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# The real effects of overconfidence and fundamental uncertainty shocks*

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**Abstract**

This study provides estimates of the real effects of macro-uncertainty decomposed into *fundamental* and *overconfidence bias* components. Crucially, overconfidence biases lower ex-ante measures of uncertainty, while fundamental uncertainty raises both ex-ante and ex-post measures. This distinction is useful since the estimates on the real effects of the overconfidence component of uncertainty mitigate endogeneity concerns. I first document evidence for overconfidence biases from survey density forecasts in the US survey of professional forecasters. Then, using a sign and zero restrictions identification scheme in a vector autoregression (VAR), I find that increases in fundamental uncertainty and declines in overconfidence tend to lower real activity.

*Keywords: uncertainty, overconfidence, survey forecasts*

*J.E.L. codes: C32, D84, E37*

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# 1. Introduction

Since the start of the *Great Recession*, macroeconomic uncertainty has featured prominently into the policy debate and among the key determinants to aggregate fluctuations. Increases in perceived uncertainty are thought to generate a slowdown in economic activity as agents hold back on investment (Bernanke, 1983; Bloom et al., 2007; Fajgelbaum et al., 2016), durable consumption (Romer, 1990), employment (Leduc and Liu, 2016; Pries, 2016), and worsens financing conditions (Straub and Ulbricht, 2017). To this end, a large literature has provided evidence on the effects of heightened uncertainty as in Bloom (2009) and many others. More recently, there has been a shift in focus going beyond the consequences but also into the causes of macro-uncertainty. For instance, Bachmann and Moscarini (2011); Straub and Ulbricht (2017), and Fajgelbaum et al. (2016) provide mechanisms in which uncertainty is an endogenous outcome.[1] This raises a question on whether evidence on the real effects of macro-uncertainty, usually demonstrated via recursively identified vector-auto regressions (VARs) confound the effects of uncertainty with whatever may be the underlying causes driving uncertainty. Ludvigson et al. (2015) point out that the use of recursively identified VARs rule out the possibility that uncertainty and other shocks contemporaneously influence each other, a possibility for which they find supporting evidence. Consequently, they provide an identification strategy which does not rely on timing to identify uncertainty shocks.[2]

In this paper, I use a simple alternative identification strategy that allows for estimates of the real effects of increases in macro-uncertainty that are not confounded

[1]See as well Bekaert et al. (2013) on the link between the monetary policy stance and uncertainty as measured in the VIX. See also Veldkamp (2005); Van Nieuwerburgh and Veldkamp (2006); Ordonez (2013) and Ambrocio (2015) for a related stream of the literature on the macroeconomic implications of endogenous information acquisition.

[2]Their strategy essentially uses (components of) external instruments to identify shocks. They also distinguish between financial and macroeconomic uncertainty. See also Ludvigson et al. (2017).

with other factors (if any) which may have caused it to rise. By contrasting forecast errors with forecast densities (or ex-ante against ex-post measures in general), I distinguish between fluctuations in perceived uncertainty that is validated by ex-post measures - *fundamental* uncertainty - and those which are not, an overconfidence bias wherein only measures of perceived uncertainty rise. The decomposition is especially useful when estimating the real effects of uncertainty shocks when uncertainty itself may be an endogenous response to aggregate conditions. Since the decomposition exploits the fact that by definition overconfidence biases are unrelated to fundamental uncertainty and only affects ex-ante (perceived) measures of forecast uncertainty, responses to shocks to these overconfidence biases may be used to provide a conservative estimate of the real effects of uncertainty that are unrelated to factors that drive fundamental uncertainty.[3]

I first document evidence on the existence of these overconfidence biases at the level of individuals and forecast horizons using survey forecast data from which I can construct both ex-ante and ex-post measures of uncertainty.[4] I use individual density forecast data for real GDP growth from the Survey of Professional Forecasters in the United States and first test for the presence of biases across forecasters and forecast horizons. I then construct both ex-ante and ex-post measures of aggregate forecast uncertainty and use sign and zero restrictions to identify fundamental uncertainty and overconfidence bias shocks in a small VAR using the first principal component of several ex-ante and ex-post measures of uncertainty used in the literature. A comparison of the impact on macroeconomic outcomes of shocks to the indices I have constructed relative to other measures of macro-uncertainty used in the literature is also done.

[3]The strategy and distinction between fundamental uncertainty and overconfidence biases shares some similarities to the strategy employed by De Graeve and Karas (2014) to distinguish bank runs from deposit supply shocks and by Benhima and Poilly (2017) to distinguish fundamental and noise shocks in a New Keynesian model with dispersed information.

[4]I define macro-uncertainty as the variance of the unforecastable component to future realizations of macroeconomic outcomes. To distinguish it from Knightian uncertainty or ambiguity, the literature has also referred to this definition of uncertainty as risk.

I find the following. First, on the individual-level evidence for biases, I test for location (mean) and scale (variance) biases in survey density forecasts and find substantial heterogeneity across forecasters. I also find that the realized values of GDP growth fall outside the range of values assigned with positive probabilities in the survey responses quite often and asymmetrically. These matter for estimates of the location bias of the density forecasts. Further, there is an increase in the relative bias towards higher growth as the forecast horizon increases. Third, and most important, a significantly larger proportion of respondents are biased towards lower variances than their forecast errors would indicate - evidence that forecasters are overconfident.

The second set of results pertain to the macroeconomic impact of shocks to uncertainty and overconfidence. I find that impulse responses from shocks to the forecaster uncertainty measure derived from professional GDP growth forecasts are qualitatively similar to those from other measures of uncertainty such as those based on stock market prices, forecast error variances, and media-based measures among others. Further, after decomposing uncertainty into fundamental and bias components using sign and zero restrictions, I find that both types of shocks reduce economic activity. As earlier argued, the evidence on the overconfidence bias component mitigates concerns of mis-measurement on the effect of uncertainty arising from uncertainty itself being endogenous to aggregate conditions. This also implies that perceived uncertainty has real effects regardless of whether they are well-founded or not. Consequently, ex-ante measures of uncertainty or measures that directly measure expectations, may provide additional information on macro-uncertainty relative to ex-post measures.

The first set of results build on the literature evaluating the accuracy and bias of survey density forecasts.[5] Deficiencies in forecast accuracy need not im-

[5] See for instance Mitchell and Wallis (2011); Patton and Timmerman (2012) as well Corradi and Swanson (2006); Pesaran and Weale (2006); Rossi (2014); Giacomini and Rossi (2015)

ply biases. Information frictions, for instance, can help explain persistence and predictability of forecast errors (Coibion and Gorodnichenko, 2012, 2015). Nevertheless, Andrade and Le Bihan (2013) note that information frictions on their own may not be enough to replicate features of the survey data. The existing evidence in the (density) forecast bias literature have focused on testing for either location (mean) or scale (variance) biases in isolation. Garcia and Manzanares (2007) find a bias towards favorable outcomes (e.g. low inflation and high output) using various measures of central tendency from density forecasts at the ECB Survey of Professional Forecasters.[6] In contrast, Giordani and Soderlind (2006) find US forecasters' point forecasts to be pessimistic. The evidence I document on US forecasters' density forecasts provide mixed support for this finding since the relative prevalence of optimism or pessimism depends crucially on how outliers in the data are treated. In addition, the apparent increase in bias towards higher growth over the forecast horizon that I document parallels the evidence in Patton and Timmerman (2010) and Andrade et al. (2016) on the term-structure of disagreement. On the evidence for overconfidence among forecasters, Kenny et al. (2015) find that low forecast accuracy is associated with a low variance in density forecasts for the ECB survey. Giordani and Soderlind (2006) find overconfidence in the US survey of professional forecasters using the coverage test of Christoffersen (1998). Consistent with their results, I also find evidence for overconfidence.[7] An important note on the findings with respect to these biases is that the survey responses are taken as primitives in the analysis.[8] The estimated biases may be interpreted simply as biases in the reported forecasts and not necessarily the forecasters themselves. For instance, Laster et al.

for surveys of the literature and Boero et al. (2011) for a comparison of alternative measures of density forecast accuracy.

[6]See also Bachmann and Elstner (2015) who find evidence for optimism among firms in the IFO business climate survey.

[7]A key difference in my methodology and theirs is that I condition on location (mean forecast or optimism/pessimism) biases using the same density forecasts whereas they use matched point forecasts to determine these biases.

[8]See Rabin (1998) and Hirshleifer (2001) for early surveys of the literature on these optimism and overconfidence biases.

(1999) show that incentives towards publicity (being right when everyone else is wrong) results in published forecasts with stronger location (mean forecast) biases.

Second, I also extend the growing body of literature concerned with the measurement of macro-uncertainty and its role in macroeconomic fluctuations. Common proxies for macro-uncertainty are typically based on spikes in financial (e.g.stock market) volatility measures as in the seminal work of Bloom (2009); estimates of the variance of the unforecast-able component of macroeconomic variables (e.g. the expected variance of the forecast error) as in Jurado et al. (2015); Scotti (2016); Rossi and Sekhoposyan (2015) and Rossi and Sekhposyan (2017); measures based on media accounts such as the economic policy uncertainty index of Baker et al. (2016); or the fraction of respondents identifying *Uncertain future* as a reason for not making large purchases (Leduc and Liu, 2016).The general finding in this stream of the literature is that the increases in macro-uncertainty measures tend to lead to a fall in output and employment. Basu and Bundick (2017) document a contraction in output, consumption, investment, and hours worked following a positive uncertainty shock; Rossi and Sekhoposyan (2015) also document a fall in output following heightened uncertainty using a host of uncertainty measures; Bloom (2014) find a fall in investment and hiring in the manufacturing sector; see also Leduc and Liu (2016) for a rise in unemployment; and finally see Buch et al. (2015); Bordo et al. (2016) and Caldara et al. (2016) for evidence on uncertainty driving tighter loan supply and credit conditions.[9]

Forecaster uncertainty derived from survey-based density forecasts provide an alternative to these measures.[10] Relative to the other measures for uncertainty, these surveys offer a direct association with agents' expectations about (the second

[9]See as well as Caggiano et al. (2014) for evidence on non-linearities and state-dependence in the effects of uncertainty shocks.

[10]This is distinct from forecaster disagreement as documented in Zarnowitz and Lambros (1987) and more recently in Boero et al. (2008); Rich and Tracy (2010); Boero et al. (2015); Bloom (2014); Abel et al. (2016). See also Manski (2017) for a recent survey of the literature on survey expectations data.

moment of) future outcomes. Most importantly, forecast densities allow us to construct both ex-ante and ex-post measures from the same responses facilitating the decomposition into fundamental and bias components.[11] Nevertheless, constructing a measure of uncertainty from survey data presents its own challenges. Jo and Sekkel (2017) note the importance of vintages of real-time data on survey-based estimates of uncertainty. Engleberg et al. (2011) highlight the importance of accounting for heterogeneity across forecasters and the changing composition of respondents over time. Similarly, Lopez-Perez (2015) finds that individuals with higher uncertainty are less likely to subsequently participate in the ECB survey of forecasters leading to a downward bias in measures of forecast uncertainty. To mitigate these issues, my measure of subjective uncertainty uses cross-sectional averages after controlling for individual and forecast horizon effects.

Finally, an alternative decomposition of uncertainty derived from density forecast data is provided by Rossi et al. (2016) who construct measures of both risk and Knightian uncertainty. In their decomposition, Knightian uncertainty is proportional to the degree by which forecasters disagree on the probabilities for each state and the degree of bias in the density forecasts. These reflect ambiguity in the sense that they capture the inability of forecasters to pin down the true probabilities of events among themselves (disagreement) and collectively (bias). The biases that I estimate at the individual level map to (signed) biases on the first two moments of density forecasts whereas theirs reflect the degree of overall bias in a density forecast.[12] Consequently, our interpretations differ. My measure of bias which evaluates signed differences in perceived and actual second moments may be interpreted as over- or under-confidence. Finally, their measure of risk is consistent with my definition of fundamental uncertainty.

[11] See also Lahiri and Sheng (2010).

[12] I also provide bias estimates using both parametric and non-parametric fits of density forecasts where the latter, similar to the approach in Rossi et al. (2016), is subject to truncation whenever forecast realizations occur in states for which forecasters assign zero probabilities.

The next section outlines the framework for estimating the optimism and confidence biases and provides a description of the survey data. Section 2 covers the main findings on the estimated biases while Section 3 conducts the analyses on the real effects of uncertainty and overconfidence. Finally, Section 4 concludes.

# 2. Bias estimation framework and data

## *A. Framework*

Let $\{x_t\}$ be a sequence of random variables, $\{F_{t-h}(x_t)\}$ a sequence of unbiased conditional density forecasts given information sets $\{\mathcal{I}_{t-h}\}$, and $\{\hat{F}_{t-h}(x_t)\}$ be any arbitrary sequence of density forecasts. Further, denote the first two moments of density forecast with the following,

$$\mu_{t-h} \equiv \int x_t f_{t-h}(x_t) dx_t \tag{1}$$

$$\sigma^2_{t-h} \equiv \int (x_t - \mu_{t-h})^2 f_{t-h}(x_t) dx_t \tag{2}$$

Further, denote with hats for the equivalent moments using the density $\hat{F}_{t-h}$ (e.g. $\hat{\mu}_{t-h}$). Finally denote the forecast error and standardized forecast error as $\epsilon_t \equiv x_t - \hat{\mu}_{t-h}$ and $z_t \equiv \epsilon_t/\hat{\sigma}_{t-h}$ respectively. I define *fundamental* uncertainty as the variance of the forecast error (unforecastable component) given the unbiased conditional density forecast and perceived (subjective) uncertainty as simply the implied variance of the density forecast. To help distinguish between the two, I make the following simplifying assumptions regarding the data.

**Assumption 1.** *The data generating process: Let the conditional distribution of forecast target be an autoregressive process with time-varying mean and variance,*

$$x_{t|t-h} = \mu_t + \rho(x_{t|t-h} - \mu_{t-1}) + \nu_t \tag{3}$$

*where* $\nu_t \sim D(0, \sigma_t^2)$ *and* $\mathbb{E}[\nu_t \nu_{t-s}] = 0 \forall s \neq 0$.

Then, the standardized forecast error $z_{i,t-h} \equiv \frac{x_{t|t-h} - \hat{\mu}_{i,t-h}}{\hat{\sigma}_{i,t-h}}$ follows,

$$z_{i,t} = \alpha_{i,t,h} + \rho_{i,t-h}(z_{i,t-1} - \alpha_{i,t-1,h})\frac{\hat{\sigma}_{i,t-h-1}}{\hat{\sigma}_{i,t-h}} + \beta_{i,t,h}\tilde{\nu}_t \tag{4}$$

where $\alpha_{i,t,h} \equiv \frac{\mu_t - \hat{\mu}_{i,t-h}}{\hat{\sigma}_{i,t-h}}$, $\beta_{i,t,h} \equiv \frac{\sigma_t}{\hat{\sigma}_{i,t-h}}$, $\rho_{i,t-h} = \rho\frac{\hat{\sigma}_{i,t-h-1}}{\hat{\sigma}_{i,t-h}}$, and $\tilde{\nu}_t \equiv \frac{\nu_t}{\sigma_t}$

Clearly, it would be infeasible to jointly identify individual, horizon, and time-varying biases. Given prior evidence on significant heterogeneity in biases across forecasters and forecast horizons, we assume that biases may vary across the individual-horizon dimensions and that these are time-invariant.[13]

**Assumption 2.** *The location and scale biases as well as the persistence parameter are time-invariant and individual-forecast horizon specific,*

$$z_{i,t} \;=\; \alpha_{i,h} + \rho_{i,h}(z_{i,t-1} - \alpha_{i,h}) + \beta_{i,h}\tilde{\nu}_{i,t,h} \tag{5}$$

Density forecasts at the individual level provide not only a measure of central tendency but also of uncertainty around the future realization of the forecast target. Thus, we are able to test for biases not only in terms of location (means) but also scale (variances).[14] In equation 5, these map to tests of whether $\alpha_{i,h} = 0$ and

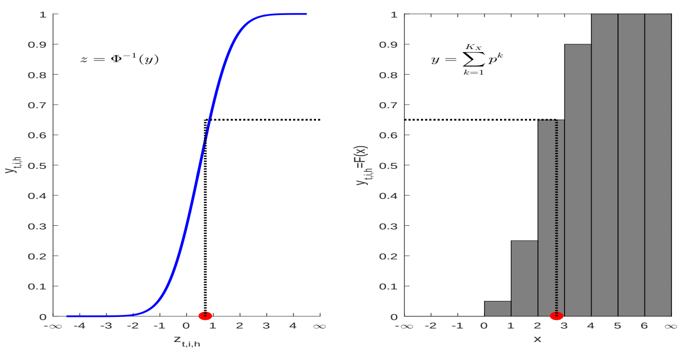
[13] See for example Kenny et al. (2015) for evidence of heterogeneity across forecasters in the ECB survey,(Boero et al., 2015) for the Bank of England survey, Engleberg et al. (2011) for the US SPF, and Davies and Lahiri (1995) for the Blue Chip survey.

[14] We may also look at biases in higher moments or the density as a whole (e.g. Rossi et al., 2016). However, in the survey data we have rather course representations of densities in the form

$\beta_{i,h} = 1$ respectively. These first two moments have a natural interpretation. A growth forecast density with a mean *higher* than actual GDP growth may be taken as an overly optimistic forecast. Similarly, a forecast density with a variance which is *lower* than the variance of the (ex-post) forecast error can be thought of as overly confident.

Equation 5 may also be derived using the inverse-Normal transform of Berkowitz (2001) which I briefly describe next. Diebold et al. (1998) propose the construction of a probability integral transform (PIT) of the forecast target using the forecast density defined as $y_{i,t,h} = \hat{F}_{i,t-h}(x_t)$. Then, if the forecast density is unbiased the PIT has a standard uniform distribution $y_{i,t,h} \sim U(0,1)$. The inverse Normal transform proposed by Berkowitz (2001) further transforms the PIT by feeding it into the inverse of a Standard Normal cdf $z_{i,t,h} = \Phi^{-1}(y_{i,t,h})$. Figure 1 illustrates this two-step procedure where the actual value (horizontal axis of the right panel) is fed into the cdf of a density forecast resulting in a random variable $y_{i,t,h}$ (vertical axis on both panels) which is then fed into an inverse-Normal density (right panel) and results in the transformed variable $z_{i,t,h}$ (horizontal axis of the left panel).

Figure 1: Inverse-Normal transform of PIT




Under the null hypothesis that the forecast density is unbiased, then the transformed variable has a Standard Normal distribution.[15] Further, the deviations of the

of probabilities over three to five intervals of the domain. Consequently, we focus on these first two moments.

[15] This is true for any distribution of $x_t$.

mean and variance of the transformed variable from zero and one respectively measure the relative difference between the true moments of the conditional distribution of the forecast target and the same moments in the forecast density. When both $F(x_t)$ and $\hat{F}(x_t)$ are Normal densities, then the two-step transformation is equivalent to a standardized forecast error as defined earlier with mean and variance given by the standardized difference in the predicted-against-actual means (optimism) and the ratio of the actual and predicted variances (overconfidence) $z_{i,t,h} \sim \mathbf{N}\left(\alpha_{i,h}, \beta_{i,h}^2\right)$.

Given the bell-shaped pattern in the survey responses, assuming a Normal distribution seems to be reasonable.[16] Nevertheless, given a large incidence of sample skewness in the data, I consider three ways to do the transformation:

$$
\begin{aligned}
z_{i,t,h}^{JB} &= \Phi^{-1}(y_{i,t,h}, 0, 1) \quad \text{where } y_{i,t,h} = \hat{F}(X_t) && (6)\\
z_{i,t,h}^{Skew} &= \Phi^{-1}(y_{i,t,h}, 0, 1) \quad \text{where } y_{i,t,h} = F(X_t|\hat{\mu}_{i,t,h}, \hat{\sigma}_{i,t,h}^2, \hat{\lambda}_{i,t,h}) && (7)\\
z_{i,t,h}^{Norm} &= \frac{x_t - \hat{\mu}_{i,t,h}}{\hat{\sigma}_{i,t,h}} && (8)
\end{aligned}
$$

In the first ($z^{JB}$), I calculate the PIT non-parametrically using the Berkowitz (2001) framework and construct cdfs by summing up reported probabilities over interval ranges. In the latter two ($z^{Skew}$ and $z^{Norm}$) I fit a Skew-Normal and Normal distribution respectively to the survey responses. Assuming these parameters for a given forecaster $i$ and forecast horizon $h$ are time-invariant, we may then use the sequence of transformations over survey dates to estimate these parameters.

As in Berkowitz (2001) I include a persistence parameter ($\rho_{i,h}$) intended to capture serial dependencies in the forecast errors and estimate the parameters in equation 5 where $\tilde{\nu}_{i,t,h} \sim$ i.i.d. $\mathcal{N}(0,1)$. The parameter $\alpha_{i,h}$ represents the optimism bias with a positive value indicating a pessimistic forecast for GDP growth (i.e. the realization of annual real GDP growth is larger than the mean of the forecast density).

[16] See as well Giordani and Soderlind (2003)

The hypothesis that $\rho$ and $\alpha$ are both zero reduces to the Mincer and Zarnowitz (1969) test of forecast rationality commonly applied to point forecasts. On the other hand, the $\beta_{i,h}$ parameter represents the confidence bias. A value of $\beta_{i,h}$ greater than one implies that the forecast error (in absolute values) is $\beta_{i,h}$ times larger than implied standard deviation of the density forecast which we define as overconfidence. Conversely, a $\beta_{i,h}$ less than one would suggest doubt or under-confidence in the forecasters' forecast. The parameters are estimated using Ordinary Least Squares (or equivalently via maximum likelihood) and parameter tests on whether $\rho = 0$ indicating independence, $\alpha = 0$ for no optimism bias and $\beta = 1$ for no confidence bias are conducted using likelihood ratio tests.

## B. Data

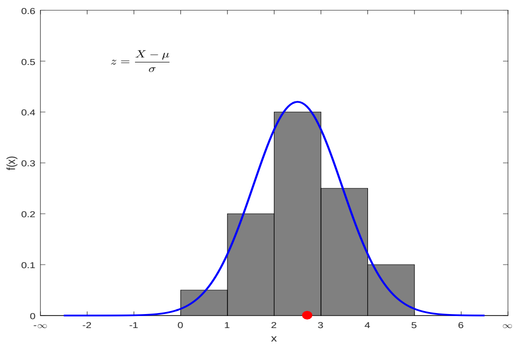
The forecasting data is taken from the Survey of Professional Forecasters managed by the Federal Reserve Bank of Philadelphia (SPF).[17] The survey asks professional forecasters to provide forecasts of the probability that current and following year real GDP growth will fall within 10 pre-defined intervals. I focus on survey responses on forecasts of current and following year annual average Real GDP growth for the surveys beginning the first quarter of 1992 and ending the fourth quarter of 2013.

Respondents are asked to assign probabilities to ten bins with the lowermost being less than negative two percent growth, followed by between negative two and negative one percent and so forth in one percent intervals with the uppermost bin being real GDP growth greater than six percent.[18] I also limit the sample to survey respondents to those who have participated in at least fifteen consecutive

[17] The survey forecasts and real-time data used for constructing forecast errors are available at the Real-Time Data Research Center of the Federal Reserve Bank of Philadelphia. http://www.philadelphiafed.org Results on bias tests for GDP deflator forecasts are also available upon request.

[18] For real GDP growth and beginning 2009Q2, the survey question has been expanded to include up to four years ahead annual growth forecasts. Prior to 1992Q1, there were only six intervals of two percent widths. After 2009Q2, an eleventh bin was added to the bottom interval.

Figure 2: Sample response and Normal fit




surveys and have made at least 25 forecasts over the sample period for either of the two questions.[19] This leaves me with 3,038 forecasts from 31 forecasters over 88 quarters (or 22 forecast targets) and at eight different forecast horizons (e.g. $h = 1$ for a forecast of the current year annual real GDP growth made in the fourth quarter of the year and $h = 8$ for a forecast of the following year real GDP growth made in the first quarter of the current year).

Figure 2 plots a typical response to which I fit a Normal distribution. The gray bars represent the probabilities that the respondent has assigned to each range of possible outcomes and the blue line represents the fitted density of a Normal distribution. The mean and variance of the Normal distribution are chosen so as to minimize the squared area in between the two densities where the areas are categorized into intervals as in the survey question and weighted with the probability given in the response.[20] The red dot represents the actual realization of the forecast target taken as of one quarter after the end of the year being forecasted. I do a similar process to estimate the parameters of a Skew-Normal distribution.

Table 1 reports mean forecast error and squared forecast error across several measures of central tendency, vintages of real time data, and the full set of observations against the restricted sample of 31 forecasters to be used in the analyses. Squared

[19]This still results in an unbalanced panel of forecast data. The maximum possible number of responses is 176 (two questions over 88 quarterly surveys).

[20]Giordani and Soderlind (2003) use the same approach in their analysis of inflation forecast uncertainty.

Table 1: Forecast error comparison by data release vintage

| | | Full Sample | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean Error | | | | Mean Sq. Error | | | |
| | | **1Q** | **5Q** | **9Q** | **2015** | **1Q** | **5Q** | **9Q** | **2015** |
| **GDP growth** | **Normal** | -0.051 | -0.147 | -0.332 | -0.139 | 1.442 | 1.741 | 2.255 | 2.361 |
| | **Skew Normal** | 0.009 | -0.088 | -0.273 | -0.081 | 1.468 | 1.753 | 2.252 | 2.370 |
| | **Midpoint** | 0.028 | -0.068 | -0.254 | -0.061 | 1.447 | 1.725 | 2.217 | 2.343 |
| | **Median** | -0.075 | -0.171 | -0.356 | -0.160 | 1.514 | 1.817 | 2.334 | 2.443 |
| | | **Restricted Sample** | | | | | | | |
| **GDP growth** | **Normal** | -0.096 | -0.222 | -0.434 | -0.303 | 1.401 | 1.728 | 2.214 | 2.270 |
| | **Skew Normal** | -0.043 | -0.168 | -0.381 | -0.251 | 1.420 | 1.730 | 2.196 | 2.257 |
| | **Midpoint** | -0.026 | -0.152 | -0.364 | -0.233 | 1.398 | 1.701 | 2.162 | 2.230 |
| | **Median** | -0.131 | -0.257 | -0.469 | -0.333 | 1.476 | 1.812 | 2.310 | 2.366 |

*Full sample takes averages from all available responses whereas the restricted sample corresponds to the 31 forecasters for which I estimate biases. Real time data vintages are those available from 1 to 9 quarters after the end of the year targeted or that available in the fourth quarter of 2015 and obtained from the Federal Reserve Bank of Philadelphia. See Croushore and Stark (2001)*

forecast errors are smaller for earlier vintages of the data, the restricted sample of respondents, and the Normal estimate of the mean as a measure of central tendency. Consequently, I construct $z_{i,t,h}$ using the vintage of real time data available in the first quarter after the end of the year forecasted. The sub-sample comparison also suggests that the estimated (frequency of) biases in the restricted sample is likely to yield lower estimates of the biases in the full sample of survey participants.

Table 2: Transformed variable descriptive statistics

| | **Mean** | **Median** | **Variance** | **Skewness** | **1st Quartile** | **Last Quartile** |
|---|---|---|---|---|---|---|
| **JB-Growth** | 0.924 | 1.036 | 2.164 | -0.655 | 0.000 | 2.576 |
| **Norm-Growth** | -0.132 | -0.051 | 11.411 | -10.867 | -0.995 | 0.940 |
| **Skew-Growth** | -0.034 | -0.038 | 4.652 | -0.044 | -0.872 | 0.860 |

*Parameters for the Normal and Skew-Normal distribution are estimated by minimizing the weighted sum of squared differences in the reported probability and the area under the pdf for each interval.*

Table 2 reports summary statistics for the estimated $z_{i,t,h}$ across the three methodologies. Differences from fitting a parametric distribution and from the non-parametric alternative arise especially when the forecast target realization is away from the provided density in the survey - outliers. This is because for the $z^{JB}$ calculation these occur at the zeroth and 100th values of the CDF and are consequently truncated to the half percent tails (i.e. $z^{JB} = \pm 2.5758$ for these cases). On the other hand, the parametric approaches extrapolate from the fitted density to provide estimates of how far - in standard deviations - these realizations are from the mean of the forecast.

These instances occur quite frequently - about 35 percent of total responses. Further, there is substantial asymmetry in the frequency and size of these outliers. Around 88 percent of these outliers were positive (higher actual growth than forecast). On the other hand, the median value of $z^{Skew}$ and $z^{Norm}$ for positive outliers is 1.27 while the same statistic for negative outliers is -5.23. That is, though it does not happen often, when forecasters miss these extremely low realizations they are way off the mark. There are also two episodes where negative outliers have primarily occurred which are the two years prior to the 2001 recession and the years during the 2008-09 recession.[21] On the other hand, the sample variance - the moment of interest - across measures indicate overconfidence (higher than one) on average with the truncated measure featuring the lowest average at 2.164.

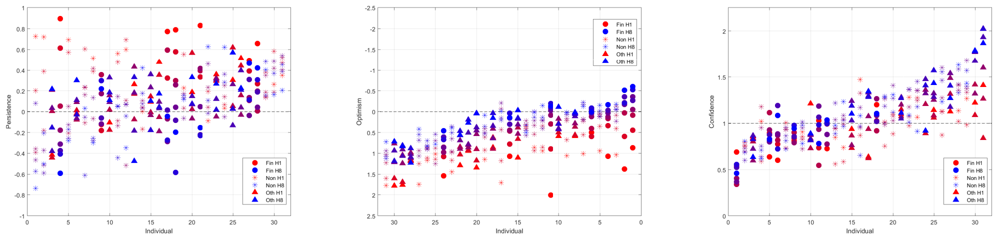
## *C. Tests for optimism and confidence*

The parameters in equation 5 are estimated for each forecaster-forecast horizon pair. Figure 3 plots estimates of the persistence ($\rho_{i,h}$), optimism ($\alpha_{i,h}$), and confidence ($\beta_{i,h}$) parameters for the real GDP growth question using $z^{JB}$. Here, I report only the results using GDP growth forecasts.[22] The estimated values of the parameters are on the vertical axis while the horizontal axis represents (sorted) estimates for each forecaster in the sample. The shape of each observation in the plot represents the sector of the forecaster, circle for financial, star for non-financial, and triangle for unknown or a respondent who has switched from financial to non-financial or vice-versa. For each forecaster, there is an estimate for each forecast horizon with red colors indicating short horizon forecasts and blue for longer horizon forecasts

[21] In the Appendix, I provide further information regarding these features of the data. The general conclusions regarding the estimated biases presented in the next section are also preserved when I use a subset of the sample which excludes these outliers.

[22] In the Appendix, one may find estimates using the Normal approximations as well as the results for the same tests applied to GDP inflation density forecasts.

Figure 3: Estimated biases: JB-Growth



(a) Persistence (b) Optimism (c) Confidence

*Point estimates of parameters from the GDP growth question using the non-parametric transformation (JB) and sorted by forecaster. Colors reflect horizon from short (red) to long (blue). The shape distinguishes between forecasters from financial institutions (circle), non-financials (star) and others (triangle).*

(from one up to eight quarters ahead).

Recall that the null hypotheses for no bias in terms of persistence, optimism, and overconfidence are, $H_0^1 : \rho = 0$, $H_0^2 : \alpha = 0$, and $H_0^3 : \beta = 1$ where $\alpha < 0$ reflects optimism and $\beta > 1$ overconfidence. Note that, as the figures indicate, there is substantial heterogeneity in the bias estimates across forecasters with some who appear to be pessimistic across all forecast horizons and others who appear unbiased and similarly for overconfidence. It also seems to be the case that longer horizon forecasts (in blue) are relatively more optimistic and overconfident than short-horizon ones. Further, forecasters from the financial sector are in general less pessimistic (or more optimistic when using $z^{Skew}$ or $z^{Norm}$) and less overconfident than their non-financial counterparts.

Table 3: Likelihood ratio test rejection rate: Growth

| | **10** | | | **5** | | | **1** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **JB** | **Norm** | **Skew** | **JB** | **Norm** | **Skew** | **JB** | **Norm** | **Skew** |
| **Persistence** ($\rho$) | 11.29 | 9.27 | 11.18 | 7.26 | 3.63 | 5.92 | 4.44 | 0.81 | 1.97 |
| **Optimism** ($\alpha$) | 36.29 | 10.12 | 10.00 | 31.05 | 4.45 | 4.67 | 19.35 | 0.40 | 0.67 |
| **Confidence** ($\beta$) | 31.45 | 76.52 | 68.00 | 25.00 | 69.64 | 62.00 | 14.52 | 62.75 | 52.67 |

*Rejection rates (in percent) at 10, five, and one percent significant levels. JB is the inverse-Normal transform of the PIT, Norm is the standardized forecast error using mean and variance estimated from a Normal distribution, and Skew is the equivalent using the Skew-Normal distribution.*

Table 3 reports the frequency of rejections of the no bias null hypotheses using likelihood ratio tests at three different significance levels, for each method of calculating the test statistic, and for each parameter. Persistence does not seem to be a significant issue as rejection rates are close to the chosen significance levels. There is some evidence for pessimism using $z^{JB}$ although estimates from the Normal and Skew-Normal generated statistics would indicate optimism instead (see earlier discussion on outliers). There is stronger evidence for overconfidence as a large fraction of the estimated biases are significantly larger than one across all tests.

In sum, in this section I have demonstrated evidence in favor of biases in both first and second moments of density forecasts, the latter of which specifically indicates a bias towards overconfidence. I have also documented substantial heterogeneity among forecasters and forecast horizons. In the next section, we are going to exploit the similarities and differences among expected (forecasted) and realized variances of GDP growth as a way to decompose perceived uncertainty into bias and fundamental components.

# 3. Overconfidence and fundamental uncertainty

In this section, I use both ex-ante and ex-post measures of uncertainty to distinguish between the effect of the *fundamental* uncertainty - or unforecastability - of the future realization of macroeconomic variables against confidence biases or agents' views about their ability to forecast the same. I construct a subjective uncertainty measure defined as the simple or equal weighted average of the estimated variance of individual survey responses for real GDP growth.[23] I then construct an adjusted measure in which, prior to averaging, each estimated variance is multiplied with the estimated confidence parameter for each individual-forecast horizon. That is, the variance of the response is adjusted to more accurately reflect the ability of the individual in forecasting the target variable for that forecast horizon. Finally,

[23] The variance is estimated by fitting a Normal distribution to the response. Similar results are obtained using alternative measures, the common variation across various measures, and measures obtained using only the subset of responses from forecasters frequently participating in the survey.

I construct an index of overconfidence by taking the simple average of estimates of the overconfidence parameter for the respondents in each survey date.

When constructing aggregate indices and analogous to Dovern et al. (2012) and Rossi et al. (2016), I convert fixed target forecasts to fixed horizon forecasts by combining forecasts made in the same quarter at different forecast horizons with varying weights.[24]. Given the transformed fixed-horizon forecasts, I control for individual fixed effects and calculate subjective uncertainty ($UNC_t$) and the average squared forecast error $SFE_t$ by,

$$
\begin{aligned}
UNC_t &= \sum_i (\hat{\sigma}_{i,t}^2) - (\bar{\sigma}_i^2 + \bar{\sigma}_h^2) \qquad (9) \\
ASFED_t &= \sum_i (\epsilon_{i,t}^2) - (\bar{\epsilon_i^2}) \qquad (10)
\end{aligned}
$$

where $\bar{\sigma}_i^2$ is the average variance for a given individual and $\bar{\sigma}_h^2$ are quarterly seasonal indices to account for differences in forecast horizon per quarter, while $\epsilon_{i,t}^2 \equiv (\mu_{i,t} - x_t - \bar{\epsilon}_i)^2$, and $(\bar{\epsilon_i^2})$ are the squared error for a given individual at time $t$ after correcting for any mean biases and the average squared error for a given individual respectively.[25] Finally, and for reference, I also construct an average measure of overconfidence $OVC$ which is a simple average of the estimated biases at the individual and forecast horizon level per survey date.[26]

[24]Essentially, $x_{t+H} = \frac{h}{H} x_{t+h} + \frac{H-h}{H} x_{t+H+h}$. See Dovern et al. (2012) for details.

[25]The conversion to fixed-horizon forecasts does not completely remove *seasonality* in the series. Consequently, the series are also de-seasonalized using iterated estimates of seasonal indices and a moving-average trend.

[26]Note that since the confidence biases were estimated at the level of individual-forecast horizon, if the same forecasters were participating in every survey, the time series for overconfidence will be constant. In the data, this is not the case and the composition (of the biases) of the forecasters participating in the survey add variation to the time series.

## *A. Comparison with other macro-uncertainty proxies*

We start the analysis with a comparison of the two indices against commonly used proxies for uncertainty in the literature. Namely, I use as benchmark variables, the $VIX$ or the option-implied volatility of the S&P 500 index, $JLN$ as a measure of the expected variance of the unforecastable component of macroeconomic variables as estimated in Jurado et al. (2015), and $EPU$ a media-based policy uncertainty measure from Baker et al. (2016). I also consider a consumer survey measure $MCSU$ which is the fraction of respondents choosing *Uncertain future* as the reason for why it is not a good time to make large purchases in the Michigan Consumer Survey (see Leduc and Liu 2016). Next we have two measures which have also been constructed using the same survey data. These are the ambiguity (Knightian uncertainty) $RSSA$ and risk (volatility) $RSSV$ measures in Rossi et al. (2016). Table 4 reports the correlations across these measures along with two indices which I construct from the forecast data.

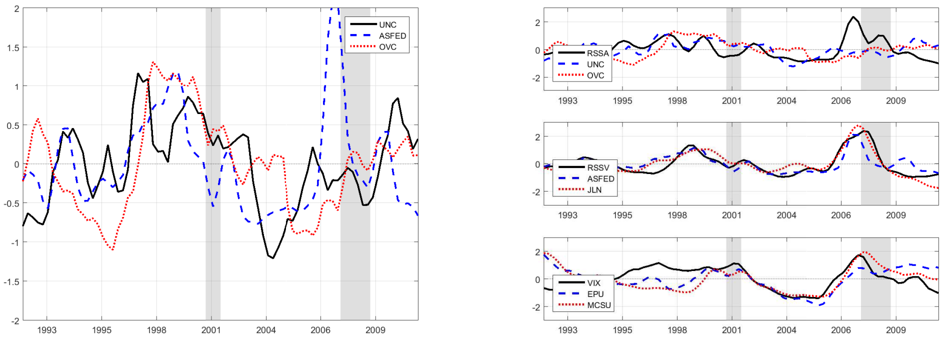
Table 4: Uncertainty correlations

| | **VIX** | **EPU** | **JLN** | **MCSU** | **RSSV** | **RSSA** | **UNC** | **ASFED** | **OVC** |
|---|---|---|---|---|---|---|---|---|---|
| **VIX** | 1.0000 | | | | | | | | |
| **EPU** | 0.4372*** | 1.0000 | | | | | | | |
| **JLN** | 0.5971*** | 0.0811 | 1.0000 | | | | | | |
| **MCSU** | 0.3051*** | 0.7399*** | 0.2971*** | 1.0000 | | | | | |
| **RSSV** | 0.4073*** | 0.1606 | 0.7740*** | 0.4060*** | 1.0000 | | | | |
| **RSSA** | 0.5116*** | 0.1419 | 0.5397*** | 0.2002* | 0.2466** | 1.0000 | | | |
| **UNC** | 0.2804** | 0.1954* | 0.0320 | 0.0616 | 0.0695 | 0.0587 | 1.0000 | | |
| **ASFED** | 0.4159*** | 0.2147* | 0.5689*** | 0.1856* | 0.4178*** | 0.6285*** | 0.0911 | 1.0000 | |
| **OVC** | 0.0659 | 0.1480 | 0.0745 | 0.0929 | 0.1380 | 0.0190 | 0.0599 | 0.0951 | 1.0000 |

*$***$,$**$, and $*$ denote the one, five, and ten significance levels respectively. $JLN$ is the forecast error uncertainty index in Jurado et al. (2015). $EPU$ is the economic policy uncertainty index from Baker et al. (2016) obtained at `http://www.PolicyUncertainty.com`. The $VIX$ is the option-implied volatility index for the S&P 500. $MCSU$ is the fraction of respondents choosing Uncertain future as the reason for not making large purchases in the Michigan Survey of Consumers. $RSSA$ and $RSSV$ are respectively the ambiguity and risk (volatility) measures in Rossi et al. (2016). $UNC$ is the averaged variance estimates of real GDP growth forecasts while $ASFED$ is the average squared forecast errors. Forecast horizon adjustments following Dovern et al. (2012) were done for both measures along with the removal of individual and quarter effects. Linear trends have been taken out from all the series.*

Figure 4a plots the smoothed and standardized subjective uncertainty ($UNC$), squared forecast error($ASFED$), and overconfidence ($OVC$) indices. Figure 4b also plots the other (smoothed) measures of uncertainty for comparison.

Figure 4: Smoothed measures of uncertainty and overconfidence



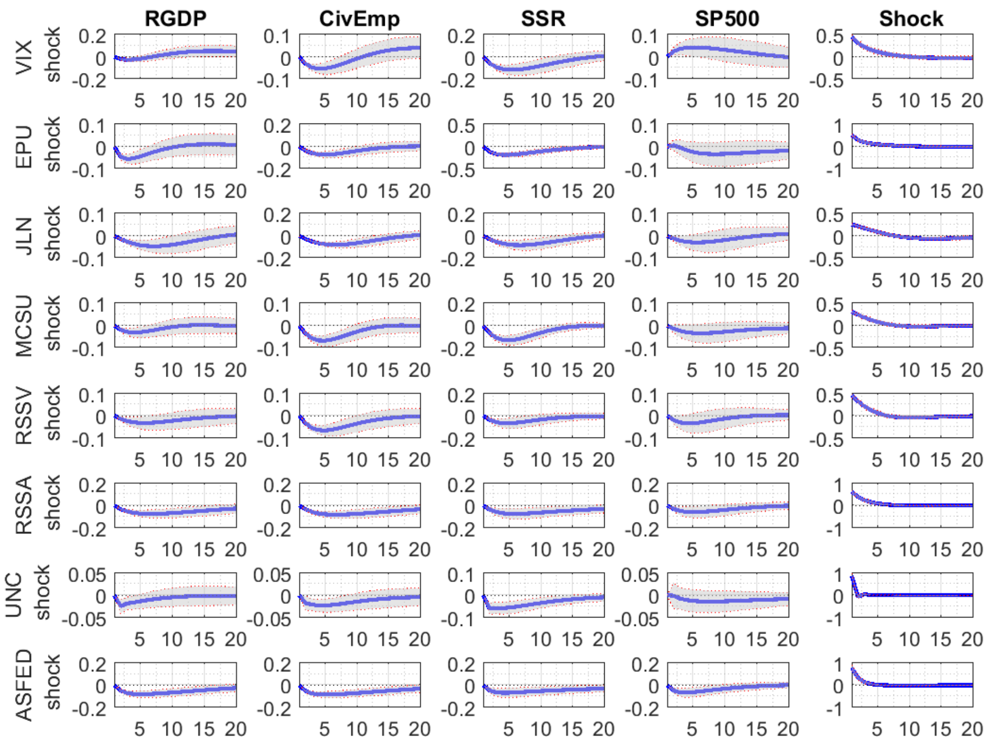

(a) Confidence and uncertainty (b) Comparison with other measures

*The left panel reports 5-quarter moving averages of standardized series after removing a linear time trend, forecast horizon, and individual fixed effects. The right panel reports 5-quarter moving averages of standardized series after removing a linear time trend, forecast horizon, and individual fixed effects. The top panel plots the Ambiguity index of Rossi et al. (2016) (RSSA) which incorporates measure of forecast bias and disagreement,the unadjusted uncertainty measure UNC, and the overconfidence index OVC which measures bias on second moments. The middle panel plots three survey forecast measures of uncertainty: The risk (volatility) measure of Rossi et al. (2016) RSSV, the adjusted average squared forecast errors ASFED, and the uncertainty measure from Jurado et al. (2015) also based on survey forecast errors. The bottom panel plots three additional measures of uncertainty: an option-implied stock market volatility index (VIX), the Baker et al. (2016) policy uncertainty index EPU, and a measure of uncertainty from the Michigan Consumer Survey (MCSU).*

The estimated confidence bias for survey participants was quite high prior to the 2001 recession but low, although trending upward, prior to the 2008-09 recession. How do we interpret this? If we take the estimated confidence biases at face value, then this would suggest that there is some self-selection going on over time and more or less overconfident forecasters participate in the survey at different points in time. Alternatively, since the panel is unbalanced, we may also be picking up some of the time variation in the variance of the unforecastable component of the forecast targets or the individual-horizon confidence bias estimates. Here we cannot distinguish between the time-varying overconfidence common to all forecasters and time-varying variance in the unforecastable component of the forecast target. At the very least, the results suggest that changes in the sample of forecasters who participate in these surveys over time can introduce additional variation in measures of uncertainty derived from averaged responses.

Next, and using the constructed ex-ante and ex-post indices of uncertainty, I

Figure 5: Comparison of impulse responses




*The column headers indicate the response variable and each row represents a different uncertainty variable used in the VAR. All shocks are recursively identified. Shaded areas represent the 68 percent band from bootstrapped impulse responses.*

run vector auto regressions (VARs) as done in Bloom (2009); Jurado et al. (2015); Baker et al. (2016); Rossi and Sekhoposyan (2015) and Leduc and Liu (2016). In particular I use the same variables in Baker et al. (2016) and Rossi and Sekhoposyan (2015) who also conduct at least part of their analyses with quarterly data. The VAR contains five variables: an uncertainty measure, the log of the S&P 500 index, the shadow short rate, the log of civilian employment, and the log of real GDP.[27] As in the referenced literature, shocks for the impulse responses are identified via recursive identification using a *slow* to *fast* ordering as was done in Rossi and Sekhoposyan (2015); Jurado et al. (2015) and Rossi et al. (2016).[28] The VARs are estimated with one lag and the sample is from the first quarter of 1992 to the fourth quarter of 2013.

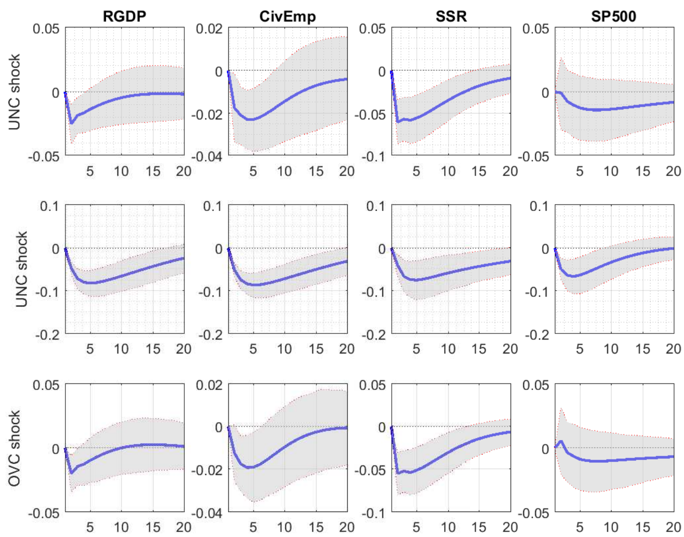
[27]The shadow short rate takes into account the zero lower bound on the federal funds target rate and is obtained from Wu and Xia (2016).

[28]Linear time trends are removed from all the variables and are standardized prior to the VAR.

Impulse responses are reported in Figure 5. We find that the impulse responses from the two indices are quite similar to alternative measures used in the literature. There is perhaps a slightly sharper *hump* in the impulse responses from the $UNC$ measure.

## ***B. The impact of overconfidence and fundamental uncertainty shocks***

Figure 6: Uncertainty and overconfidence shock responses




*The column headers indicate the response variable and each row represents a different uncertainty variable used in the VAR. All shocks are recursively identified. Shaded areas represent the 68 percent band from bootstrapped impulse responses.*

To understand the role that overconfidence biases play on the macroeconomic impact of subjective uncertainty, I first repeat the VAR exercise using the subjective uncertainty measure ($UNC$) and include the squared forecast error index ($ASFED$) where the squared errors are ordered above the ex-ante uncertainty measure. Given the recursive ordering, I will interpret the shock associated with the last variable $UNC$, which does not contemporaneously affect all the other variables including $ASFED$, as an overconfidence shock. On the other hand the second-to-the-last shock, which does not affect all the other variables contemporaneously except for $ASFED$ and $UNC$, is interpreted as a fundamental uncertainty shock. Impulse responses are reported in Figure 6. In the first row, I plot impulse responses to uncertainty shocks from the baseline specification (using only $UNC$) while the bottom two rows report impulse responses from the VAR with both the uncertainty and squared forecast error indices. Except for the response of the stock market index, we find very similar responses to fundamental uncertainty and (negative) overconfidence shocks. While a negative overconfidence shock does not appear to influence the stock market index, all other variables respond negatively to both uncertainty and negative overconfidence shocks.

Table 5: Zero and sign restrictions

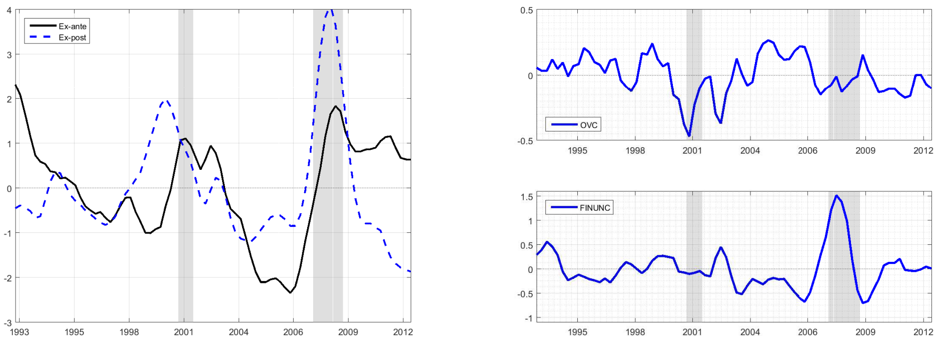
| | RGDP | DEF | SSR | SP500 | PCEA | PCEP |
|---|---|---|---|---|---|---|
| FINUNC shock | | | | - | + | + |
| OVC shock | | | | | - | 0 |
| DEM shock | + | + | + | | | |
| SUP shock | + | - | - | | | |
| MP shock | | - | + | | | |
| UNID shock | | | | | | |

*Restrictions are imposed contemporaneously. $PCEA$ is the first principal component of $UNC$, $MCSU$, and $EPU$. $PCEP$ is the first principal component of $ASFED$, $JLN$, and $RSSV$.*

We now move on to the main identification scheme where I use the subjective uncertainty index along with an average squared forecast error series and use sign and zero restrictions to identify uncertainty and overconfidence shocks. In a VAR with output (RGDP), inflation (DEF), the short rate (SSR), the stock market index (SP500), and measures of both ex-ante and ex-post uncertainty, the restrictions are (1) an overconfidence shock lowers ex-ante measures of uncertainty and does not contemporaneously affect ex-post measures of uncertainty; and (2) the fundamental uncertainty shock raises both both ex-ante and ex-post measures of uncertainty while lowering the stock market index. Note that adverse financial shocks would have similar implications as a fundamental uncertainty shock. These restrictions, along with several others used to identify other conventional shocks, are outlined in Table 5 and are on contemporaneous effects.[29]

[29] See the appendix for results using the minimum set of restrictions to identify only overconfidence shocks. Similar results are also obtained for an alternative timing assumption on the ex-post

Figure 7: Principal components and shocks




(a) Smoothed 1st principal components (b) Structural shocks

*The left panel plots 5-quarter moving averages of the first principal component of $UNC$, $MCSU$, and $EPU$ for $Ex-ante$ and $ASFED$, $JLN$, and $RSSV$ for $Ex-post$. The right panel plots 5-quarter moving averages of the estimated (financial or) fundamental uncertainty $FUNC$ and overconfidence $OVC$ shocks identified using sign and zero restrictions. Gray-shaded areas represent NBER recessions.*

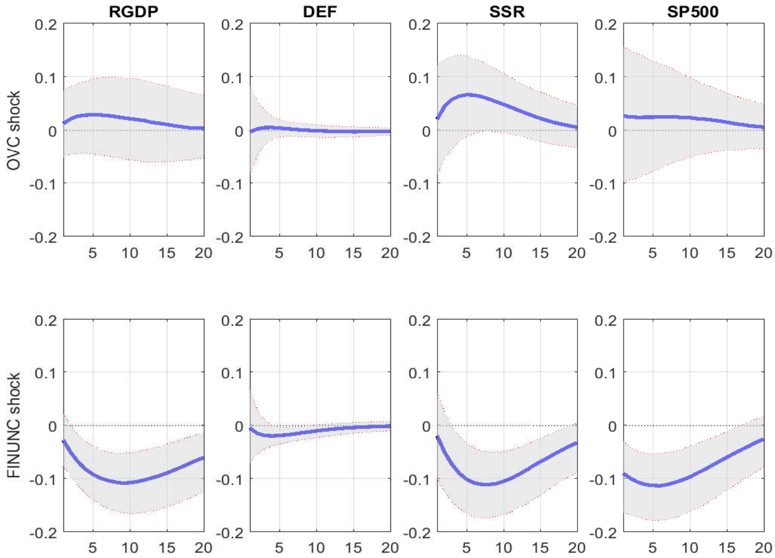
To represent ex-ante and ex-post uncertainty, I take the first principal component of $UNC$, $MCSU$, $EPU$ which represent professional forecasters', households', and media expectations or opinion to capture ex-ante uncertainty (PCEA) whereas for ex-post uncertainty (PCEP), I take the first principal component of $ASFED$, $JLN$, and $RSSV$ all of which are measures based on mean squared forecast errors. Figure 7 provides a time-series plot of the principal components. Figure 8 report impulse responses from this identification strategy.[30]

We find that, as in the previous exercise, both uncertainty and negative overconfidence shocks lower output. Note however that fundamental uncertainty shocks are not well-identified and may be indistinguishable in the model from financial shocks. Further, negative overconfidence shocks also lead to a decline in output (although at smaller magnitudes) similar to shocks which contemporaneously increase both ex-ante and ex-post measures of uncertainty. These results suggests that perceived uncertainty, regardless of whether it is well-founded or not, induces real effects. Second, the decomposition of uncertainty into fundamental and over-

uncertainty measures which are dated at the time of the forecast target realization (four quarters ahead) and not when the forecast was made (also in the appendix).

[30] I used the BEAR toolbox in the estimation. See Dieppe et al. (2016).

Figure 8: Sign and zero restriction identification impulse responses




*The column headers indicate the response variable and each row indicates the shock source. Shaded areas reflect the 68 percent interval. See Table 5 for the identifying restrictions. The ex-ante measure of uncertainty is the first principal component of $UNC$, $MCSU$, and $EPU$. The ex-post measure is the first principal component of $ASFED$, $JLN$, and $RSSV$.*

confidence components also implies that the identified overconfidence component is not influenced by other factors which may drive fundamental uncertainty. Thus, it provides a conservative estimate on the real effects of uncertainty which mitigates endogeneity concerns. Table 6 provides forecast error variance decompositions. We find that overconfidence shocks can account for about 10 percent of the variance in other variables. Further overconfidence shocks account for similar shares as fundamental uncertainty (and/or financial) shocks in the variation of ex-ante uncertainty measures at the 1-quarter horizon at 12 percent.

# 4. Conclusion

Survey density forecasts provide us with a rich dataset to help gain insight on the expectations formation process. In this paper, I use these forecasts to construct ex-ante and ex-post measures of uncertainty and obtain estimates for fundamental

Table 6: Forecast error variance decomposition

| | RGDP H1 | RGDP H4 | RGDP H8 | RGDP H20 | DEF H1 | DEF H4 | DEF H8 | DEF H20 |
|---|---|---|---|---|---|---|---|---|
| **OVC** | 0.102 | 0.099 | 0.093 | 0.094 | 0.100 | 0.103 | 0.107 | 0.116 |
| **FINUNC** | 0.078 | 0.161 | 0.234 | 0.256 | 0.070 | 0.090 | 0.115 | 0.132 |
| **DEM** | 0.129 | 0.085 | 0.074 | 0.086 | 0.099 | 0.107 | 0.113 | 0.121 |
| **SUP** | 0.093 | 0.116 | 0.120 | 0.117 | 0.119 | 0.109 | 0.119 | 0.133 |
| **MP** | 0.087 | 0.090 | 0.090 | 0.090 | 0.104 | 0.114 | 0.121 | 0.128 |

| | SSR H1 | SSR H4 | SSR H8 | SSR H20 | SP500 H1 | SP500 H4 | SP500 H8 | SP500 H20 |
|---|---|---|---|---|---|---|---|---|
| **OVC** | 0.112 | 0.115 | 0.110 | 0.107 | 0.121 | 0.115 | 0.109 | 0.106 |
| **FINUNC** | 0.064 | 0.108 | 0.172 | 0.232 | 0.117 | 0.164 | 0.206 | 0.229 |
| **DEM** | 0.135 | 0.151 | 0.130 | 0.127 | 0.081 | 0.074 | 0.074 | 0.085 |
| **SUP** | 0.076 | 0.078 | 0.082 | 0.098 | 0.079 | 0.076 | 0.077 | 0.097 |
| **MP** | 0.112 | 0.099 | 0.097 | 0.104 | 0.090 | 0.093 | 0.097 | 0.103 |

| | PCEA H1 | PCEA H4 | PCEA H8 | PCEA H20 | PCEP H1 | PCEP H4 | PCEP H8 | PCEP H20 |
|---|---|---|---|---|---|---|---|---|
| **OVC** | 0.126 | 0.115 | 0.109 | 0.115 | 0.000 | 0.005 | 0.016 | 0.043 |
| **FINUNC** | 0.124 | 0.177 | 0.213 | 0.225 | 0.374 | 0.378 | 0.345 | 0.320 |
| **DEM** | 0.089 | 0.091 | 0.097 | 0.105 | 0.080 | 0.084 | 0.101 | 0.122 |
| **SUP** | 0.076 | 0.081 | 0.095 | 0.114 | 0.077 | 0.076 | 0.081 | 0.102 |
| **MP** | 0.073 | 0.075 | 0.086 | 0.097 | 0.082 | 0.084 | 0.093 | 0.115 |

*These are median values of the forecast error variance due to shocks (in rows) for the variables and forecast horizons listed in columns. PCEA is the first principal component of $UNC$, $MCSU$, and $EPU$. PCEP is the first principal component of $ASFED$, $JLN$, and $RSSV$. Shocks identified via zero and sign restrictions in Table 5.*

uncertainty and overconfidence biases. I first document the existence of overconfidence biases wherein a large fraction of forecasters tend to report smaller forecast variances than their forecast errors would imply. Second, using the first principal components from a host of ex-ante and ex-post uncertainty measures, I use sign and zero restrictions in a small VAR to distinguish between fundamental uncertainty shocks and overconfidence biases. I find that fundamental uncertainty and negative overconfidence shocks produce similar effects on real activity. The identification strategy allows for both ex-ante and ex-post measures to contemporaneously respond to other shocks and influence other observables. Further, by distinguishing between fundamental uncertainty and overconfidence biases, I show that the real effects of perceived uncertainty arise both from uncertainty that is well-founded and affirmed by ex-post measures and from biases or expectations that do not materialize. Second, estimates on the real effects of the bias component to uncertainty also provides evidence which mitigate concerns that the evidence on the real effects of uncertainty may be confounded with factors that drive (fundamental) uncertainty itself. A caveat on the results is that we do not have a strong identification strategy to distinguish between financial shocks and fundamental uncertainty shocks. This is a challenge at the forefront of the literature and is an area for future work. Finally, I have ignored the potential for state dependence and non-linearities in the macroeconomic analyses of the effects of subjective uncertainty and overconfidence. This is also another area for future work.

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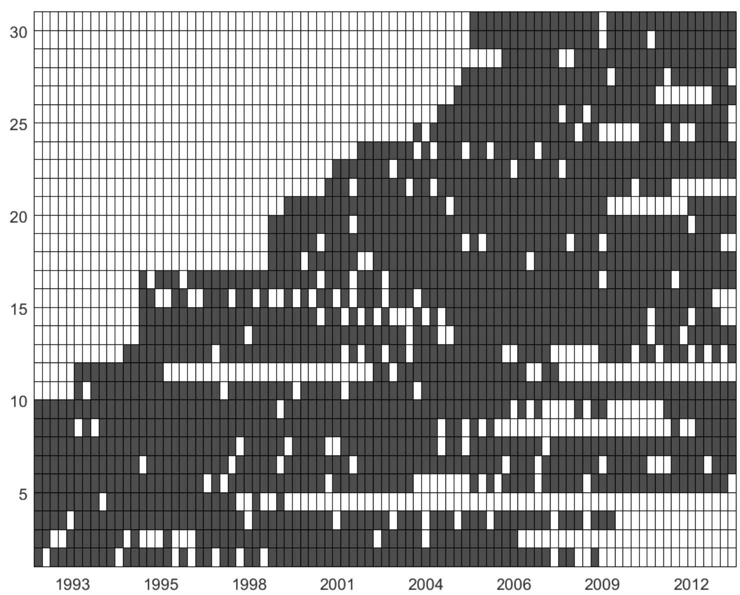
# Appendix

## A. *The SPF survey*

I restrict the sample to include only those forecasters who have participated in at least fifteen consecutive surveys and responded to at least 25 times for each of the two questions. This leaves me with 31 forecasters over 8 quarterly forecast horizons and 22 forecast target years (annual real GDP growth from 1992 to 2013).[31] Figure A.1 visualizes when each of the included forecasters participated in the survey.

Figure A.1: Participation indicator for Forecasters




The following table replicates two survey responses (forecaster ID 30 and 35) made in the 1992 first quarter survey for annual real GDP growth. The values represent the probabilities each respondent assigns to the interval given by the column headers where *Cur* is for the current year and *Fol* is the following year. In this exam-

[31]Limiting the analysis up to forecasts for 2013 allows for forecast error comparison across different vintages of data from those available in the first quarter of the following year to the revised values two years after the forecast target.

ple, respondent 35 appears to be relatively more optimistic and less confident than respondent 30 in that his responses put more probability mass on higher intervals and are also more dispersed.

Sample Response

| year | quarter | id | Cur > 6 | Cur 5 to 5.9 | Cur 4 to 4.9 | Cur 3 to 3.9 | Cur 2 to 2.9 | Cur 1 to 1.9 | ... | Cur < −2 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1992 | 1 | 30 | 0 | 0 | 10 | 60 | 30 | 0 | ... | 0 |
| 1992 | 1 | 35 | 0 | 0 | 10 | 10 | 20 | 50 | ... | 0 |
| year | quarter | id | Fol > 6 | Fol 5 to 5.9 | Fol 4 to 4.9 | Fol 3 to 3.9 | Fol 2 to 2.9 | Fol 1 to 1.9 | ... | Fol < −2 |
| 1992 | 1 | 30 | 0 | 0 | 30 | 50 | 20 | 0 | ... | 0 |
| 1992 | 1 | 35 | 0 | 10 | 20 | 20 | 40 | 10 | ... | 0 |

To estimate the mean and variance of each forecast, I fit an (unbounded) Normal distribution by minimizing the squared difference between the cumulative probability associated with each bin by a Normal distribution against the probability given in the survey response. Each of these squared differences are then weighted by the probabilities in the survey response and the mean and variance are chosen so as to minimize the sum of these weighted squared differences. That is:

$$\{\hat{\mu}, \hat{\sigma}\} = argmin_{\mu,\sigma} \sum_{k=1}^{K} p_k \Big( \int_{k_l}^{k_u} \phi(x|\mu, \sigma) - p_k \Big)^2$$

where $p_k$ is the probability assigned to bin $k$ in the survey with lower and upper edges $k_l$ and $k_u$ and $\phi(x|\mu, \sigma)$ is the Normal pdf.[32] A similar procedure is done for the Skew-Normal distribution.[33]

The following tables report summary statistics for the responses to each of the survey questions in the sample. For comparison, I include estimates of the mean variance using midpoints of the bins, the median (calculated as the midpoint of the bin containing the 50th percentile probability), and the mode for each of the survey

[32] This is similar to minimizing the Kullback-Leibler divergence between the two densities.
[33] I use a modified version of Andrew Patton's code for the Skewed student t distribution in Hansen (1994).

responses.

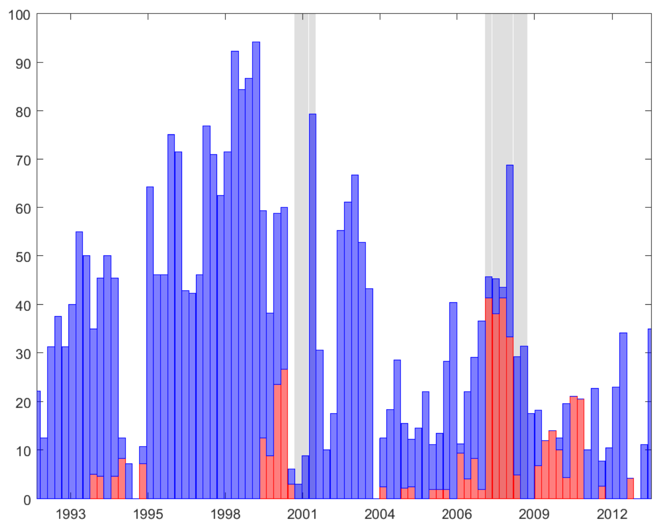
Table A.1: Sample Statistics: GDP growth responses

| | Mean | Median | Variance | 1st Quartile | Last Quartile |
|---|---|---|---|---|---|
| **RPS** | 4.16 | 4.07 | 1.75 | 3.23 | 4.83 |
| **PIT** | 0.71 | 0.85 | 0.11 | 0.50 | 1.00 |
| **JB** | 0.92 | 1.04 | 2.16 | 0.00 | 2.58 |
| **Mean (Norm)** | 2.60 | 2.63 | 1.52 | 2.15 | 3.38 |
| **St. dev (Norm)** | 0.63 | 0.58 | 0.13 | 0.34 | 0.80 |
| **Mean (Skew)** | 2.55 | 2.60 | 1.53 | 2.03 | 3.31 |
| **St. dev (Skew)** | 0.65 | 0.60 | 0.14 | 0.35 | 0.84 |
| **Skewness** | -0.14 | -0.06 | 0.19 | -0.28 | 0.06 |
| **ENT** | 0.43 | 0.42 | 0.04 | 0.30 | 0.56 |
| **Median** | 2.64 | 2.50 | 1.62 | 2.50 | 3.50 |
| **Mode** | 2.64 | 2.50 | 1.65 | 2.50 | 3.50 |
| **Mean (midpoint)** | 2.53 | 2.60 | 1.53 | 2.03 | 3.30 |
| **St. dev (midpoint)** | 0.69 | 0.61 | 0.16 | 0.41 | 0.91 |
| **Num bins** | 4.03 | 3.00 | 3.91 | 3.00 | 5.00 |

*RPS is the rank probability score measuring forecast accuracy (lower is better). ENT is the entropy measure of disperion in probabilities (lower is less uncertainty). Numbins is the number of bins with non-zero probabilities. Errors are calculated taking the value of Real GDP growth as available in the first quarter of the year following the forecast target using the real time data set at the Federal Reserve Bank of Philadelphia. See Croushore and Stark (2001)*

The following figure plots the frequency of cases when the forecast target realization is in an interval assigned with zero probability by a respondent. These *neglected risk* cases are plotted in the figure below.

Figure A.2: Percent realizations outside responses



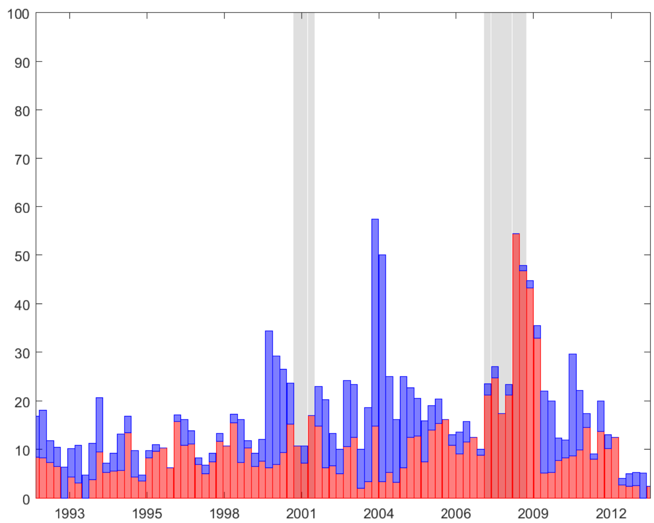

*Percent of total for each survey question. The blue area is for target realizations higher than the range with non-zero probabilities in density responses whereas red is for lower realizations. Gray shaded areas are NBER recession periods.*

Note that the survey data may suffer from a truncation bias in that the lowest and highest interval ranges for the responses are open (e.g. less than two percent for real GDP growth). An indicator for possible truncation bias in the survey responses is the proportion of responses for which the leftmost or rightmost bins have non-zero probabilities. Figure A.3 plots the frequency of these cases across survey dates. There are three notable periods where a significant fraction of respondents had non-zero outer bins for the real GDP growth question. These are 2000 and 2004 survey dates for the upper threshold and the 2009 surveys for the lower threshold.[34] This suggests that, during these times and had there been more categories below or above these thresholds, survey respondents may have distributed the assigned probability

[34]On the other hand, for the GDP price growth question, there are generally two episodes - one quarter in 1998 and the 2009-11 period - where a significant fraction of respondents had non-zero probabilities in the lowest bin whereas non-zero values in the highest bin is rare all the time.

in the lowest or highest bins to more categories. Hence, we may be underestimating the variance and mis-estimating the mean of survey forecasts around these periods and may be introducing artificial skewness in the data.

Figure A.3: Non-zero outer bins



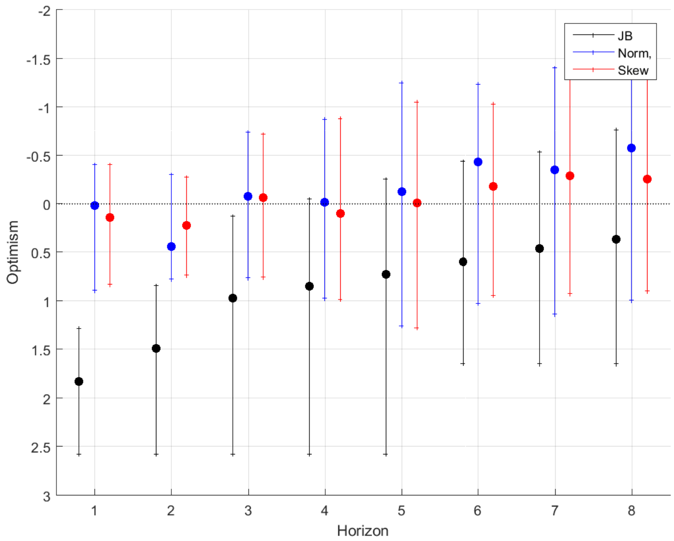

*Stacked bars are in percent. Red is for non-zero lower bins (e.g. less than 2 percent real GDP growth) and blue are for non-zero upper bins.*

## B. *Additional results on bias estimates*

As a first pass, I calculate simple estimates of the mean and variance of the transformed variables. Figure B.1 plots sample means and the corresponding interquartile range across subsamples based on forecast horizons. The forecast horizon is on the horizontal axis while relative optimism is on the vertical axis (higher is more optimistic).

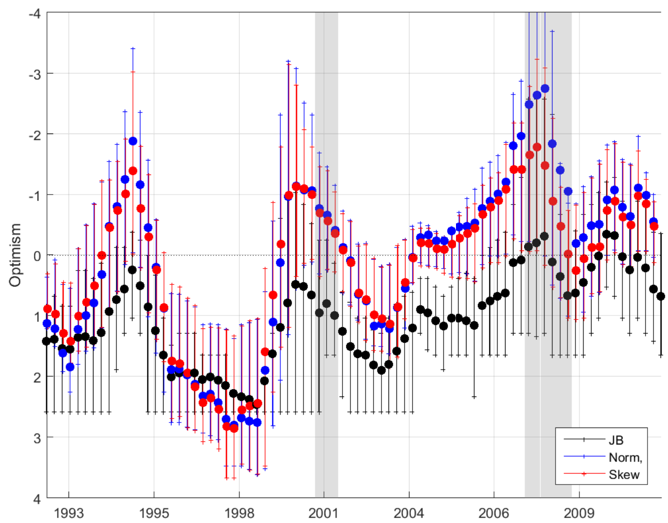
Recall that the null hypothesis of zero bias is $H_0 : \alpha = 0$ where $\alpha < 1$ reflects optimism for GDP growth.The $JB$ statistic tends to report higher values of $z_{i,t,h}$ relative to the Normal or Skew-Normal transformations. Further, the $JB$ statistic also indicates forecasts at shorter horizons being relatively more pessimistic for growth - a low output bias in short horizon forecasts.

Figure B.1: Optimism by Horizon




*Values of the transformed variable across forecasters and time by forecast horizon. Dots in the middle report the average while the ends of the whiskers give the 25th and 75th percentile values. The black points use the non-parametric transformation while the blue and red points use the Normal and Skew-Normal approximation estimates respectively.*

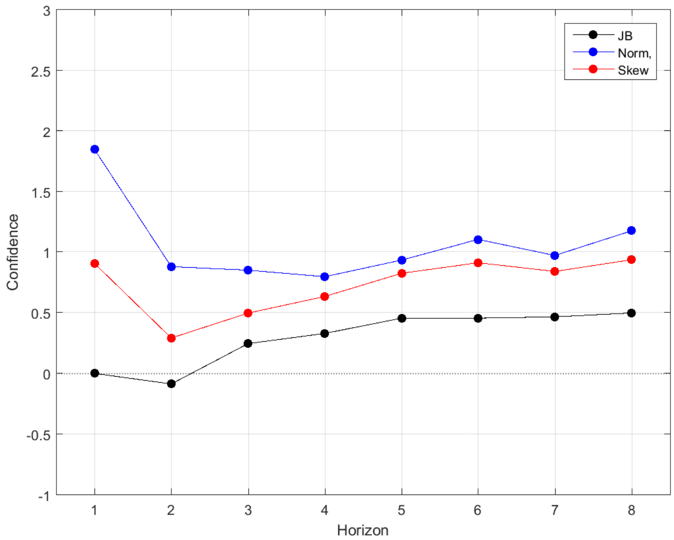
Figure B.2: Optimism by survey date




*Values of the transformed variable across forecasters and forecast horizon by time. Dots in the middle report the average while the ends of the whiskers give the 25th and 75th percentile values. The black points use the non-parametric transformation while the blue and red points use the Normal and Skew-Normal approximation estimates respectively.*

Figure B.2 plots averages and interquartile ranges from a rolling window of five consecutive survey dates. Consistent with the findings of Croushore (2012) and Giordani and Soderlind (2006) on point forecasts from the same survey, there seems to be a prevalence of pessimism from 1993 to 2002 and an increase in optimism through the 2000s for real GDP growth.[35]

Figure B.3: Confidence by Horizon



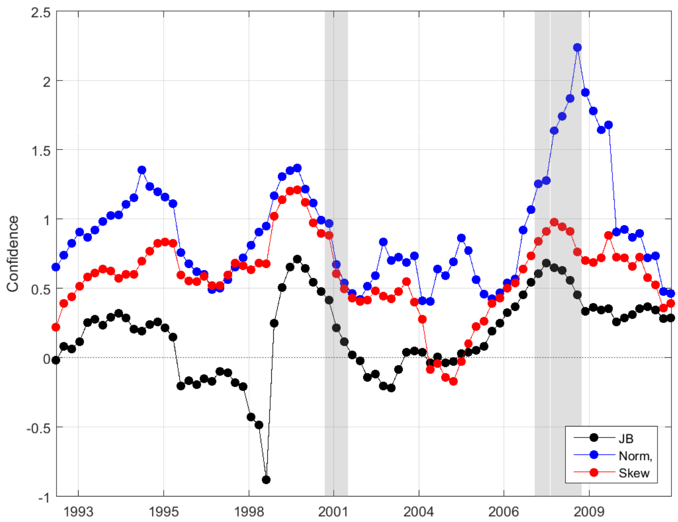

*The dots reflect the log variance of the transformed variable across forecasters and time for a given forecast horizon. The black points use the non-parametric transformation while the blue and red points use the Normal and Skew-Normal approximation estimates respectively.*

In Figures B.3 and B.4, I plot estimates of the sample (log) variances across forecast horizons and survey dates. The log-variance or relative confidence is on the vertical axis (higher is more confident) and the forecast horizon is on the horizontal axis in Figure B.3 while the target year is on the horizontal axis for Figure B.4.

With regard to the overconfidence bias, estimates suggest forecasts are consistently overconfident (log variance above zero) as also documented in Giordani and Soderlind (2006). The cyclical variation in estimates of the optimism and confidence biases over rolling windows of survey dates are remarkably similar for the GDP growth

[35]Note that, by averaging across forecasters, these may alternatively be interpreted as the (smoothed) time series of unforecastable aggregate shocks hitting real GDP growth. In this case, optimism in Growth is an unexpected negative output shock.

Figure B.4: Confidence by survey date

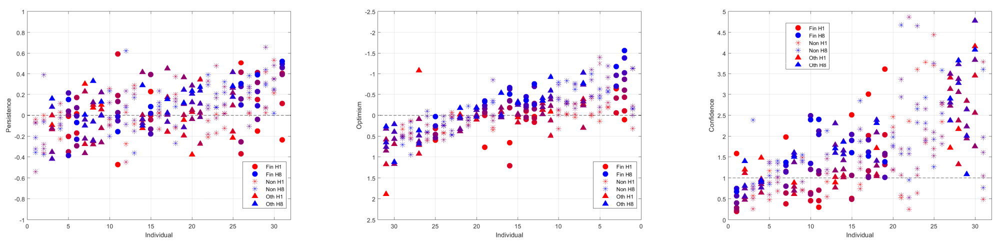



*The dots reflect the log variance of the transformed variable across forecasters and forecast horizon for a given survey date. The black points use the non-parametric transformation while the blue and red points use the Normal and Skew-Normal approximation estimates respectively.*

survey question. Around survey dates where average optimism is high, average confidence is also high.

The following figures report estimated coefficients assuming Normal and Skew-Normal density forecasts not reported in the main text.

Figure B.5: Estimated biases: Normal-Growth

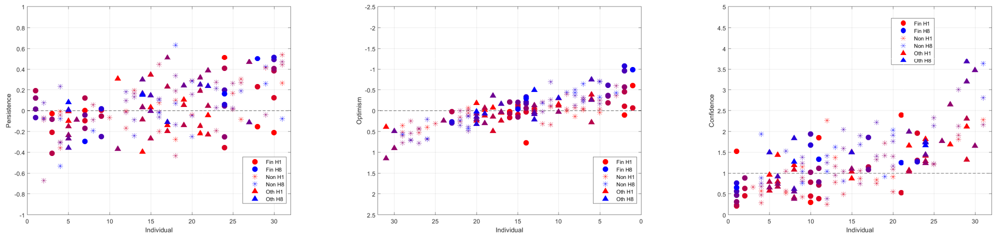


(a) Persistence (b) Optimism (c) Confidence

## C. *Relationship between confidence and optimism*

I also explore the relationship between the estimated optimism and confidence biases. Figure C.1 plots the estimated individual-forecast horizon parameters for these

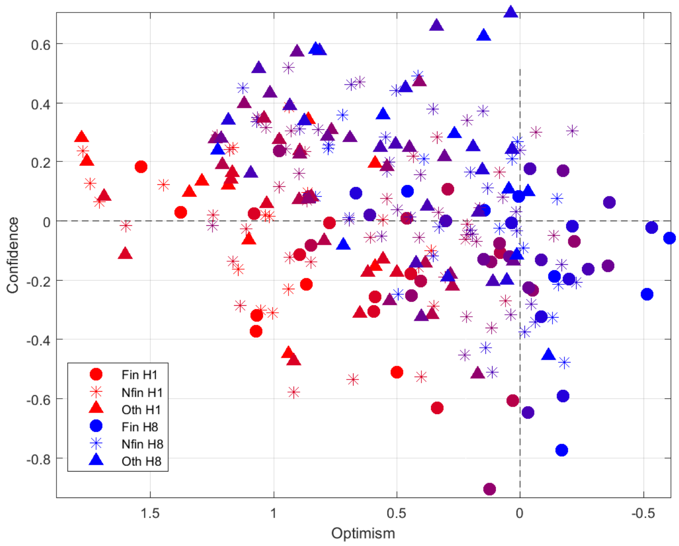
Figure B.6: Estimated biases: Skew-Growth



(a) Persistence (b) Optimism (c) Confidence

biases with optimism on the horizontal axis (right is more optimistic) and confidence on the vertical axis (higher is more confident) for $z^{JB}$.

Figure C.1: Estimated Optimism and confidence biases: JB



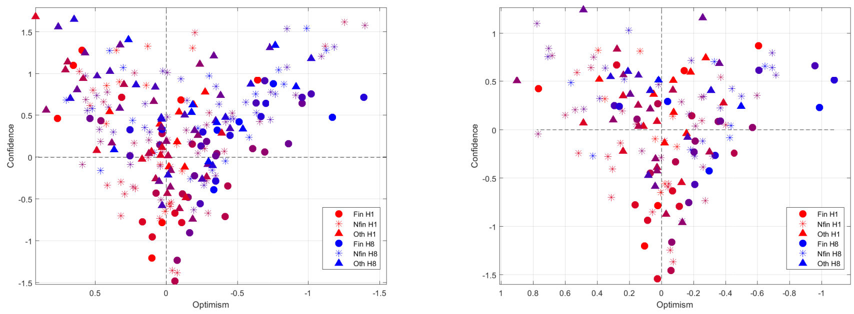

*Point estimates of optimism (horizontal) and confidence (vertical) parameters using the non-parametric transformation (JB). Colors reflect horizon from short (red) to long (blue). The shape distinguishes between forecasters from financial institutions (circle), non-financials (star) and others (triangle).*

The black dotted lines represent the null of no bias and thus the lower left quadrant reflects pessimism and doubt and the upper right would be optimistic and overconfident.

Again we have that the color represent the forecast horizon (red is short and blue is long) whereas the shapes represent the sector of the respondent (circle is financial and star is non-financial). In general there appears to be a negative relationship between relative pessimism and relative confidence for real GDP growth.

The next set of figures replicates Figure C.1 using estimates assuming Normal and Skew-Normal densities.

Figure C.2: Estimated Optimism and confidence biases




(a) Normal (b) Skew-Normal

## *D. Likelihood ratio tests excluding zero probability results*

In this exercise, we exclude survey responses for which the actual realization of the forecast target is outside the intervals with non-zero probabilities. For these tests, the forecast horizon biases are estimated at the level of current year ($H \in [1 \ldots 4]$) and following year ($H \in [5 \ldots 8]$) forecasts. This reduces the number of parameters estimated from 248 sets for each survey question in the exercise in the main text to 62 sets of parameters for each question from a sample of 3,825 responses.

Table D.1: Likelihood ratio test rejection rate: Growth

| | **10** | | | **5** | | | **1** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **JB** | **Norm** | **Skew** | **JB** | **Norm** | **Skew** | **JB** | **Norm** | **Skew** |
| **Persistence** ($\rho$) | 100.00 | 87.50 | 15.00 | 97.50 | 82.50 | 12.50 | 95.00 | 70.00 | 12.50 |
| **Optimism** ($\alpha$) | 15.00 | 5.00 | 0.00 | 15.00 | 2.50 | 0.00 | 7.50 | 0.00 | 0.00 |
| **Confidence** ($\beta$) | 62.50 | 97.50 | 12.50 | 55.00 | 92.50 | 10.00 | 50.00 | 92.50 | 7.50 |

*Rejection rates (in percent) at 10, five, and one percent significant levels. JB is the inverse-Normal transform of the PIT, Norm is the standardized forecast error using mean and variance estimated from a Normal distribution, and Skew is the equivalent using the Skew-Normal distribution.*

## *E. VAR results using minimum sign and zero restrictions*

In this section, I use the minimum set of restrictions to identify overconfidence shocks. I also identify a shock which raises both ex-ante and ex-post measures which I associate with financial and fundamental uncertainty ($FINUNC$). The restrictions are reported in Table E.2 below and are on contemporaneous effects.

Table E.2: Minimum zero and sign restrictions

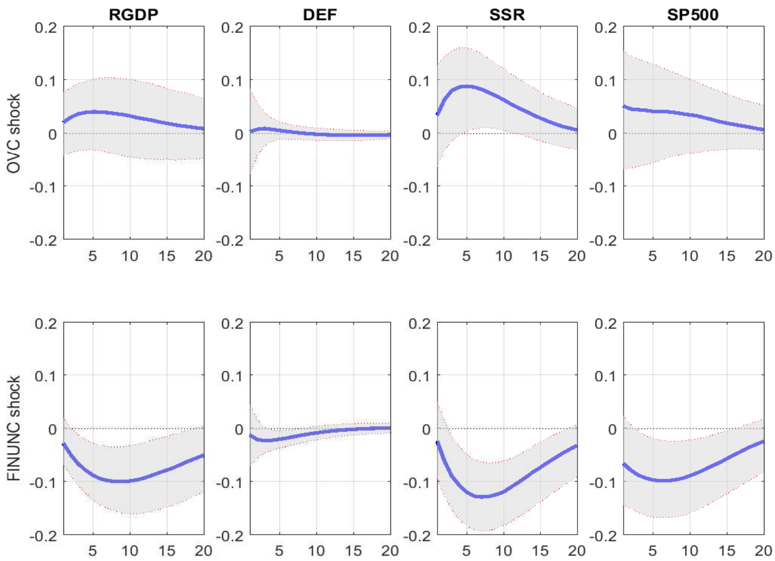
| | RGDP | DEF | SSR | SP500 | ExAnteUnc | ExPostUnc |
|---|---|---|---|---|---|---|
| FINUNC shock | | | | | + | + |
| OVC shock | | | | | - | 0 |
| X1 shock | | | | | 0 | 0 |
| X2 shock | | | | | 0 | + |
| X3 shock | | | | | - | + |
| X4 shock | | | | | | + |

*Restrictions are imposed contemporaneously. ExAnteUnc is the first principal component of $UNC$, $MCSU$, and $EPU$. ExPostUnc is the first principal component of $ASFED$, $JLN$, and $RSSV$.*

The restrictions on the last four shocks only emphasize the identification strategy that it is only overconfidence shocks which negatively affect ex-ante measures of uncertainty while having no impact on ex-post measures contemporaneously. Impulse responses are plotted in Figure E.3. In the bottom row, I also include impulse responses from the financial-fundamental uncertainty shock.

The contribution of overconfidence and financial-fundamental uncertainty shocks to forecast error variances are reported in Table E.3.

Figure E.3: Minimum restrictions impulse responses




*The column headers indicate the response variable and each row indicates the shock source. Shaded areas reflect the 68 percent interval. See Table E.2 for the identifying restrictions. The ex-ante measure of uncertainty is the first principal component of $UNC$, $MCSU$, and $EPU$. The ex-post measure is the first principal component of $ASFED$, $JLN$, and $RSSV$.*

Table E.3: Forecast error variance decomposition: minimum restriction

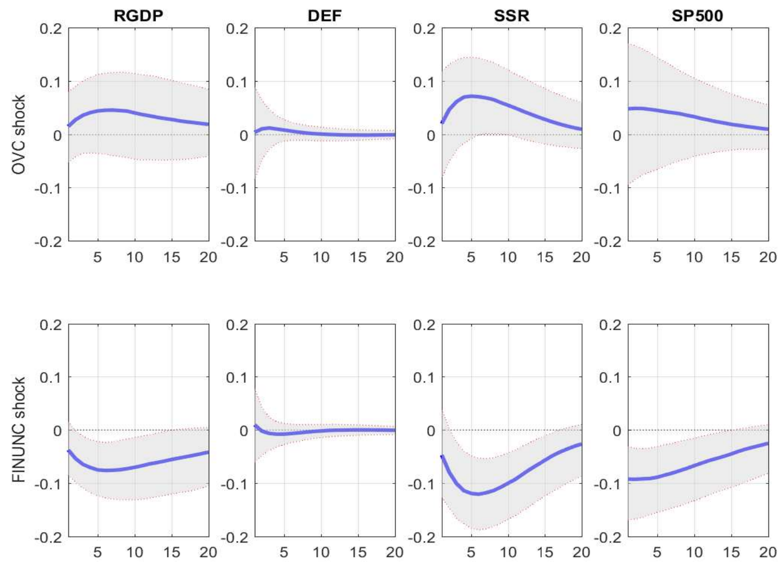
| | **RGDP** | **DEF** | **SSR** | **SP500** | **PCEA** | **PCEP** |
|---|---|---|---|---|---|---|
| **OVC H1** | 0.104 | 0.088 | 0.099 | 0.112 | 0.221 | 0.000 |
| **OVC H4** | 0.109 | 0.095 | 0.138 | 0.105 | 0.202 | 0.005 |
| **OVC H8** | 0.097 | 0.103 | 0.148 | 0.102 | 0.178 | 0.018 |
| **OVC H20** | 0.095 | 0.114 | 0.137 | 0.102 | 0.172 | 0.052 |
| **FINUNC H1** | 0.074 | 0.051 | 0.054 | 0.086 | 0.200 | 0.401 |
| **FINUNC H4** | 0.154 | 0.076 | 0.139 | 0.122 | 0.261 | 0.402 |
| **FINUNC H8** | 0.214 | 0.103 | 0.229 | 0.160 | 0.290 | 0.359 |
| **FINUNC H20** | 0.225 | 0.120 | 0.289 | 0.196 | 0.288 | 0.331 |

*Table reports median values of the forecast error variance due to shocks at given forecast horizons (in rows) for the variables listed in columns. The ex-ante measure of uncertainty is the first principal component of $UNC$, $MCSU$, and $EPU$. The ex-post measure is the first principal component of $ASFED$, $JLN$, and $RSSV$. Shocks identified via zero and sign restrictions posted on Table E.2*

# F. *VAR results using a different timing assumption for ex-post measures*

One may be concerned that the ex-post uncertainty measures, being largely based on four-quarter-ahead squared forecast errors (e.g. $ASFED_t$ is the adjusted squared forecast error for a forecast made at time $t$ for real GDP growth at time $t + 4$), contain information not only on fundamental uncertainty in the next four quarters known to agents in the current period but also other information only available after four quarters. To resolve this concern, I repeat the VAR exercise in the main text using the same variables but with the ex-post measures for uncertainty dated at the forecast target realization date. That is, I run a VAR(1) on the vector $[RGDP_t\ DEF_t\ SSR_t\ SP500_t\ PCEA_t\ PCEP_{t-4}]$ using the same sign and zero restrictions in Table 5. Impulse responses from this exercise are plotted below. We find

Figure F.4: Sign and zero restriction identification impulse responses




*The column headers indicate the response variable and each row indicates the shock source. Shaded areas reflect the 68 percent interval. See Table 5 for the identifying restrictions. The ex-ante measure of uncertainty is the first principal component of $UNC$, $MCSU$, and $EPU$. The ex-post measure is the first principal component of $ASFED$, $JLN$, and $RSSV$.*

that the impulse responses using this slight variation in timing are virtually identical to the responses shown in Figure 8. The actual median responses are marginally smaller in magnitude.

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