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The Role of Macroeconomic and Policy Uncertainty

in Density Forecast Dispersion

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Abstract

We explore empirically the role of macroeconomic and policy uncertainty in explaining dispersion in professional forecasters' density forecasts, and in explaining individual forecaster uncertainty (defined as the uncertainty expressed by individual forecasters in their density forecasts). We focus on US real output growth and inflation, using data from the Philadelphia Fed's quarterly Survey of Professional Forecasters (SPF), 1992-2016. We find that dispersion in individual density forecasts is related to macroeconomic uncertainty, especially in longer horizon forecasts, but not policy or forecaster uncertainty. There is also little evidence that forecaster uncertainty reflects macroeconomic or policy uncertainty.

Keywords: Surveys of Professional Forecasts, Density Forecasts, Forecast Dispersion, Macroeconomic Uncertainty, Policy Uncertainty

JEL Codes: D80, E17, E27

1. Introduction

Surveys of professional macroeconomic forecasters show that forecasters generally disagree with each other. This is true for both point and density forecasts, both of which are typically dispersed. Pervasive evidence of forecast dispersion, even among a group of economic agents who should be reasonably homogeneous in terms of ability and motivation, suggests that expectations may in general be heterogeneous. Empirical investigations into point and density forecast dispersion can help us better understand the formation of expectations and the underlying reasons for heterogeneity, with follow-on implications for how expectations can affect business cycles, and the effectiveness of policy. Dispersion in point forecasts has been well-studied, but dispersion in density forecasts less so. Studying dispersion in density forecasts, in particular, may help us better understand the connections and relationships between individual forecaster uncertainty and uncertainty in the macroeconomic environment, and how they relate to disagreement among forecasters in particular. This is the main focus of our study.

Dispersion of (point) forecasts is often used as a proxy for uncertainty, whereas density forecasts appear to offer a direct measure of forecaster uncertainty. An important part of understanding forecast dispersion is to see how it differs from individual forecaster uncertainty, as expressed in their density forecasts. This a second focal point of our study.

As an example of dispersion in point forecasts, we show in Figure 1 point forecasts for annual 1996 US PGDP (GDP price index) inflation made by economic forecasters surveyed by the Philadelphia Fed in their quarterly Survey of Professional Forecasters (SPF) over the period 1995Q1 to 1996Q4, i.e., these are forecasts made at horizons of 7 quarters down to 0 quarters. The point forecasts are dispersed at long horizons, with dispersion falling as the forecasters approach the full realization of the forecast event. Some persistence in the forecasts can be observed, with relatively optimistic and pessimistic forecasts tending to remain so. Similar patterns can be observed in many other similar datasets. Explanations put forward for these and other patterns in dispersion of point forecasts include the use of different information sets by forecasters, perhaps due to different degrees of information rigidities among them (Mankiw, Reis and Wolfers, 2003), different interpretation of information by forecasters (Kandel and Zilberfarb, 1999; Manzan, 2011), different loss functions among forecasters (Capistran and Timmermann, 2009), and different priors held by forecasters regarding the unconditional distribution of the variables being forecasted (Patton and Timmermann, 2010).

[Figure 1 around here]

The objective of this paper is to study patterns of dispersion in density forecasts. In addition to point forecasts, forecasters participating in the SPF are also asked to provide density forecasts in the form of histograms. In each survey, forecasters are given a set of intervals and asked to provide for each interval an estimate of the probability with which the variable's realization is expected to appear in that interval. Figure 2 displays an individual forecaster's density forecast of growth in PGDP inflation for the year 1996, taken from the 1996Q2 survey.

[Figure 2 around here]

In order to show dispersion in density forecasts over forecasters, we derive, for each individual density forecast, the median, central 0.90 probability interval, and a measure of skewness, and we study dispersion in these descriptive statistics. The construction of these statistics (or 'characteristics') is illustrated in Figure 2, and discussed in more detail in later sections. The panels in the right column of Figure 1 plot these statistics for individually reported density forecasts of 1996 annual PGDP inflation, taken from the same set of surveys as the point forecasts in the left panel. The dispersion patterns in the medians match those of the point forecasts. The dispersion patterns in the range and asymmetry of the density forecasts are less clear, but there is certainly dispersion. Density forecasts, of course, offer us the potential of observing a forecaster's expectations in a more complete form. The spread of a density forecast might be considered a possible direct measure of the level of individual uncertainty perceived by the forecaster. Asymmetries in the density forecasts, for a given level of uncertainty, may indicate some degree of optimism or pessimism.

The plots in Figure 1 focus on the change in dispersion with respect to forecast horizon, but there is also considerable variation in dispersion over time, as can be observed in Figure 3, which plots the medians of all of the density forecasts of PGDP inflation in our chosen sample period.

[Figure 3 around here]

The primary objective in this paper is to understand the time variation in dispersion of the medians, spread, and skewness of the density forecasts reported by forecasters. In particular, we are interested in the role of forecaster uncertainty, and uncertainty in the macroeconomic and policy environment on dispersion among individual density forecasts. Throughout we make a clear distinction between forecaster uncertainty versus uncertainty in the macroeconomic environment. It is generally accepted that there is time-variation in the volatility of macroeconomic variables, so that these variables are easier to predict in some periods, but harder to predict in others. However, it is not difficult to imagine an overconfident forecaster who always issues very narrow density forecasts. As part of the broader concept of uncertainty in the macroeconomic environment, one might also include policy uncertainty, which again is not the same as forecaster uncertainty or variations in predictability. We use density forecasts to construct a measure of forecaster uncertainty, and take advantage of recently developed indices of macroeconomic uncertainty, which focus on whether the economy has become more or less predictable (Jurado, Ludvigson and Ng, 2015), and of policy uncertainty, that rely on the prevalence of 'uncertainty' keywords in news articles (Baker, Bloom, and Davis, 2016). We correlate our measures of dispersion in density forecasts with these direct measures of uncertainty.

Our work differs from much of the forecast dispersion literature in that we explore dispersion of density forecasts, and not point forecasts. While there are several papers that have documented dispersion of density forecasts (Boero, Smith and Wallis, 2008), the literature has in general focused on explaining the behavior of individual uncertainty (Lahiri and Liu, 2006). Our interest is in the behavior of dispersion in the location, spread, and skewness in individual density forecasts, using the average levels of these as well as indices of macroeconomic and policy uncertainty as explanatory variables. Whereas most studies focus on inflation expectations, we also study output growth expectations; it turns out that there are some interesting differences in the behavior of the two. This paper is also closely related to research aimed at establishing whether or not point forecast dispersion is a good proxy for forecaster uncertainty (Zarnowitz and Lambros, 1987; Giordani and Soderlind, 2003; Rich and Tracy, 2010; Boero, Smith and Wallis, 2008, 2015), which boils down to asking if dispersion can explain individual uncertainty (the general consensus appears to be, mostly, 'no'.) The objective of our exercise, on the other hand, is to see if various forms of uncertainty can explain forecast dispersion, which we take to be a reflection of heterogeneity in expectations. We find, in general, that dispersion is correlated with macroeconomic uncertainty, less so with policy uncertainty, and not correlated with forecaster uncertainty.

In the next section, we describe the SPF survey dataset briefly, focusing on the density forecasts and the percentile-based summary statistics that we use to characterize them. We also describe the patterns of dispersion in these summary statistics. We take a closer look at forecaster uncertainty in Section 3, and its relationship to the macroeconomic uncertainty and policy uncertainty indices. Our main results regarding dispersion are reported in Section 4, and Section 5 concludes.

2. Characteristics and Dispersion of Density Forecasts

2.1 *Data*

The primary data includes forecasts of US variables elicited from professional forecasters by the Philadelphia Fed through their Survey of Professional Forecasters. Every quarter the Philadelphia Fed surveys a panel of professional forecasters for their expectations regarding a range of macroeconomic variables at various forecast horizons. The survey is sent out after the release of advanced estimates for the variables for the previous quarter. The variables for which point forecasts are collected include quarterly and annual frequency real and nominal GDP, unemployment, 3-month treasury bill and 10-year treasury bond rates, price indices (GDP price index, CPI and PCE indices), among many others. Besides point forecasts, the surveys also elicit density forecasts for growth in the annual averages of real GDP (RGDP), the GDP price index (PGDP), core CPI and core PCE, and the civilian unemployment rate.

Our focus in this paper is on the density forecasts for the annual average of real GDP growth and PGDP inflation, since density forecasts for the other variables are recent additions to the survey (2007Q1 for CPI and PCE inflation, 2009Q2 for unemployment). Density forecasts are elicited for the annual outcomes for the current year and the following year, so for each target year we have forecasts made at horizons $h = 0$ to $h = 7$ quarters. The Q1 surveys contain forecasts 3- and 7-quarters ahead (corresponding to the current year and following year forecasts respectively), the Q2 surveys contain forecasts at 2- and 6-quarter horizons, the Q3 survey contains forecasts 1- and 5-quarters ahead, and the Q4 survey contains forecasts at 0- and 4-quarter horizons. From 2009Q2 onwards, the survey began requesting, for certain variables, density forecasts for the current and next three years, so in more recent surveys we have forecasts up to 15 quarters ahead. For this study we only consider forecasts made 0 to 7 quarters ahead.

We only consider forecasts starting with the 1992Q1 survey, even though point and density forecasts for output and inflation are available all the way back to the first survey in 1968Q4. There are several reasons for using only post-1992Q1 sample period. First, there were several definition changes to the variables forecasted prior to the 1992Q1 survey (for output, from nominal GNP to real GNP to real GDP). In some years prior to 1992Q1 the survey asked for forecasts for the previous and current year, instead of the current and following year. Since 1992Q1 the definitions have been stable. Second, in the surveys in the 1980s, the interval widths given for density forecasts were switched from one percentage point intervals to two percentage point intervals, leading to much cruder density forecasts. In addition to this, the intervals provided in some of the earlier surveys were sometimes completely misaligned with the expectations of the forecasters, resulting in density forecasts with probabilities concentrated in the first or last open-ended bins. In contrast, the sample period that we use is much cleaner in terms of variable and forecast definitions, and have fewer instances of 'misaligned bins', and only very few instances where the percentile-based descriptive statistics that we use cannot be computed. Our sample period ends with the 2016Q4 survey.

2.2 *Descriptive Statistics for Density Forecasts*

We summarize each density forecast using its median, central 0.90 probability range, and a Bowley-type skewness statistic to describe the location, spread, and shape features of the density forecast respectively. The Bowley statistic that we use to measure skewness in the density forecasts is

$$S = \frac{(x_{95} - x_{50}) - (x_{50} - x_5)}{x_{95} - x_5}$$

where x_α represents the α-th percentile of the density forecast. Bowley skewness statistics are usually calculated using the median and the interquartile range, but here we use instead the median x_{50}, and the central 0.90 probability range $x_{95} - x_5$. The interquartile version of the Bowley statistic is usually applied to a sample of observations, where the 5th and 95th percentiles are often not meaningful unless the sample size is large. In our application, we use the Bowley statistic to describe a density forecast rather than a sample of data, and using the central 0.90 probability range is feasible, and preferred, as it covers more of the distribution. Whereas the range might be considered a measure of individual uncertainty, the skewness statistic might be interpreted as a direct measure of optimism/pessimism of the forecaster.

Our main reason for using percentile-based descriptions of the density forecasts is that the end bins are unbounded intervals (see Figure 2 for an example). Using percentile-based descriptions avoids the strong assumptions that are needed for moment- and entropy-based measures, primarily to accommodate the fact that the two end-intervals provided to forecasters are open-ended, and assuming a particular parametric form for the subjective distribution. Of course, the percentile-based approach that we use also has its disadvantages, e.g., it requires interpolation within the bins (we use linear interpolation of the cumulative probabilities, thus assume probabilities to be evenly spread within each bin). Furthermore, the 5th (95th) percentiles cannot be computed if the probabilities reported for the first or last bins are greater than 5 (probabilities are reported out of 100). While our assumption regarding the shape of the density forecasts is strong, this is mitigated by the fact that the assumption is applied only in the bins in which the 5th, 50th, and 95th percentiles fall. The fact that the 5th and 95th percentiles cannot be computed in some cases is also not a major issue for our sample period, as these instances are few. Finally, recent papers have considered moment- and entropy-based statistics (Rich and Tracy, 2010; Boero, Smith and Wallis, 2008, 2015) for some of the issues we examine, so it is interesting to see how our results compare with these studies when using different measures.

We use

$$M_{i,t,h}\text{, } R_{i,t,h}\text{, and } S_{i,t,h}$$

to denote the median, range, and skewness statistics for forecaster i's period t density forecast of annual GDP growth or annual inflation made h-quarters ahead, $h = 0,1,...,7$. The subscript t is a quarterly date index (1992Q1, 1992Q2, etc.) and represents the survey date. The target year is not represented in this notation, and must be derived from the survey date t and the horizon. We use the sample period $t = 1992q1,...,2016q4$.

The data set is a panel covering 160 forecasters for PGDP and 161 forecasters for RGDP, and spanning a period of 100 quarters. It is, however, a highly unbalanced panel, with an average of around 34 forecasters in each period, and with the average forecaster appearing over around 20 quarters. Furthermore, each forecaster makes two forecasts each period (one for the current year, and one for the following year), so we have two observations per forecaster per period. Altogether there are 6734 observations.

We are interested in the dispersion in the three density forecast characteristics among forecasters. Dispersion measures are calculated as standard deviations over the forecasters in each period. We denote our dispersion measures as

$$M^{\sigma}_{t,h} = \text{std.dev.}(M_{i,t,h}),\ R^{\sigma}_{t,h} = \text{std.dev.}(R_{i,t,h}),\ S^{\sigma}_{t,h} = \text{std.dev.}(S_{i,t,h}).$$

We will also be referring to the mean levels of the characteristics, which we denote as

$$M^{m}_{t,h} = \text{mean}(M_{i,t,h}),\ R^{m}_{t,h} = \text{mean}(R_{i,t,h}),\ S^{m}_{t,h} = \text{mean}(S_{i,t,h}).$$

The variable $M_{t,h}^{m}$ is included as there may be a relationship between the level of inflation (which should be correlated with the expected level of inflation) and inflation uncertainty (Ball, 1992), which several previous studies have confirmed (Lahiri and Liu, 2006; Rich and Tracy, 2010). We include $M_{t,h}^{m}$ for our output growth regressions as well. The variable $R_{t,h}^{m}$ is the average of individual uncertainty. The variable $S_{t,h}^{m}$ is included as an elaboration of average individual uncertainty, indicating asymmetries in relative upside vs downside risks.

2.3 Dispersion Patterns in Density Forecasts

Figure 4(a) summarizes the behavior of individual PGDP inflation density forecasts, and the dispersion of these forecasts. The top row displays the average over all forecasters of the median, range, and skewness of the individual density forecasts, for each horizon and each target year. The bottom row shows the standard deviation of these characteristics over the individual forecasts. Each line in each subfigure corresponds to a target year (1992 to 2017), all plotted against forecast horizon. The top row shows how, on average, the forecasters revise their forecasts each quarter for each target year in our sample, and the bottom row shows the disagreements among the forecasters. Figure 4(b) shows the corresponding figures for RGDP growth.

The subfigures marked M^{m} show moderate revisions to the density forecast medians on average, except for a sharp drop in the RGDP growth forecasts for 2009. The subfigures marked R^{m} show that average individual uncertainty falls as the forecast horizon approaches zero, with the fall accelerating from horizons 3 to 0 quarters. The accelerating fall should be due in large part to the fact that fewer quarters are being forecasted in these horizons (these are forecasts of annual growth for the year in which the quarterly surveys are taken). We might also expect average uncertainty to fall because more information is (presumably) being incorporated into the forecasts each quarter. This seems more the case for RGDP growth than for PGDP inflation. The subfigure for forecaster uncertainty R^m in PGDP inflation also shows something that might be of concern. There is a systematic drop in average range from the 2014Q1 surveys onwards. This corresponds to a change in bin definitions for PGDP inflation to match those of CPI and core PCE, with the overall range reduced substantially (from "<0",…, ">8", to "<0", …, ">4"). This is worrying because it might indicate a framing effect as far as the spread of elicited density forecasts are concerned. A much smaller change in the RGDP bin definitions was made in 2009Q2, from "<-2",…, ">6" to "<-3",…, ">6". Though it is hard to see from the figures the effects of this change, nonetheless, our regressions will include a new indicator variable $newbin_t$ for both PGDP inflation and RGDP growth. This variable is equal to '0' up to 2013Q4 and '1' thereafter for PGDP inflation forecasts, and '0' up to 2009Q1 and '1' thereafter for RGDP growth forecasts. The subfigures for average skewness S^m show that inflation density forecasts tend to be positively skewed whereas output growth forecasts tend to be negatively skewed. That is, forecasters tend to perceive ‘upside risks’ for inflation and ‘downside risks’ for output growth. A major exception is at the end of 2009 when there was a sudden swing to positive skewness in real output growth forecasts. The largest changes in skewness comes in horizons 0 and 1.

[Figure 4 around here]

The patterns of dispersion in the bottom rows of Figures 4(a) and (b) show larger dispersion in the forecast medians at long horizons for both variables, and smaller dispersion at shorter horizons. At the short horizons this might again be due to the fact that there is less to disagree about, but the fall in dispersion seems to be present at all horizons. There appears to be more disagreement at horizon 0 for PGDP inflation than RGDP growth. This has also been noticed in point forecast datasets (e.g. Patton and Timmermann, 2010). Dispersion appears to fall slightly for the range, and rise slightly for the skewness, of RGDP growth forecasts as horizon decreases. These patterns are less noticeable for PGDP inflation forecasts. Nonetheless, there is variation over time in the dispersion of all three characteristics of the density forecasts.

3. Macroeconomic, Policy, and Forecaster Uncertainty

We have already described our measure of self-reported individual forecaster uncertainty $R_{i,t,h}$, and its average $R^m_{t,h}$ taken over all forecasters for each horizon at each survey date. In this section, we discuss recently developed measures of two different notions of uncertainty, namely macroeconomic uncertainty, and policy uncertainty, and explore the relationship between these measures of uncertainty, and forecaster uncertainty. Our main objective, which we will turn to in the next section, is to see how dispersion in density forecasts correlate with these three different "types" of uncertainty.

It is a well-established fact that macroeconomic variables are easier to forecast in some periods than at others because the volatilities of their unpredictable components vary over time. Jurado, Ludvigson and Ng (2015) develop an index of macroeconomic uncertainty (which we refer to as MU_t) comprising a weighted average of conditional root mean square forecast errors for a wide range of macroeconomic variables $\{y_{it}\}_{i=1}^{N_y}$:

$$MU_t = \sum_{j=1}^{N_y} w_j U_{jt}^{y}(k)$$

$$U_{jt}^{y}(k) = \sqrt{E[(y_{j,t+k} - E[y_{j,t+k} \mid I_t])^2 \mid I_t]}$$

where k refers to the forecast horizon, and I_t is a large information set on which the forecasts are based. Their set of macroeconomic variables include real output and income, employment, manufacturing and trade sales, consumer spending, housing starts, and many more, totaling 132 variables. The forecast errors for these variables were derived from a factor model utilizing these and 147 financial variables. They calculate macroeconomic uncertainty indices for $k = 1, 3,$ and 12 months. We utilize all three, but report results only for $k = 3$.

Baker, Bloom and Davis (2016) develop an economic policy uncertainty index based on human and automated searches of the archives of ten large newspapers. This index quantifies the volume of relevant news coverage by counting the number of articles related to policy uncertainty starting from January 1985 (monthly average of the standardized number of articles, scaled to an average of 100). We use this data series, downloaded from their website and referred to hereafter as PU_t, as a direct measure of policy uncertainty. We aggregate the monthly index to quarterly frequency by taking the average over each quarter. The left column of Figure 5 displays the two indices, where it can be seen that PU_t is considerably more volatile than MU_t. The two series are correlated, but only moderately so, at approximately 0.40.

[Figure 5 around here]

The three uncertainty indices considered in this paper MU_t, PU_t and $R^m_{t,h}$, can be viewed along the objective-subjective spectrum, with MU_t being a purely objective measure, $R^m_{t,h}$ being a purely subjective notion, and PU_t being somewhere in between. We are interested in how dispersion of density forecasts is correlated with these. The right column of Figure 5 displays $R^m_{t,h}$, with the higher line representing average forecaster uncertainty relating to forecasts for the following year, and the lower line relating to forecasts for the current year. These figures give a time-series view of $R^m_{t,h}$ whereas the upper middle diagrams in Figures 4(a) and (b) show $R^m_{t,h}$ as a function of horizon, for various years. The declining forecaster uncertainty gives rise to the periodicity, especially for the lower horizon forecasts.

Although our main focus is to explore the role of macroeconomic and policy uncertainty on density forecast dispersion, relative to the role played by individual forecaster uncertainty, we begin by showing the individual forecaster uncertainty does not appear to reflect macroeconomic and policy uncertainty. To explore how subjective forecaster uncertainty relates to the two other measures of uncertainty, we run the panel regression

$$\begin{aligned} R_{i,t,h} = \beta_{i,0} + \beta_1 h_{1t} + \ldots + \beta_7 h_{7t} + \beta_8 newbins_t \\ + \beta_9 R_{i,t-1,h^*} + \beta_{10} M_{i,t,h} + \beta_{11} PU_t + \beta_{12} MU_t + \varepsilon_{i,t,h} \end{aligned} \quad (1)$$

for both PGDP inflation and RGDP growth, where $h_{1t},\ldots,h_{7t}$ are horizon dummies. The variable $R_{i,t-1,h^*}$, which we will refer to as "lagged individual uncertainty", is included to capture persistence in range across consecutive surveys ($h^* = h+1$ for $h = 0,1,2,4,5,6$ and $h^* = h-3$ for $h = 3,7$). We estimate the fixed effect specification (1) by least squares dummy variables (LSDV), as implemented in Stata's `areg` command. Because each of the forecast horizon pairs (0,4), (1,5), (2,6) and (3,7) are made on the same survey quarter, and to allow for possible omitted factors at each survey date, we cluster standard errors by year and quarter. This allows errors to be correlated at horizon pairs (0,4), (1,5), (2,6) and (3,7) within each year. The regression results are displayed in Table 1. We also produce 'split-sample' versions of each regression, separating observations associated with 'current-year' forecasts (forecast horizons 0 to 3) from 'next-year' forecasts (forecast horizons 4 to 7).

[Table 1 around here]

The results for PGDP inflation and RGDP growth are very similar, with some differences. The coefficients on lagged individual forecaster uncertainty ($R_{i,t-1,h^*}$) show strong persistence in individual uncertainty across both variables and all subsamples. This is consistent with previous research using different methodologies. However, the coefficients on both macroeconomic and policy uncertainty are insignificant for both PGDP inflation and RGDP growth regressions, and across all subsamples; while individual forecaster uncertainty is persistent, they do not respond to current levels of macroeconomic and policy uncertainty.

One difference between the results for PGDP inflation and RGDP growth is in the coefficients on $M_{i,t,h}$, which represents the short-run response of individual forecaster uncertainty to an increase in expected inflation. The full sample regression shows that the short run response to a 1 percentage point increase in anticipated inflation is a short-run increase in the width of individual forecasters density forecast range by 0.139 percentage points. The long-run response is slightly higher, at 0.139/(1-0.308) = 0.2 percentage points. This result is consistent with results from previous research that positive changes in anticipated inflation is associated with greater uncertainty (Lahiri and Liu, 2006; Rich and Tracy, 2010). For RGDP growth, however, the coefficients on $M_{i,t,h}$ are much weaker, and not significant at the longer horizons. Another difference is that the coefficient on $newbins_t$ is large and significant for PGDP inflation, but not RGDP growth. The $newbins_t$ variable is included to capture a change in the bin structure offered to forecasters in the survey. The strong significant (negative) coefficients on $newbins_t$ in the PGDP inflation regressions confirm that the substantial reduction in the overall bin range for PGDP inflation that occurred after the 2013Q4 survey led to a large decline in the range reported by forecasters. This is also obvious from Figure 4(a) and Figure 5. As mentioned earlier, this suggests that measures of individual uncertainty derived from density forecasts may be subject to a framing effect, although it may also be the case that both forecast surveyor and forecasters are reacting to the same information. This does not necessarily invalidate our use of direct measures of individual uncertainty from density forecasts, although it does emphasize the need to control for changes in bins offered to the forecasters, and warrant caution in the interpretation of self-reported measures of uncertainty, at least as elicited using the methods currently employed in surveys of density forecasts. For RGDP growth, the overall range of the bins in the RGDP growth survey provided to the forecasters to input their density forecasts was only very slightly widened from (-2,6) to (-3,6) in 2009Q2, which may explain the insignificant coefficients on $newbins_t$ for the RGDP growth regressions.

As for the coefficient estimates on the horizon dummies, they are as expected. Earlier we noted from the top diagrams of the second columns of Figures 4(a) and (b) that range falls with horizon, and this could be due to less uncertainty because forecasters have more information: for example, in horizons 0, 1, and 2, only 1, 2, and 3 quarters of growth are being forecasted respectively.

We run regressions similar to (1) for skewness, replacing $R_{i,t,h}$ with $S_{i,t,h}$, and include $R_{i,t,h}$ as a regressor:

$$\begin{aligned} S_{i,t,h} = \beta_{i,0} + (\text{horz. dummies}) + \beta_8 newbins_t ... \\ + \beta_9 S_{i,t-1,h*} + \beta_{10} M_{i,t,h} + \beta_{11} R_{i,t,h} + \beta_{12} PU_t + \beta_{13} MU_t + \varepsilon_{i,t,h} \end{aligned} \quad (2)$$

The results are reported in Table 2. Overall the results are harder to interpret. We leave out the horizon dummies and constant as there is nothing interesting to report. We noted earlier that density forecasts for inflation tend to be positive skewed, whereas density forecasts for output growth tend to be negatively skewed. From the estimation results, we again detect a persistence in individual skewness for both PGDP inflation and RGDP growth density forecasts, and a negative correlation between expected levels and skewness, meaning that as expected levels go up, density forecasts become less skewed (inflation) or more negatively skewed (output growth). Overall, increased uncertainty appears to reduce skewness (inflation) or increase negative skewness (output growth). Skewness in density forecasts of inflation appears to be negatively correlated with policy uncertainty and macroeconomic uncertainty for long-horizon forecasts. We will show later, however, that these results are not robust.

[Table 2 around here]

Our primary interest in regression equations (1) and (2) was whether individual forecast characteristics were affected by the uncertainty indices, and the inclusion of the lagged dependent variable is to control for persistence within each forecaster. However, this raises a concern about bias as a result of the dynamic specification. We check our results in two ways. First, we re-estimated our split sample regressions in Tables 1 and 2 using the higher-ordered expansion techniques of Kiviet (1999) and Bun and Kiviet (2003), and which were extended in Bruno (2005) to handle unbalanced panels, and implemented in the Stata command `xtlsdvc`. The results show that the estimate of the coefficient on the lagged dependent variable is slightly biased downwards, but there are no qualitative changes to any of the results presented in Tables 1 and 2. We also explored dropping the lagged dependent specification and instead accounting for correlation within forecaster by applying two-way clustering of standard errors, by year-quarter and by forecaster id. Again we find no qualitative differences between these results and those presented in Tables 1 and 2. These additional results are not reported here, but are collected in an online appendix.

4. Main Results

We explore in this section the behavior of dispersion in the individual density forecasts, as summarized by their location, range, and skewness statistics $M^{\sigma}_{t,h}$, $R^{\sigma}_{t,h}$, $S^{\sigma}_{t,h}$. We examine in particular the relative degrees to which average forecaster uncertainty ($R^{m}_{t,h}$) and uncertainty in the macroeconomic environment (as measured by MU_t and PU_t) can explain the degree of dispersion observed in these three statistics. We also include the average values of location and skewness, $M^m_{t,h}$ and $S^m_{t,h}$, in the regressions, and lagged dispersion to capture persistence in dispersion from one quarter to the next. We include as a further control, dispersion in the forecasters' yield spread (nominal rate on 10-year T-bonds minus the nominal rate of 3-month T-bills) in the inflation forecast dispersion regressions. The yield spread is commonly viewed as a good predictor of inflation (even if recent evidence suggests that this might not be the case, e.g., Ang, Bekaert and Wei, 2007; Stock and Watson, 2009; Rossi and Sekhposyan, 2010). The yield spread may also have good predictive power for output growth (Estrella and Hardouvelis, 1991; Estrella and Mishkin, 1998; Hamilton and Kim, 2002), although there is evidence that short-term interest rates forecast output growth better than spreads (Ang, Piazzesi and Wei, 2006). Although we have run the regressions for both the short-rate and the yield spreads for output growth forecast dispersion, we report only the regressions with the short rate, and mention the changes that occur when the spread is used. Finally, dispersions were seen in Figures 4(a) and (b) to change systematically with horizon, and we include horizon dummies to allow for this.

$$\begin{aligned} M^{\sigma}_{t,h} = \beta_0 + (\text{horz. dummies}) + \beta_8 newbins_t \ldots \\ + \beta_9 M^{\sigma}_{t-1,h*} + \beta_{10} M^m_{t,h} + \beta_{11} R^m_{t,h} + \beta_{12} S^m_{t,h} \ldots \\ + \beta_{13} spread^{\sigma}_{t,h} + \beta_{14} PU_t + \beta_{15} MU_t + \varepsilon_{t,h} \end{aligned} \tag{3}$$

The regressions are repeated for $R^{\sigma}_{t,h}$ and $S^{\sigma}_{t,h}$:

$$
\begin{aligned}
R^{\sigma}_{t,h} = \beta_0 + (\text{horz. dummies}) + \beta_8 newbins_t \ldots \\
+ \beta_9 R^{\sigma}_{t-1,h*} + \beta_{10} M^{m}_{t,h} + \beta_{11} R^{m}_{t,h} + \beta_{12} S^{m}_{t,h} \ldots \\
+ \beta_{13} spread^{\sigma}_{t,h} + \beta_{14} PU_t + \beta_{15} MU_t + \varepsilon_{t,h}
\end{aligned} \tag{4}
$$

$$
\begin{aligned}
S^{\sigma}_{t,h} = \beta_0 + (\text{horz. dummies}) + \beta_8 newbins_t \ldots \\
+ \beta_9 S^{\sigma}_{t-1,h*} + \beta_{10} M^{m}_{t,h} + \beta_{11} R^{m}_{t,h} + \beta_{12} S^{m}_{t,h} \ldots \\
+ \beta_{13} spread^{\sigma}_{t,h} + \beta_{14} PU_t + \beta_{15} MU_t + \varepsilon_{t,h}
\end{aligned} \tag{5}
$$

As with equations (1) and (2), we again cluster standard errors by survey date (year and quarter) to account for possible correlations in the error terms associated with the two forecasting horizons at each time period.

4.1 Dispersion in Medians

We present the results for PGDP inflation in Table 3 and for RGDP growth in Table 4, with five versions of each equation, a baseline (a) without spread, macro uncertainty, and policy uncertainty, a second (b) including spread, and a third version including all variables (c). For the full set of variables, we run the regression for all horizons (c), and then split the sample into that for the shorter horizons (d) and the longer horizons (e). Splitting the sample allows us to analyze the behavior of dispersion of 'short'-horizon and 'long-horizon' forecasts.[1]

[1] We check our 'short'-horizon and 'long-horizon' time series regressions in Tables 3 and 4 for structural stability using the recursive CUSUM test for parameter stability as implemented in STATA's `estat sbcusum`, and the Breush-Godfrey LM test for autocorrelation. The CUSUM test does not reject the null of no structural break in all cases. The LM test does not reject the null of no autocorrelation in most cases, with the exception of some regressions for dispersion of range and skewness for RGDP

[Table 3 around here]

[Table 4 around here]

The key results from these regressions is that the coefficients on macroeconomic uncertainty are significant and positive in the long-horizon regressions, while policy and forecaster uncertainty play little role in explaining dispersion of medians. The estimates in column (c) in Tables 3 and 4 show that for both variables, dispersion is positively correlated with direct measures of macroeconomic uncertainty, even after controlling for forecast horizon, lagged dispersion, and other variables. The coefficient on MU_t is larger in the long-horizon regression (column (d)) than in the short horizon regression (column (e)), where the coefficient is not significant. This is particularly interesting as the macro-uncertainty index that we use measures predictability at a 3-month horizon.

For PGDP inflation, columns (a) to (d) show that the coefficient on the dispersion of forecasts on yield-spread is significant, i.e., the dispersion in forecasters' views regarding inflation is positively correlated to their dispersed views regarding spread. The coefficient on spread remains significant, though smaller, after inclusion of the uncertainty indices, except in the long horizon regressions, where it is no longer significant. Similarly, for RGDP growth, the

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growth in the long horizon. The results do not change when we use autocorrelation-consistent standard errors. Test results are presented in the online appendix.

coefficient on the T-bill rate forecast dispersion is positive and significant in columns (a) to (d). The coefficient of the spread forecast dispersion is much weaker, when we replace the T-bill rate dispersion with the dispersion in yield spread, which is consistent with the evidence in Ang, Piazzesi, and Wei (2006) that short-term interest rates forecast output growth better than spread. The coefficient on the T-bill rate forecast dispersion becomes insignificant in the long horizon regression.

The results therefore show that the interest rate dispersion variable is significant in the short-horizon regressions and not in the long-horizon regressions, and MU_t is significant in the long-horizon regressions but not the short-horizon regressions. This suggests that dispersion in the medians of density forecasts of both PGDP inflation and RGDP growth may be correlated with prevailing 'spot' levels of macroeconomic uncertainty in the long-horizon where presumably there is less information of relevance to the forecasted variable. In the short horizon, dispersion appears to be more to do with disagreement on the interpretation of information.

Different versions of MU_t and PU_t are available, depending on how the monthly indices are aggregated to quarterly frequency (average, or last value of quarter), and in the case of MU_t, we also consider different uncertainty horizons (our tables show results for 3-month uncertainty horizon, averaged over each quarter). It turns out that the uncertainty horizon does not matter; our results are very similar whichever is used.

There is naturally a concern about the interpretation of the correlations on macroeconomic uncertainty, in particular the extent to which we can give it a causal interpretation. The regressions have controlled for some important variables, but may have omitted others. There may be a reverse causality issue. For instance, Carroll (2003) demonstrates that that professional forecasts can shape the expectations of households (and, consequently, potentially macroeconomic uncertainty). On the other hand, it may take some time for the professional forecasters' opinions to feedback into the economy. For example, Lanne, Luoma and Luoto (2009) show, with Michigan survey data, that households update their expectations slightly less frequently than twice per year on average. We will further explore this issue in the robustness section.

While the key results of interest are regarding the uncertainty indices, Table 3 and 4 also contain a number of other interesting results. The regression results for PGDP inflation in Table 3 show that lagged dispersion is insignificant, so there is little persistence in the level of dispersion of inflation median forecasts from survey to survey. The coefficients of lagged dispersion in the RGDP growth regressions in Table 4, however, are large and significant, indicating that there is persistence in the level of dispersion from survey to survey, and this is true after controlling for horizons. This result is different from the persistence in the relative 'optimism' and 'pessimism' of individual forecasters (e.g., as observed in Consensus Economics forecast data by Patton and Timmermann 2010) which has more to do with relative rankings of the forecasters; our result says that the degree of dispersion is persistent.

The coefficients on the average level of density forecast medians $M_{t,h}^{m}$ are significant across Tables 3 and 4, positive for inflation forecasts, and negative for output growth forecasts. Forecasters disagree more in their median forecasts when inflation is forecasted to be higher, and less when growth is forecasted to be higher. As noted in Patton and Timmermann (2010), this is consistent with macroeconomic models that incorporate heterogeneous information.

The coefficients on the mean level of density forecast range are insignificant across Tables 3 and 4. The mean level of skewness is significant in the PGDP inflation short horizon regressions (though not in the long horizon regression). Dispersion in PGDP inflation medians is higher when the density forecasts are on average more skewed to the right.

The coefficient estimates on the horizon dummies also show some interesting patterns. In column (a) of Table 3, the horizon dummies imply decreasing dispersion with decreasing horizon, though this pattern is no longer present once uncertainty indices and the interest rate forecast dispersion is included. The decreasing dispersion with decreasing horizon is also noticeable in the output growth regressions (Table 4). There appears to be a spike in the dispersion at horizons 3 and 7, which corresponds to forecasts made in the first survey of the year. The spike in dispersion at the start of each year may suggest that views and information tend to be re-evaluated or incorporated at the start of the year. These findings may support information-rigidity type explanations for dispersion, or it may be that annual-frequency variables (or annual-frequency versions of variables) are taken into account at the start of the year.

4.2 Dispersion in Range and Skewness

The regressions for the dispersion of individual density forecast range are given in Table 5. Columns (a) and (d) are regressions on the full-sample, whereas columns (b) and (e) are the short-horizon forecasts, and (c) and (f) are the long-horizon forecasts. The horizon dummies show that the forecasters disagree more on uncertainty as the forecast horizon declines. This is quite different from what was found for forecaster uncertainty and disagreement in medians. With the arrival of new information, forecasters adjust the shape of their forecasts and become more heterogeneous. This is generally true for both variables. For inflation, there appears to be very little persistence in the average level of forecaster uncertainty, whereas the coefficient on lagged range dispersion is much stronger in the short-horizon regressions for output growth. The coefficients on the average level of forecaster uncertainty is significant and positive, i.e., there is more disagreement in individual uncertainty when the average level of forecaster uncertainty is high. This indicates that there are some forecasters who tend always to report low uncertainty, even as others are reporting high uncertainty. More interesting is that dispersion in forecaster uncertainty for output growth do not respond to policy or macro uncertainty. Dispersion in forecaster uncertainty for inflation responds to macroeconomic uncertainty for long-horizon forecasts, indicating that the degree of heterogeneity in perceived uncertainty of long run projections increases during more volatile periods. The coefficient on policy uncertainty is significant in the short-horizon regressions, though weak and negative.

[Table 5 around here]

Table 6 shows the regressions for dispersion in skewness. The horizon dummies are all insignificant, and are left out of the output. Columns (a) and (d) are regressions on the full-sample, whereas columns (b) and (e) are the short-horizon forecasts, and (c) and (f) are the long-horizon forecasts. There is no response to policy uncertainty for both variables. The coefficients on MU_t are significant in the RGDP growth regressions. There are also no significant effects from either the dispersion of yield spreads or T-bill rates. There are some significant results regarding average levels of skewness, but these are hard to interpret.

[Table 6 around here]

4.3 Robustness Analysis

We find that individual uncertainty does not appear to be driven by macroeconomic or policy uncertainty and individual skewness appears to be correlated with macroeconomic and policy uncertainty in the long horizon regressions. Our results suggest that dispersion of density forecast medians is correlated with macroeconomic uncertainty especially in the long-horizon regressions. This is the case for both PGDP inflation and RGDP growth. For dispersion of forecast density range, i.e., dispersion in individual forecaster uncertainty, the correlation is present only for inflation, whereas for dispersion of density skewness, the correlation is present only for RGDP growth. Density forecast dispersion does not appear to be correlated with policy uncertainty.

In this section, we check the robustness of these results to various specifications and assumptions and summarize the results of these robustness analyses. Details of the methods and full results can be found in the online appendix that accompanies this paper. In particular, we focus on MU_t and PU_t.

4.3.1 *Lags of Policy and Macroeconomic Uncertainty*

We are primarily interested in examining the contemporaneous correlation between the key characteristics of density forecasts (average forecaster uncertainty and dispersion of individual density forecast) and the two uncertainty measures (policy uncertainty and macroeconomic uncertainty). However, it is possible that average forecaster uncertainty and dispersion of medians react to the macroeconomic and policy uncertainty with a lag. Lagging the uncertainty indices may also help to mitigate concerns as to reverse causality. We re-run all of our regressions with lagged policy and macroeconomic uncertainty to capture possible dynamic interactions between the variables of interest. Partial results are given in Panel A of Tables 7 and 8. Full results can be found in the online appendix.

The results for individual uncertainty can be found in Table 7, Panel A, Eq 1. The conclusion that individual uncertainty is not correlated with MU_t and PU_t continues to hold. For individual skewness (Table 7, Panel A, Eq 2), PU_t

is no longer significant for both PGDP inflation and RGDP growth. However MU_t is strongly negatively significant for PGDP inflation.

For the dispersion of medians regressions (Table 8 Panel A Eq 3), the results support the evidence in Tables 3 and 4 that policy uncertainty does not affect dispersion of medians, but macroeconomic uncertainty does especially in the long horizon regressions. This result seems even more emphatic when lagged indices of uncertainty are used. There are also no essential differences for the dispersion of range and skewness regressions (see Table 8 Panel A Eqs 4-5, compared with PU_t and MU_t rows of Tables 5 and 6).

4.3.2 Alternative Measures of Location, Spread, and Shape

We choose our percentile based measures of location, spread and shape as they depend only on three numbers, the 5th, 50th, and 95th percentiles, and can be obtained from the density forecasts even when the forecasters concentrate their probabilities in one or two bins. The percentiles cannot be computed only if the probabilities reported in the first or last bins are greater than 0.05. However, these measures do rely heavily on the linear interpolation of the cumulative probabilities. We evaluate the robustness of our results by using alternative measures of location, spread, and shape. Following Engelberg et al (2009), where the density forecast assigns positive probability to three or more intervals, we assume that the distribution is a member of the generalized Beta family. Where the density forecast only assigns positive probability to one or two intervals, we assume that the subjective distribution has the shape of an isosceles triangle whose base includes the interval with greater probability mass, and part of the other interval (if there is one). After fitting the triangle and beta distributions to the density forecasts, we are able to compute the median, variance, and skewness of the forecasts, and re-do the analysis.

The results are summarized in Panel B of Tables 7 and 8, with full results in the online appendix. Again, we find no important differences between these results and those of the main analysis, using our chosen measures of the location, spread, and shape of the density forecasts, except that MU_t is no longer significant for the PGDP equations in Table 7, Panel B, equation 2. For the dispersion regressions, there are no essential differences compared with our main analysis. Macroeconomic uncertainty continues to be correlated with dispersion of density forecast medians in the long-horizon regressions for both PGDP inflation and RGDP growth. For dispersion of forecast density range the correlation is present only for inflation, whereas for dispersion of density skewness, the correlation is present only for RGDP growth. Density forecast dispersion does not appear to be correlated with policy uncertainty.

4.3.3 Controlling for Loss Functions

Finally, we limit our sample to include only density forecasts where the median of a density forecast matches the forecaster's point forecast. As noted earlier, one possible reason for disagreement among forecasters is simply that they have different loss functions. By matching point and density forecasts, we control for major differences in loss function by limiting ourselves to forecasters with symmetric loss functions, where the point forecasts should (more or less) coincide with the mean or median of the density forecast.

The matching method we use is based on the bounds implied by the density forecasts (Engelberg, Manski and Williams, 2009). The first step to construct the matched sample is to calculate the lower and upper bounds of both subjective median and mean. The interval in which the median lies can be obtained from the probabilistic responses directly. To calculate lower and upper bounds on the subjective mean, we assume that each bin's probability mass is placed at the bin's lower and upper endpoint respectively. The results are then generated by averaging the lower and upper endpoints weighted by the probabilities. If the point forecast is located within any of the two sets of bounds, the density forecast is counted as 'matched' to the point forecast. The final matched sample includes 5784 observations for PGDP inflation and 6260 observations for RGDP growth, which means that we retain roughly 30 forecasters in each quarter. The matching takes care of another issue in the sample, that is the presence of outliers and unusual observations that may be reporting or recording errors of some sort, or at least difficult to otherwise justify.

The results are summarized in Panel C of Tables 7 and 8, with full results in the online appendix. As before, the results are broadly similar to those of the main analysis. One difference is that MU_t is no longer significant for the dispersion of skewness in long-horizon regressions for RGDP output (Table 8, Panel C, equation 5, column f). Otherwise, the results again reflect the conclusion in Tables 3 and 4 that dispersion of medians is significantly correlated with macroeconomic uncertainty, especially in the long horizon regressions.

4.3.4 *Summary of robustness checks*

It appears that the most robust result we have for individual forecaster uncertainty is that it is not correlated with either macroeconomic or policy uncertainty. Any evidence to the contrary is weak and not robust. There is some evidence that individual skewness is correlated with the two uncertainty indices, but this evidence is either weak or not robust. For dispersion of density forecast, the most robust result is that dispersion of medians for both RGDP inflation and RGDP growth is correlated with macroeconomic uncertainty in the long horizon regressions. Dispersion of forecaster uncertainty is not correlated with the two uncertainty indices for RGDP growth, though for PGDP, there is some evidence that this dispersion is influenced by macroeconomic uncertainty in the long horizon regressions. A similar statement can be made about dispersion of density forecast skewness.

5. Concluding remarks

We explore the role of uncertainty in explaining dispersion in the median, central 90% probability interval, and a skewness measure of professional forecasters' density forecasts of real output growth and inflation. We consider three separate notions of uncertainty: an objective measure of macroeconomic uncertainty capturing the fact that macroeconomic variables are easier to forecast at some times than at others, policy uncertainty, and average forecaster uncertainty.

The empirical evidence suggests that dispersion among forecasters in medians is related to macroeconomic uncertainty, but not to policy uncertainty. The dispersion shows a stronger correlation with macroeconomic uncertainty for the longer horizon forecasts, which suggests current macroeconomic uncertainties play a role in the dispersion of long horizon density forecasts. For shorter horizon forecasts, the degree of dispersion is related to controls closely linked to new information, such as dispersion in interest rates. Overall, average forecaster uncertainty appears to have little role in explaining forecast dispersion, and there is only weak, non-robust evidence linking density forecast dispersion to policy uncertainty.

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Table 1 Panel Analysis for Individual Forecaster Uncertainty

Variable	PGDP Inflation			RGDP Growth		
	(a)	(b)	(c)	(d)	(e)	(f)
h_{1t}	0.333***	0.343***		0.484***	0.532***	
	(7.47)	(8.88)		(11.74)	(13.52)	
h_{2t}	0.488***	0.505***		0.805***	0.881***	
	(11.07)	(12.16)		(16.07)	(17.66)	
h_{3t}	0.760***	0.718***		1.404***	1.316***	
	(14.91)	(14.91)		(30.42)	(27.77)	
h_{4t}	0.568***			1.020***		
	(15.28)			(27.75)		
h_{5t}	0.666***		0.100***	1.147***		0.134***
	(14.78)		(2.80)	(25.72)		(3.57)
h_{6t}	0.725***		0.155***	1.225***		0.203***
	(15.47)		(4.48)	(24.36)		(5.26)
h_{7t}	0.780***		0.221***	1.435***		0.429***
	(16.05)		(5.73)	(28.70)		(10.09)
$newbins_t$	-0.600***	-0.581***	-0.726***	0.001	-0.037	0.023
	(-9.31)	(-8.27)	(-11.37)	(0.02)	(-0.86)	(0.52)
$R_{i,t-1,h^*}$	0.308***	0.204***	0.285***	0.350***	0.188***	0.369***
	(12.37)	(6.28)	(9.71)	(17.04)	(6.68)	(15.30)
$M_{i,t,h}$	0.139***	0.153***	0.123***	-0.023*	-0.029*	-0.014
	(8.21)	(7.41)	(5.38)	(-1.72)	(-1.82)	(-0.61)
PU_t	0.033	0.069	-0.005	0.054	0.077	0.052
	(0.91)	(1.57)	(-0.13)	(1.20)	(1.44)	(1.20)
MU_t	0.110	0.069	0.183	0.099	0.197	0.048
	(0.68)	(0.45)	(0.86)	(0.56)	(1.04)	(0.21)
Constant	0.695***	0.881***	1.355***	0.873***	1.203***	1.830***
	(4.86)	(7.03)	(6.58)	(5.01)	(6.09)	(8.33)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	5,528	2,879	2,649	6,268	3,148	3,120
R^2	0.68	0.62	0.74	0.66	0.60	0.69

Notes: Panel regression results for equation (1) with full sample and individual uncertainty $R_{i,t,h}$ as dependent variable, t-statistics in parentheses, calculated from standard errors clustered by year and quarter. Regressions (a) and (d) for full sample, regressions (b) and (e) for current year forecasts, and regressions (c) and (f) for next year forecasts. Several observations are lost due to the lag specification. For the PGDP (RGDP) regressions, we have an average of 30 (33.9) forecasters in each period. The average number of periods per forecaster is 20.1 (22.7).

Table 2 Panel Analysis for Individual Skewness

Variable	PGDP Inflation			RGDP Growth		
	(a)	(b)	(c)	(d)	(e)	(f)
$newbins_t$	-0.015*	0.009	-0.049***	0.012	0.016	0.007
	(-1.85)	(0.66)	(-4.48)	(1.14)	(0.95)	(0.79)
$S_{i,t-1,h^*}$	0.149***	0.109***	0.146***	0.159***	0.103***	0.190***
	(8.94)	(4.52)	(6.40)	(8.83)	(4.32)	(8.16)
$M_{i,t,h}$	-0.037***	-0.030***	-0.043***	-0.026***	-0.031***	-0.022***
	(-5.96)	(-3.44)	(-6.63)	(-5.14)	(-4.60)	(-4.42)
$R_{i,t,h}$	0.033***	0.035***	0.021***	-0.037***	-0.030***	-0.046***
	(7.95)	(6.53)	(3.77)	(-11.27)	(-5.73)	(-11.46)
PU_t	-0.022**	-0.023	-0.019**	-0.028*	-0.045*	-0.012
	(-2.02)	(-1.28)	(-2.00)	(-1.83)	(-1.79)	(-1.21)
MU_t	-0.082**	-0.091	-0.088**	-0.046	-0.159	0.047
	(-2.38)	(-1.63)	(-2.57)	(-0.75)	(-1.59)	(0.92)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	5,528	2,879	2,649	6,268	3,148	3,120
R^2	0.18	0.17	0.24	0.18	0.15	0.27

Notes: Panel regression results for equation (2) with full sample and individual skewness $S_{i,t,h}$ as dependent variable. Robust t-statistics in parentheses, calculated from standard errors clustered by year and quarter. Constant and horizon dummies included but omitted from the table. Regressions (a) and (d) for full sample, regressions (b) and (e) for current year forecasts, and regressions (c) and (f) for next year forecasts. Several observations are lost due to the lag specification. For the PGDP (RGDP) regressions, we have an average of 30 (33.9) forecasters in each period. The average number of periods per forecaster is 20.1 (22.7).

Table 3 Dispersion of Individual PGDP Inflation Density Forecast Median

	(a)	(b)	(c)	(d)	(e)
h_{1t}	0.011	0.001	0.018	0.018	
	(0.30)	(0.02)	(0.44)	(0.39)	
h_{2t}	0.057	0.037	0.062	0.058	
	(1.12)	(0.71)	(1.19)	(0.89)	
h_{3t}	0.107**	0.066	0.092*	0.064	
	(1.99)	(1.16)	(1.72)	(0.94)	
h_{4t}	0.121***	0.066	0.100**		
	(2.88)	(1.34)	(2.17)		
h_{5t}	0.078	0.014	0.057		-0.044
	(1.51)	(0.23)	(0.94)		(-1.54)
h_{6t}	0.109*	0.033	0.084		-0.011
	(1.75)	(0.45)	(1.21)		(-0.33)
h_{7t}	0.139**	0.045	0.097		0.002
	(2.31)	(0.63)	(1.39)		(0.04)
$newbin_t$	-0.055	-0.056	-0.057	-0.044	-0.076
	(-1.16)	(-1.17)	(-1.39)	(-0.88)	(-1.29)
M^{σ}_{t-1,h^*}	0.185	0.149	0.117	0.007	0.203*
	(1.53)	(1.21)	(0.98)	(0.04)	(1.85)
$M^{m}_{t,h}$	0.050*	0.059**	0.085***	0.087***	0.095***
	(1.90)	(2.26)	(3.09)	(2.87)	(2.80)
$R^{m}_{t,h}$	0.010	-0.001	-0.028	-0.049	-0.011
	(0.19)	(-0.02)	(-0.57)	(-0.74)	(-0.18)
$S^{m}_{t,h}$	0.420**	0.391*	0.541***	0.562**	0.246
	(2.04)	(1.93)	(2.74)	(2.01)	(0.76)
$spread^{\sigma}_{t,h}$		0.256**	0.182*	0.375*	0.118
		(2.34)	(1.68)	(1.79)	(1.01)
PU_t			0.032	0.031	0.039
			(1.20)	(1.04)	(1.26)
MU_t			0.320**	0.187	0.432***
			(2.49)	(1.33)	(2.75)
Constant	0.150	0.145	-0.133	0.030	-0.202
	(1.61)	(1.58)	(-1.02)	(0.20)	(-1.25)
Obs	198	198	198	99	99
R^2	0.38	0.40	0.44	0.32	0.46

Notes: Estimation results for equation (3) for dispersion of individual PGDP inflation density forecast median ($M^{\sigma}_{t,h}$) regressions. Robust t-statistics in parentheses, calculated from standard errors clustered by year and quarter.

Table 4 Dispersion of Individual RGDP Growth Density Forecast Median

	(a)	(b)	(c)	(d)	(e)
h_{1t}	0.074	0.073	0.079	0.061	
	(1.57)	(1.52)	(1.55)	(1.03)	
h_{2t}	0.079	0.070	0.088	0.040	
	(1.41)	(1.23)	(1.51)	(0.52)	
h_{3t}	0.309***	0.274***	0.278***	0.211**	
	(4.74)	(4.01)	(4.00)	(2.23)	
h_{4t}	0.198**	0.150*	0.171**		
	(2.62)	(1.89)	(2.28)		
h_{5t}	0.248***	0.170**	0.201**		0.039
	(3.27)	(2.06)	(2.42)		(1.29)
h_{6t}	0.241***	0.147	0.186*		0.035
	(2.83)	(1.54)	(1.97)		(0.91)
h_{7t}	0.319***	0.213**	0.244**		0.093**
	(3.47)	(2.11)	(2.44)		(2.12)
$newbin_t$	-0.037	-0.012	-0.017	0.019	-0.028
	(-1.59)	(-0.48)	(-0.55)	(0.39)	(-0.76)
$M^{\sigma}_{t-1,h*}$	0.427***	0.366***	0.310***	0.299**	0.289***
	(5.35)	(4.75)	(3.70)	(2.53)	(2.93)
$M^{m}_{t,h}$	-0.060***	-0.063***	-0.045**	-0.048*	-0.065**
	(-3.31)	(-3.57)	(-2.24)	(-1.83)	(-2.37)
$R^{m}_{t,h}$	-0.077	-0.091	-0.079	-0.078	-0.084
	(-1.28)	(-1.48)	(-1.31)	(-0.78)	(-1.33)
$S^{m}_{t,h}$	-0.179	-0.222	-0.094	-0.213	0.071
	(-1.03)	(-1.36)	(-0.51)	(-1.02)	(0.21)
$TBill^{\sigma}_{t,h}$		0.268***	0.195**	0.526**	0.147
		(2.96)	(2.23)	(2.23)	(1.50)
PU_t			0.021	-0.011	0.032
			(0.60)	(-0.20)	(0.81)
MU_t			0.397*	0.236	0.489**
			(1.80)	(0.89)	(2.13)
Constant	0.465***	0.495***	0.120	0.262	0.313
	(2.96)	(3.16)	(0.47)	(0.66)	(1.16)
Obs	198	198	198	99	99
R^2	0.52	0.55	0.57	0.53	0.52

Notes: Estimation results for equation (3) for dispersion of individual RGDP growth density forecast median ($M^{\sigma}_{t,h}$) regressions. Robust t-statistics in parentheses, calculated from standard errors clustered by year and quarter.

Table 5 Dispersion of Individual Density Forecast Range

Variable	PGDP Inflation			RGDP Growth		
	(a)	(b)	(c)	(d)	(e)	(f)
h_{1t}	-0.177***	-0.134***		-0.071	-0.116	
	(-4.01)	(-2.63)		(-1.15)	(-1.60)	
h_{2t}	-0.257***	-0.187***		-0.142*	-0.210**	
	(-4.82)	(-2.92)		(-1.89)	(-2.37)	
h_{3t}	-0.353***	-0.252***		-0.221**	-0.299***	
	(-6.27)	(-3.45)		(-2.37)	(-2.73)	
h_{4t}	-0.381***			-0.284***		
	(-7.24)			(-2.98)		
h_{5t}	-0.396***		-0.023	-0.272**		0.021
	(-5.91)		(-0.65)	(-2.62)		(0.58)
h_{6t}	-0.388***		-0.030	-0.303***		0.001
	(-5.12)		(-0.64)	(-2.70)		(0.01)
h_{7t}	-0.433***		-0.081*	-0.299***		0.003
	(-5.49)		(-1.73)	(-2.68)		(0.05)
$newbin_t$	0.280***	0.195***	0.390***	0.085***	0.077*	0.095***
	(5.87)	(3.36)	(5.37)	(3.21)	(1.74)	(2.64)
$R^{\sigma}_{t-1,h*}$	0.027	0.050	-0.027	0.183**	0.174*	0.155
	(0.40)	(0.65)	(-0.30)	(2.47)	(1.83)	(1.61)
$M^{m}_{t,h}$	0.034	0.022	0.061	0.002	0.003	-0.028
	(1.08)	(0.59)	(1.44)	(0.16)	(0.19)	(-0.90)
$R^{m}_{t,h}$	0.580***	0.524***	0.659***	0.348***	0.426***	0.298***
	(10.96)	(6.77)	(9.45)	(5.38)	(4.84)	(3.06)
$S^{m}_{t,h}$	0.493**	0.472*	0.550	-0.123	-0.165	-0.097
	(2.16)	(1.82)	(1.16)	(-0.56)	(-0.60)	(-0.24)
$Spread\ /\ TBill^{\sigma}_{t,h}$	0.084	-0.259	0.140	0.099	-0.031	0.133
	(0.77)	(-1.42)	(1.09)	(1.04)	(-0.12)	(1.41)
PU_t	-0.043	-0.067*	-0.011	-0.028	-0.065	-0.009
	(-1.47)	(-1.91)	(-0.29)	(-0.76)	(-1.13)	(-0.23)
MU_t	0.155	0.039	0.347*	-0.232	-0.261	-0.243
	(1.36)	(0.23)	(1.94)	(-1.47)	(-1.06)	(-1.27)
Constant	-0.469***	-0.213	-1.276***	0.215	0.155	0.174
	(-3.88)	(-1.35)	(-5.88)	(1.01)	(0.50)	(0.54)
Obs	198	99	99	198	99	99
R^2	0.67	0.62	0.72	0.58	0.50	0.51

Notes: Results for equation (4), dispersion of individual density forecast range ($R^{\sigma}_{t,h}$) regressions with full sample. Robust t-statistics in parentheses, calculated from standard errors clustered by year and quarter. Dispersion of yield spread forecasts (*spread*) used for PGDP regressions, dispersion of T-Bill rate forecasts (*TBill*) used for RGDP regressions.

Table 6 Dispersion of Individual Density Forecast Skewness

Variable	PGDP Inflation			RGDP Growth		
	(a)	(b)	(c)	(d)	(e)	(f)
$newbin_t$	-0.021**	-0.008	-0.040**	-0.007	-0.004	-0.002
	(-2.03)	(-0.61)	(-2.33)	(-1.33)	(-0.43)	(-0.28)
$S^{\sigma}_{t-1,h*}$	0.074	0.161	-0.036	0.006	-0.004	-0.088
	(1.08)	(1.46)	(-0.34)	(0.09)	(-0.04)	(-0.88)
$M^{m}_{t,h}$	-0.005	-0.007	0.001	0.003	0.002	0.007
	(-1.02)	(-1.12)	(0.16)	(1.00)	(0.67)	(1.45)
$R^{m}_{t,h}$	0.007	0.017	-0.011	0.018	0.016	0.001
	(0.75)	(1.21)	(-0.73)	(1.39)	(1.05)	(0.07)
$S^{m}_{t,h}$	-0.059*	-0.095**	-0.004	0.054*	0.068*	-0.046
	(-1.68)	(-2.50)	(-0.05)	(1.85)	(1.95)	(-0.70)
$Spread\ /\ TBill^{\sigma}_{t,h}$	0.017	-0.049	0.043	-0.013	0.084	-0.031*
	(0.72)	(-1.25)	(1.46)	(-0.67)	(1.12)	(-1.81)
PU_t	-0.009	-0.008	-0.015*	-0.005	-0.003	-0.003
	(-1.45)	(-0.80)	(-1.75)	(-0.78)	(-0.41)	(-0.45)
MU_t	0.023	0.027	0.034	0.057**	0.040	0.069**
	(0.97)	(0.76)	(1.04)	(2.01)	(0.97)	(2.02)
Constant	0.143***	0.114***	0.177***	0.094***	0.106**	0.106**
	(4.83)	(2.66)	(3.71)	(2.65)	(2.11)	(2.08)
Obs	198	99	99	198	99	99
R^2	0.22	0.21	0.25	0.25	0.18	0.14

Notes: Results for equation (5), dispersion of individual density forecast skewness ($S^{\sigma}_{t,h}$) regressions with full sample. Robust t-statistics in parentheses, calculated from standard errors clustered by year and quarter. Dispersion of yield spread forecasts (*spread*) used for PGDP regressions, dispersion of T-Bill rate forecasts (*TBill*) used for RGDP regressions. The horizon dummies are included in the regression but are not included in the table. Columns (a) and (d) are regressions on the full-sample, whereas columns (b) and (e) are the short-horizon forecasts, and (c) and (f) are the long-horizon forecasts.

Table 7 Individual Forecaster Uncertainty and Skewness, Robustness Checks

	Eq.	Var.	PGDP Inflation			RGDP Growth		
			(a)	(b)	(c)	(d)	(e)	(f)
Panel A	(1)	PU_{t-1}	-0.012	0.007	-0.027	-0.029	-0.002	-0.015
			(-0.32)	(0.16)	(-0.64)	(-0.78)	(-0.03)	(-0.35)
		MU_{t-1}	0.275	0.237	0.340*	0.263	0.338	0.246
			(1.62)	(1.32)	(1.74)	(1.66)	(1.54)	(1.36)
	(2)	PU_{t-1}	-0.009	-0.012	-0.004	0.004	0.007	-0.000
			(-1.04)	(-0.78)	(-0.44)	(0.32)	(0.28)	(-0.05)
		MU_{t-1}	-0.124***	-0.141**	-0.123***	-0.066	-0.214	0.021
			(-3.61)	(-2.43)	(-3.23)	(-0.92)	(-1.65)	(0.35)
Panel B	(1)	PU_t	0.039*	0.046**	0.029	0.005	0.027	-0.018
			(1.97)	(2.25)	(1.38)	(0.17)	(0.97)	(-0.47)
		MU_t	0.188	0.148	0.255*	-0.037	0.049	-0.072
			(1.62)	(1.30)	(1.97)	(-0.34)	(0.44)	(-0.43)
	(2)	PU_t	-0.017***	-0.023**	-0.011	-0.012	-0.029	0.007
			(-2.74)	(-2.48)	(-1.26)	(-1.09)	(-1.54)	(0.58)
		MU_t	0.026	0.050	0.004	0.046	0.111	0.003
			(0.99)	(1.32)	(0.10)	(1.20)	(1.16)	(0.05)
Panel C	(1)	PU_t	0.013	0.067	-0.042	0.049	0.087	0.038
			(0.40)	(1.55)	(-1.19)	(1.14)	(1.62)	(0.84)
		MU_t	0.078	0.017	0.145	0.181	0.175	0.203
			(0.50)	(0.11)	(0.73)	(0.95)	(0.86)	(0.80)
	(2)	PU_t	-0.021*	-0.016	-0.023**	-0.028*	-0.041	-0.016
			(-1.73)	(-0.78)	(-2.26)	(-1.69)	(-1.49)	(-1.45)
		MU_t	-0.112***	-0.165**	-0.072*	-0.043	-0.149	0.061
			(-2.66)	(-2.47)	(-1.85)	(-0.69)	(-1.32)	(1.17)

Notes: Excerpts of results from robustness analysis of panel regression of individual forecaster uncertainty (eq. 1) and individual forecaster skewness (eq. 2). **Panel A**: equations (1) and (2) with lagged policy and macroeconomic uncertainty; **Panel B**: equations (1) and (2) with measures of location, variance, and skewness derived from the triangular-beta distribution fit of the density forecasts; **Panel C**: equations (1) and (2) with subsample matching point and density forecast medians. All panels show only rows pertaining to policy- and macro-uncertainty. Full results are available in the online appendix. Regressions (a) and (d) for full sample, regressions (b) and (e) for current year forecasts, and regressions (c) and (f) for next year forecasts. Robust t -statistics in parentheses, calculated from standard errors clustered by year and quarter.

Table 8 Density Forecast Dispersion, Robustness Checks

	Eq.	Var.	PGDP Inflation			RGDP Growth		
			(a)	(b)	(c)	(d)	(e)	(f)
Panel A	(3)	PU_{t-1}	0.028	0.032	0.035	0.010	-0.008	0.025
			(0.89)	(0.72)	(1.28)	(0.26)	(-0.13)	(0.71)
		MU_{t-1}	0.420***	0.252**	0.589***	0.475**	0.324	0.606***
			(3.75)	(2.01)	(4.04)	(2.34)	(1.21)	(2.83)
	(4)	PU_{t-1}	-0.047*	-0.061*	-0.033	-0.020	-0.060	0.008
			(-1.75)	(-1.86)	(-0.78)	(-0.66)	(-1.18)	(0.24)
		MU_{t-1}	0.080	-0.058	0.278	-0.262	-0.352	-0.205
			(0.72)	(-0.37)	(1.62)	(-1.53)	(-1.34)	(-1.05)
	(5)	PU_{t-1}	0.001	0.003	-0.004	-0.007	-0.004	-0.009
			(0.22)	(0.43)	(-0.39)	(-1.29)	(-0.51)	(-1.32)
		MU_{t-1}	0.016	0.017	0.028	0.067**	0.060	0.069*
			(0.61)	(0.49)	(0.70)	(1.99)	(1.44)	(1.68)
Panel B	(3)	PU_t	0.022	0.023	0.033	-0.001	-0.049	0.014
			(0.91)	(0.79)	(1.26)	(-0.02)	(-0.68)	(0.38)
		MU_t	0.193*	0.026	0.381***	0.380**	0.240	0.559***
			(1.80)	(0.18)	(3.26)	(2.16)	(1.14)	(2.82)
	(4)	PU_t	-0.026	-0.051**	-0.006	-0.038	-0.054*	-0.050
			(-1.24)	(-2.18)	(-0.22)	(-1.08)	(-1.71)	(-0.94)
		MU_t	0.290***	0.061	0.675***	0.086	0.029	0.265
			(3.24)	(0.58)	(4.74)	(0.62)	(0.16)	(1.38)
	(5)	PU_t	0.021**	0.029**	0.011	-0.011	-0.013	-0.003
			(2.45)	(2.36)	(0.99)	(-0.77)	(-0.57)	(-0.23)
		MU_t	0.014	0.005	-0.030	0.167***	0.269**	0.105*
			(0.32)	(0.08)	(-0.71)	(3.20)	(2.61)	(1.83)
Panel C	(3)	PU_t	0.036**	0.032	0.025	0.045**	0.038	0.040
			(2.22)	(1.42)	(0.89)	(2.41)	(1.57)	(1.29)
		MU_t	0.184*	0.135	0.259**	0.233**	0.019	0.387**
			(1.85)	(0.93)	(2.47)	(2.06)	(0.17)	(2.30)
	(4)	PU_t	-0.039	-0.015	-0.050	-0.017	-0.005	-0.040
			(-1.38)	(-0.41)	(-1.48)	(-0.44)	(-0.09)	(-0.78)
		MU_t	0.196	-0.019	0.472***	-0.238	-0.149	-0.376*
			(1.63)	(-0.09)	(2.71)	(-1.30)	(-0.48)	(-1.83)
	(5)	PU_t	-0.011*	-0.008	-0.017	0.000	0.006	-0.001
			(-1.79)	(-0.95)	(-1.64)	(0.05)	(0.85)	(-0.12)
		MU_t	0.030	0.019	0.061	0.040	0.055	0.044
			(1.28)	(0.55)	(1.24)	(1.62)	(1.44)	(1.27)

Notes: Excerpts of results from robustness analysis of regressions for dispersion of median (eq 3), range (eq 4) and skewness (eq 5). **Panel A**: with lagged policy and macroeconomic uncertainty; **Panel B**: with measures of location, variance, and skewness derived from the triangular-beta distribution fit of the density forecasts; **Panel C**: with subsample matching point and density forecast medians. All panels show only rows pertaining to policy- and macro-uncertainty. Full results are available in the online appendix. Regressions (a) and (d) for full sample, regressions (b) and (e) for current year forecasts, and regressions (c) and (f) for next year forecasts. Robust t -statistics in parentheses, calculated from standard errors clustered by year and quarter.

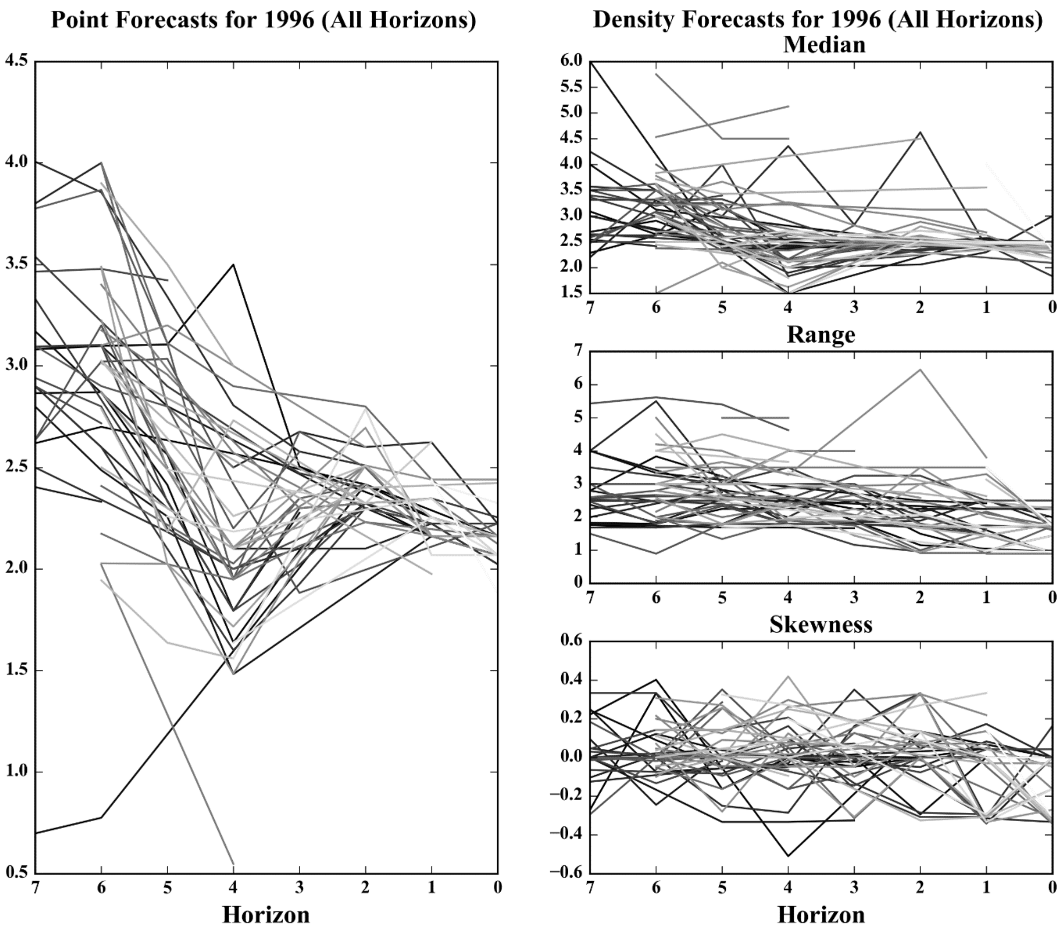

Figure 1 Example of Dispersion in SPF Point and Density Forecasts. Left panel shows point forecasts of 1996 PGDP inflation made by all SPF forecasters at forecast horizons spanning two years. Horizons 7 to 4 forecasts were made in the 1995Q1-Q4 surveys, and horizons 3 to 0 forecasts were made in the 1996Q1 - Q4 surveys. Right column shows the three key characteristics (median, range and skewness) of density forecasts of all forecasters for 1996 PGDP inflation from the same 8 surveys.

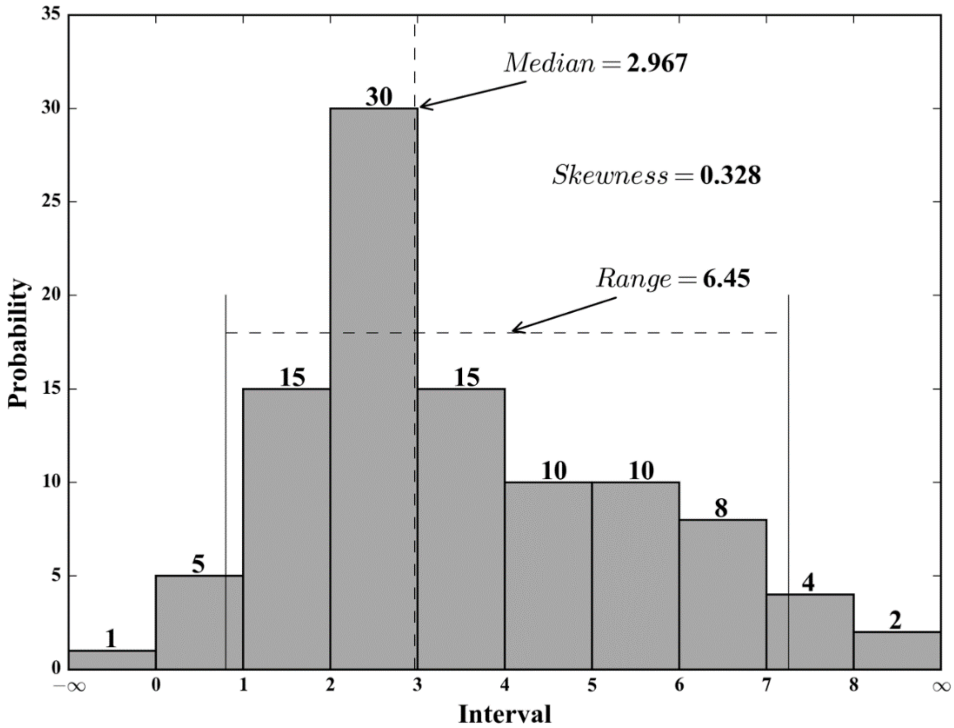

Figure 2 SPF Density Forecast Example. Density forecast of annual average 1996 PGDP inflation reported by Forecaster 464 in the 1996Q2 survey, with accompanying descriptive statistics. The range is defined as the central 0.90 probability interval. The skewness statistic is a Bowley-type measure, defined as the difference in the lengths of the two halves of the range, standardized by the range (see text for formula). A density forecast that is skewed right will have a positive S, and one that is skewed left will have a negative S.

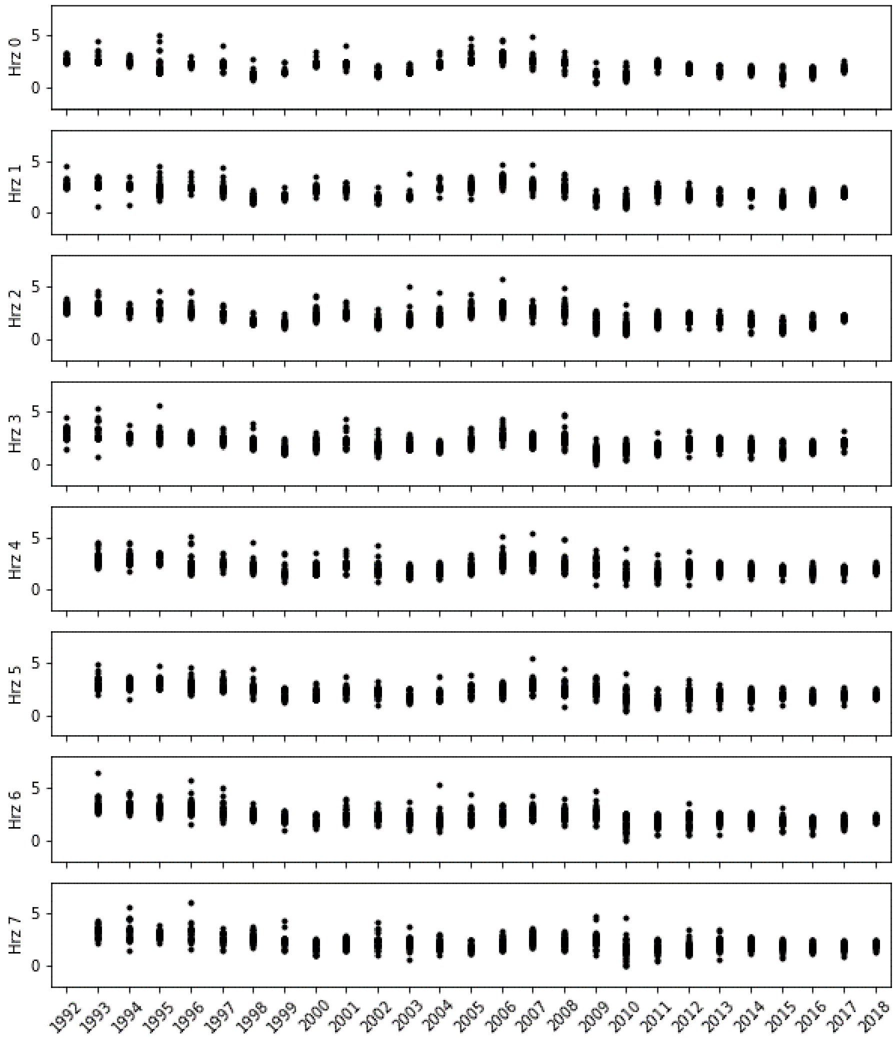

Figure 3 Dispersion in PGDP Inflation Density Forecast Medians. Each subplot shows, for a given horizon, the medians of every density forecast of annual-average PGDP inflation from the SPF surveys from 1992Q1 to 2017Q4. The years on the x-axis represent target years, e.g., forecasts made in the Hrz 7 panel were made in the first quarter of the previous year. The y-axis are measured in percentage points.

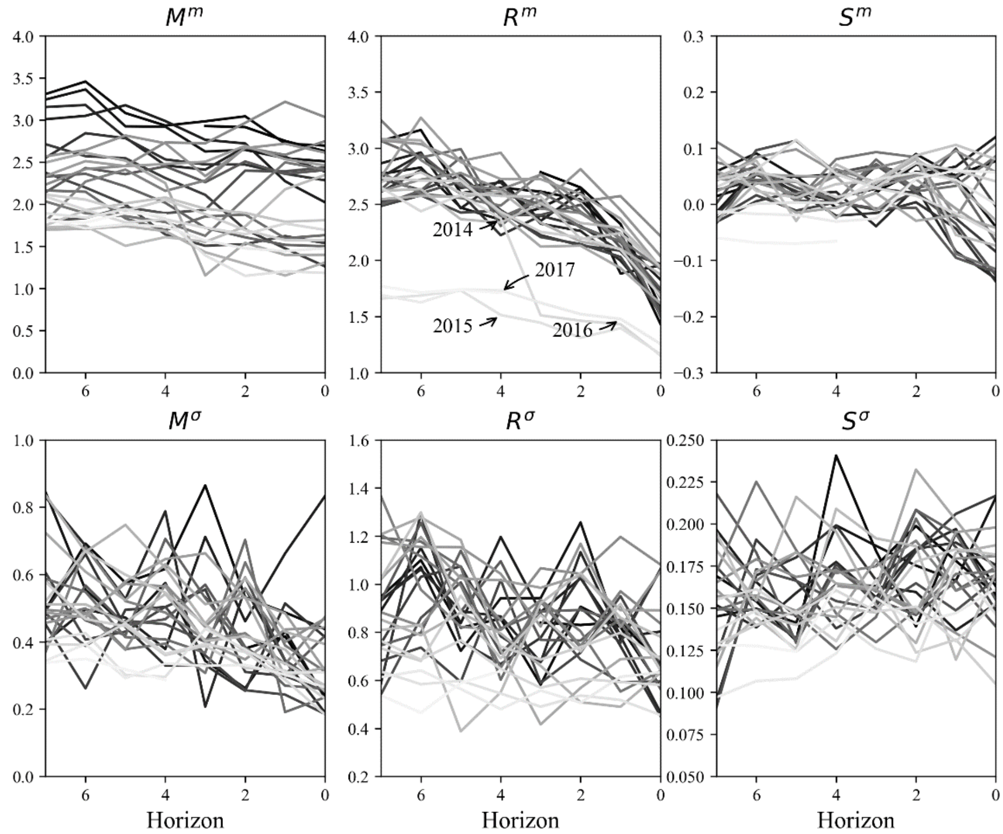

Figure 4(a) Top row: average of individual PGDP inflation density forecast medians, range, and skewness. Bottom row: standard deviation of individual PGDP inflation density forecast medians, range, and skewness, depicting density forecast dispersion. Each line corresponds to a target year, all plotted against forecast horizon.

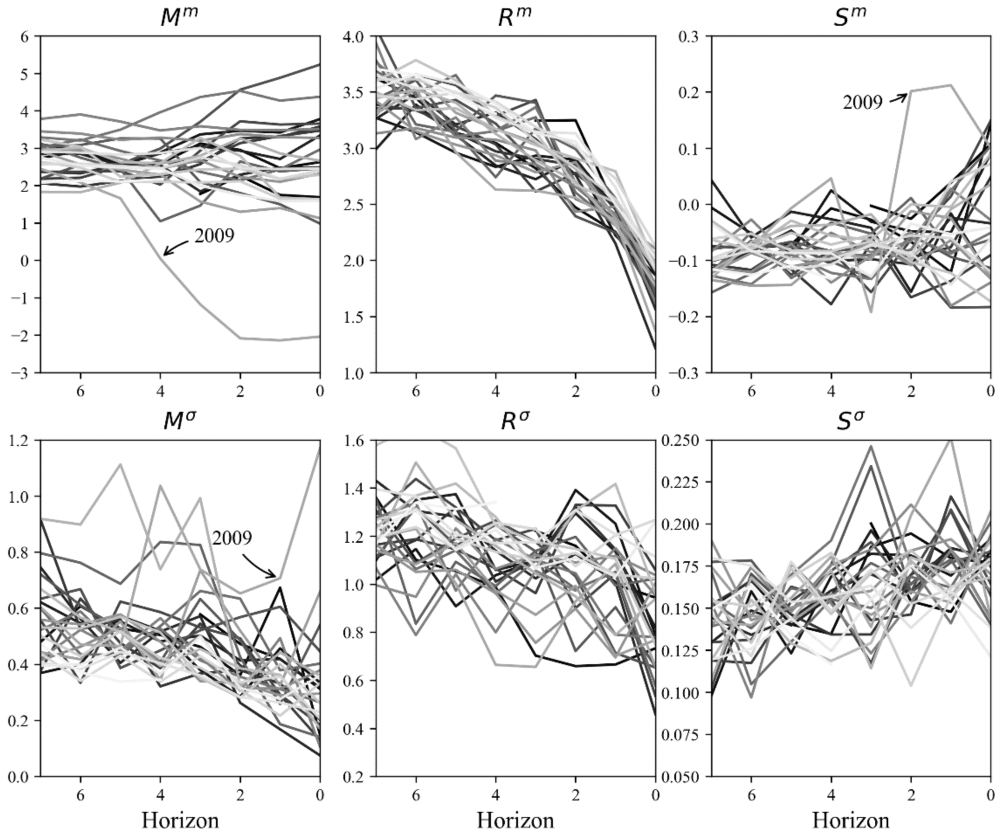

Figure 4(b) Top row: average of individual RGDP growth density forecast medians, range, and skewness. Bottom row: standard deviation of individual RGDP growth density forecast medians, range, and skewness, depicting density forecast dispersion. Each line corresponds to a target year, all plotted against forecast horizon.

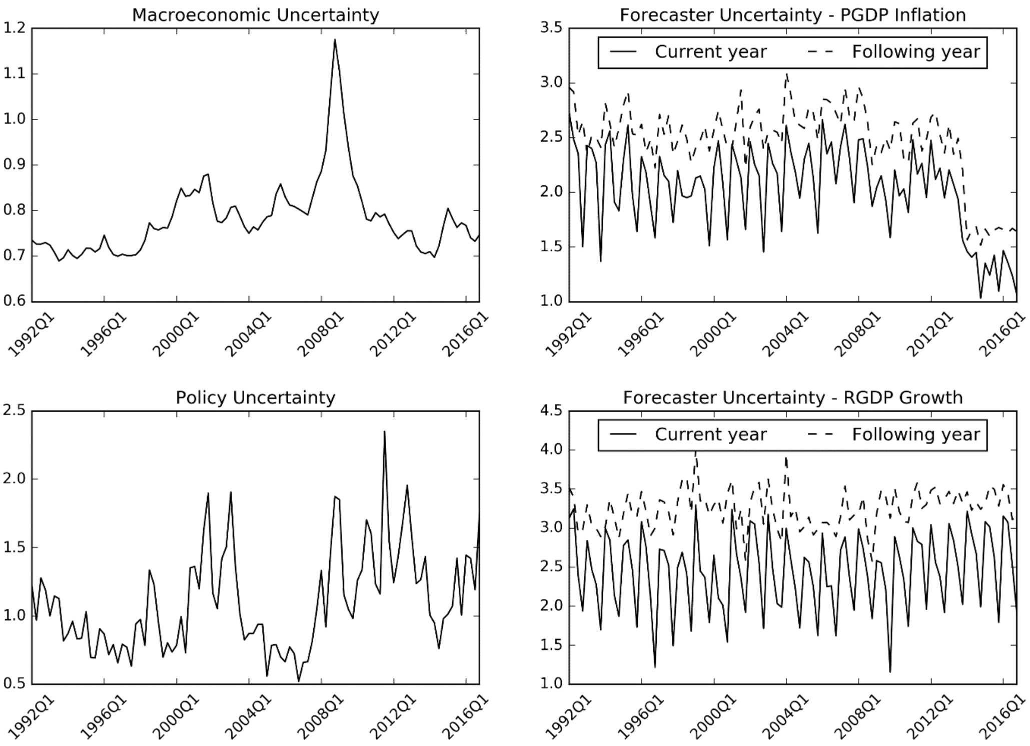

Figure 5 Top left displays the time series plot of macroeconomic uncertainty MU_t. Bottom left shows the time series plot of policy uncertainty PU_t. Diagrams in the right column show forecast uncertainty for PGDP Inflation and RGDP growth corresponding to the current and following year forecasts made at each survey. The policy uncertainty index is divided by 100. Macroeconomic index is quarterly average of the original monthly index.