The Role of Macroeconomic, Policy, and Forecaster Uncertainty in Forecast Dispersion

You Li and Anthony Tay

School of Economics, Singapore Management University

90 Stamford Road, Singapore 178903, Singapore

you.li.2013@phdecons.smu.edu.sg anthonytay@smu.edu.sg

This draft: Nov 2017

Abstract

We explore the role of uncertainty in explaining dispersion in professional forecasters' density forecasts of real output growth and inflation. We consider three separate notions of uncertainty: general macroeconomic uncertainty (the fact that macroeconomic variables are easier to forecast at some times than at others), policy uncertainty, and forecaster uncertainty. We find that dispersion in individual density forecasts is related to overall macroeconomic uncertainty and policy uncertainty, while forecaster uncertainty (which we define as the average in the uncertainty expressed by individual forecasters) appears to have little role in forecast dispersion.

1. Introduction

Surveys of macroeconomic forecasts show that forecasters generally disagree with each other. Point forecasts are typically dispersed, with patterns not unlike those shown in the left panel of Figure 1. This panel displays point forecasts for year 1996 PGDP inflation made by forecasters surveyed by the Philadelphia Fed in their quarterly Survey of Professional Forecasters (SPF) over the period 1995Q1 to 1996Q4, i.e., at horizons 7 down to 0 quarters. The point forecasts are dispersed at long horizons, with dispersion falling as the forecaster approaches the full realization of the forecast event. Some persistence in the forecasts can also be observed, with relatively optimistic and pessimistic forecasts tending to remain so. Similar patterns have been observed in many other similar datasets, including surveys carried out by Consensus Economics and the European Central Bank (ECB). Explanations put forward for these and other patterns in dispersion 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).

Several surveys of macroeconomic forecasts also elicit density forecasts and these too tend to be dispersed, as can be seen from the figures in the right column of Figure 1. These figures show the median, central 90% interval, and a skewness measure of individual density forecasts for the same variable as the point forecast in the left panel. 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 would seem a reasonable direct measure of the level of uncertainty perceived by the forecaster. Asymmetries in the density forecasts, for a given level of uncertainty, may indicate some degree of optimism or pessimism. Dispersion patterns in the SPF density forecasts have been studied by Lahiri and Liu (2006) who explore in particular the determinants of inflation forecast uncertainty. Dispersion patterns in the density forecasts elicited via the Bank of England's Survey of External Forecasters have been documented in Boero, Smith, and Wallis (2008, 2015).

Pervasive evidence of (point and density) forecast dispersion, even among a group of economic agents who should be reasonably homogeneous in terms of ability and motivation, suggest that expectations may in general be heterogeneous. If this is so, then heterogeneous expectations should be taken into account when constructing macroeconomic models for policy and forecasting. But why are expectations dispersed, and does uncertainty play any role? Declining dispersion from long to short horizons suggests a link between dispersion and uncertainty, though the nature of this link is not at all clear. From the point of view of forecasting theory, this pattern is somewhat perplexing. At long horizons, point forecasts should be close to the unconditional mean if forecasters have a mean squared error loss function. Dispersion at longer horizons could therefore imply that different forecasters have different loss functions (Capistran and Timmermann 2009). Or it might be simply that different forecasters have different priors regarding the unconditional distribution of the variables being forecast (Patton and Timmermann 2010). If information is interpreted differently or absorbed at different rates, then we might expect greater dispersion at shorter horizons.

In this paper, we explore the role of uncertainty in explaining forecast dispersion, making a distinction between forecaster uncertainty and general uncertainty in the macroeconomic environment. While we might expect the two to be related, they are not necessarily identical. 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, and 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 might be expected to be related to, but not identical to 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 overall 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 to 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*

Our expectations data are forecasts 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 others. Besides point forecasts, the surveys also elicit density forecasts for growth in the annual averages of real GDP, the GDP price index (PGDP), core CPI and core PCE, and the civilian unemployment rate. The density forecasts take the form of histograms; 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 forecasts from the 2009Q1 and 2010Q1 surveys, for growth in the annual-average of real GDP for the year 2010.

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 of $h = 0$ 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. However, for this study we only consider forecasts made 0 to 7 quarters ahead.

We also 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 the 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 summary statistics that we use cannot be computed. Our sample period ends with the 2016Q4 survey.

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 constructing 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 and 6260 observations for RGDP 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 appear to be errors of some sort, or at least difficult to otherwise justify. These outliers are removed via the matching process. Figure 3 shows the scatter plots of the median of density forecasts and point forecasts in both the full and the matched samples.

2.2 Descriptive Statistics for Density Forecasts

We summarize each density forecast using its median, central 90% 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 90% 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 90% range is feasible, and preferred, as it covers more of the distribution. Whereas the range might be considered a measure of individual uncertainty, the Bowley 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 open-ended, which complicate the computation of moment-based and entropy-based statistics. Using percentile-based descriptions avoids the strong assumptions which are needed for moment- and entropy-based measures. Of course, the percentile-based statistics 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. 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

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

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 $t = 1992q1,...,2016q4$.

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

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

In particular, we treat $R^{m}_{t,h}$, the average of individual uncertainty, as a measure of overall forecaster uncertainty. We discuss this variable more in the next section, together with measures of macroeconomic and policy uncertainty. The variable $S^{m}_{t,h}$ is included as an elaboration of average individual uncertainty, indicating asymmetries in relative upside vs downside risks. 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), a relationship 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.

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 of the median, range, and skewness of the individual density forecasts. The bottom row shows the standard deviation of these characteristics of 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.

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 other point forecast datasets (e.g. Patton and Timmermann, 2010), and it is seen here that this regularity extends to density forecasts as well. Dispersion appears to fall slightly for the range, and rise slightly for the skewness, for 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 forecaster uncertainty, namely $R^{m}_{t,h}$, the average of individual density forecast range $R^{m}_{i,t,h}$ taken over all forecasters 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-known fact that macroeconomic variables are easier to forecast in some periods than at others because the volatility 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:

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

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

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,

The three uncertainty indices considered in this paper MU_t, PU_t and $R_{t,h}^{m}$, can be viewed along the objective-subjective spectrum, with MU_t being a purely objective measure, $R_{t,h}^{m}$ being a purely subjective notion, and PU_t being somewhere in between. We are interested in how dispersion of density forecasts are correlated with these. The right column of Figure 5 displays $R_{t,h}^{m}$, 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 $R_{t,h}^{m}$ whereas the upper middle diagrams in Figures 4(a) and (b) show $R_{t,h}^{m}$ as a function of horizon, for various years. The declining forecaster uncertainty gives rise to the periodicity, especially for the lower horizon forecasts. To explore how subjective forecaster uncertainty relates to the two other measures of uncertainty, we run the regression

$$R^m_{t,h} = \beta_0 + \beta_1 h_{1t} + ... + \beta_7 h_{7t} + \beta_8 newbins_t + \beta_9 R^m_{t-1,h*} + \beta_{10} M^m_{t,h} + \beta_{11} PU_t + \beta_{12} MU_t + \varepsilon_{t,h} \quad (1)$$

for both PGDP inflation and RGDP growth, where $h_{1t},...,h_{7t}$ are horizon dummies. The variable $R^m_{t-1,h*}$, 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 $h = 3,7$). To allow for omitted factors at each survey date, we cluster standard errors by year and quarter, allowing 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 from 'next-year' forecasts.

Overall, there are substantial differences in the results for PGDP inflation and RGDP growth. Some of our results are consistent with previous research using different methodologies. For instance, the coefficients on lagged individual uncertainty show persistence, especially for short-horizon RGDP growth forecasts whereas for PGDP inflation this persistence is weaker and only for longer-horizon forecasts. The coefficients on $M^m_{t,h}$ are significant for PGDP inflation (short-horizon). This is consistent with results from previous research which find that positive changes in anticipated inflation is associated with greater uncertainty (Lahiri and Liu 2006, Rich and Tracy 2010).

For PGDP inflation, the correlations between average individual uncertainty and either macro or policy uncertainty seems non-existent, except for a small negative correlation with PU_t for the longer-horizon density forecasts. This suggests little co-movement between forecaster uncertainty and the two other measures of uncertainty. For RGDP growth, the coefficients on PU_t suggest that average forecaster uncertainty is correlated with policy uncertainty for RGDP growth, and that this correlation is mainly at short-horizon forecasts. Average forecaster uncertainty is strongly negatively correlated with MU_t. This is most likely because the largest variation in MU_t in our sample occurred during the 2007-2009 recession, when there was little doubt regarding the state of RGDP growth.

Another interesting set of results can be derived from the horizon dummies. Earlier we noted from the top diagrams of the second columns of Figures 4(a) and (b) that range falls with horizon, and that this could be due to less uncertainty because forecasters have more information, or because in horizons 0, 1, and 2, only 1, 2, and 3 quarters worth of growth is being forecasted, whereas for horizons 3 to 7, all four quarters of annual growth are being forecasted. If we assume annual growth to be the sum of four independent quarters of growth $x_1 + x_2 + x_3 + x_4$, each with variance σ^2, then at horizon 0 only x_4 is being forecasted, with variance σ^2, whereas at horizon 1, it is $x_3 + x_4$ that is being forecasted, with variance $2\sigma^2$. If we take the range as equivalent to some multiple of standard deviation, the ratio of the horizon 1 to horizon 0 range should be $\sqrt{2}$. Likewise, the ratio of the horizon 2 to horizon 1 range should be $\sqrt{3/2}$, and the ratio of the horizon 3 to horizon 2 range should be $2/\sqrt{3}$. Thereafter, the ratio of the ranges should be one. The ratios implied by the constant term and horizon dummy coefficients is consistent with this pattern for RGDP growth, though for PGDP inflation forecasts we only observe the fall in range as we move into the lowest horizon.

Finally, the strong significant (negative) coefficient on $newbins_t$ confirms that the reduction in the overall bin range for PGDP inflation that occurred after the 2013Q4 survey led to a large reduction in the range reported by forecasters. This is, of course, obvious from Figure 4(a) and Figure 6. The smaller (positive) effect in RGDP growth where there was a smaller widening of the overall range provided to the forecasters is also significant at the longer horizons. As mentioned earlier, this may suggest that measures of individual uncertainty derived from density forecasts may be subject to a framing effect. It may of course be the case that both forecast surveyor and forecasters are reacting to the same information. Furthermore, 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 it does 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.

We noted earlier that density forecasts for inflation tend to be positive skewed, whereas density forecasts for output growth tend to be negative. We run regressions similar to (2), replacing R^m with S^m, and include R^m as a regressor:

$$\begin{aligned} S_{t,h}^{m} &= \beta_0 + (\text{horz. dummies}) + \beta_8 newbins_t \ldots \\ &\quad + \beta_9 S_{t-1,h*}^{m} + \beta_{10} M_{t,h}^{m} + \beta_{11} R_{t,h}^{m} + \beta_{12} PU_t + \beta_{13} MU_t + \varepsilon_{t,h} \end{aligned} \tag{2}$$

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 note a persistence in 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). Skewness in density forecasts of output growth appears to be negatively correlated with policy uncertainty, whereas skewness in density forecasts of inflation are negatively correlated with macro-uncertainty. Overall, increased uncertainty appears to reduce skewness (inflation) or increase negative skewness (output growth).

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 $M_{t,h}^{\sigma}$, $R_{t,h}^{\sigma}$, $S_{t,h}^{\sigma}$. We explore in particular the relative degrees to which average forecaster uncertainty ($R_{t,h}^{m}$) and uncertainty in the overall 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 overall 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, as the year spread is commonly viewed as good predictors of inflation (even if recent evidence suggest 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.

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

The regressions are repeated for $R^{\sigma}_{t,h}$ and $S^{\sigma}_{t,h}$. As with equations (1) and (2), we again cluster standard errors by survey date 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 splitting 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.

The key results from these regressions is that the coefficients on macroeconomic uncertainty are significant and positive, while forecast uncertainty plays little role in explaining dispersion of medians. The estimates in column (c) in both Tables 3 and 4 show that for both variables, dispersion is positively correlated with direct measures of macroeconomic (and policy) uncertainty, even after controlling for forecast horizon, lagged dispersion, and other variables. The evidence for the macroeconomic uncertainty index is more convincing than that for the policy uncertainty index, the coefficients on which are insignificant in columns (d) and (e) for both variables. The coefficient on MU is larger in the 'long-horizon' regression than in the short horizon regression, where the coefficient is not significant. This is particularly interesting as the macro-uncertainty index that we use measures predictability of a 3-month horizon. This suggests that dispersion is correlated to prevailing 'spot' levels of macroeconomic uncertainty, more so in the long-horizon where presumably there is less information of relevance to the forecasted variable. The coefficient in the short-horizon regression is not significant, though the value is still reasonably large. For PGDP inflation, the coefficients on average levels of forecast uncertainty are largely insignificant (they are only mildly significant in columns (d) and (e) of Table 3, the latter of the 'wrong' sign).

While the key results of interest are regarding the uncertainty indices, Table 3 also contain a number of other interesting results. The regression result for PGDP inflation in Table 3 show that lagged dispersion is 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 overall degree of dispersion is persistent. The coefficient becomes smaller as more explanatory variables are included, first spread then the uncertainty indices. It is interesting that the coefficient on lagged dispersion is larger for the short horizon forecasts than the long-horizon ones (comparing columns (d) and (e)) which may say something regarding the way the forecasters process information. The regression result for RGDP growth in Table 4 show similar results, with some important differences. Again, lagged dispersion in density forecast medians is large, positive, and significant, decaying as more explanatory variables are included. However, this coefficient is much smaller (and not significant) in the short-horizon regression, whereas it remains large and significant in the long-horizon regression. This may indicate more information processing in the shorter horizons as new information arrives.

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 less so in the regressions with the uncertainty indices. The decreasing dispersion with decreasing horizon is also less clear in for output growth, except perhaps for horizons 0 and 1. However, there does appear 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 reevaluated 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.

For PGDP inflation, 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. Similarly, for RGDP growth, the coefficient of the T-bill rate forecast dispersion is positive and significant in the short-horizon forecasts. (The coefficient of the spread forecast dispersion is much weaker, when we replace the T-bill rate dispersion with the dispersion in spread), which is consistent with the Ang, Piazzesi, and Wei (2006) evidence that short-term interest rates forecast output growth better than spread.

As for the average levels of density forecast medians and skewness, they are by and large insignificant across Tables 3 and 4. The exception appears to be for overall level of the density forecast median. In regressions (a) and (b) of Table 4, dispersion in density forecast medians are negatively correlated with the overall expected levels of growth. As noted in Patton and Timmermann (2010), this is a result consistent with macroeconomic models that incorporate heterogeneous information. However, this correlation vanishes when macro and policy uncertainty are included in the regression.

4.2 Dispersion in Range and Skewness

The regressions for the dispersion of individual density forecast ranges are given in Table 5. 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 overall 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 forecast uncertainty is significant and positive, i.e., there is more disagreement in individual uncertainty when the average level of 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 inflation and output growth forecaster uncertainty do not respond to policy uncertainty at all, or macro uncertainty in the short horizon, and respond differently to macroeconomic uncertainty for long-horizon forecasts. Dispersion in inflation forecaster uncertainty rises as macroeconomic uncertainty, indicating that the degree of heterogeneity in perceived uncertainty increases during more volatile periods. However, for output growth the effect is strongly and negatively significant, which may suggest that in periods where substantial uncertainty in real output growth is detected, forecasts update their perceived uncertainty to a higher level consistently and thus demonstrate a lower disagreement in forecaster uncertainty.

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. It does not appear that any of our variables can explain variations in the dispersion of individual density forecast skewness. There is no response to either policy and macroeconomic uncertainty for both variables. There are also no significant effects from either the dispersion of yield spreads or T-bill rates. There are some significant results regarding overall levels of skewness, but these are harder to interpret. While there are interesting results explaining the behavior of overall levels of skewness (Table 2), it seems there is no accounting for why the forecaster differ in the shape of their forecast densities.

5. Concluding remarks

We explore the role of uncertainty in explaining dispersion in the median, central 90% 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 forecaster uncertainty.

The empirical evidence suggests that dispersion among forecasters in medians is related to overall macroeconomic uncertainty, and to a lesser extent policy uncertainty. The dispersion shows a different pattern in short horizon versus longer horizon. In longer horizon, we observe a larger but smoother degree of disagreement which relies more on past information (e.g., lagged dispersion) and overall macroeconomic uncertainty index while the degree of dispersion is more related to controls closely linked to new information such as dispersion in interest rates in short horizons.

The link between macroeconomic uncertainty and forecast dispersion appears to apply mainly to the location of the density forecasts, and is much weaker for dispersion in forecaster uncertainty. As for the dispersion in forecaster uncertainty, our results provide evidence that professional forecasters are heterogeneous in the way they revise their subjective forecast distributions: the dispersion in forecaster uncertainty rises as forecast horizon shortens, and exhibits a positive correlation with average forecaster uncertainty, suggesting that some forecasters tend not to revise their reported levels of uncertainty upwards. Dispersion in forecaster uncertainty is positively correlated with macroeconomic economy uncertainty only in the long run, though in opposite directions for inflation and for real output forecasters. In the latter case, forecasters disagree less on perceived uncertainty when there is an increase in real output uncertainty. For skewness there appears no link whatsoever between dispersion and macro, policy, or forecaster uncertainty (or any of our other controls).

Overall, average forecaster uncertainty appears to have little role in explaining forecast dispersion. Furthermore, there is evidence that forecaster uncertainty appears to be affected by survey design; there appears a need for further research into forecaster uncertainty elicitation methods.

References

Ang, A., G. Bekaert, and M. Wei (2007), "Do Macro Variables, Asset Markets, or Surveys Forecast Inflation Better?", Journal of Monetary Economics, 54(4), 1163-1212.

Ang, A., M. Piazzesi, and M. Wei (2006), "What Does the Yield Curve Tell Us About GDP Growth?", Journal of Econometrics, 131(1-2), 359–403.

Baker, S.R., N. Bloom, and S.J. Davis (2016), "Measuring Economic Policy Uncertainty", The Quarterly Journal of Economics, 131(4), 1593-1636.

Ball, L. (1992), "Why Does Higher Inflation Raise Inflation Uncertainty?", Journal of Monetary Economics, 29(3), 371-388.

Boero, G., J. Smith, and K.F. Wallis (2008), "Uncertainty and Disagreement in Economic Prediction: The Bank of England Survey of External Forecasters", The Economic Journal, 118(530), 1107-1127.

Boero, G., J. Smith, and K.F. Wallis (2015), "The Measurement and Characteristics of Professional Forecasters' Uncertainty", Journal of Applied Econometrics, 30(7), 1029-1046.

Capistran, C. and A. Timmermann (2009), "Disagreement and Biases in Inflation Expectations", Journal of Money, Credit and Banking, 41(2-3), 365-396.

Engelberg, J., C.F. Manski, and J. Williams (2009), "Comparing the Point Predictions and Subjective Probability Distributions of Professional Forecasters", Journal of Business & Economic Statistics, 27(1), 30-41.

Estrella, A. and G.A. Hardouvelis (1991), "The Term Structure as Predictor of Real Economic Activity", The Journal of Finance, 46(2), 555-576.

Estrella, A. and F.S. Mishkin (1998), "Predicting U.S. Recessions: Financial Variables as Leading Indicators", The Review of Economics and Statistics, 80(1), 45-61.

Giordani, P. and P. Soderlind (2003), “Inflation Forecast Uncertainty”, European Economic Review, 47(6), 1037-1059.

Hamilton, J.D. and D.H. Kim (2002), “A Re-Examination of the Predictability of Economic Activity Using the Yield Spread”, Journal of Money, Credit and Banking, 34(2), 340-360.

Jurado, K., S.C. Ludvigson, and S. Ng (2015), “Measuring Uncertainty”, The American Economic Review, 105(3), 1177-1216.

Kandel, E. and B-Z. Zilberfarb (1999), “Differential Interpretation of Information in Inflation Forecasts”, The Review of Economics and Statistics, 81(2), 217-226.

Lahiri, K. and F. Liu (2006), “Modelling Multi-Period Inflation Uncertainty Using a Panel of Density Forecasts”, Journal of Applied Econometrics, 21(8), 1199-1219.

Mankiw, N.G., R. Reis and J. Wolfers (2003), “Disagreement about Inflation Expectations”, NBER Macroeconomic Annual, 18, 209-248.

Manzan, S. (2011), “Differential Interpretation in the Survey of Professional Forecasters”, Journal of Money, Credit and Banking, 43(5), 993-1017.

Patton, A.J. and A. Timmermann (2007), “Testing Forecast Optimality under Unknown Loss”, Journal of the American Statistical Association, 102(480), 1172-1184.

Patton, A.J. and A. Timmermann (2010), “Why Do Forecasters Disagree? Lessons from the Term Structure of Cross-Sectional Dispersion”, Journal of Monetary Economics, 57(7), 803-820.

Rich, R. and J. Tracy (2010), “The Relationships among Expected Inflation, Disagreement, and Uncertainty: Evidence from Matched Point and Density Forecasts”, The Review of Economics and Statistics, 92(1), 200-207.

Rossi, B. and T. Sekhposyan (2010), "Have Economic Models' Forecasting Performance for US Output Growth and Inflation Changed over Time, and When?", International Journal of Forecasting, 26(4), 808-835.

Stock, J. H. and M.W. Watson (2009), "Phillips Curve Inflation Forecasts", in J. Fuhrer, Y. Kodrzycki, J. Little, G. Olivei (eds), Understanding Inflation and the Implications for Monetary Policy, 99-202, Cambridge, MIT Press.

Zarnowitz, V. and L.A. Lambros (1987), "Consensus and Uncertainty in Economic Prediction", Journal of Political Economy, 95(3), 591-621.

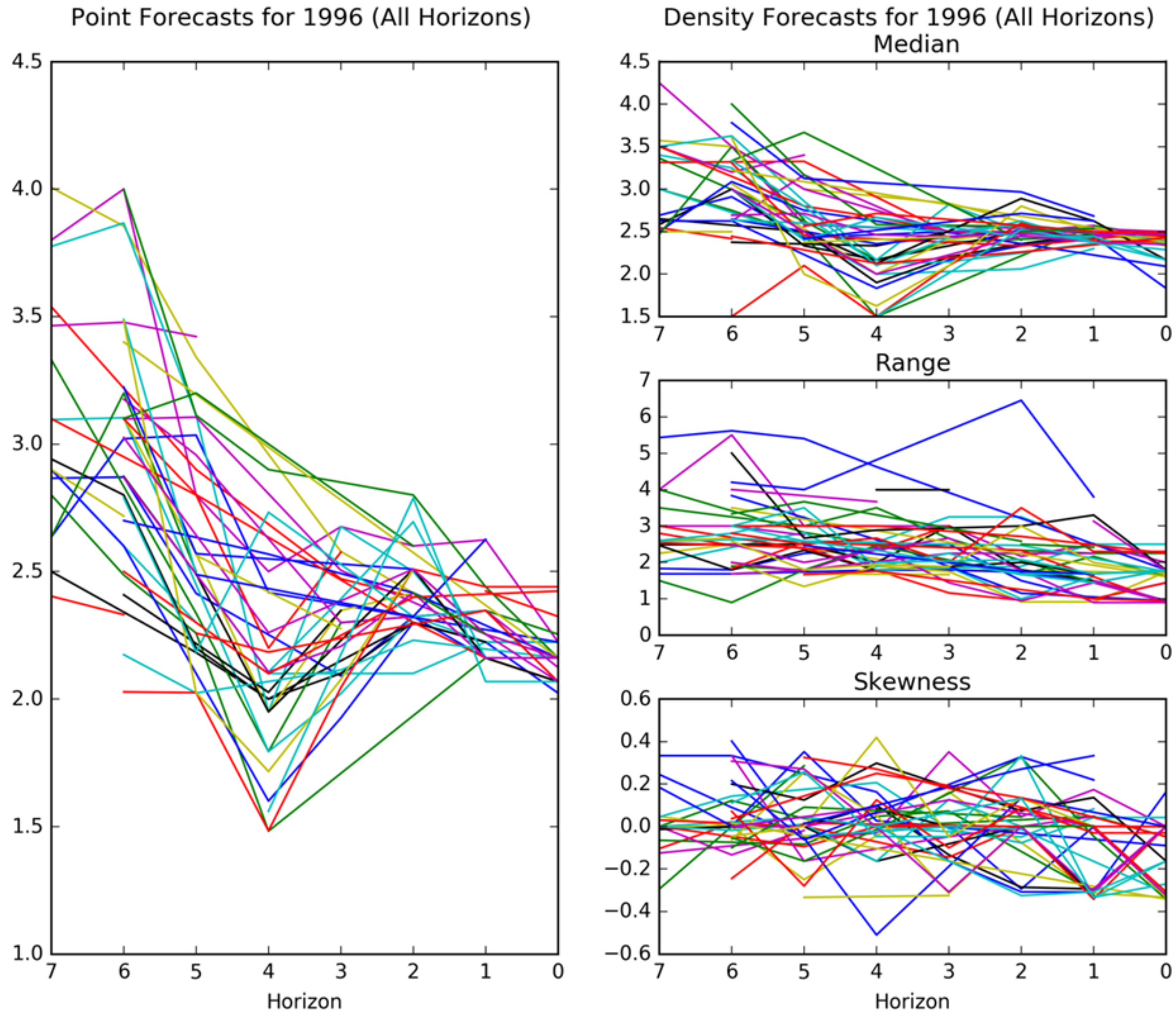

Figure 1 Left diagram: point forecasts of all forecasters for 1996 PGDP inflation from 8 surveys. Horizons 7 to 4 forecasts were made in the 1995Q1-Q4 surveys, and horizons 3 to 0 forecasts were made in the 1996Q1-Q4 surveys. Right column shows the three key characteristics (median, range and skewness) of density forecasts of all forecasters for 1996 PGDP inflation from the same 8 surveys.

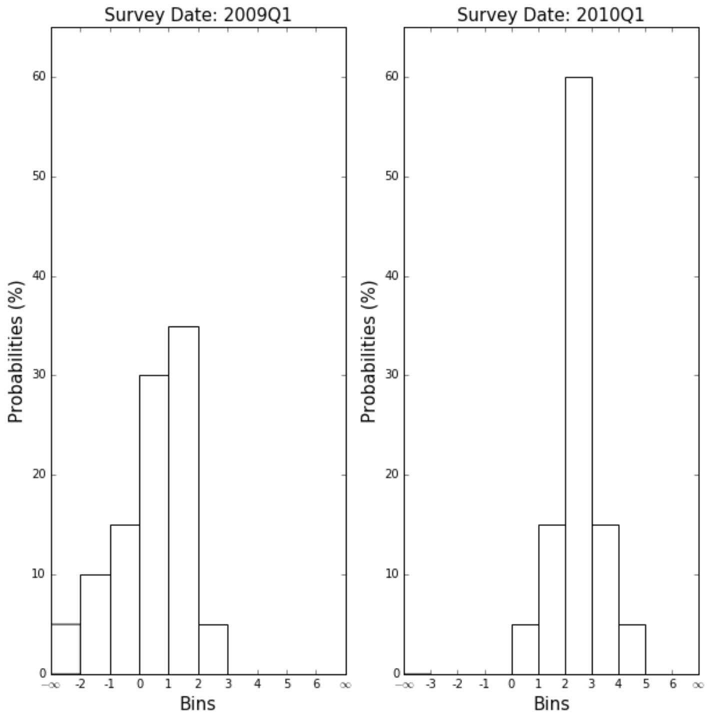

Figure 2 Density forecasts of annual average RGDP growth in 2010 made by Forecaster 516 in the 2009Q1 and 2010Q1 surveys.

Figure 3 Plots of density forecast medians against forecasters corresponding point forecast, full and matched samples.

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.

Table 1 Average Forecaster Uncertainty

Variable	PGDP Inflation			RGDP Growth		
	(a)	(b)	(c)	(d)	(e)	(f)
h_1	0.376***	0.394***		0.536***	0.520***	
	(7.18)	(7.85)		(10.08)	(10.17)	
h_2	0.513***	0.552***		0.841***	0.820***	
	(9.47)	(9.92)		(11.81)	(11.14)	
h_3	0.653***	0.617***		1.340***	1.373***	
	(11.86)	(11.26)		(17.69)	(15.69)	
h_4	0.629***			1.121***		
	(11.48)			(14.82)		
h_5	0.753***		0.123***	1.222***		0.107**
	(12.17)		(3.16)	(15.96)		(2.10)
h_6	0.819***		0.181***	1.369***		0.249***
	(12.47)		(4.42)	(16.49)		(4.77)
h_7	0.821***		0.200***	1.489***		0.351***
	(13.87)		(3.87)	(19.43)		(5.62)
Newbin	-0.723***	-0.716***	-0.735***	0.089**	0.061	0.119**
	(-10.00)	(-10.12)	(-7.30)	(2.31)	(1.31)	(2.31)
lagged R^m	0.103	-0.020	0.182*	0.224***	0.273***	0.156
	(1.41)	(-0.25)	(1.83)	(3.32)	(2.94)	(1.60)
M^m	0.118***	0.179***	0.069	0.004	0.001	0.024
	(3.90)	(5.03)	(1.49)	(0.19)	(0.06)	(0.48)
PU	-0.024	0.066	-0.106**	0.101**	0.153**	0.055
	(-0.66)	(1.52)	(-2.44)	(2.03)	(2.32)	(0.81)
MU	0.194	0.113	0.225	-0.467**	-0.512*	-0.411*
	(1.12)	(0.61)	(1.01)	(-2.53)	(-1.68)	(-1.69)
Constant	1.155***	1.241***	1.764***	1.434***	1.310***	2.722***
	(5.86)	(6.11)	(6.07)	(4.91)	(2.98)	(6.82)
Obs.	198	99	99	198	99	99
R^2	0.88	0.86	0.84	0.88	0.85	0.40
r(1)	1.326	1.317		1.374	1.397	
r(2)	1.089	1.097		1.155	1.164	
r(3)	1.084	1.036		1.219	1.260	
r(4)	0.987			0.921		
r(5)	1.070		1.070	1.040		1.039
r(6)	1.035		1.031	1.055		1.050
r(7)	1.001		1.010	1.043		1.034

Notes: Regression results for average individual uncertainty R^m, 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. The entries r(k) are the ratios of the average range at horizon k to horizon $k-1$.

Table 2 Average Individual Skewness

Variable	PGDP Inflation			RGDP Growth		
	(a)	(b)	(c)	(d)	(e)	(f)
Newbin	0.005	0.013	-0.009	0.013	0.010	0.013
	(0.22)	(0.37)	(-0.48)	(1.16)	(0.53)	(1.62)
lagged S^m	0.392***	0.403***	0.271**	0.323***	0.292***	0.319***
	(4.46)	(3.70)	(2.49)	(4.04)	(3.14)	(2.83)
M^m	-0.022**	-0.022	-0.015	-0.029***	-0.036***	-0.011
	(-2.26)	(-1.50)	(-1.61)	(-3.66)	(-3.84)	(-1.35)
R^m	0.043*	0.035	0.048**	-0.034	-0.015	-0.054***
	(1.79)	(0.82)	(2.44)	(-1.53)	(-0.39)	(-3.20)
PU	-0.012	-0.012	-0.011	-0.029*	-0.051*	-0.005
	(-1.06)	(-0.63)	(-1.23)	(-1.72)	(-1.89)	(-0.42)
MU	-0.086**	-0.106	-0.059*	-0.039	-0.103	0.018
	(-2.28)	(-1.52)	(-1.88)	(-0.58)	(-0.87)	(0.29)
Obs	198	99	99	198	99	99
R^2	0.34	0.31	0.46	0.40	0.44	0.25

Notes: Results for average skewness S^m regressions. 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.

Table 3 Dispersion of Individual PGDP Inflation Density Forecast Medians

	Dep. Var. PGDP Inflation Density Forecast Medians M^m				
	(a)	(b)	(c)	(d)	(e)
h_1	0.005	-0.001	0.009	-0.026	
	(0.20)	(-0.04)	(0.34)	(-0.94)	
h_2	0.060*	0.046	0.065**	0.016	
	(1.84)	(1.32)	(1.99)	(0.47)	
h_3	0.157***	0.123***	0.132***	0.076**	
	(4.39)	(3.44)	(3.94)	(2.04)	
h_4	0.107***	0.066	0.090**		
	(2.84)	(1.59)	(2.33)		
h_5	0.145***	0.097**	0.126***		0.048**
	(3.87)	(2.28)	(3.09)		(2.25)
h_6	0.170***	0.110**	0.145***		0.072***
	(3.71)	(2.10)	(2.99)		(2.81)
h_7	0.197***	0.118**	0.149***		0.065***
	(4.51)	(2.42)	(3.18)		(2.71)
newbin	-0.055	-0.058	-0.057	0.023	-0.179***
	(-1.48)	(-1.53)	(-1.63)	(0.68)	(-2.90)
lagged M^{δ}	0.334***	0.288***	0.225***	0.231**	0.157*
	(5.47)	(4.85)	(3.85)	(2.57)	(1.68)
M^m	0.000	0.009	0.027	0.006	0.052*
	(0.01)	(0.52)	(1.49)	(0.33)	(1.91)
R^m	0.015	0.003	-0.006	0.081*	-0.112*
	(0.36)	(0.07)	(-0.15)	(1.94)	(-1.69)
S^m	0.082	0.065	0.167	0.149	0.064
	(0.73)	(0.60)	(1.65)	(1.31)	(0.23)
spread		0.219***	0.178***	0.193**	0.220***
		(3.37)	(2.83)	(2.07)	(3.21)
PU			0.036**	0.032	0.025
			(2.22)	(1.42)	(0.89)
MU			0.184*	0.135	0.259**
			(1.85)	(0.93)	(2.47)
constant	0.090	0.086	-0.104	-0.174	0.165
	(1.37)	(1.29)	(-1.01)	(-1.37)	(0.84)
Obs	198	198	198	99	99
R^2	0.64	0.66	0.69	0.56	0.48

Notes: Results for dispersion of individual PGDP inflation density forecast medians (M^{σ}) regressions. Robust t-statistics in parentheses, calculated from standard errors clustered by year and quarter.

Table 4 Dispersion of Individual RGDP Growth Density Forecast Medians

	Dep. Var. RGDP Growth Density Forecast Medians M^m				
	(a)	(b)	(c)	(d)	(e)
h_1	-0.020	-0.019	-0.013	-0.005	
	(-0.61)	(-0.57)	(-0.39)	(-0.15)	
h_2	0.026	0.023	0.039	0.046	
	(0.68)	(0.59)	(0.93)	(0.93)	
h_3	0.215***	0.194***	0.192***	0.138**	
	(4.65)	(3.83)	(3.84)	(2.47)	
h_4	0.113*	0.089	0.105*		
	(1.95)	(1.49)	(1.76)		
h_5	0.117**	0.081	0.103		0.007
	(2.03)	(1.29)	(1.62)		(0.26)
h_6	0.107*	0.062	0.094		0.003
	(1.72)	(0.90)	(1.34)		(0.10)
h_7	0.205***	0.151*	0.173**		0.086**
	(2.90)	(1.95)	(2.27)		(2.33)
newbin	-0.044***	-0.033*	-0.046***	-0.041*	-0.047*
	(-2.79)	(-1.96)	(-2.67)	(-1.97)	(-1.88)
lagged M^δ	0.441***	0.394***	0.343***	0.141	0.377***
	(5.08)	(4.26)	(4.42)	(1.36)	(4.09)
M^m	-0.021**	-0.022**	-0.008	-0.010	-0.033
	(-2.35)	(-2.54)	(-0.94)	(-1.32)	(-1.38)
R^m	0.041	0.039	0.051	0.055	0.050
	(1.09)	(1.02)	(1.37)	(1.40)	(0.91)
S^m	-0.046	-0.064	0.035	0.008	0.196
	(-0.44)	(-0.60)	(0.34)	(0.10)	(0.61)
TBill		0.134**	0.086	0.322**	0.045
		(2.13)	(1.29)	(2.01)	(0.52)
PU			0.045**	0.038	0.040
			(2.41)	(1.57)	(1.29)
MU			0.233**	0.019	0.387**
			(2.06)	(0.17)	(2.30)
constant	0.065	0.070	-0.204	0.001	-0.136
	(0.83)	(0.89)	(-1.53)	(0.01)	(-0.59)
Obs	198	198	198	99	99
R^2	0.70	0.71	0.73	0.71	0.51

Notes: Results for dispersion of individual RGDP growth density forecast medians (M^σ) 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_1	-0.135**	-0.093		-0.045	-0.061	
	(-2.38)	(-1.43)		(-0.71)	(-0.79)	
h_2	-0.207***	-0.141*		-0.138*	-0.153	
	(-3.17)	(-1.83)		(-1.72)	(-1.48)	
h_3	-0.297***	-0.212**		-0.206**	-0.199	
	(-3.94)	(-2.36)		(-2.12)	(-1.52)	
h_4	-0.340***			-0.272***		
	(-4.86)			(-2.87)		
h_5	-0.344***		-0.013	-0.280***		-0.005
	(-4.07)		(-0.37)	(-2.69)		(-0.13)
h_6	-0.360***		-0.044	-0.302***		-0.029
	(-3.98)		(-0.93)	(-2.68)		(-0.59)
h_7	-0.381***		-0.065	-0.286**		-0.029
	(-4.02)		(-1.36)	(-2.40)		(-0.51)
Newbin	0.239***	0.114	0.374***	0.076**	0.045	0.118***
	(3.57)	(1.50)	(3.85)	(2.38)	(0.84)	(2.90)
lagged R^{δ}	0.081	0.033	0.039	0.225***	0.315***	0.078
	(1.27)	(0.35)	(0.44)	(2.96)	(3.31)	(0.70)
M^m	0.023	0.033	0.028	0.003	0.016	-0.047
	(0.67)	(0.72)	(0.62)	(0.14)	(0.65)	(-1.37)
R^m	0.501***	0.435***	0.578***	0.389***	0.418***	0.374***
	(6.19)	(4.06)	(4.75)	(5.49)	(4.32)	(3.83)
S^m	0.300	0.296	0.479	0.073	0.171	-0.188
	(1.31)	(1.12)	(0.91)	(0.31)	(0.56)	(-0.45)
Spread/TBill	0.170	-0.075	0.195	0.086	-0.025	0.170*
	(1.41)	(-0.38)	(1.53)	(0.91)	(-0.07)	(1.71)
PU	-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	0.196	-0.019	0.472***	-0.238	-0.149	-0.376*
	(1.63)	(-0.09)	(2.71)	(-1.30)	(-0.48)	(-1.83)
Constant	-0.431***	-0.134	-1.159***	-0.009	0.047	-0.193
	(-2.86)	(-0.66)	(-4.31)	(0.20)	(-0.59)	(0.51)
Obs	198	99	99	196	97	99
R^2	0.55	0.50	0.62	0.59	0.55	0.49

Notes: Results for dispersion of individual RGDP growth density forecast range (R^{σ}) regressions. 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			RGDP		
	(a)	(b)	(c)	(d)	(e)	(f)
Newbin	-0.017	-0.005	-0.038	-0.007	-0.017*	0.002
	(-1.24)	(-0.35)	(-1.65)	(-1.36)	(-1.81)	(0.33)
lagged S^{δ}	0.103	0.113	0.039	0.084	0.136	-0.039
	(1.28)	(1.05)	(0.33)	(1.27)	(1.51)	(-0.38)
M^{m}	-0.006	-0.012*	0.002	0.004	0.004	0.009*
	(-1.35)	(-1.90)	(0.28)	(1.56)	(1.17)	(1.80)
R^{m}	0.011	0.027*	-0.023	0.004	0.010	-0.014
	(0.86)	(1.77)	(-1.09)	(0.37)	(0.72)	(-1.05)
S^{m}	-0.033	-0.084**	0.132	0.031	0.072**	-0.137**
	(-1.00)	(-2.44)	(1.27)	(0.94)	(2.05)	(-2.01)
Spread/TBill	0.005	-0.071*	0.029	-0.026	-0.059	-0.021
	(0.19)	(-1.82)	(0.97)	(-1.35)	(-0.78)	(-1.19)
PU	-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	0.030	0.019	0.061	0.040	0.055	0.044
	(1.28)	(0.55)	(1.24)	(1.62)	(1.44)	(1.27)
Constant	0.132***	0.123***	0.173**	0.106***	0.075	0.142***
	(3.94)	(2.90)	(2.59)	(3.17)	(1.58)	(2.70)
Obs	198	99	99	196	97	99
R^2	0.20	0.22	0.25	0.22	0.16	0.17

Notes: Results for dispersion of individual RGDP growth density forecast skewness (S^{σ}) regressions. 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.