The Measurement and Transmission of Macroeconomic Uncertainty: Evidence from the U.S. and BRIC Countries

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Abstract

We propose a new measure of macroeconomic uncertainty based on U.S. SPF density forecast dataset. Our uncertainty measure incorporates a rich information set, captures perceived uncertainty for economic agents and is an ex ante measure that does not require the knowledge of realized outcomes. We study the behavior of this uncertainty index and explore its impact on real economic activities within U.S. and for BRIC countries.

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1 Measuring Macroeconomic Uncertainty

1.1 Subjective Uncertainty and its Origin

One consensus among the large body of economic uncertainty literatures is that uncertainty is not directly observable and relies on proxies. However, the choice of proxy varies from study to study. In finance, model-based uncertain measure has been extensively studied by tracking 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 becomes an interchangeable notion of 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, Bloom, and Davis (2016). In macroeconomics, forecast error-based uncertainty measures have been proposed by Jurado, Ludvigson, and Ng (2015).

The contrasting approaches in those studies signify a potential inconsistency in the underlying notion of uncertainty. The discussion by Jaynes(1957)Jaynes (1957) regarding the development of probability theory inspires the thinking that current uncertainty study might as well follow two distinct directions: objective vs. subjective uncertainty. The 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 considered as ex-post or post-event uncertainty. Notable examples of ex post uncertainty include Jurado, Ludvigson,

[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 “Knigtian Risk” Knight (2012) or simply “the game of chance”.

and Ng (2015) and Ozturk and Sheng (2016). Both 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 uncertainties. They differ in that the former generates forecast based on statistical models and the latter uses expert forecasts directly. Despite these differences, they require the knowledge of realized values and give ex post measure of uncertainty.

In contrast, the 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 the probability 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 the implied volatility in the stock market, e.g. Bloom (2009). The implied volatility tracks the unobserved but perceived volatility of underlying securities based on the observed price of its derivatives, which is entirely determined by the expected future values of securities. The accuracy of implied volatility as an uncertainty measure, to a large extent, depends on the validity of underlying securities estimated by models such as Black and Scholes (1973) and is often driven by non-fundamental factors, such as risks. The second popular measure 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 measure is the policy uncertainty recently proposed by Baker, Bloom, and Davis (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, Ludvigson, and Ng (2015), among others.

In this paper we focus on the subjective side of uncertainty and study how economic agents "contemplate" the state of the economy. Recall that subjective uncertainty arises when agents are unsure about and impossible to infer the true state due to limited information. In order to formalize agents' complete understanding of an uncertain event, probability expression becomes a natural choice. The virtue of probability forecasts is that they contain not only perceived outcomes, but also the likelihood. Taking advantage of the unique dataset on density forecasts of output growth, we propose a new measure of macro uncertainty as the common variation in their uncertainty perceived by professional forecasters. 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.

1.2 Data Description and Parametric Fitting on Probability Forecasts

Out 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 records experts' predictions for GDP and inflation. We use 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 theory emphasizes the origin of uncertainty from real economic activities.[2] At each quarter, experts give their probability forecasts for both current and next year output growth in the form of histograms.

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

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 questionaires are sent out at the end of the first month of each quarter together with the BEA's advanced release in real GDP and so experts are aware of the values from last quarter when they make new forecasts.

After filtering out all missing values, we are left with 4639 observations. Each observation contains forecasts for "current year" and "next year" real GDP growth and thus we have a total of 9278 probability forecasts. About 15% of the 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.

The probability distributions in the SPF take the form of histograms. Several problems arise with such a format and prevent us from using these histograms directly for uncertainty estimation. First of all, experts assign probabilities to different bins. Once the continuous support is divided into adjacent bins, the support is no longer continuous and thus moment conditions cannot apply. Second, 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 have infinite (positive or negative) values. Finally, the histogram has no information regarding the distribution within each bin and poses significant challenges in deriving the variance.

To address the first problem, we use parametric methods to smooth out the polygonal empirical distribution. To close open intervals for more reasonable fitting results, we use either the minimum and maximum historical values or simply double the regular bin size, depending on the support variation associated with the survey periods. Finally, we use the uniform distribution for values 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 probability forecast. We fit parametric distributions to the combined sample and estimate the parameters by the maximum likelihood method. The estimation method used in this paper 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.

The choice of parametric distributions is critical for the studies using the SPF density forecasts. Yet, the literature reaches no consensus. While Giordani and Söderlind (2003) use normal distributions to fit the data, Engelberg, Manski, and Williams (2009) adopt a mixed strategy that fits generalized beta distributions to observations with more than 2 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 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 and more bins and triangle distribution for the rest, e.g. Engelberg, Manski, and Williams (2009). Figure 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.[3] Therefore, we fit the generalized beta distribution with support

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

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}.

1.3 Constructing 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, as shown in Figure 2 that 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 questionaires 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 variable 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 create one dummy for each forecaster. Specifically, we run the following regression:

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

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. Finally, we construct macro uncertainty index as the cross-sectional median of individual uncertainty values.[4] We do so for both current and next year, representing the short- and median-run uncertainty.[5] For easy comparison, we normalize the index between 0 and 1. We emphasize two features of these definitions: (i) our macro uncertainty 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; and (ii) it is an ex ante measure of macro uncertainty that does not require the knowledge of realized outcomes and is available in real time.

Figure 3 plots short-term uncertainty at one-year ahead and medium-term uncertainty at two-year ahead. The 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 predictable in 1990s and 2000s than 1980s. The macro uncertainty at the medium term is on average higher than its counterpart at the short term, consistent with our expectation, and has two largest spikes during Saudi Oil Glut and Post Iraq War periods.

Table 1 shows the correlation between our macro uncertainty and other uncertainty measures. Those measures include the VIX in Bloom (2009), the EPU by Baker, Bloom, and Davis (2016), the JLN index in Jurado, Ludvigson, and Ng (2015), forecast disagreement computed from the same dataset,

[4]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.

[5]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.

and the OS uncertainty in Ozturk and Sheng (2016). 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. The low correlations with both JLN and OS uncertainty indexes reflect the key difference between these measures: our measure captures the perceived uncertainty by market participants and 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 measure of uncertainty. The low correlations with the VIX and EPU can be explained by different targets of these measures: while our measure captures the economy-wide uncertainty, the VIX most likely reflects the uncertainty in the stock market and EPU emphasizes the policy aspect of uncertainty. To summarize, our uncertainty estimates display independent variations from other leading uncertainty proxies, suggesting that much of their variation is not driven by perceived macro uncertainty.

Figure 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 indexes reach their peaks during most of the recessionary episodes and remain low during expansions.

2 The Impact of Macro Uncertainty

2.1 U.S. Evidence

The impact of uncertainty shocks on real economic activities has been given some theoretical insights by Bernanke (1980) and Bloom (2009). There are also abundant empirical supports such as Romer (1988) and Jurado, Ludvigson, and Ng (2015), among others. Almost all studies find a negative effect of uncertainty shocks on real economic activities, but the persistence of those shocks is quite different from one uncertainty measure to another. 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, Ludvigson, and Ng (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 eight variables in the following order:

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

All monthly data are converted to quarterly to match the our macro uncertainty index. Following Bloom (2009), we detrend all series using HP filter with the smoothing parameter λ as 1600.[6] 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. The number of lags is set according to the information criterion.

Figure 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 eventually goes back to the initial value and rebounds slightly but insignificantly, unlike the

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

strong rebound shown by Bloom (2009). Following the uncertainty shock, the unemployment rate increases by about 5% immediately, recovers and rebounds insignificantly after ten quarters.

2.2 Evidence from BRIC Countries

While international trade substantially raises the efficiency of production as well as the variety of consumption goods worldwide, countries become more dependent and rely heavily on trades to maintain their consumptions as well as productions. With modern communication and transportation technologies, economic shocks in one country can quickly transmit to its trading partners. In addition, as many shocks in uncertainty are identified as conflicts or war related, the transmission of uncertainty shocks across countries becomes an important topic. The transmission of policy uncertainty among developed countries is discussed by Klößner and Sekkel (2014).

The spillover phenomenon of uncertainty shocks is especially true for the U.S., and the impact is also stronger than other countries. There are many reasons: (1). U.S consumption accounts for more than a quarter of world's consumption and a big portion of its consumption relies on imports. Since uncertainty shocks have negative effects on consumption spending, shrinks of U.S consumption following uncertainty shocks would bring demand problem to international producers; (2). U.S. locates at the top of production chain and thus it leads the world production in many areas. Such a role is not only reflected in the large amount of intermediate goods imports by U.S., but also seen in its outsourcing and offshore economy. A fall of U.S. production can easily transmit to its lower international suppliers, and slowdown offshore U.S companies; (3). U.S. has the largest economy in the world and its small economic fluctuation could be hard to digest by small economies.

In this paper, we focus on the transmission of U.S. economic uncertainty to BRIC countries. All those countries were given high hope in the past, but their performances in recent years are quite diversified. While China and India become the fastest growing economies in the world, Brazil and Russia are currently experiencing some hard time economically and politically. In addition, the relationship between U.S. and BRIC countries are quite distinct. Russia has been U.S. political and military rival since the mid-20th century and their tension is recently elevated by the civil war in Syria. China is currently the second largest economy in the world and is therefore considered U.S. biggest economic competitor. Although China has been U.S. largest trading partner for quite sometime, the huge difference in their political and value system has been preventing them from becoming allies. Brazil has been experiencing the worst economic recession in recent years and its trading volume with U.S. shrinks at an accelerating speed after China replaces U.S. as its largest trading partner. India has been U.S. loyal ally for a very long time and their economic relations are quite stable.

We study how U.S. uncertainty shocks affect real economic activities in BRIC countries. Included macro variables are stock market index, short-term interest rate, CPI and real GDP. Moreover, in order to control for those countries' domestic uncertainty, we also include their EPU series in the VAR.[7] All other macro variables are obtained from IMF database. Due to data limitations, we only have 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:

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

[7] 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 Global Financial Data and Yahoo Finance.

We estimate separate VAR models for each BRIC country and report country-specific response of real GDP to U.S. uncertainty shock. Figure 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. However, both countries has more insignificant rebound comparing to U.S. and China shows a small second round dip three year after the shock. Since China has been the largest trading partner of U.S. for quite long, the uncertainty transmission likely originates from economic section. However, since the economic cooperation between Russia and U.S. is quite rare, the drop of Russia real GDP after U.S. uncertainty shocks are more likely through the political tensions between the two countries. The response of Brazil real GDP shows a quick insignificant rebound after the initial dip but drop and recover similarly as other countries. For India, we do not see any significant impact of U.S. uncertainty on its real economic activities.

Although we see the general pattern in all BRIC countries, the relative short time series might be the main reason for the insignificant responses for Brazil and India. In order to improve the precision of our estimation, we apply panel VAR on the pooled dataset from all BRIC countries and report the impulse response function in Figure 7. After controlling for country-specific effect, the real GDP of all BRIC countries displays an immediate drop following U.S. uncertainty shock. Both the magnitude and recovery time are similar to the U.S. domestic case that we have seen earlier, again confirming the transmission of U.S. uncertainty shocks to BRIC countries.

3 Conclusion

In this paper we explore the semantic meaning of uncertainty and propose a direct measure for subjective uncertainty based on forecasts in probability format. Although parametric fitting on density forecast data has been experimented by other researchers, we are the first to provide empirical evidence for the parametric setting that gives optimal results. A subsample study of SPF data suggests that generalized beta distribution with support individually determined by the end points of each forecast returns better fitting results than all other settings experimented in the literatures. The macro uncertainty index is therefore computed by applying this fitting strategy on 9272 probability forecasts for real GDP growth.

The links between our uncertainty and other popular uncertainty proxies are carefully examined in this paper. We find a positive significant relationship between lagged disagreement and macro uncertainty, implying that high disagreement could potentially cause high subjective uncertainty. In addition, lagged forecast errors also have a positive and significant effect on macro uncertainty. The low correlations with other popular uncertainty indexes such as VIX, EPU, JLN and OS suggest that all uncertainty measures are significantly different from each other and each captures a certain aspect of the "big concept" of uncertainty. By matching the evolution of macro uncertainty index with historical shocking events, we find that our uncertainty index experiences spikes during recessions, presidential elections and wars.

The economic effect of macro uncertainty is studied in a VAR regression and the results are consistent with previous empirical work and theoretical models. The transmission of uncertainty in U.S. to BRIC countries is studied separately in a standard VAR model and for all countries together using the panel VAR framework. We find that uncertainty in U.S. will not only have significant domestic impact, but also transmit to BRIC countries through different channels.

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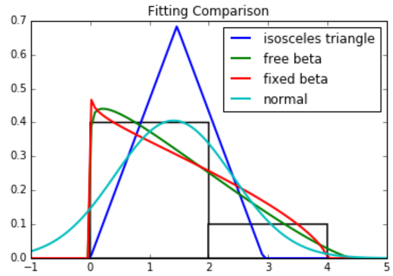
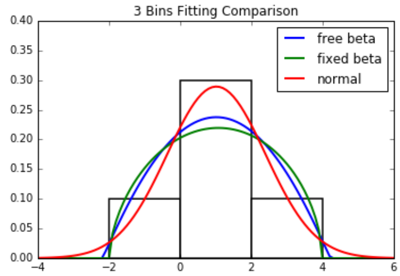
	DIS	VIX	EPU	JLN	OS
Macro Uncertainty	0.25***	0.27***	0.17*	0.30***	0.19*
DIS		0.25**	0.017	0.53***	0.42***
VIX			0.52***	0.66***	0.61***
EPU				0.31***	0.22***
JLN					0.82***

*** 1% ** 5% *10%

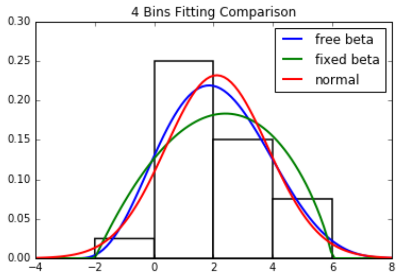
Table 1: Correlation among uncertainty measures



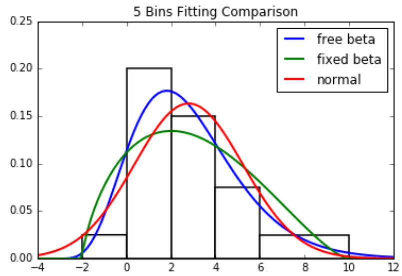
(a) Probability Forecast with 2 Bins



(b) Probability Forecast with 3 Bins



(c) Probability Forecast with 4 Bins



(d) Probability Forecast with 5 Bins

Figure 1: Parametric Fitting on Histograms Using Different Distributions

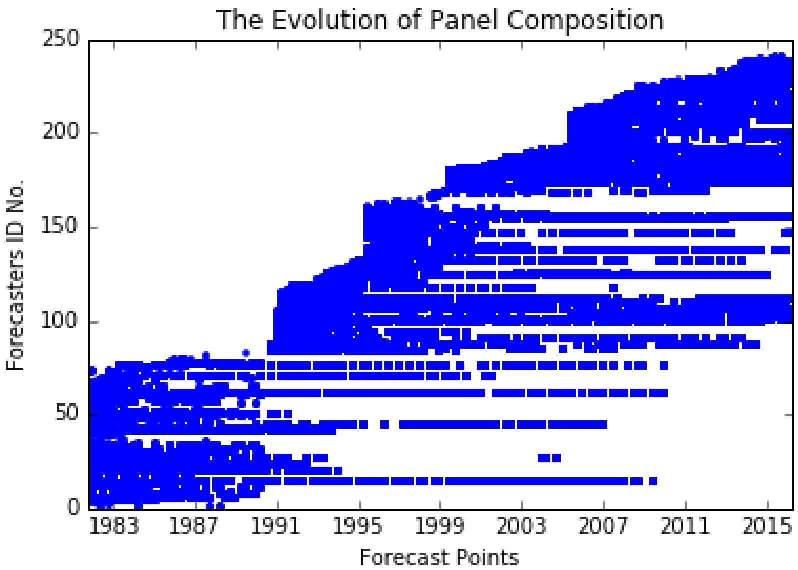


Figure 2: Panel Composition in the U.S. SPF

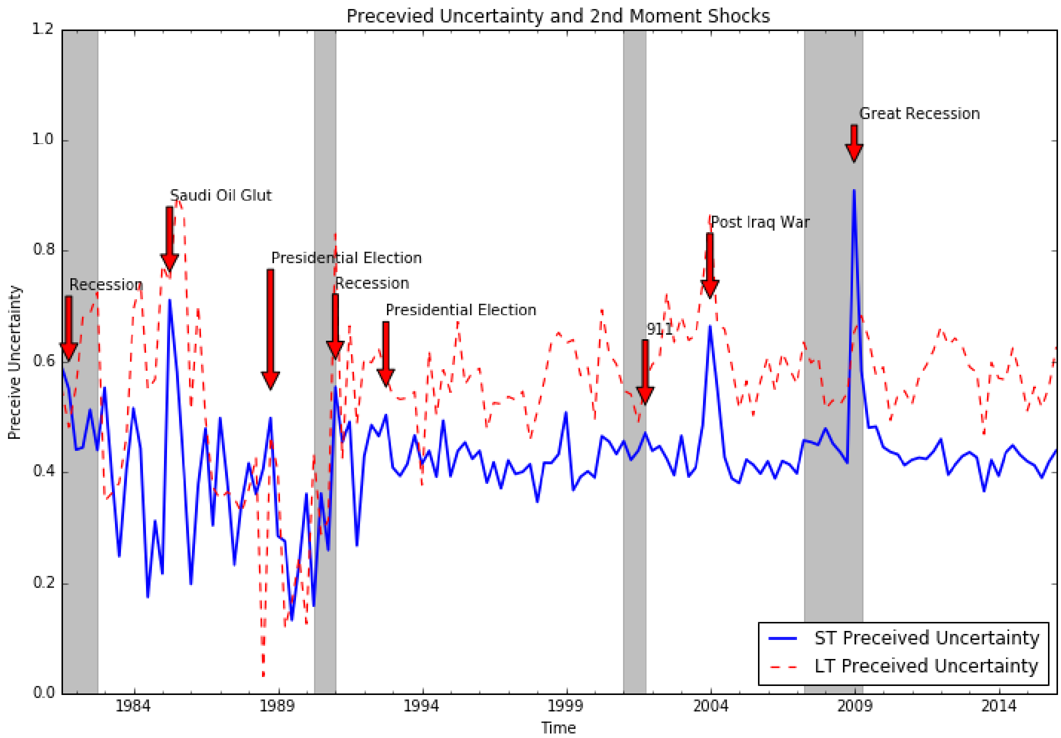


Figure 3: Short- and Medium-term Macro Uncertainty

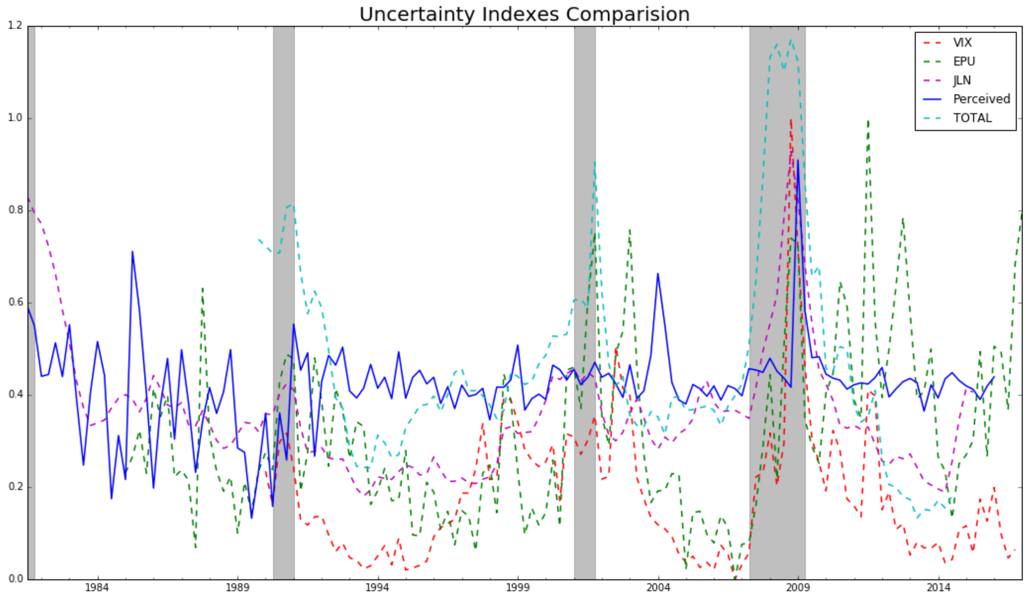
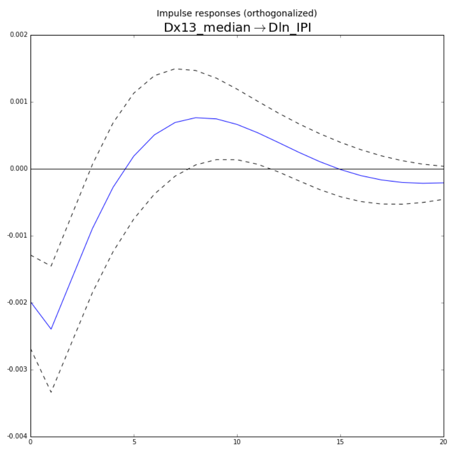
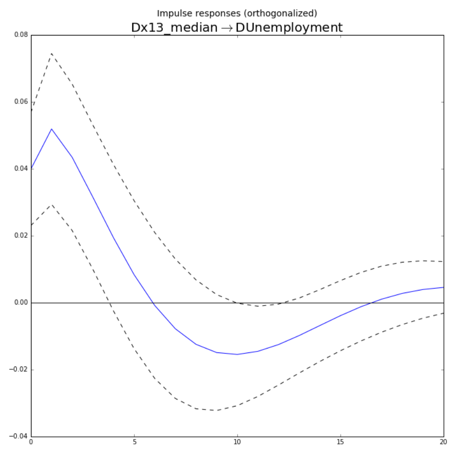


Figure 4: Comparison of Alternative Uncertainty Measures

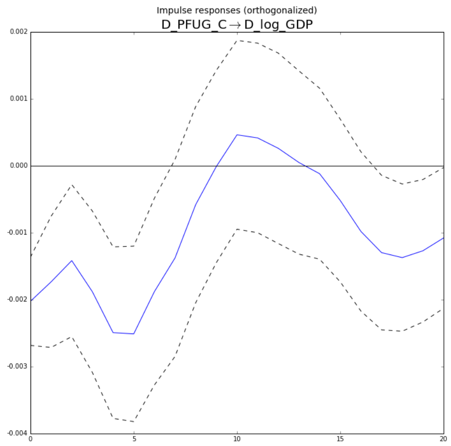


(a) IRF of Industrial Production

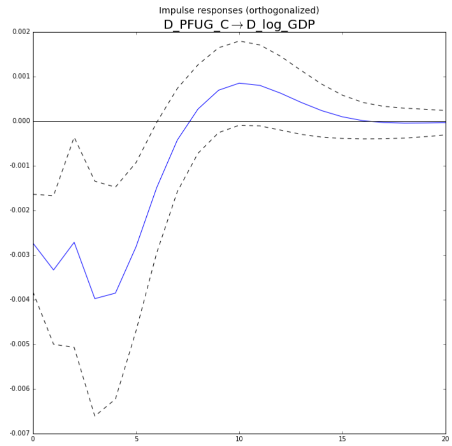


(b) IRF of Unemployment

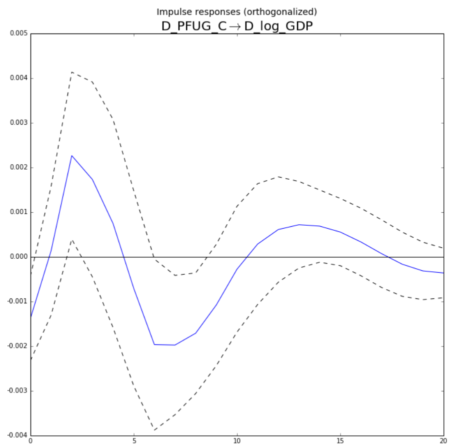
Figure 5: Response of Industrial Production and Unemployment to Macro Uncertainty



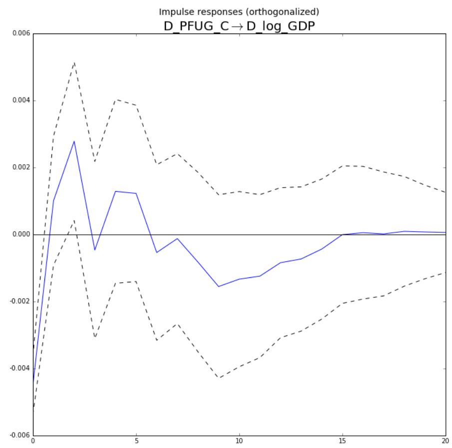
(a) China



(b) Russia



(c) Brazil



(d) India

Figure 6: Response of Real GDP in BRIC Countries to U.S. Uncertainty Shocks

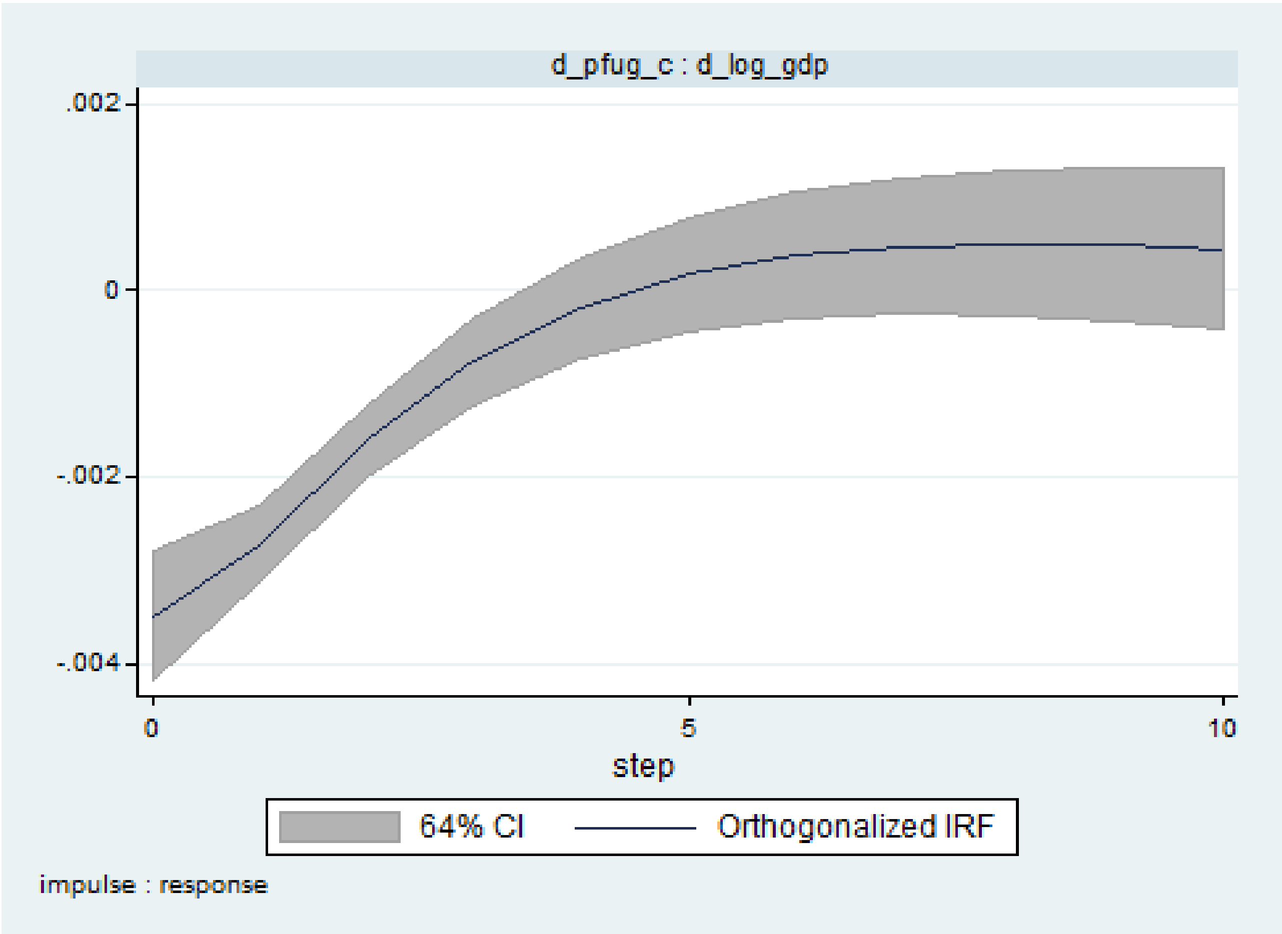


Figure 7: Average Impact of U.S. Uncertainty Shocks on Real GDP in BRIC Countries