

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

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Objective Uncertainty and its Origin

- Originates from the underlying structure of events which in nature generates outcomes in a stochastic manner.
- “Knightian Risk” or “the game of chance”.
- Irreducible by information and can be partially observed by examining post event outcomes.
- Ex-post or post-event uncertainty.
- Examples: Jurado et al (2015); Ozturk and Sheng (2016).
- Capturing objective uncertainty is still a challenge in Economics.

Subjective Uncertainty and its Origin

- Core idea of subjective school of probability theory -- regards the probability merely a formal expression of human ignorance.
- Exist when the true state is unknown. Caused by incomplete information.
- Examples: Implied volatility of financial instruments; Forecast disagreement (Lahiri and Sheng, 2010); Policy uncertainty (Baker, et al. 2016).

Measure of Subjective Uncertainty

- We propose a new measure of macro uncertainty as the common variation in the uncertainty perceived by professional forecasters.
- We emphasize two features of this definition:
 - I. Our uncertainty measure captures perceived uncertainty of economic agents. As such, it does not have to be tightly linked with the realized outcomes.
 - II. It is an ex ante measure of macro uncertainty that can be tracked in real time.

Data: Survey of Professional Forecasters (SPF)

Density Forecast

- Originally maintained by American Statistical Association and taken over by Philadelphia Fed in 1990Q2.
- We focus on the annual-average over annual-average percent change in real GDP, available since 1981Q3.
- Each survey reports two probability forecasts for “current year” and “next year” real GDP growth; a total of 9278 probability forecasts.

Data: Challenges

- Continuous support is discretized into adjacent bins and thus, standard statistics cannot be directly calculated.
- Two open intervals allows infinite positive or negative values.
- No information regarding the sub-distribution within each bin.

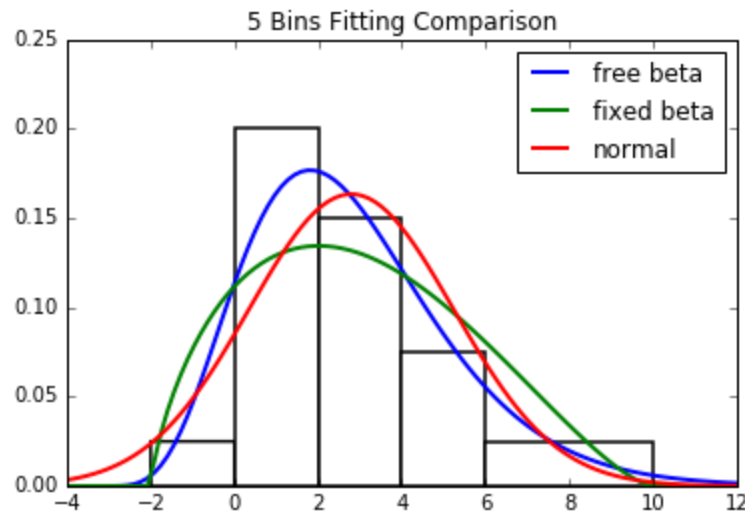
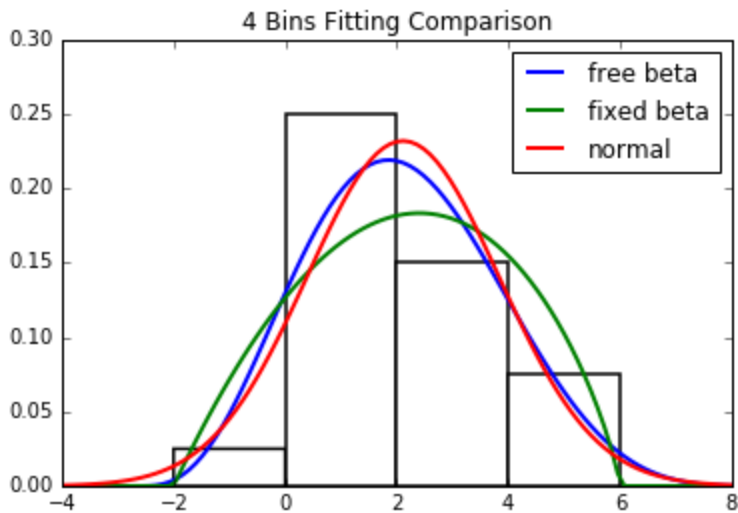
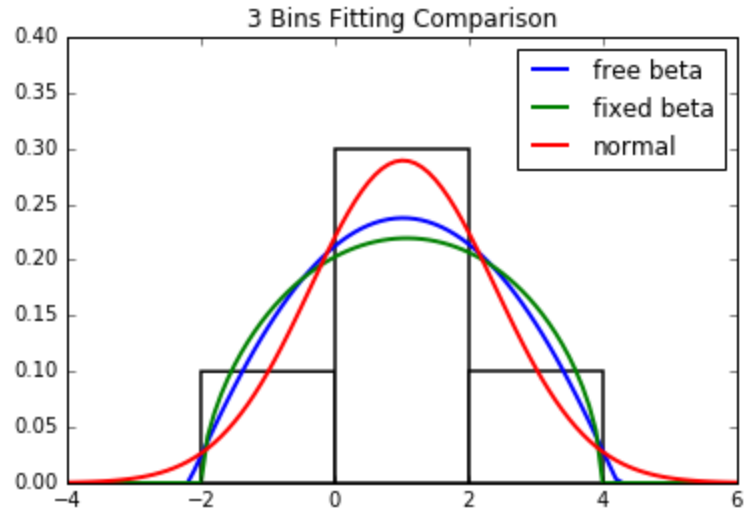
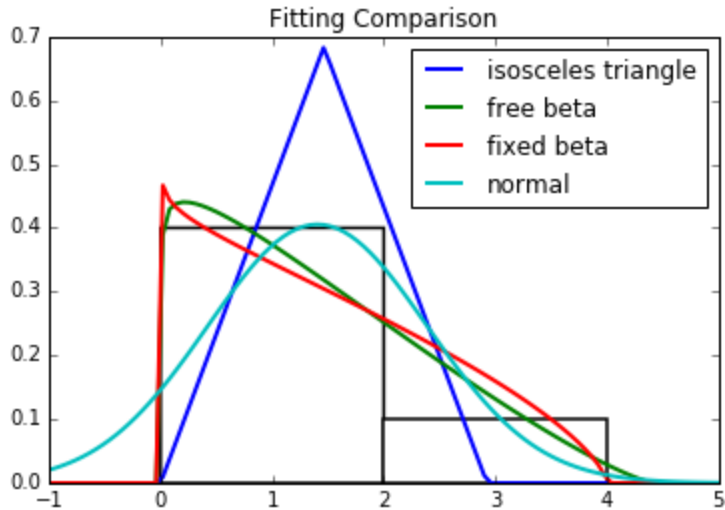
Data: Solutions

- We use parametric method to smooth out the polygonal empirical distribution.
- Open intervals are closed with “historical” maximum or minimum values (or extend with regular bin length).
- Within-bin sub-distributions are set to be uniform.
- For each forecast, we generate separate samples from uniform distributions. Then we combine these samples together to represent one probability forecast.
- The histogram from the combined sample looks exactly like the bar plots of the original probability forecast.

Data: Parametric Fitting

- The choice of parametric distributions is critical for the studies. Yet, the literature reaches no consensus:
 - Giordani and Soderlind (2003) use normal distribution.
 - Engelberg, Manski, and Williams (2009) adopt a mixed strategy that fits generalized beta to observations with more than 2 bins and isosceles triangle to the rest.
- We conduct the experiment with four different distributions:
 1. Normal Distribution.
 2. Generalized Beta with no constraint on all parameters.
 3. Generalized Beta with support determined by the end points of individual forecasts.
 4. Mixed strategy by following Engelberg, et al. (2009)

Data: Parametric Fitting



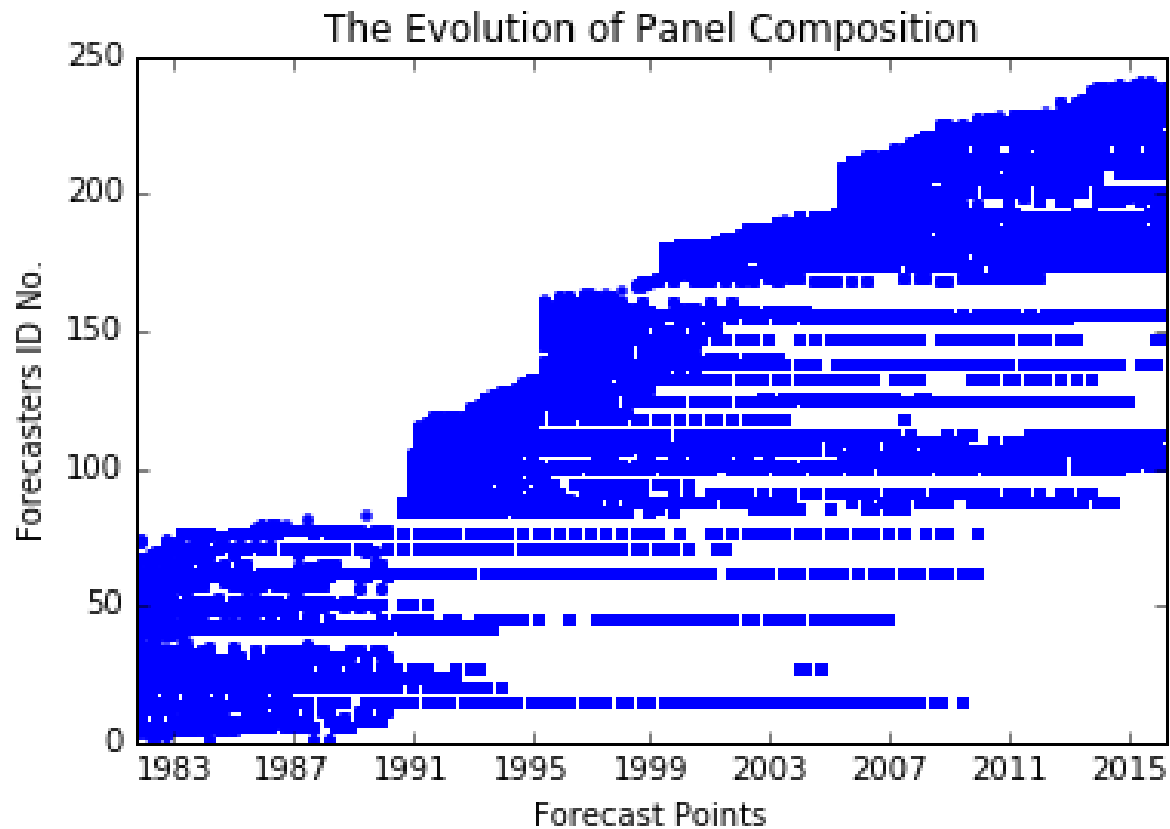
Data: Parametric Fitting Results

- We evaluate all four settings based on their performance in terms of goodness of fit, consistency with point forecasts, forecast accuracy, and variance consistency.
- We find that Generalized Beta with support determined by the end points of individual forecasts gives the best fitting results.
- We calculate the variance of each fitted distribution as expert i 's uncertainty at period t , denoted by U_{it} .

Constructing Macro Uncertainty Index

1. Seasonality: forecast horizons change from 8- to 1-quarter ahead and consequently, macro uncertainty becomes lower at shorter horizons.
2. Structural changes: survey experiences multiple structure breaks due to changes in survey format and maintainer.
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.
4. Measurement errors: wrong-target questions in 1985Q1, 1986Q1 and 1990Q2.

Constructing Macro Uncertainty Index



Constructing Macro Uncertainty Index

- To deal with structural change and panel composition, we regress

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

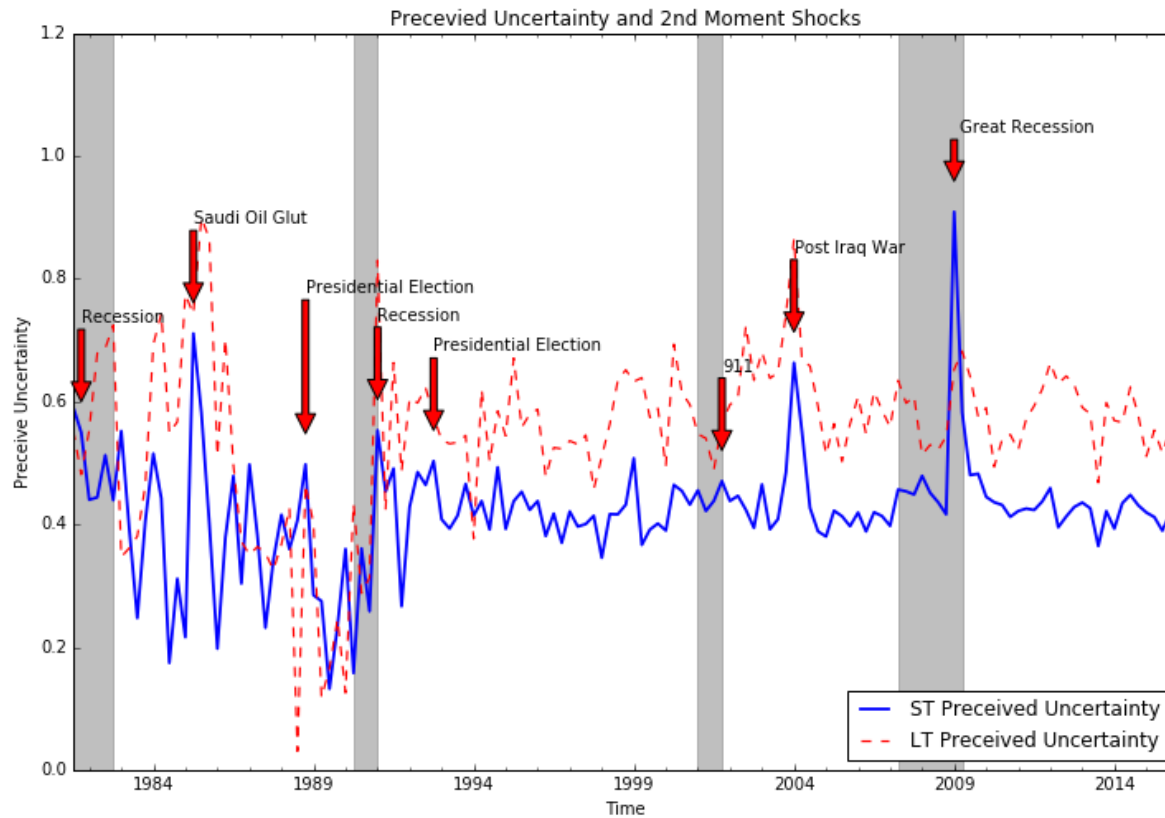
S - dummy variables controlling for different survey structures

P - dummy for the change in survey maintainers

F - a series of dummies for individual forecasters

- To remove seasonality, we perform X13 on the residual.
- We construct macro uncertainty index as the cross-sectional median of individual uncertainty values.
- We do so for both current and next year, representing the short- and median-run uncertainty.

Constructing Macro Uncertainty Index



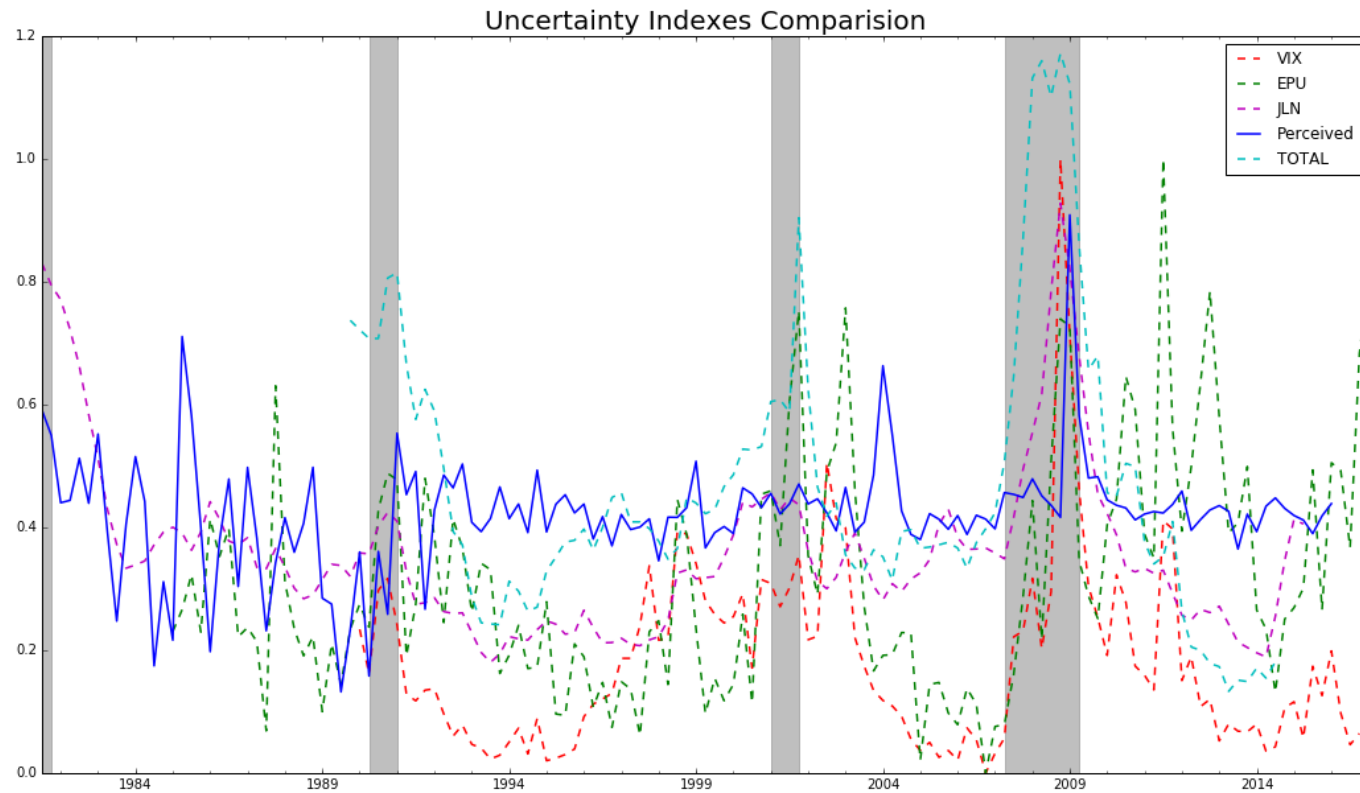
Comparing with Other Uncertainty Measures

	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

Comparing with Other Uncertainty Measures



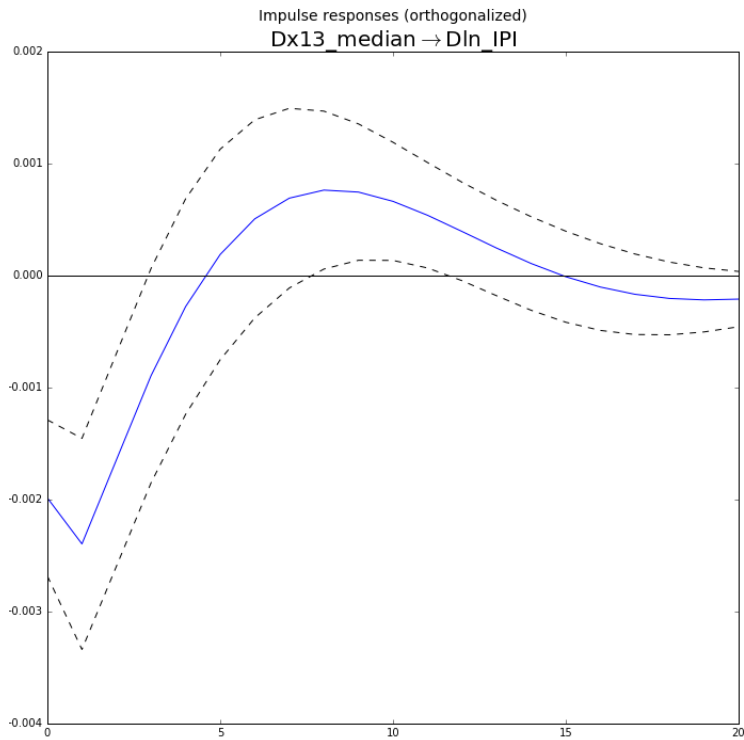
The Impact of Macro Uncertainty: U.S. Evidence

- The impact of Macro Uncertainty is examined in VAR:

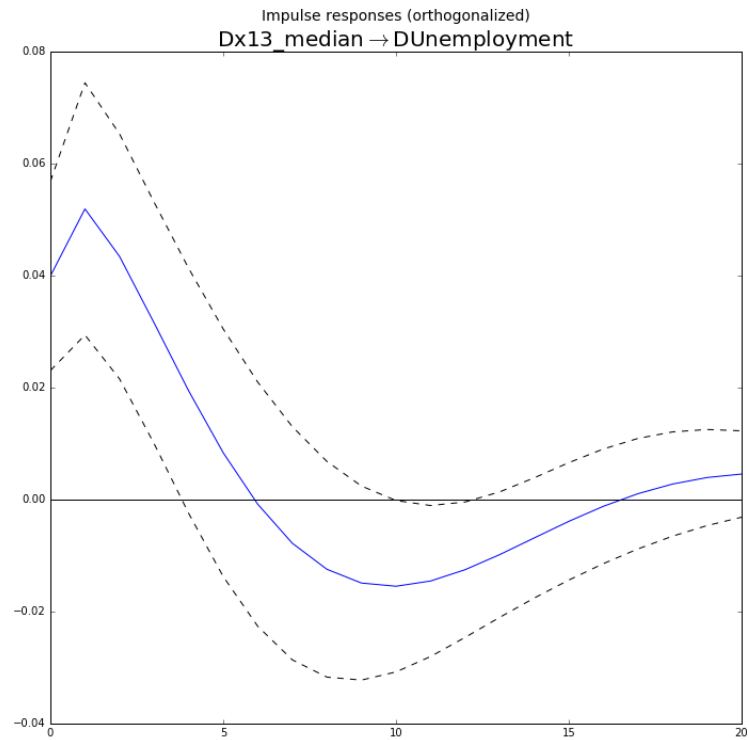
$$\begin{bmatrix} \log(\text{S\&P 500 Index}) \\ \text{Uncertainty} \\ \log(\text{Wage}) \\ \text{Federal Funds Rate} \\ \log(\text{CPI}) \\ \text{Unemployment Rate} \\ \log(\text{Industrial Production}) \end{bmatrix}$$

- All series are detrended by using HP filter.
- We use the original macro uncertainty series without defining uncertainty shocks.

The Impact of Macro Uncertainty: U.S. Evidence



Uncertainty impact on Industrial Production



Uncertainty impact on Unemployment

Transmission of Macro Uncertainty: BRIC Countries

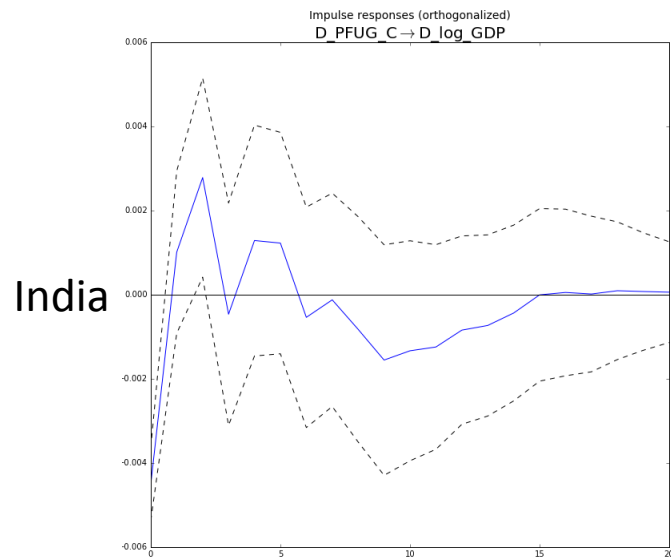
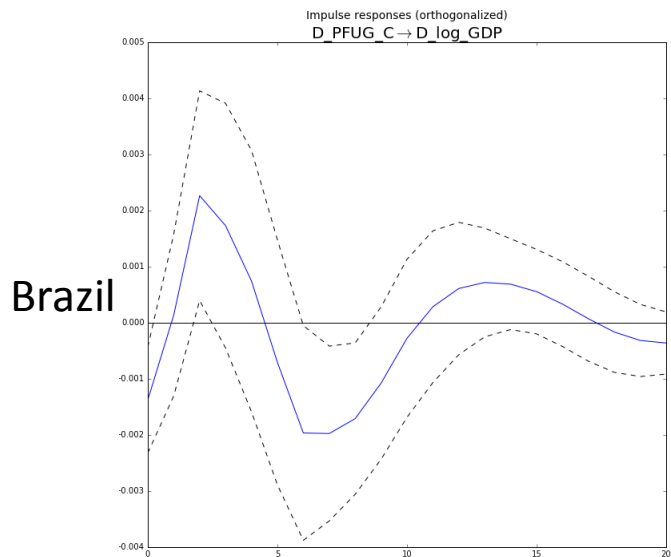
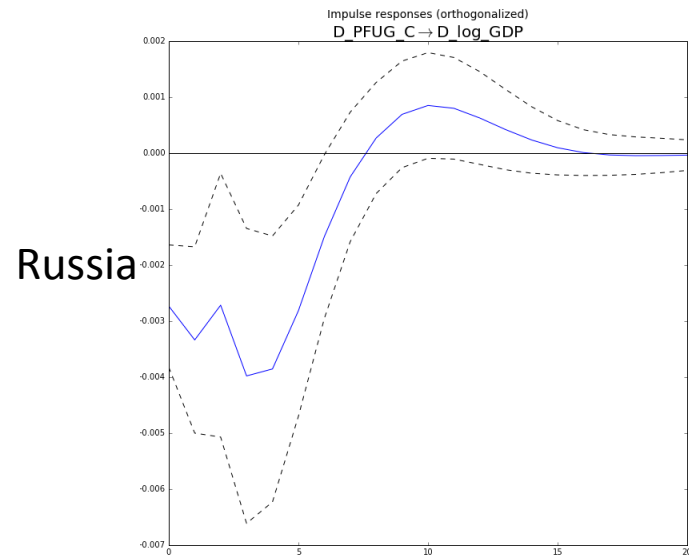
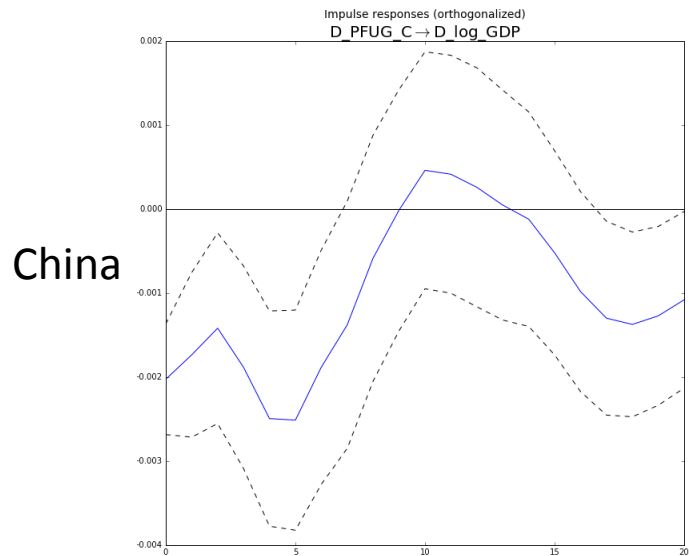
- Economic shocks in one country can quickly transmit to its trading partners with the help of modern communication and transportation technologies.
- The uncertainty “shockwave” is especially powerful for U.S. for many reasons, e.g. huge demand that largely depend on imports; leading technology in many industries and large-size outsourcing and offshore economy.

Transmission of Macro Uncertainty: BRIC Countries

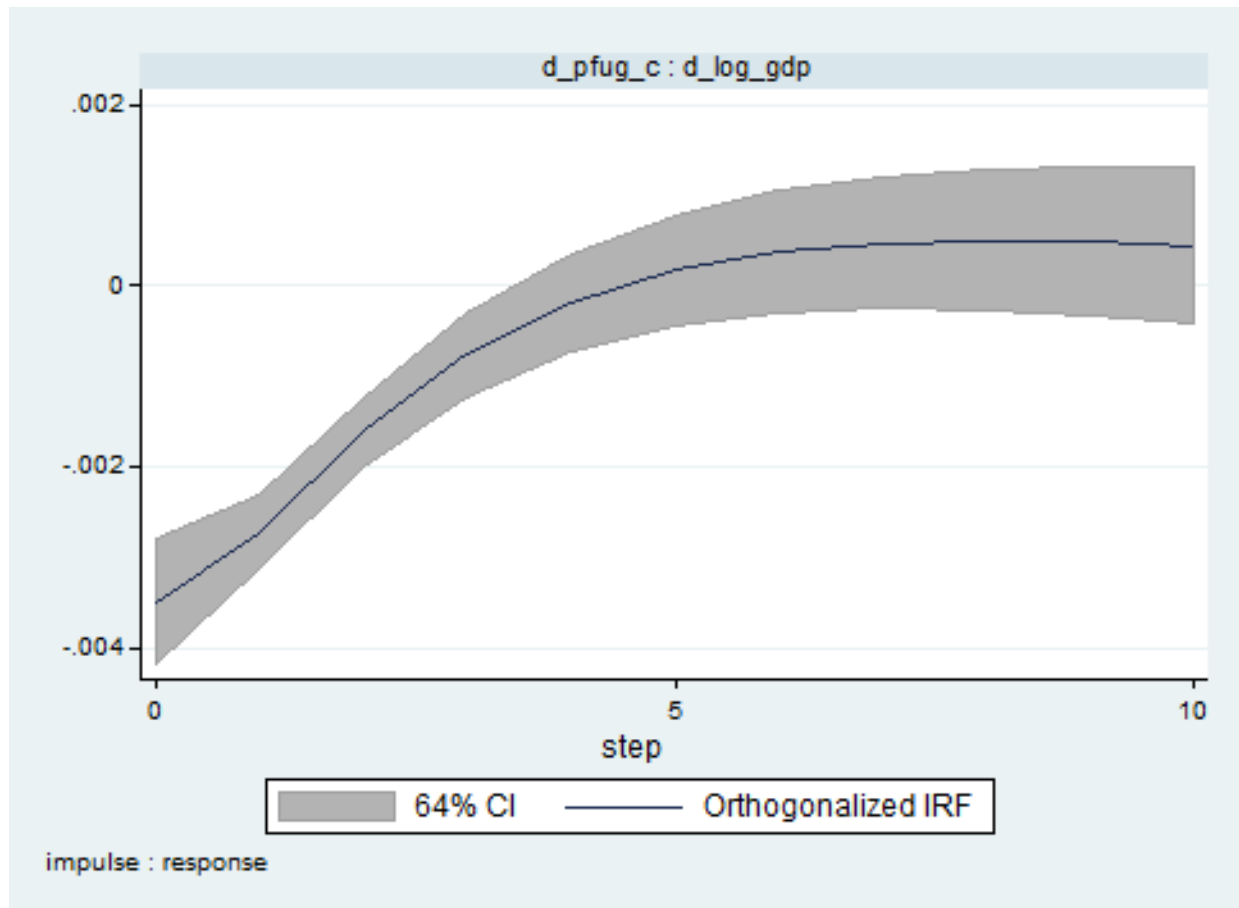
- The transmission of U.S. Macro Uncertainty to BRIC Countries is studied in separate VARs.
- We use Baker, et al. (2016)'s EPU to control for BRIC countries domestic uncertainty.

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

Transmission of Macro Uncertainty: BRIC Countries



Transmission of Macro Uncertainty: BRIC Countries



Conclusions

- We propose a new measure of macro uncertainty as the common variation in the uncertainty perceived by professional forecasters. Our uncertainty index displays independent variations from other leading uncertainty proxies, suggesting that much of their variation is not driven by perceived macro uncertainty.
- We find that U.S. macro uncertainty shocks not only slowdown its own economy, but also transmit to BRIC countries through various channels, and have similarly negative impacts on their economies, especially for China and Russia.
- We conduct a detailed analysis on the parametric fitting to density forecasts and find that the generalized beta distribution with individual support gives the best fitting results.