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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 that incorporates a 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; and (ii) it is an *ex ante* measure that does not require a 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 for BRIC countries.

1. Introduction

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

The contrasting approaches in those studies indicate a potential inconsistency in the underlying notion of uncertainty. Similarly to the philosophical differences in probability theory discussed by Jaynes (1957), uncertainty is multifaceted, and may be either 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 observed in part by examining post-event outcomes. In consequence, this type of uncertainty cannot be reduced by the use of additional information.[1] Since the observation of objective uncertainty requires a knowledge of event realizations, it is also known as ex-post or post-event uncertainty. Notable examples of ex-post uncertainty include the studies by Jurado et al. (2015), Jo and Sekkel (2017) and Ozturk and Sheng (2018). All papers define the uncertainty in predicting a single variable as the volatility of its forecast error, and measure macro uncertainty as the common component of the 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

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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 the players fully understand this structure, they are still not capable of predicting every toss correctly, 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".

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differences, they all require a knowledge of realized values and provide ex-post measures of the uncertainty.[2]

In contrast, subjective uncertainty regards uncertainty as a type of human feeling that is caused by limited information or stochastic factors. This notion is exactly the core idea of the 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, see e.g. Bloom (2009). Option prices reflect market participants' perceptions of the expected volatility in underlying securities. The accuracy of the implied volatility as an uncertainty measure depends to a large extent on the volatility of the underlying securities estimated by models such as that of 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 interpersonal dispersion is a good proxy for the intra-personal uncertainty. As was pointed out aptly by Lahiri and Sheng (2010), disagreement captures only one component of uncertainty and misses the other component: the volatility of aggregate shocks. Furthermore, the main source of disagreement might be heterogeneity among forecasters, rather than uncertainty. The third common measure of uncertainty is policy uncertainty, proposed by Baker et al. (2016) who 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.

This paper focuses on subjective uncertainty and studies the way in which economic agents "contemplate" the state of the economy. Recall that subjective uncertainty arises when agents have limited information about the true state. Thus, probability expression is a natural choice for formalizing agents' complete understanding of an uncertain event. 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 from the U.S. Survey of Professional Forecasters, 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 the perceived uncertainty for economic agents, meaning that it does not have to be linked tightly with fluctuations in the volatility of realized outcomes; and (ii) it is an ex-ante measure of macro uncertainty that does not require a knowledge of realized outcomes, and thus can be tracked in real time.

The rest of the paper proceeds as follows. Section 2 describes the dataset and compares the performances obtained by fitting various parametric distributions to density forecasts. Section 3 discusses the construction of the macroeconomic uncertainty index and examines its properties. Section 4 explores the impact of uncertainty shocks on real economic activities both within the U.S. and across BRIC countries. Section 5 concludes. Additional discussions of the choice of parametric distributions are relegated to the appendix.

2. Data description and parametric fitting on probability forecasts

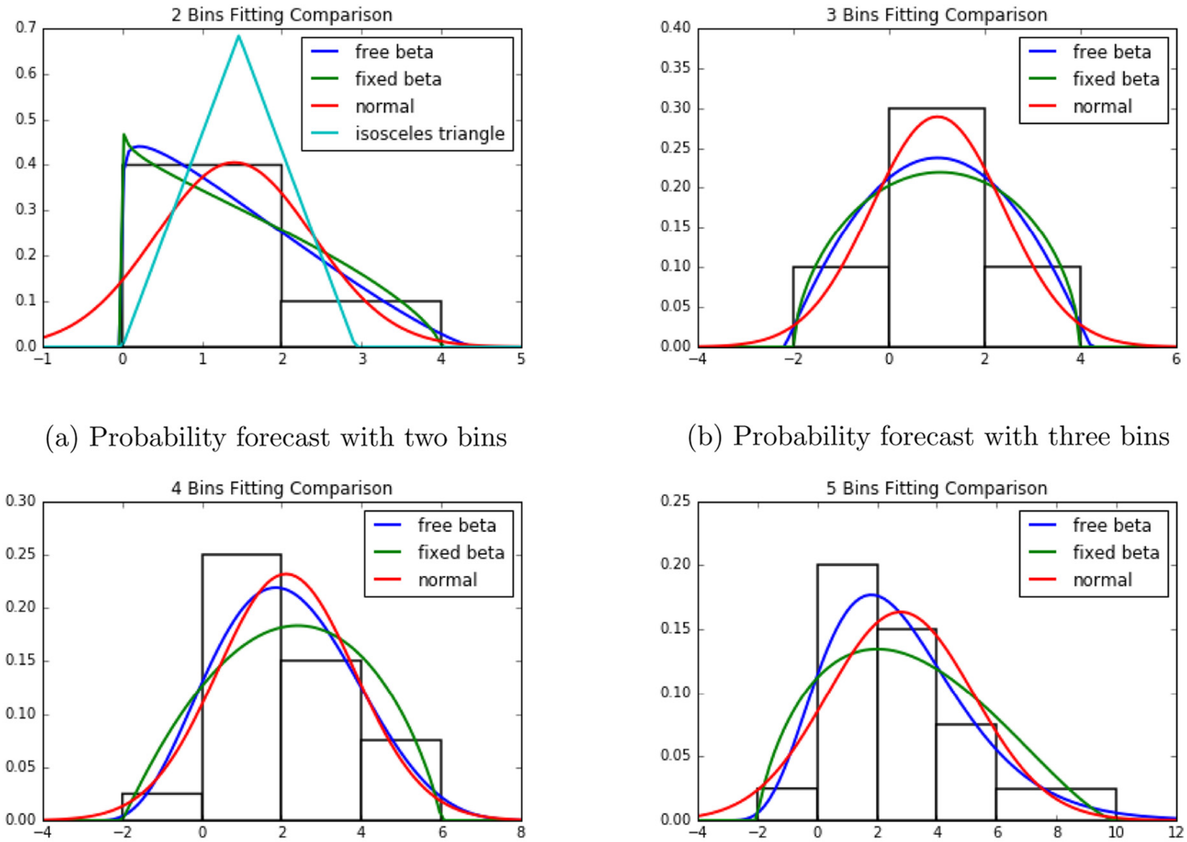
Our dataset comes from the Survey of Professional Forecasters (SPF), which was originally maintained by the American Statistical Association and taken over by Philadelphia Fed in 1990Q2. In addition to a long history of point forecasts for many macro variables, the SPF also contains probability forecasts that record experts' predictions for GDP and inflation. We use forecasts for the annual-average over annual-average percent change in real GDP, which are available for the period since 1981Q3. Although the survey also offers probability forecasts for inflation, we focus on the probability distribution of real GDP only, because the uncertainty literature emphasizes the origin of uncertainty as being real economic activities.[3] At each quarter, experts provide probability forecasts for both the current and next year output growth levels in the form of histograms. One of the challenges in analyzing this dataset is that the survey structures experienced many rounds of changes regarding 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, meaning that the experts are aware of the BEA's advance 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 both the "current year" and "next year" real GDP growth, giving us 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. However, we fix the rounding problems by proper scaling, and no observations are removed from the data.[4] The probability distributions in the SPF take the form of histograms. Several problems arise with such a format that prevent us from using these histograms directly for uncertainty estimation. First of all, the histograms have open intervals at both ends, implying that their support covers the entire real number space, but professional forecasters are unlikely to assign probabilities to infinite positive/negative values. We therefore

2 Istrefi and Mouabbi (2018) propose an ex post measure of interest rate uncertainty that accounts for both disagreement among forecasters and the perceived variability of future aggregate shocks.

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

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



(a) Probability forecast with two bins

(b) Probability forecast with three bins

(c) Probability forecast with four bins

(d) Probability forecast with five bins

Fig. 1. Parametric fitting of histograms using different distributions.

close these open intervals in order to obtain more reasonable fitting results by using either the minimum and maximum historical values or simply the 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. We then combine these samples to represent one probability forecast. The histogram generated 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]

The choice of parametric distributions is critical for studies that use the SPF density forecasts. However, the literature has no standard methodology. While Giordani and Söderlind (2003) use normal distributions to fit the data, Engelberg, Manski, and Williams (2009) and Clements (2014) adopt a mixed strategy that fits generalized beta distributions to observations with more than two bins and triangle distributions to the rest. Karaca (2015) experiments with a mixture of constrained and unconstrained beta distributions. 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) a normal distribution, e.g. Giordani and Söderlind (2003); (ii) a generalized beta distribution with no parameter constraint; (iii) a generalized beta distribution with supports determined by individual forecast values; and (iv) a combination of generalized beta and triangle distributions, e.g. Engelberg et al. (2009). Fig. 1 illustrates all four fittings on a small sample. Due to its high flexibility and closed support, the third setting performs very well at 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 those from the first setting of a normal distribution. We go on to evaluate all four settings based on their performances in terms of goodness

5 The estimation method used in this paper differs from those in all previous studies, in which the minimum distance estimation is used. The advantage of using the maximum likelihood method is that it yields consistent and most efficient estimates.

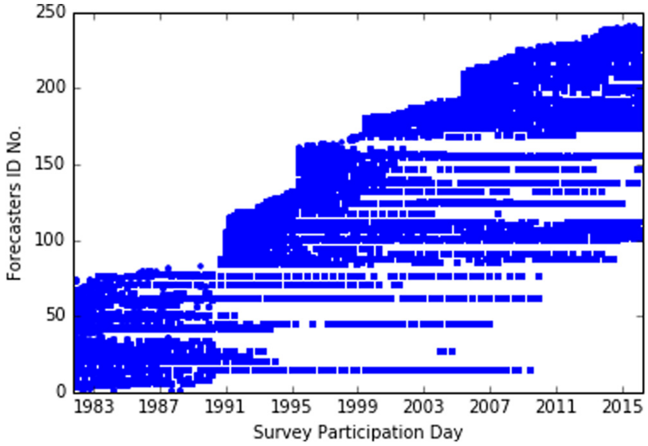


Fig. 2. Panel composition in the U.S. SPF.

of fit, consistency with point forecasts, forecast accuracy and variance consistency. Not surprisingly, the third setting gives the best-fitting results.[6] We therefore fit the generalized beta distribution with support determined individually 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}.

3. Constructing the macro uncertainty index

We have to deal with four complications in the survey when constructing the time series of the macro uncertainty index. (1) Seasonality: Forecast horizons change from eight to one quarter(s) ahead, and as a consequence, the macro uncertainty is lower at shorter horizons. (2) Structural changes: The survey experiences multiple structure breaks due to changes in the 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 participants. Fig. 2 plots the forecaster identification number against the survey periods in which they participated. Controlling for changes in panel composition requires probability forecasts at the individual level. This is the main reason why this study does not use aggregate probability distributions. (4) Measurement errors: The values in 1985Q1 and 1986Q1 suffer from the "wrong target asked" issue, so they are replaced with 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 detail later. We include two dummy variables to control for three different survey structures and one dummy to separate two survey maintainers. We address the changes in panel composition by first removing all forecasters who participated only once during the entire survey period and then including a fixed effect for each forecaster.[7] Specifically, we run the following regression:

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

where S are dummy variables that control for different survey structures, P is a 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 that controls for changes in the survey structure, survey maintainer and panel composition. Furthermore, we apply X13 to $\hat{\epsilon}_{it}$ to remove any remaining seasonality and obtain the perceived uncertainty at the individual level.[8] Finally, we construct our macro uncertainty index as the cross-sectional median of individual uncertainty values.[9] We do this for both the current year and the next year, representing the short- and medium-term uncertainty.[10] For the sake of 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 that is perceived by professional forecasters, and does not have to be linked tightly with fluctuations in the volatility of realized outcomes; and (ii) it is a real-time measure that does not require a knowledge of realized outcomes.[11]

6 The details regarding this experiment are given in the appendix.

7 We also conducted an analysis based on a subsample study of forecasters who provided at least eight forecasts, and our uncertainty estimates remained the same after removing these additional infrequent forecasters.

8 We also experimented with seasonal dummies and obtained 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.

10 The erroneous values in 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 relates to 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 that was established by Lahiri and Sheng (2010).

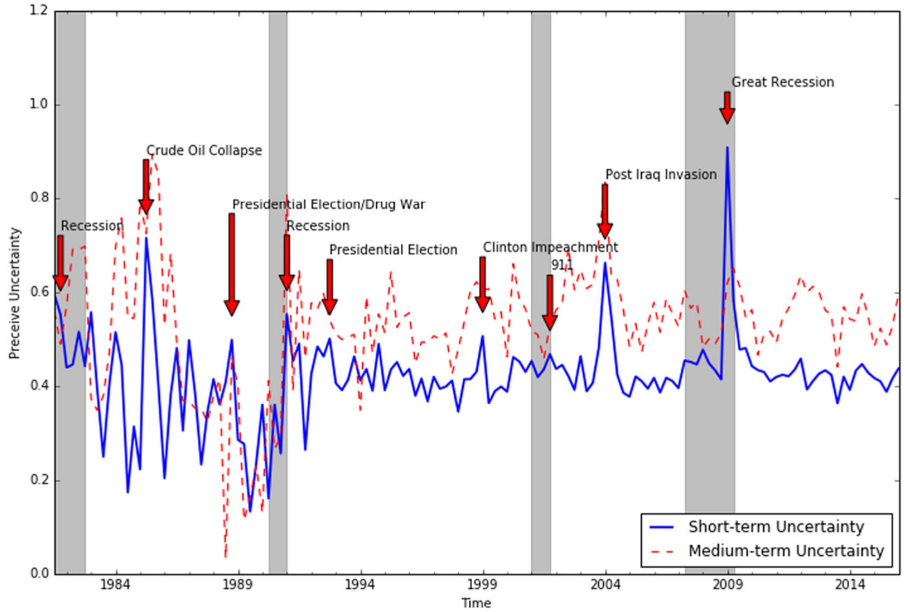


Fig. 3. Short- and medium-term macro uncertainty.

Fig. 3 plots the short-term uncertainty at one year ahead and the medium-term uncertainty at two years ahead. The short-term uncertainty experiences many spikes during recessions, wars and presidential elections, with the largest one occurring during the 2007–09 recession. With the exception of two big spikes, the short-term uncertainty is less volatile after 1992, implying that real economic variables such as the real GDP became more consistent and predictable in the 1990s and 2000s than in the 1980s. The spike in 2004 is associated with events such as the presidential election and the Iraq war, which are not documented well 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 dispersed much more than in run-of-the-mill periods. The macro uncertainty at the medium term is higher than its short-term counterpart on average, and surges during the crude oil collapse and post Iraq war periods. The correlation between the short- and medium-term uncertainty during our sample period is about 0.47. We explore what may drive the uncertainty over these different time horizons. Consistent with the work of Barrero, Bloom, and Wright (2017), we find that the oil price volatility and currency volatility are particularly important for short-term uncertainty, while EPU and oil price volatility affect the medium-term uncertainty.[12]

Table 1 shows the correlations between our macro uncertainty and other uncertainty measures. These measures include the VIX of Bloom (2009), the EPU proposed by Baker et al. (2016), the JLN index of Jurado et al. (2015), the forecast disagreement computed from the same dataset, and the OS uncertainty of Ozturk and Sheng (2018). For ease of comparison, all monthly uncertainty measures are converted to quarterly values by using the monthly average. Our macro uncertainty index is correlated weakly 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 heterogeneity among forecasters rather than to high uncertainty.[13] The low correlations with both the JLN and OS uncertainty indexes reflect the key differences with these measures. Our measure captures the uncertainty perceived by market participants but does not have to be associated tightly with the volatility of realizations. In contrast, both JLN and OS require a knowledge of realized values and provide ex-post measures of uncertainty.[14] The low correlations with the VIX and EPU can be explained by the fact that these measures have different targets. Our measure captures the economy-wide uncertainty, while the VIX most likely reflects uncertainty in the stock market and EPU emphasizes the policy aspect

12 The correlations of the 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 the 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, Smith, and Wallis (2008), Rich and Tracy (2010) and Abel, Rich, Song, and Tracy (2016) find little support for the use of disagreement as a proxy for uncertainty.

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

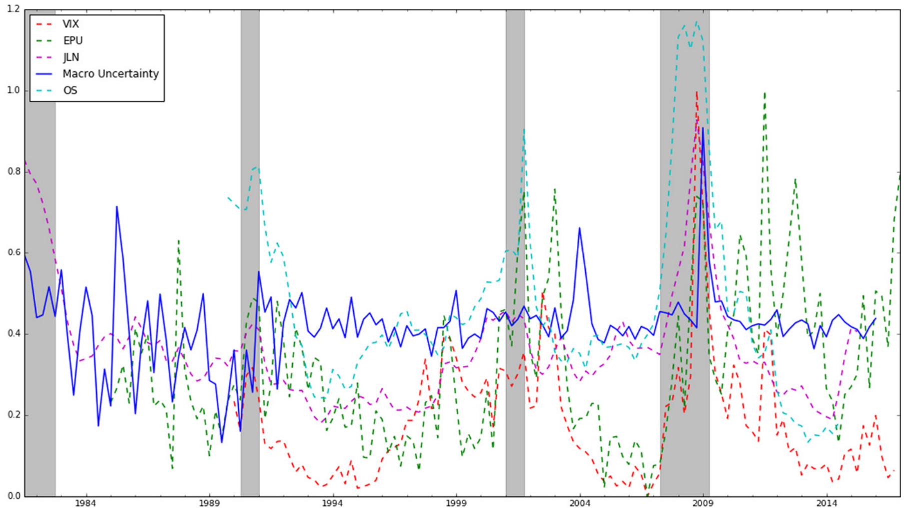


Fig. 4. Comparison of alternative uncertainty measures.

of uncertainty.[15] To summarize, our uncertainty estimates display independent variations from other leading uncertainty proxies, suggesting that much of their variation is not driven by the perceived macro uncertainty.

Fig. 4 compares our macro uncertainty with those of 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, the OS and our index reach their peaks during most of the recessionary episodes and remain low during expansions.[16]

Table 1
Correlations 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 are the VIX of Bloom (2009), the EPU of Baker et al. (2016), the JLN index of Jurado et al. (2015), the forecast disagreement computed from the same dataset, the OS uncertainty of Ozturk and Sheng (2018), and the macro uncertainty introduced in this paper.
***Indicate significance at the 1% levels.
**Indicate significance at the 5% levels.
*Indicate significance at the 10% levels.

4. The impact of macro uncertainty

4.1. U.S evidence

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

For ease of comparison with the results in the literature, we adopt a similar VAR framework that includes seven variables in the following order:

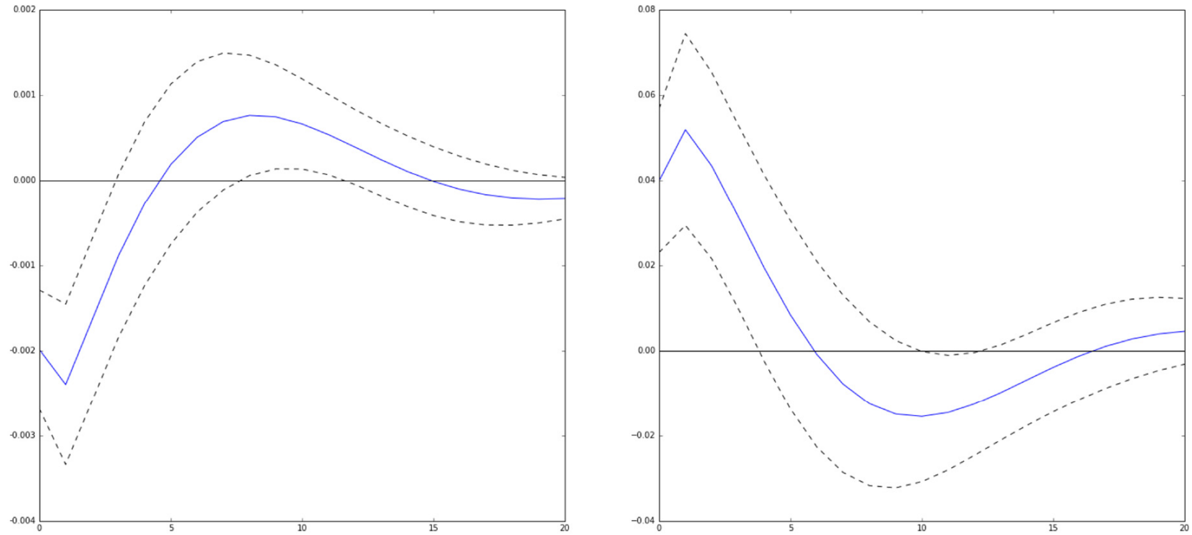
$$\begin{bmatrix} \log(\text{S\&P 500 Index}) \\ \text{Uncertainty} \\ \log(\text{Wage}) \\ \text{Federal Funds Rate} \\ \log(\text{CPI}) \\ \text{Unemployment Rate} \\ \log(\text{Industrial Production}) \end{bmatrix}.$$

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

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

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 a lower persistence than any of the other measures.

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



(a) IRF of industrial production

(b) IRF of unemployment

Fig. 5. Response of industrial production and unemployment to macro uncertainty (64% confidence interval).

Fig. 5 illustrates the impulse response function of industrial production and the unemployment rate to a one-standard-deviation uncertainty shock. Industrial production falls by about 0.25% immediately after an uncertainty shock and then recovers slowly. By five quarters after the shock, industrial production has recovered and rebounded slightly but insignificantly, unlike the strong rebound shown by other measures.[18] Following the uncertainty shock, the unemployment rate immediately increases by about 0.05 percentage points, then recovers and rebounds insignificantly up until ten quarters afterward.

4.2. Evidence from BRIC countries

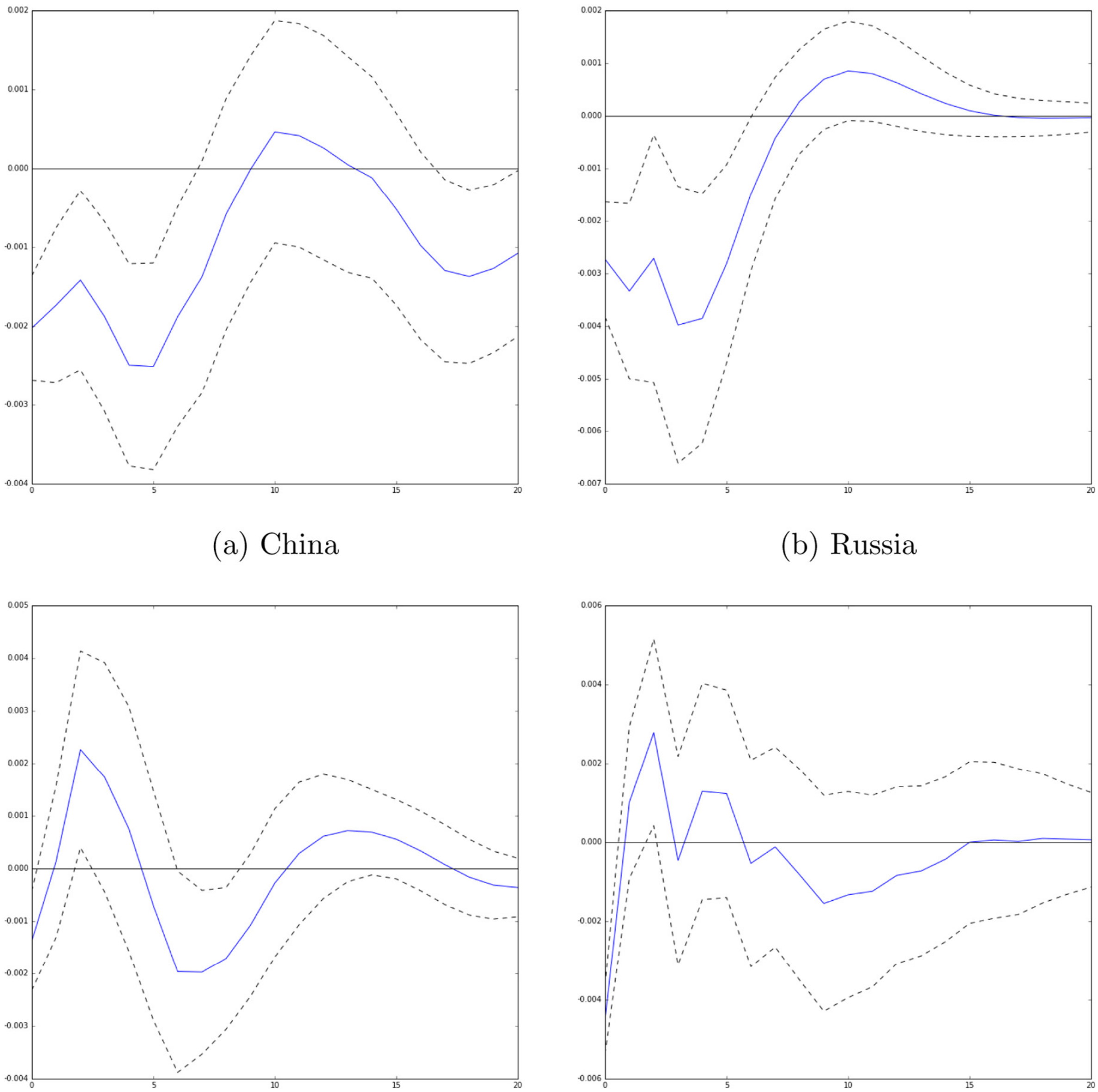
As is well known, the U.S. has the world's largest GDP (based on exchange rates), accounting for roughly 22% of global output. The size of the economy makes it one of the top two countries in terms of exports, imports and foreign direct investment. Due to its large share in global real economic activities 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 be transmitted easily to the rest of the world through U.S. dollar denominated assets. A recent review of the role of the U.S. in the global economy is given by Kose, Lakatos, Ohnsorge, and Stocker (2017), who document that U.S.-originated economic shocks have significant global spillovers through trade, monetary policy and financial markets.

Although uncertainty shocks might have larger effects on emerging markets than advanced economies, there have been few studies of the former. Choi (2018) explores the spillover effect of U.S. uncertainty on emerging market economies. Carriere-Swallow and Cespedes (2013) find that emerging economies suffer deeper and more prolonged impacts from uncertainty shocks. This section focuses on the transmission of U.S. macro uncertainty to BRIC countries, due to their interconnectedness to global markets and their vulnerability to uncertainty shocks. The acronym BRIC refers to the countries of Brazil, Russia, India and China, which are all deemed to be at similar stages of newly-advanced economic development. Despite this similarity, though, each country is unique in its economic development and its relationship with the U.S. In particular, China has grown to become 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 over the past decade, and its relationship with U.S. has been intimate both economically and politically. In contrast, Russia and Brazil have been trapped in economic turmoil in recent years, but are still related closely to the U.S. economy via different channels. For China, the large trade volume with the U.S. ensures a major trade channel, but its relatively closed financial market partially shuts off the financial credit channel. For India and Brazil, their tight link with U.S. in both real and financial sectors means that the channels are most likely to be a combination of both.

The effects of U.S. uncertainty shocks on BRIC real economies are studied again under the VAR framework. The variables include the stock market index, the short-term interest rate, CPI and real GDP.[19] We control for

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

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



(a) China (b) Russia

(c) Brazil (d) India

Fig. 6. Response of real GDP in BRIC countries to U.S. uncertainty shocks (64% confidence interval).

the BRIC countries' domestic uncertainty by also including their own policy uncertainty measures, downloaded from the Economic Policy Uncertainty website.[20] All other macro variables are obtained from the IMF. Due to data limitations, we only have a complete set of variables for China since 2002, for Brazil since 1995, for Russia since 1997, and for India since 2003. 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 responses of real GDP to a U.S. uncertainty shock. Fig. 6 shows that both China's and Russia's real GDP drop immediately after U.S. uncertainty shocks,

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

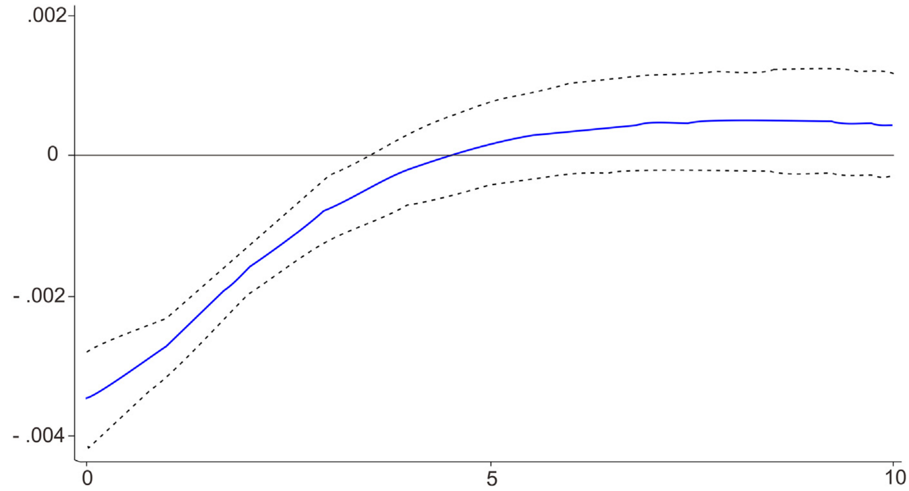


Fig. 7. Average impact of U.S. uncertainty shocks on real GDP in BRIC countries (64% confidence interval).

and their patterns of recovery are similar to that for the U.S. For example, a one standard deviation shock to U.S. uncertainty results in an immediate decline in Chinese real GDP of about 0.2%. However, both countries have less significant rebounds than the U.S. For China, there is a small, second-round dip three years after the shock. For Brazil, its real GDP shows a quick, insignificant rebound after the initial dip following U.S. uncertainty shocks, but then drops and recovers similarly to other countries. However, we do not see any significant impact for India. One important caveat is in order. The insignificant impacts on Brazil and India might be due to their relatively short time series. We increase the number of observations by applying a panel VAR to the pooled dataset for all BRIC countries, and report the impulse response function in Fig. 7. After controlling for the country-specific uncertainty, the real GDP displays an immediate drop on average following a U.S. uncertainty shock, then recovers after four quarters. Both the magnitude and the recovery time are similar to the U.S. domestic case we saw earlier, highlighting the significant spillover effect of U.S. uncertainty onto emerging market economies.[21]

5. Conclusion

We take advantage of the unique dataset on density forecasts of output growth and propose a direct measure of macro uncertainty as the common variation in the uncertainty perceived by professional forecasters. Our uncertainty measure is (i) an ex-ante measure that does not require a knowledge of realized outcomes and (ii) a subjective measure that does not have to be linked tightly with fluctuations in the objective volatility. We calculate the individual uncertainty as the variance of the 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.

This paper provides a careful examination of the links between our measure and other popular uncertainty proxies. 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 by 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 surges during recessions, presidential elections and wars, and is related closely to oil price volatility and currency volatility.

We explore the impact of macro uncertainty on real economic activities in a VAR framework for both the U.S. and BRIC countries. Within the U.S., the results are consistent with those of 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. Following U.S. uncertainty shocks, we observe a persistent decline in real GDP for Russia and China, but mostly insignificant effects for Brazil and India. For BRIC countries as a whole, uncertainty shocks originating in the U.S. have a significant effect on their output growth through various channels, even after controlling for their own country-specific uncertainty shocks.

Acknowledgments

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Appendix A. Appendix

This appendix discusses and compares different parametric distributions for fitting probability forecasts.

[21] The graphs in Figs. 6 and 7 show the results when local uncertainty is placed *before* U.S. uncertainty. We also repeat the analysis when local uncertainty is placed *after* U.S. uncertainty, and find that the two sets of graphs are very similar.

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. The survey participants assign probabilities for current-year output growth to 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, in 1990Q2 the SPF maintainer changed from the ASA/NBER to the Philadelphia Fed. Second, the survey structure, including both the number of bins and the length of each bin, underwent many changes before 1992 and after 2009. Thus, this subsample is the longest sample that is free of such structural inconsistencies. In addition, all of the rounding issues in this subsample are minor and carefully fixed. None of the 2456 observations during this survey period are deleted. The lower and upper bounds for the open intervals are set at -5 and 9, respectively.

The choice of parametric distributions is critical for studies that use the SPF density forecasts. However, the literature has no standard methodology. In the absence of clear guidance, we conduct the experiment on the above subsample with four different distribution settings. We choose the normal distribution as the baseline. However, it is well known that the normal distribution cannot deal with asymmetry, which is quite common in the SPF survey. As an alternative, we experiment with the beta distribution, due to its flexibility in matching the irregular and highly-skewed empirical distribution in the data. We use two different versions of beta distribution. The first version is a generalized beta with fixed support, where the support is determined individually 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 the triangle distribution, as originally introduced by Engelberg et al. (2009). Although the authors mentioned that their choice of such a distribution for fitting the density forecast with fewer than three bins is due to software limitation, this method has been adopted by many researches since; see e.g. Clements (2014), Clements and Galvao (2017). The triangle distribution basically fits an isosceles triangle to two adjacent bins. Assuming that the two bins are not assigned equal probabilities, part of the support for the bin with a lower probability is removed based on the difference between the two probabilities.

In summary, we fit four different settings to each of 2456 density forecasts: (i) a normal distribution with no parameter constraint, e.g. Giordani and Söderlind (2003); (ii) a generalized beta distribution with no parameter constraint; (iii) a generalized beta distribution with supports determined by individual forecast values; and (iv) a combination of a generalized beta distribution for three bins and more, and a 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 its (1) goodness of fit, (2) consistency with the 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 the "true" mean is $[1.4, 3.4]$. The range for the "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 numbers of means and medians from the fitting result that lie inside and outside the ranges of the true mean and true median in the sample. The beta distribution with fixed support (i.e., Fix Beta) and the combination of the beta and triangle distributions (i.e., Fix Beta+Tri) show the best performances. The normal distribution gives many median values outside the range, apparently due to data skewness issues. Of all 2449 non-missing observations, only 422 appear symmetric. In addition, of all 519 observations with positive probabilities assigned to two bins, only 50 have equal probabilities. As a symmetric distribution, the triangle distribution does not seem a good choice for the remaining 469 skewed distributions.

An alternative measure of the goodness of fit is the entropy ratio. The expression of the 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, the 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 integrates through the entire support s of a random variable X. In our study, the advantages of using the entropy are twofold: (i) it

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

Table A.2
Entropy ratios.

Fitting choice	Fix Beta+Tri	Fix Beta	Free Beta	Normal
Mean entropy ratio	1.08	1.16	4.05	1.18

depends not on realized outcomes but only on the 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 for measuring the goodness of fit for each distribution. The intuition is straightforward. If we use the correct parametric distribution 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 the 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 bins used; 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 is canceled out in the equation; and μ is a proper measure of x. The entropy ratios for all parametric fitting distributions are shown in Table A.2.

Each differential entropy associated with a parametric distribution is higher than the entropy of the data. With the exception of the beta distribution with no parameter constraint (i.e., Free Beta), all other three distributions provide similar mean entropy ratio values, slightly over 1.

A.2.2. Consistency with point forecast

In addition to real GDP probability forecasts, the SPF survey also contains panelists' point forecasts. Although the survey provides no information regarding the way in which 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 tendencies of density forecasts with the point forecasts.

The point forecasts in the SPF take the form of levels instead of growth rates. When converting these level forecasts into growth rate forecasts such that they are comparable to those from probability forecasts, it is essential to use the information that was available to the professionals when they made their forecasts. Using real-time data from the Philadelphia Fed, we obtain point forecasts in terms of real GDP growth rates.[22] We measure the distance of the point forecast from the mean or median value of the probability forecast by defining

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

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

Table A.3 shows both one-sided and two-sided test results. If the point forecast is the mean of the probability forecast, the normal distribution will perform slightly better than others, and the beta distribution without parameter constraints will be substantially worse. If the point forecast is the median of the probability forecast, then the combination strategy will give the best results. The beta distribution with fixed support gives balanced results in both cases. It is worth noting that all of these test results are conditional on the assumed relationship between the point and probability forecasts. Thus, the evidence provided here should be interpreted with caution.

A.2.3. Forecast accuracy

The third criterion is a check of the forecast accuracy based on the mean/median values 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 that we are analyzing. We use both the mean and median from each of the four distributions to calculate two different squared forecast errors, then conduct another round of paired t-tests to see whether the forecast accuracy of one distribution is statistically different from that of another.

Table A.4 shows the test results. Interestingly, the normal distribution dominates in terms of accuracy regardless of whether we use the mean or the median, but

[22] The last column in Table A.1 shows the number of cases in which 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 of Engelberg et al. (2009).

Table A.3
Relationships between point forecasts and probability forecasts.

Comparison group	Two-sided t-test	One-sided t-test
Based on the means of the probability forecasts		
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 the medians of the probability forecasts		
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	$Mean(D_{fb} - D_{bt}) = 0.069\% ***$	$D_{bt} < D_{fb} ***$

Table A.4
Forecast accuracy comparison.

Comparison group	Two-sided t-test	One-sided t-test
Squared forecast error based on the mean of the probability forecast		
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 the median of the probability forecast		
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	$Mean(SE_{fb} - SE_{bt}) = 0.558 ***$	$SE_{bt} < SE_{fb} ***$

the margins are very small compared to both the beta distribution with fixed support and the combination strategy. However, the beta distribution without parameter constraint yields the least satisfactory results.

A.2.4. Variance consistency

The last criterion that we consider is the consistency in the estimated variances (i.e., the uncertainty) from different parametric distributions. At three and four quarters ahead, all four settings give similar levels and dynamics of perceived uncertainty. At shorter horizons, though, the combination of the beta and triangle distributions results in substantially higher levels of perceived uncertainty than the other three, with these differences being statistically significant on average.[23] A further investigation shows that these elevated uncertainty estimates are due solely to the triangle distribution when fitted into two bins or fewer. This finding casts doubt on the use of the triangle distribution for measuring the uncertainty in density forecasts.

To conclude, of our four different settings, the second, namely the generalized beta distribution with no parameter constraint, performs the worst in terms of the goodness of fit, consistency with point forecasts and forecast accuracy. Of the remaining three settings, the normal distribution gives many median values outside the range, due to its inability to deal with asymmetric probability forecasts. The combination strategy fails to provide 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 for fitting the U.S. SPF density forecasts.

[23] For the sake of brevity, we do not report these graphs here, but they are available upon request.

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