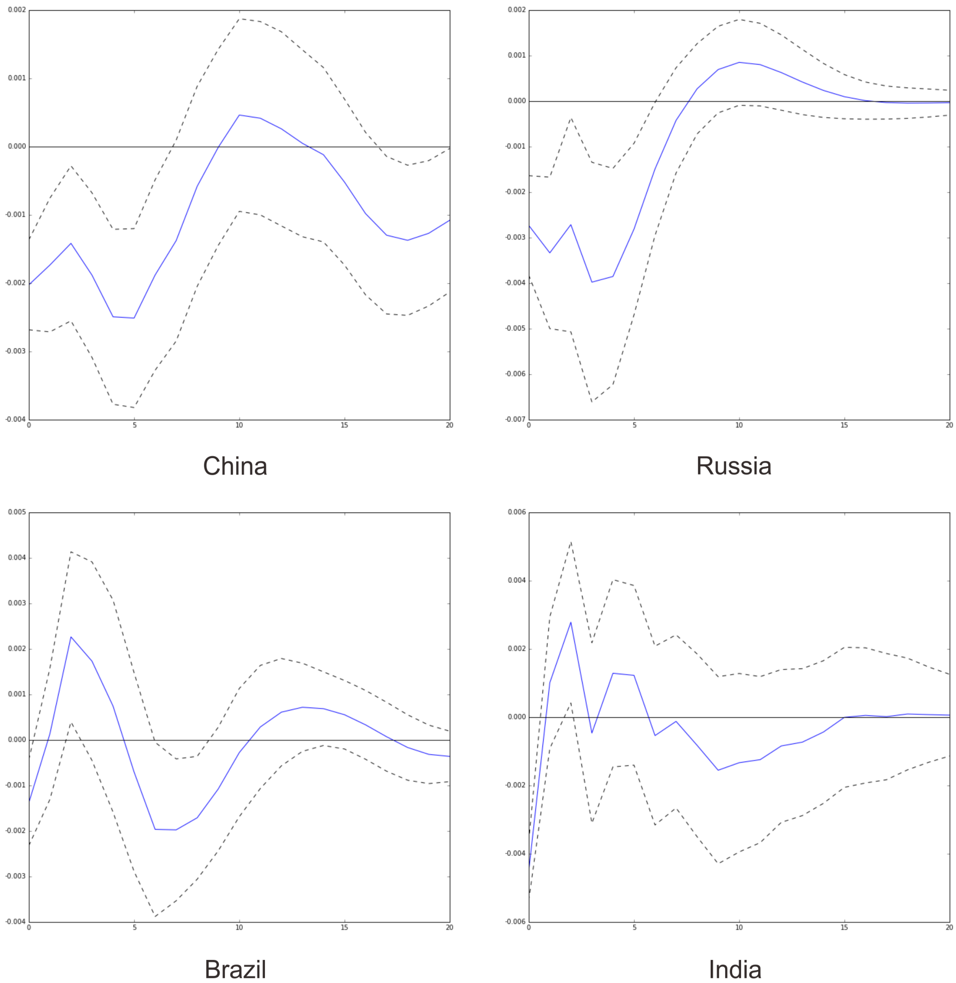

Figure 3.6: Response of Real GDP in BRIC Countries to U.S. Uncertainty Shocks (64% Confidence Interval)

[21]The graphs in Figure 3.6 and 3.7 show the results when local uncertainty is placed *before* U.S. uncertainty. We repeat the analysis when local uncertainty is placed *after* U.S. uncertainty. These two sets of graphs are very similar.

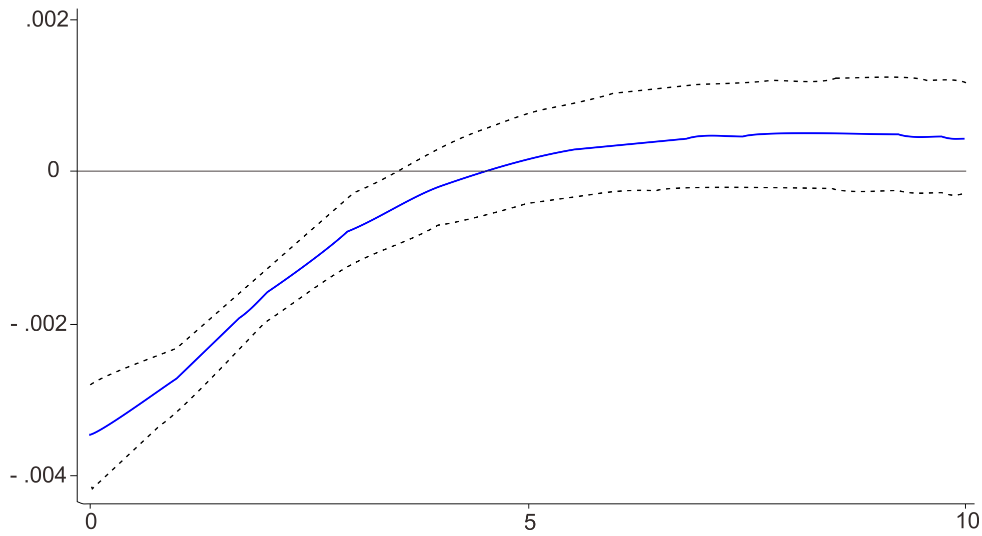

Figure 3.7: Average Impact of U.S. Uncertainty Shocks on Real GDP in BRIC Countries (64% Confidence Interval)

3.3 Conclusion

Taking advantage of the unique dataset on density forecasts of output growth, we propose a direct measure of macro uncertainty as the common variation in perceived uncertainty by professional forecasters. Our uncertainty measure is (i) an ex-ante measure that does not require the knowledge of realized outcomes and (ii) a subjective measure that does not have to be tightly linked with fluctuations in the objective volatility. We calculate expert' uncertainty as the variance of the fitted distribution by fitting the generalized beta distribution with supports determined by individual forecast values to each histogram. We choose the generalized beta distribution since it provides the best results in terms of goodness of fit, consistency with point forecasts, forecast accuracy and variance consistency.

The links between our measure and other popular uncertainty proxies are carefully examined in this chapter. We find a low, albeit significant, relationship between disagreement and macro uncertainty, implying that much of the movement in our measure is driven by the volatility of aggregate shocks, rather than heterogeneity across forecasters. The low correlations with other popular uncertainty indexes such as VIX, EPU, JLN and OS suggest that much of their variation is not driven by perceived macro uncertainty. The short-term (i.e. one-year ahead) macro uncertainty experiences spikes during recessions, presidential elections and wars, and is closely related to oil price volatility and currency volatility.

We explore the impact of macro uncertainty on real economic activities in a VAR framework both for the U.S. and BRIC countries. Within the U.S., the results are consistent with Bloom (2009) and Jurado et al. (2015) in that we see both the significant effect on industrial production and unemployment within a year and the small rebounds afterwards. For BRIC countries, we observe a persistent decline in real GDP for Russia and China but mostly insignificant effects for Brazil and India. Taking four countries together, the uncertainty shocks originated in the U.S. significantly affect their output growth through various channels, even after controlling for their own country-specific uncertainty shocks.

APPENDIX A

WHICH DISTRIBUTION TO USE?

This appendix is a supplement to chapter 3. It discusses and compares different parametric distributions in fitting probability forecasts.

A.1 Data and Choices of Parametric Distributions

The dataset used for this experiment is a subsample of real GDP growth forecasts from the U.S. Survey of Professional Forecasters (SPF). This subsample contains 2456 probability forecasts for "current year" output growth from 1992Q1 to 2009Q2. Survey participants assign probabilities to current-year output growth into the following intervals: $[6, \infty)$, $[5, 5.9]$, $[4, 4.9]$, $[3, 3.9]$, $[2, 2.9]$, $[1, 1.9]$, $[0, 0.9]$, $[-1, -0.1]$, $[-2, -1.1]$, $(-\infty, -2]$. We focus on this sample for two reasons. First, the SPF maintainer has changed in 1990Q2 - from the ASA/NBER to the Philadelphia Fed. Second, the survey structures, including both the number of bins and the length of bins, have undergone many changes before 1992 and after 2009. This subsample is the longest sample that is free of these structural inconsistency. In addition, all of the rounding issues in this subsample are minor and carefully fixed. None of these 2456 observations during this survey period are deleted. The lower and upper bound for the open intervals are set at -5 and 9, respectively.

The choice of parametric distributions is critical for studies using SPF density forecasts. However, the literature has no standard methodology. Without clear guidance, we conduct the experiment with four different distribution settings on the above subsample. We choose normal distribution as the baseline. As is well known, normal distribution cannot deal with asymmetry, which is quite common in the SPF survey. As an alternative, we experiment with beta distribution due to its flexibility to match the irregular and highly skewed empirical distribution in the data. We use two different versions of beta distribution. The first version is generalized beta with fixed support, where the support is individually determined by the two endpoints of bins that have positive probability values. If the open interval is used, the bounds are set at the historical maximum or minimum. The second version simply allows the maximum likelihood estimation to determine all four parameters, including the location and scale parameters. Finally, we include triangle distribution, as originally introduced by Engelberg et al. (2009). Although the authors mention that choosing such a distribution to fit the density forecast with less than three bins is due to software limitation, this method has been adopted by many researches afterwards; see, e.g. Clements (2014) and Clements and Galvao (2017). The triangle distribution basically fits an isosceles triangle to two adjacent bins. So far as the two bins are not assigned equal probabilities, part of the support for the bin with a lower probability is removed.

In summary, we fit four different settings to each of 2456 density forecasts: (i) normal distribution with no parameter constraint, e.g. Giordani and Söderlind (2003), (ii) generalized beta distribution with no parameter constraint, (iii) generalized beta distribution with supports determined by individual forecast values, and (iv) combination of generalized beta distribution for three bins and more, and triangle distribution for the rest, e.g. Engelberg et al. (2009).

A.2 Comparing Parametric Fitting Results

We evaluate the performance of each setting in terms of (1) goodness of fit, (2) consistency with point forecast, (3) forecast accuracy and (4) variance consistency.

A.2.1 Goodness of Fit

For goodness of fit, we assess how well those parametric distributions mimic observed empirical ones by studying their mean/median forecasts and entropy ratios.

By comparing values of mean and median from our fitting results with the true ones, we are able to see whether parametric fitting leads to biased estimation. Although the data do not offer the exact number for "true" mean or median, they provide interval values. The range for the "true" mean can be obtained by assuming that all forecast values within each bin have a mass at one of the two endpoints. For instance, given the following probability forecast,

< -2	$-2-0$	$0-2$	$2-4$	$4-6$	> 6
0	10	30	40	20	0

the range for "true" mean is $[1.4, 3.4]$. The range for "true" median can also be obtained from the data by locating the interval that contains the 50th percentile value, which is $[2, 4]$ in this example. If the median falls in the middle of two adjacent bins, we construct an interval of the same length around the median point.

Table A.1 shows the number of means and medians from fitting result that lies inside and outside the range of true mean and median in the sample. The beta distribution with fixed support (i.e. Fix Beta) and the combination of beta and triangle distributions (i.e. Fix Beta+Tri) show the best performance. Normal distribution gives many median values outside the range due to apparent data skewness issues. Among all 2449 non-missing observations, only 422 appear symmetric. In addition, among all 519 observations with positive probabilities assigned to two bins, only 50 have equal probability. As a symmetric distribution, the triangle distribution seems not a good choice for the remaining 469 skewed distributions.

Table A.1: Goodness of Fit

FITTING	Fix Beta+Tri	Fix Beta	Free Beta	Normal	Point Forecast
Inside Median Interval	2210	2211	2209	2195	2059
Outside Median Interval	239	238	240	254	361
Missing	7	7	7	7	36
Inside Mean Interval	2449	2449	2414	2449	1922
Outside Mean Interval	0	0	35	0	498
Missing	7	7	7	7	36

An alternative measure for goodness of fit is entropy ratio. Expression of Shannon Entropy for discrete cases is:

$$\text{Entropy} = -\sum_k p_k log_2 p_k,$$

where k is the number of dimensions of the outcomes and p_k is the probability associated with outcome k of a random variable. For continuous cases, Shannon Entropy becomes

$$\text{Differential Entropy} = -\int_s f(x) log_2 f(x) d\mu(x),$$

where $f(x)$ is the density function and it integrates through the entire support s of a random variable X. In our study, the advantages of using entropy are twofold: (i) it does not depend on realized outcomes but only on probabilities associated with them; and (ii) it does not require information regarding the sub-distribution within each bin.

Taking advantage of these properties of entropy, we propose an entropy ratio to measure the goodness of fit for each distribution. The intuition is straightforward. If the correct parametric distribution is used to fit the data, then the differential entropy should be close to the entropy of the data. Using the inappropriate parametric distribution adds spurious information and thus increases uncertainty and entropy. To this end, we define the mean entropy ratio (MER) as:

$$MER = \frac{-\sum_n \int_s f(x|\boldsymbol{\theta}) log_2 f(x|\boldsymbol{\theta}) d\mu(x)}{-\sum_n \sum_k p_k log_2 p_k},$$

where k is the dimension of the used bins; s is the true support; $f(x|\boldsymbol{\theta})$ is the assumed parametric distribution with parameters $\boldsymbol{\theta}$ estimated from MLE; n is the number of observations in the data and it is canceled out in the equation; μ is a proper measure of x. The entropy ratios for all parametric fitting distributions are shown in Table A.2.

Table A.2: Entropy Ratio

Fitting choice	Fix Beta+Tri	Fix Beta	Free Beta	Normal
Mean Entropy Ratio	1.08	1.16	4.05	1.18

Each differential entropy associated with a parametric distribution is higher than the entropy of the data. Except for the beta distribution with no parameter constraint (i.e. Free Beta), all other three distributions provide similar mean entropy ratio values, slightly larger than 1. However, the smaller ratio from the mixed strategy is largely due to the support cut-off by the isosceles triangle distribution rather than the closeness between data and fitted results.

A.2.2 Consistency with Point Forecast

Besides real GDP probability forecasts, the SPF survey also contains panelists' point forecasts. Although the survey provides no information regarding how professionals connect their probability forecasts with point forecasts, it is natural to assume that point forecasts are the mean, median or mode of their corresponding probability forecasts. Here, we assess the performance of each distribution by comparing the central tendency of density forecasts with point forecasts.

The point forecasts in the SPF take the form of levels instead of growth rates. In order to convert these level forecasts into growth rate forecasts such that they are comparable to those from probability forecasts, it is essential to use the information available to professionals when they made forecasts. Using real-time data from the Philadelphia Fed, we obtain point forecasts in terms of real GDP growth rate.[1] To measure the distance of the point forecast from the mean or median value of the probability forecast, we define

$$D_i = |F_i^{point} - F_i^{mean\ or\ median}|$$

at the individual level. We then conduct paired t tests to see if the values of a parametric distribution are systematically different from another.

Table A.3 shows both one-sided and two-sided test results. Suppose that the point forecast is the mean of probability forecast, normal distribution performs slightly better than others, and beta distribution without parameter constraint is substantially worse. Suppose that the point forecast is the median of probability forecast, then the combination strategy gives the best results. Beta distributions with fixed support give balanced results in both cases. It is worth noting that all these test results are conditional on the

[1] The last column in Table A.1 shows the number of cases where point forecasts are inside the true mean and median intervals of their probability forecasts. More than 85% of all point forecasts lie inside the bounds for the mean and 80% for the median. These results are consistent with those in Engelberg et al. (2009).

preassumed relationship between point forecast and probability forecast. For this reason, the evidence provided here should be interpreted with caution.

Table A.3: Relationships between Point Forecast and Probability Forecast

Based on Mean of Probability Forecast

Comparison Group	Two-Sided t Test	One-Sided t Test
Normal vs. Fix Beta	$Mean(D_n - D_{xb}) = -0.008\% ***$	$D_n < D_{xb} ***$
Normal vs. Free Beta	$Mean(D_n - D_{fb}) = -0.008\% ***$	$D_n < D_{fb} ***$
Normal vs. Fix Beta + Tri	$Mean(D_n - D_{bt}) = -0.006\% ***$	$D_n < D_{bt} ***$
Fix Beta vs. Free Beta	$Mean(D_{xb} - D_{fb}) = -0.066\% ***$	$D_{xb} < D_{fb} ***$
Fix Beta vs. Fix Beta+Tri	$Mean(D_{xb} - D_{bt}) = 0.001\% ***$	$D_{bt} < D_{xb} ***$
Free Beta vs. Fix Beta+Tri	$Mean(D_{fb} - D_{bt}) = 0.068\% ***$	$D_{bt} < D_{fb} ***$

Based on Median of Probability Forecast

Comparison Group	Two-Sided t Test	One-Sided t Test
Normal vs. Fix Beta	Not Significant	Not Significant
Normal vs. Free Beta	$Mean(D_n - D_{fb}) = -0.064\% ***$	$D_n < D_{fb} ***$
Normal vs. Fix Beta + Tri	$Mean(D_n - D_{bt}) = 0.005\% ***$	$D_{bt} < D_n ***$
Fix Beta vs. Free Beta	$Mean(D_{xb} - D_{fb} = -0.065\% ***$	$D_{xb} < D_{fb} ***$
Fix Beta vs. Fix Beta+Tri	$Mean(D_{xb} - D_{bt}) = 0.004\% ***$	$D_{bt} < D_{xb} ***$
Free Beta vs. Fix Beta+Tri	$Mean(D_{fb} - D_{bt}) = 0.069\% ***$	$D_{bt} < D_{fb} ***$

A.2.3 Forecast Accuracy

The third criterion is to check forecast accuracy based on the mean/median generated from different parametric distributions. We define the squared forecast errors as

$$SE_{it} = (F_{it} - A_t)^2,$$

where F_{it} is the forecast made by agent i at time t and A_t is the actual value. As is well known, the NIPA data, such as real GDP, often go through serious revisions. Here, we choose the so-called "final" estimates, which are released roughly three months after the end of the quarter. We believe that this vintage is the appropriate series to use because it is based on relatively complete data, but is still roughly contemporaneous with the forecasts we are analyzing. We use both the mean and median from each of four distributions to calculate two different squared forecast errors. We conduct another round of paired t-tests to see if the forecast accuracy from one distribution is statistically different from another.

Table A.4 shows the test results. Interestingly, normal distribution dominates in terms of accuracy regardless of using mean or median, but the margins are very small compared to beta distribution with fixed support and the combination strategy. Beta distribution without parameter constraint, however, yields the least satisfactory results.

Table A.4: Forecast Accuracy Comparison

Squared Forecast Error based on Mean of Probability Forecast

Comparison Group	Two-Sided t Test	One-Sided t Test
Normal vs. Fix Beta	$Mean(SE_n - SE_{xb}) = -0.012***$	$SE_n < SE_{xb}***$
Normal vs. Free Beta	$Mean(SE_n - SE_{fb}) = -0.567***$	$SE_n < SE_{fb}***$
Normal vs. Fix Beta + Tri	$Mean(SE_n - SE_{bt}) = -0.013***$	$SE_n < SE_{bt}***$
Fix Beta vs. Free Beta	$Mean(SE_{xb} - SE_{fb}) = -0.554***$	$SE_{xb} < SE_{fb}***$
Fix Beta vs. Fix Beta+Tri	Not significant	Not significant
Free Beta vs. Fix Beta+Tri	$Mean(SE_{fb} - SE_{bt}) = 0.554***$	$SE_{bt} < SE_{fb}***$

Squared Forecast Error based on Median of Probability Forecast

Comparison Group	Two-Sided t Test	One-Sided t Test
Normal vs. Fix Beta	$Mean(SE_n - SE_{xb}) = -0.011***$	$SE_n < SE_{xb}***$
Normal vs. Free Beta	$Mean(SE_n - SE_{fb}) = -0.562***$	$SE_n < SE_{fb}***$
Normal vs. Fix Beta + Tri	$Mean(SE_n - SE_{bt}) = -0.0053*$	$SE_n < SE_{bt}*$
Fix Beta vs. Free Beta	$Mean(SE_{xb} - SE_{fb}) = -0.551***$	$SE_{xb} < SE_{fb}***$
Fix Beta vs. Fix Beta+Tri	$Mean(SE_{xb} - SE_{bt}) = 0.006***$	$SE_{bt} < SE_{xb}***$
Free Beta vs. Fix Beta+Tri	$Mean(SE_{fb} - SE_{bt}) = 0.558***$	$SE_{bt} < SE_{fb}***$

A.2.4 Variance Consistency

The last criterion we consider is to check consistency in the estimated variances (i.e. uncertainty) from different parametric distributions. At 3- and 4-quarter ahead, all four settings give similar levels and dynamics of perceived uncertainty. At shorter horizons, however, the combination of beta and triangle distributions results in substantially higher level of perceived uncertainty than the other three, and these differences are statistically significant on average.[2] A further investigation shows that these elevated uncertainty estimates are solely due to the triangle distribution when fitted into two bins or less. This finding casts doubt on using the triangle distribution to measuring uncertainty in density forecasts.

A.3 Conclusion

To conclude, among four different settings, the second setting, i.e. generalized beta distribution with no parameter constraint, performs the worst in terms of goodness of fit, consistency with point forecast and forecast accuracy. For the remaining three settings, normal distribution gives many median values outside the range due to its inability to deal with asymmetric probability forecasts. The combination strategy fails to give consistent variance estimates because the triangle distribution tends to overestimate the associated uncertainty. Therefore, the generalized beta distribution with supports determined by individual forecast values provides the most satisfactory results across all different criteria and is the most appropriate parametric distribution to fit the U.S. SPF density forecasts.

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[2]For brevity, these graphs are not reported here. They are available upon request.

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