The Measurement and Behavior of Uncertainty: Evidence from the ECB Survey of Professional Forecasters

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Abstract

We use matched point and density forecasts of output growth and inflation from the ECB Survey of Professional Forecasters to derive measures of forecast uncertainty, forecast dispersion and forecast accuracy. We construct uncertainty measures from aggregate density functions as well as from individual histograms. The uncertainty measures display countercyclical behavior, and there is evidence of increased uncertainty for output growth and inflation since 2007. The results also indicate that uncertainty displays a very weak relationship with forecast dispersion, corroborating the findings of other recent studies that disagreement is not a valid proxy for uncertainty. In addition, we find no correspondence between movements in uncertainty and predictive accuracy, suggesting that time-varying conditional variance estimates may not provide a reliable proxy for uncertainty. Last, using a regression equation that can be interpreted as a (G)ARCH-M-type model, we find limited evidence of linkages between uncertainty and levels of output growth and inflation.

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I. Introduction

Uncertainty is of considerable interest for understanding the expectations formation process as well as for explaining movements in key economic and financial time series. Despite its importance, the measurement of uncertainty, like the measurement of expectations, is problematic due to the inherent difficulty of observing individuals' subjective magnitudes. While surveys can provide direct measures of expectations, their scope typically does not extend to measures of uncertainty. There are, however, a limited number of survey instruments that report both point forecasts and density (histogram) forecasts, with the latter forecasts providing a basis to construct measures of uncertainty.

This paper examines matched point and density forecasts of output growth and inflation from the Survey of Professional Forecasters conducted by the European Central Bank (ECB-SPF). We use the data to derive measures of forecast uncertainty using two alternative approaches. One approach draws upon the work of Wallis (2004, 2005) and uses a decomposition of the variance of the aggregate density forecast distribution. The second approach is based on the distribution of uncertainty calculated from the individual density forecasts of survey respondents. We use both approaches to judge their relative merits and the robustness of results.

We also use the data to derive measures of forecast dispersion – disagreement among forecasters – and predictive accuracy. The motivation for looking at these measures stems from the common practice of researchers who, faced with the need to derive measures of uncertainty, have used the extent of disagreement among reported point forecasts or time-varying conditional variance estimates as proxies for uncertainty. Underlying the former practice is the assumption that episodes characterized by high (low) dispersion of point forecasts are indicative of a high (low) level of uncertainty shared by respondents regarding the forecasted outcome variable. Underlying the latter practice is the assumption that episodes characterized by low (high) predictive accuracy are indicative of a high (low) level of uncertainty shared by respondents regarding the forecasted outcome variable. The validity of these assumptions, however, is an open empirical question that is best answered by direct measurement and testing.

Last, we explore the issue of the impact of uncertainty on inflation and output growth. Using both forecasts and uncertainty measures of inflation and output growth from the ECB-SPF, we specify a regression equation that can be interpreted as a univariate (G)ARCH-M (Generalized ARCH in mean) model. The (G)ARCH-M model has been widely adopted in empirical studies investigating the effects of uncertainty on inflation and output growth.

Our findings provide evidence of an increase in uncertainty over output growth and inflation since 2007. The results also indicate that uncertainty displays only a very weak relationship with forecast dispersion, corroborating the findings of recent studies that disagreement is not a valid proxy for uncertainty. There is also an absence of co-movement between uncertainty and predictive accuracy, suggesting that model-based conditional variance estimates also may not provide a reliable proxy for uncertainty. Finally, we find limited evidence of a meaningful effect of uncertainty on inflation and output growth.

Our analysis of the ECB-SPF also provides insights for the recent literature in macroeconomics investigating the role of uncertainty as a source of business cycle fluctuations. The seminal contribution of Bloom (2009) and the subsequent work of Bloom *et al.* (2009), Bachmann *et al.* (2010), and Bachmann and Bayer (2011) allow the degree of uncertainty to vary over time and examine how these fluctuations affect economic activity. Issues related to the measurement and behavior of uncertainty as well as the reliability of selected proxies is critical for assessing the evidence from such studies.

In the next section, we provide an overview of the ECB-SPF data. Section III discusses the construct of the measures of uncertainty and disagreement used in the analysis. We examine the relationship between disagreement and uncertainty in section IV, with the relationship between uncertainty and predictive accuracy analyzed in the subsequent section. Section IV explores the effects of uncertainty on movements in real activity and inflation. We then conclude with a short summary of our findings.

II. The European Central Bank's Survey of Professional Forecasters

A. Background

The ECB-SPF is a quarterly survey started in 1999 that solicits euro area macroeconomic expectations for the harmonized index of consumer price (HICP) inflation, real GDP growth, and the unemployment rate. The ECB-SPF questionnaire asks for forecasts at short-, medium-, and longer-term horizons that include both rolling and calendar year horizons. The survey panel consists of respondents from both financial and non-financial institutions, with 75 active panelists throughout the euro area and an average response of 60 panelists. Further details about the features of the ECB-SPF are provided in Garcia (2003) and Bowles *et al.* (2008). While the ECB-SPF shares many design features of the longer running Survey of Professional Forecasters covering U.S. data and currently conducted by the Federal Reserve Bank of Philadelphia (US-SPF), there are important differences that we discuss more closely in the next section.

For the three macroeconomic variables, the ECB-SPF asks each respondent to provide a point and density forecast. The point forecast is a single value of the macroeconomic variable for each of the time horizons. For the density forecasts, respondents are asked to provide a probability distribution of forecasted outcomes. The respondents report their probability distribution along a given set of intervals provided by the ECB for each macroeconomic variable.

For the analysis, we examine matched point and density forecasts of output growth and HICP inflation that involve a "rolling" horizon. Essentially, the forecasts are at a quarterly frequency and are for one-year-ahead and one-year/one-year forward output growth and HICP inflation. An important consequence of this structure is that the horizons remain constant for the one-year-ahead and one-year/one-year forward forecasts, so that the data can be treated as quarterly observations on homogenous series.[1]

As Garcia (2003) notes, however, the target variables for the forecasts of output growth and inflation differ because of differences in the data frequency and publication lags of the variables. Output growth is published quarterly with a two quarter lag, while HICP inflation is published monthly with a one month lag. As an example, the 2010Q1 survey questionnaire asks respondents to forecast output growth from 2009Q3 to 2010Q3 and from 2010Q3 to 2011Q3. For HICP inflation, respondents report forecasts from December 2009 to December 2010 and from December 2010 to December 2011. While the difference in target variables for GDP growth and HICP inflation does not matter for most of the analysis, it places some limitations on our investigation into the effects of uncertainty on inflation and output growth. Specifically, while we can study the effects of inflation uncertainty on inflation and the effects of output growth uncertainty on output growth, we will not be able to study the effect of inflation (output growth) uncertainty on output growth (inflation).

B. Survey Features

One advantage of the ECB-SPF compared to the US-SPF is that the interval widths used to solicit the respondents' density forecasts have remained fixed over time. The intervals have a

[1] As discussed shortly, this is not the case for the US-SPF.

width of 0.4 percentage point with a 0.1 percentage point gap between the interior intervals. The lower-end and upper-end intervals are left open. The number of intervals, however, has occasionally changed to ensure that the open intervals do not have either a significant proportion of the probability assigned to them or consistently little to no probability assigned to them. For example, the ECB added four lower intervals to the inflation density forecast and added ten lower intervals to the GDP growth density forecast for the 2009Q2 survey due to a "pile up" of probability at the lower open GDP growth interval for 2009Q1 survey. However, after deflation and recession risks subsided in early 2010, the ECB removed two of the lower intervals for inflation and ten of the lower bins for GDP growth from the survey.[2]

The rolling window forecast horizons and the inclusion of medium- and longer-term horizons are also an improvement on the US-SPF survey design. The US-SPF uses a fixed target date horizon so that the length of the forecast window follows an "accordion" profile – shortening within a cycle of surveys and then reverting back to the initial length to begin another cycle. This accordion feature reduces the comparability of adjacent surveys because one must adjust for the changing horizon lengths.[3] In addition, the availability of medium- and longer-term forecast horizons in the ECB-SPF allows researchers to gauge the persistence of respondent beliefs as well as to assess how well inflation expectations are anchored at longer horizons.

C. Diagnostics to Screen Respondents

Our study covers the sample period 1999Q1 through 2011Q4 and has 3,031 completed surveys. We exclude, however, any respondent who in that survey for HICP inflation or GDP growth at a

[2] Additional details on the changes to the density forecast bins can be found on the ECB Survey of Professional Forecasters website. We provide further discussion of this issue and the 2009Q1 survey in Section III which details the construct of the measures of uncertainty.

[3] For the US-SPF, the time-varying forecast horizon arises from the target variable adjusting every four quarters. Consequently, data comparisons are problematic except for observation for the same quarter. For their empirical analysis of the US-SPF, Rich and Tracy (2010) adopt a seemingly unrelated regression (SUR) framework to account for this feature of the data.

given horizon did not report both a point and a density forecast, or whose density forecast probabilities did not sum to unity. This removed 611 observations from the one-year-ahead HICP inflation sample, 849 observations from the one-year/one-year forward HICP inflation sample, 669 observations from the one-year-ahead GDP growth sample, and 877 observations from the one-year/one-year forward GDP growth sample.

As a result of our sample selection criteria, there was an average of 44-51 respondents per quarter with matched point and density forecasts. We do not control for compositional effects in the survey instrument due to the small sample size and the mixed evidence on this issue. On the one hand, Engelberg, Manski, and Williams (2011) suggest that changing panel composition is an especially important issue for the US-SPF, with Boero, Smith and Wallis (2012) finding substantial heterogeneity of individual forecast uncertainty for the Bank of England Survey of External Forecasters. In contrast, D'Agostino, McQuinn and Whelan (2012) argue that ex post differences in forecaster performance for the US-SPF is more reflective of sampling variation than innate abilities.

III. Measuring Uncertainty

A. Variable Definitions

Abstracting from difference in target variables for output growth and inflation, let ${}^{q,\tau+1}_{q,\tau}\phi_{q,t}(\Delta y)$ and ${}^{q,\tau+1}_{q,\tau}\phi_{q,t}(\pi)$ denote, respectively, a respondent's 4-quarter density forecasts in quarter *q* of year *t* of output growth (Δy) and inflation (π) for the current year and the next year. Therefore, ${}^{q,t+1}_{q,t}\phi_{q,t}(\Delta y)$ and ${}^{q,t+2}_{q,t+1}\phi_{q,t}(\Delta y)$ will denote, respectively, a respondent's one-year-ahead and one-year/one-year forward density forecasts of output growth in quarter *q* of year *t*. We will then let

${}^{q,\tau+1}_{q,\tau}\phi^{e}_{q,t}(\Delta y)$ and ${}^{q,\tau+1}_{q,\tau}\sigma^{2}_{q,t}(\Delta y)$ denote, respectively, the mean and variance of the corresponding density forecast of output growth.

With regard to the point forecasts, the ECB-SPF also asks respondents for predictions of output growth and inflation over the same one-year-ahead and one-year/one-year forward forecast horizons. Accordingly, we will let ${}^{q,\tau+1}_{q,\tau}f^{e}_{q,t}(\Delta y)$ and ${}^{q,\tau+1}_{q,\tau}f^{e}_{q,t}(\pi)$ denote, respectively, a respondent's point forecast in quarter *q* of year *t* of output growth and inflation at the relevant one-year-ahead and one-year/one-year forward horizons.

Our study considers two alternative approaches to derive measures of uncertainty. The first is based on the statistical framework of Wallis (2004, 2005). Specifically, let ${}^{q,\tau+1}_{q,\tau}\overline{\phi}_{q,t}$ denote the aggregate density forecast in quarter *q* of year *t* that averages the individual density forecasts across all respondents, where for convenience we subsequently suppress the explicit reference to either GDP growth or HICP inflation. As Wallis notes, the combined density forecast is a finite mixture distribution. If we assume that each individual's point forecast $({}^{q,\tau+1}_{q,\tau}f^{e}_{q,t})$ is the mean of the individual's density forecast $({}^{q,\tau+1}_{q,\tau}\phi^{e}_{q,t})$, then Wallis (2004, 2005) shows the variance of ${}^{q,\tau+1}_{q,\tau}\overline{\phi}_{q,t}$ can be expressed as:[4]

$$Var[(\overline{\phi})] = \overline{\sigma}^{2} + s^{2}_{f} \tag{1}$$

The first term on the right-hand side of (1) is the average individual variance $(\overline{\sigma}^{2})$ that provides the basis for the measure of aggregate uncertainty. The second-term is the cross-sectional variance of the point forecasts (s^{2}_{f}) that provides the basis for the measure of disagreement.

[4] As part of a special questionnaire conducted in autumn 2008, ECB-SPF forecasters were asked whether they report their mean, modal or median forecast. The replies indicated that a clear majority of respondents (75%) provide the point estimate that corresponds to the mean of their reported density forecast. We thank Aidan Meyler for bringing this information to our attention.

Given an estimate of $Var[(\bar{\phi})]$ and a calculated value of s_f^2, the decomposition in (1) can be used to back out the $\bar{\sigma}^2$ series. Because equation (1) is derived from moment conditions relating to the individual forecast densities and the aggregate density, we refer to the uncertainty measure $\bar{\sigma}^2$ as an (implied) moment-based measure of uncertainty.[5]

The decomposition in (1) requires an estimate of the variance of the aggregate density distribution. We calculate the aggregate density distribution at each survey date by averaging the reported probability in each bin of the individual's density forecasts, and then fitting a general beta distribution to the aggregate histogram to obtain an estimate of the variance. While we estimate the shape parameters, the upper and lower bounds of the estimated distribution are fixed.[6] Compared to a normal distribution, the general beta distribution is attractive because it is bounded on both sides and is extremely flexible in the forms it can accommodate, including skewness.

Our second measure of uncertainty draws upon information from the individual histogram of survey respondents. Let $iqr[\phi_{q,t}(\Delta y)]$ and $iqr[\phi_{q,t}(\pi)]$ denote, respectively, the interquartile range (IQR) of a respondent's density forecast of output growth and inflation in quarter q of year t.[7] At each survey date, we can order the IQR values for each set of density

[5] As Wallis (2005) notes, Lahiri, Tiegland and Zaporowski (1988) calculate the first four moments of the individual US-SPF, and then use time series of their average values in their study. In the course of their analysis, they obtain a version of the decomposition in equation (1). However, they don't identify the left-hand side of the equation as the variance of the aggregate density forecast. In addition, they work directly with the individual density forecasts rather than the mean density forecast, and they do not use any underlying statistical model.

[6] We fix the bounds at the endpoints of the left-most and right-most bins that have a non-zero density. If the left-most (right-most) bin is one of the interior bins, we set the bound at the closed left (right) endpoint of the bin. If the left-most (right-most) bin is the exterior (open-ended) bin, we set the bound one percentage point below (above) the right (left) endpoint of the lowest (highest) open bin during the history of the survey. While we maintain the same bounds for the left and right open bins even though the value of the open bounds has differed during the survey, this choice does not materially affect the estimated variance of the aggregate density distribution because of the low probability typically assigned to the exterior bins.

[7] To construct the interquartile range for an individual density forecast, we adopt the assumption that the probability mass is uniformly distributed within each of the intervals.

forecasts from lowest to highest. Let $\tilde{\phi} = [{}^{1}iqr_{\phi}, {}^{2}iqr_{\phi}, \ldots, {}^{N-1}iqr_{\phi}, {}^{N}iqr_{\phi}]$ denote the ordered array for one such set of the density forecasts from *N* respondents. Using the value of the IQR as a measure of individual uncertainty, the median of the individual uncertainty measures provides the basis for the measure of aggregate uncertainty:[8]

$$median_{\tilde{\phi}} = {}_{0.50}\tilde{\phi} \tag{2}$$

We follow a similar procedure to derive the corresponding measure of disagreement. Specifically, at each survey date, we can construct an ordered array for each set of point forecasts. Let $\tilde{f} = [{}^{1}f^{e}, {}^{2}f^{e}, \ldots, {}^{N-1}f^{e}, {}^{N}f^{e}]$ denote the ordered array for one such set of point forecasts from *N* respondents. We then use the IQR of the ordered array as the basis for the measure of disagreement:

$$iqr_{\tilde{f}} = {}_{0.75}\tilde{f} - {}_{0.25}\tilde{f} \tag{3}$$

There are advantages to each of the two approaches used in the analysis. The statistical framework of Wallis (2004, 2005) is attractive because it yields a formal relationship among the measures of uncertainty and disagreement. On the other hand, the IQR-based approach has the advantage of being computationally less demanding and more robust to outliers. The use of both approaches, however, has the benefit of allowing us to compare the movements and properties of the derived series as well as to check the robustness of the results concerning the economic and statistical significance of the various estimated relationships.

[8] This approach bears some similarity to Bruine De Bruin, Manski, Topa and Van Der Klaauw (2011). However, the latter study replaces the individual histograms with continuous distributions, and then computes the IQR to derive a measure of individual uncertainty. Following the approach of Engelberg, Manski and Williams (2009), estimation of the individual densities depends on the number of non-zero probability histogram bins reported by respondents. The median of the individual uncertainty measures provides the measure of aggregate uncertainty.

B. Empirical Measures of Uncertainty and Disagreement

Figures 1 to 4 present the time profiles from 1999Q1 through 2011Q4 for the measures of uncertainty and disagreement from the forecasts of HICP inflation and GDP growth, where the series are plotted according to the survey date. The top panel of each figure depicts the variables at the one-year-ahead horizon, while the bottom panel depicts the variables at the one-year/one-year forward horizon. For each figure, we include a vertical line at 2007Q2. We view the post-2007Q2 episode as a period containing a number of events that could meaningfully impact inflation and output growth: the dramatic 2007-2008 run-up in commodity prices; the Great Recession; the second pronounced run-up in commodity prices starting in Summer 2010; and the European sovereign debt crisis that emerged almost two years ago. To gauge if and how these observations may unduly influence the results, we conduct the analysis using data through the 2007Q2 subperiod as well as from the full sample period.[9]

Abstracting from mean differences of the series, the general behavior of the inflation uncertainty measures depicted in Figures 1 and 2 is qualitatively similar across the two approaches. Both measures are fairly stable through the middle of 2007, but then generally increase in a steady manner through the present. In terms of the two forecast horizons, each approach associates a higher level of uncertainty with the one-year/one-year forward horizon as compared to the one-year-ahead horizon.

The qualitative behavior of the disagreement measures is also broadly similar across the two approaches. There is a noticeable increase in disagreement starting in 2008, with some fairly dramatic spikes evident during the Great Recession. More recently, disagreement has declined and returned to levels more consistent with the range observed over most of the sample period.

[9] There was an initial run-up of commodity prices around March 2009, but we view this largely as an initial recovery after the sharp drop following the recent global recession.

There is, however, a noticeable difference in the movements of the uncertainty and disagreement measures across the two approaches in 2003Q2 at the one-year/one-year forward horizon. While the IQR approach shows little change in the behavior of the series, the moment-based approach shows a marked upward spike in disagreement and downward spike in uncertainty. The reason for the different behavior of the series across the two approaches reflects the presence of an outlier response – one individual reported an inflation point forecast of -1.0%, with a density forecast that also assigned significant probability to deflation outcomes.[10]

The IQR measures by design display a low sensitivity to the presence of outliers, so the deflation forecast outlier in 2003Q2 has little impact on the measures of disagreement and uncertainty. For the moment-based approach, however, an outlier can have a large impact on the disagreement measure, but much less of an impact on the estimated variance of the aggregate density forecast. As a consequence, given the decomposition in equation (1), the presence of the deflation forecast outlier essentially results in the uncertainty measure moving in a marked countervailing manner to the disagreement measure. As such, the observed inverse co-movement between disagreement and uncertainty is not only an artifact of the presence of an outlier, but also could have an outsized effect on the estimated relationship between the series. Therefore, our subsequent analysis will exclude the 2003Q2 HICP measures of disagreement and uncertainty from the moment-based approach at the one-year/one-year forward horizon. These considerations offer one argument in favor of the IQR-based approach to measuring uncertainty and disagreement.[11]

[10] We view the consistency of the point and density forecasts as precluding the possibility that the response was the result of some type of reporting error. The other reported point forecasts fell within a range of 1.25% - 2.5%.
[11] Boero, Smith and Wallis (2008, 2012) have proposed a modification to equation (1), which they view more as a useful conceptual framework rather than as an exact relation. Their modification includes a more robust measure of disagreement, as well as an uncertainty measure derived as the square root of the average of estimated variances of the individual histograms.

Turning to the output growth uncertainty measures depicted in Figures 3 and 4, the behavior of the series is again qualitatively similar across the two approaches. The latter part of the sample period is marked by an increase in uncertainty that also occurs around 2007, similar to that observed for inflation. There is also a brief increase in uncertainty during 2002-2004, which is particularly noticeable at the one-year/one-year forward horizon. As before, each approach associates a higher level of uncertainty with the one-year/one-year forward horizon as compared to the one-year-ahead horizon. The disagreement measures also display similar behavior across the two approaches, and are marked by the same dramatic spike during the Great Recession observed in the point forecasts of inflation.

As in the case of the HICP forecasts, there is one survey date for the growth forecasts that warrants special discussion. Specifically, there is a marked decline in uncertainty that coincides with a spike in disagreement in 2009Q1 across both approaches at the one-year-ahead horizon. The observed decline in uncertainty seems especially anomalous because the time period coincides with the depth of the global-wide contraction in economic activity.

A closer inspection of the data reveals that the decline in uncertainty is an artifact of the survey design in which the density forecasts were unable to provide sufficient coverage for the reported point forecasts – that is, there was a "pile up" of probability at the lower open interval. Specifically, respondents' point forecasts indicate that they held a wide range of largely pessimistic views of growth prospects in 2009Q1 at the one-year-ahead horizon, resulting in a high measure of disagreement. For the density forecasts, however, the lowest available bin at the time corresponded to a growth rate of –1% or less. Consequently, for individuals who wanted to indicate significant downside risk to their point forecast or for individuals who reported point forecasts below –1%, they elected to assign almost all of their probability to the lowest three bins of the growth histogram, with most of the probability assigned to the open-ended interval corresponding to growth of –1% or less.[12]

Because so much of the probability mass is concentrated in only a few bins, both the moment-based approach and IQR-based approach yield an artificially low measure of uncertainty, with the corresponding spike in disagreement likely biasing the evidence in favor of an inverse relationship between the series. Moreover, the reactive approach of adding intervals following a "pile up" of probability in an open interval can make the adjacent surveys non-comparable at a point in time when it is especially important to be able to accurately measure changes in respondents' beliefs.[13] Consequently, our subsequent analysis will also exclude the 2009Q1 GDP growth measures of disagreement and uncertainty from the moment-based and IQR-based approaches at the one-year-ahead horizon.

Before turning to a formal analysis of whether disagreement is a good proxy for uncertainty, we report basic cyclical properties of the uncertainty measures. Table 1 displays the contemporaneous correlations of the uncertainty measures with, respectively, output growth and the unemployment rate. Output growth (Δy_t) is at a quarterly frequency, while the unemployment rate (U_t) is at a monthly frequency.[14] As shown in Table 1, the uncertainty measures are almost all countercyclical, with the exception of the one-year/one-year-forward IQR-based measure of inflation over the 2007Q2 subperiod using the unemployment rate as the

[12] An inspection of the aggregate histogram reveals that over 90% of the aggregate probability was assigned to the lowest three bins (-0.1% – -0.5%, -0.6% – -1.0%, < -1.0%), with over a 60% probability assigned to the open-ended interval. The ECB responded to this outcome by extending the number of bins in the lower range of the histogram. As previously discussed, ten lower intervals were added to the GDP growth density forecast for the 2009:Q2 survey.

[13] An alternative and likely preferable survey design is to avoid any piling up of probability in one of the open intervals by providing a wide range of closed intervals. This design would insure that the ability to accurately measure uncertainty is not compromised when there is a sharp shift in the allocation of respondents' tail probabilities.

[14] The unemployment rate corresponds to the month when the survey was conducted, while output growth is calculated as the quarter-to-quarter percentage change from the quarter preceding the conduct of the survey. For the 2010Q1 survey, the cyclical variables are the January 2010 unemployment rate and 2009Q4-2010Q1 output growth.

cyclical indicator. These results are consistent with the previous findings of Bloom (2009), Bloom et al. (2010), Chugh (2011) and Bachmann and Bayer (2011) who also find that their measures of uncertainty, using different data sources and constructs, are countercyclical. Our results indicate, however, that there is some variation in the nature of the cyclicality of the uncertainty measures, with fairly low correlations associated with the unemployment rate over the 2007Q2 subperiod.

IV. The Disagreement - Uncertainty Relationship

A. Previous Evidence

A key issue concerns the co-movement between measures of average uncertainty and the degree of disagreement in the point predictions of respondents. Most studies exploring the question of whether disagreement is a valid proxy for uncertainty have relied on U.S. data from the Survey of Professional Forecasters (US-SPF) for their analysis. The reason is the US-SPF was the first survey instrument to report both point forecasts and density forecasts.

The evidence from the US-SPF has been mixed concerning the relationship between disagreement and uncertainty. Zarnowitz and Lambros (1987) examine matched point and density forecasts and report a modest positive association between disagreement and uncertainty. However, they base their findings on a relatively short sample that runs from 1968Q4 to 1981Q2. Giordani and Soderlind (2003) extend the sample period as well as fit density functions to the individual histograms to derive a smoother measure of uncertainty. The results of Giordani and Soderlind indicate a positive association between disagreement and uncertainty that is both economically and statistically significant. Rich and Tracy (2010) argue that Giordani and Soderlind's conclusion is problematic due to the poor fit of the normal approximation to many of the individual histograms, as well as to their use of a measure of disagreement derived from the density forecast data rather than from the point forecast data.[15] Examining matched point and density forecasts, as well as deriving uncertainty measures based on the Wallis decomposition and the concept of entropy, Rich and Tracy find little evidence to support the claim that disagreement is a useful proxy for uncertainty.

The Bank of England and the European Central Bank have developed survey instruments that also feature matched point and density forecasts starting in 1996 and 1999, respectively. Using data from the Bank of England's Survey of External Forecasters (BOE-SEF), Boero *et al.* (2008) find a weak correlation between measures of disagreement and uncertainty. More recently, two studies have suggested that the relationship between disagreement and uncertainty depends on the stability of the forecasting environment, although the comparative results are contradictory. Lahiri and Sheng (2010) examine the US-SPF and find a meaningful co-movement between disagreement and uncertainty during low volatility episodes, while Boero, Smith and Wallis (2012) find a strong positive correlation between disagreement and uncertainty when the Bank of England dataset used in their 2008 article is extended to include the recent crisis period.

Our study uses the ECB-SPF to revisit the question of the co-movement between measures of forecast dispersion and forecast uncertainty. In addition to providing another source of data to complement earlier analysis on the US-SPF and BOE-SEF, we have previously discussed features of the ECB-SPF that make it particularly attractive to investigate this empirical issue. Moreover, the analysis using data for the full sample period as well as through the 2007Q2 subperiod allows us to investigate whether the relationship between disagreement and uncertainty is episodic and depends on the stability of the forecasting environment.

[15] Boero, Smith and Wallis (2012) also discuss the problematic nature of fitting normal distributions to two-bin histograms. As they point out, this issue extends beyond Giordani and Soderlind and is applicable to several studies.

To gauge whether disagreement is a useful proxy for uncertainty, we adopt the following linear regression models:

$$\ln(\bar{\sigma}) = \alpha + \beta \cdot (s_f) + \varepsilon \tag{4}$$

$$\ln(median_{\tilde{\phi}}) = \alpha + \beta \cdot (iqr_{\tilde{f}}) + \varepsilon \tag{5}$$

where the measures of uncertainty and disagreement are consistent across the moment- and IQR-based approaches, and ε is a mean-zero, random disturbance term. For the moment-based approach, our preferred measure of aggregate uncertainty and disagreement are $\bar{\sigma}\left(=\sqrt{(\bar{\sigma}^2)}\right)$ and $s\left(=\sqrt{s^2}\right)$, respectively. Taking the square root of the uncertainty and disagreement variables in equation (4) makes their units of measurement coincide with that of GDP growth and inflation as well as the IQR-based measures $(median_{\tilde{\phi}}, iqr_{\tilde{f}})$ in equation (5). Because the uncertainty measures are strictly positive, the log transformation helps support the assumption of a normally distributed disturbance term.[16]

We can employ the method of Ordinary Least squares (OLS) to obtain consistent estimates of the parameters of equations (4) and (5). However, because there is an overlap of forecast horizons associated with the surveys, the OLS regression residuals may display autocorrelation. For each regression, we apply the sequential testing procedure of Cumby-Huizinga (1992) to determine the appropriate moving-average (MA) order of the residuals. We then use the Newey-West (1987) variance-covariance estimator to obtain the standard errors of the parameter estimates. Because the use of disagreement as a proxy for uncertainty assumes a

[16] For robustness we also examined the results from using the unadjusted measures of disagreement and uncertainty from the moment-based approach, as well as from not imposing the log transformation in the regression models. There was little change to the findings reported in this section and the next section.

positive association between the variables, we conduct a one-sided test of statistical significance for the parameter β.

B. Estimated Relationships Between Uncertainty and Disagreement

Tables 2-3 report the results from estimating equations (4) and (5) for the measures of uncertainty and disagreement using the moment-based and IQR-based approaches. Table 2 reports the findings for HICP inflation and GDP growth over the full sample period, while Table 3 reports the findings for HICP inflation and GDP growth for the 2007:Q2 subperiod. In addition to presenting the estimated parameters and standard errors of the regression equation, we report correlations and $\bar{R}^2$'s. While there is little difference in the information conveyed by the two statistics, the reporting of each statistic allows for a basis of comparison to the results of earlier studies.

The results generally speak to a very weak relationship between disagreement and uncertainty, both in terms of statistical and economic significance. As shown in Table 2, there is a positive association between the variables over the full sample period. For HICP inflation, the moment-based approach shows a stronger relationship between disagreement and uncertainty at the one-year-ahead horizon than at the one-year/one-year forward horizon. With regard to the IQR-based approach, there is no noticeable difference in the strength of the relationship across the two horizons. For GDP growth, the IQR-based approach shows a stronger relationship between disagreement and uncertainty across the two horizons compared to the moment-based approach. In terms of statistical significance, the estimated $\beta's$ are positive and statistically significant for two of the GDP growth regressions and for one of the HICP inflation regressions.

Any discussion of statistical significance, however, is overshadowed by the extremely low explanatory content of disagreement for movements in uncertainty. Specifically, the most favorable finding indicates that disagreement can only account for 20% of the variation in uncertainty, with the explanatory content of the other regressions on the order of 10% or less. Interestingly, the observed low correlations of disagreement and uncertainty are comparable to those reported in Rich and Tracy (2010) for the US-SPF.

Table 3 reports the findings excluding the post-2007Q2 data. The pre-financial crisis results again speak to a very weak relationship between movements in disagreement and uncertainty. More importantly, however, the results now reveal a marked difference in the direction of the relationship. Specifically, six of the eight relationships, including all of those for the HICP inflation forecasts, reveal a negative correlation. Moreover, there is only one regression that displays a statistically significant positive association between disagreement and uncertainty. To the extent there are concerns that the full sample results may be unduly influenced by a number of recent events, Table 3 offers even less support for the use of disagreement as a proxy for uncertainty.[17]

Taken together, the evidence from the ECB-SPF provides little support for the use of disagreement as a proxy for uncertainty. In particular, the correlations are generally too weak across measures derived from either our moment-based or IQR-based approaches, or they display the wrong sign. Moreover, we find little support for the claim that the nature of the co-movement between disagreement and uncertainty depends on the extent of volatility in the sample period.[18] These results, along with those of Rich and Tracy (2010) for the US- SPF and

[17] Several studies [Vroman (1989), Emery (1993) and Davis and Kanago (1997)] have argued that a measure of relative uncertainty is more appropriate. We also examined the results using a coefficient of variation $[(\bar{\sigma} / f^{e}), (median_{\bar{\phi}} / f^{e})]$ to measure uncertainty. While the correlations between uncertainty and disagreement increased, the estimated relationships remained weak.

[18] The pre-2007Q2 results for the ECB-SPF do not support the claim of Lahiri and Sheng (2010) that there is a meaningful co-movement between disagreement and uncertainty during low volatility episodes. Our results appear more consistent with those of Boero, Smith and Wallis (20012). While we still observe low correlations between disagreement and uncertainty over the full sample period, they are higher using the post-2007Q2 sample..

Boero, Smith and Wallis (2008) for the BOE-SEF, offer compelling evidence that the distinction between disagreement and uncertainty as concepts extends to their empirical counterparts. Further, the evidence from these three studies drawn from three different survey instruments raises questions about the validity of previous empirical findings based on using disagreement as a proxy for uncertainty.

V. The Predictive Accuracy – Uncertainty Relationship

A. Ex-post Forecast Error Variance as a Measure of Uncertainty

A large literature has also developed that uses measures based on the ex-post forecast error variance to proxy for uncertainty. Within this approach, the estimation of time series models of heteroskedasticity has been widely adopted by researchers. The most popular example of this modeling strategy is the Autoregressive Conditional Heteroskedaticity (ARCH) model of Engle (1982) and its extensions in which the conditional variance surrounding a prediction is allowed to change over time.[19] The (objective) conditional variance of a time series is equated to temporal variation in the (subjective) probability distribution of the variable's different possible outcomes, with episodes of decreased (increased) predictability associated with heightened (diminished) uncertainty.

The widespread use of time-series models of heteroskedasticity to generate measures of uncertainty is largely motivated by the characteristics and attractiveness of these models for econometric applications. Nevertheless, there may be reasons to question whether these models provide good proxies for uncertainty. For example, there is the key modeling assumption that the ex-post predictability of a series is a good proxy for the ex-ante confidence that a forecaster

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Nevertheless, the choice and reliability of a proxy for a particular variable of interest is predicated on the unconditional correlation, and not the conditional correlation, between series.

[19] The conditional variance of an ARCH model is specified as a linear function of past squared forecast errors. The Generalized ARCH (GARCH) model of Bollerslev (1986) extended Engle's original work by allowing the conditional variance to follow an ARMA process.

attaches to a prediction. In addition, it is unlikely that changes in uncertainty related to the anticipation or possible incidence of regime changes/extreme events would be picked up by models in which the conditional variance is a function only of past data. While the reliability of model-based measures of uncertainty is an important issue, empirical verification is problematic because of the absence of a comparison benchmark uncertainty measure. The availability of matched point and density forecasts from the ECB-SPF, however, provides a unique opportunity to formally address this issue. Moreover, we can draw upon the work of Rich and Tracy (2003) and use simple moment conditions for the data to conduct the analysis.

Let X denote the variable of interest (GDP growth or inflation). Time series models of heteroskedasticity simultaneously model variation in the mean and the variance of a series. Within the context of the ECB-SPF and using our earlier notation, we can describe this approach as:

$$\begin{aligned} {}^{q,\tau+1}_{q,\tau}X^{e}_{q,t} &= E\left[{}^{q,\tau+1}_{q,\tau}X \mid I_{q,t} \right] \\ {}^{q,\tau+1}_{q,\tau}h_{q,t} &= E\left[\left({}^{q,\tau+1}_{q,\tau}X - {}^{q,\tau+1}_{q,\tau}X^{e}_{q,t} \right)^2 \mid I_{q,t} \right] \end{aligned} \tag{6}$$

where ${}^{q,\tau+1}_{q,\tau}X$ denotes the relevant ECB-SPF target variable, and ${}^{q,\tau+1}_{q,\tau}X^{e}_{q,t}$ and ${}^{q,\tau+1}_{q,\tau}h_{q,t}$ denote, respectively, the mean and variance of ${}^{q,\tau+1}_{q,\tau}X$ conditional on all information available at the time of the survey conducted in quarter q of year t $(I_{q,t})$. The value of the conditional variance process $({}^{q,\tau+1}_{q,\tau}h_{q,t})$ is then used to measure the uncertainty associated with the expectation of the target variable from the survey conducted in quarter q of year t. Going forward, we restrict the analysis to the one-year-ahead horizon to conserve on the reporting and discussion of results.[20]

[20] The results for the one-year/one-year forward horizon were generally consistent with those for the one-year-ahead horizon, and are available upon request from the authors.

Under the assumption that respondents make efficient use of their information, the system of equations in (6) implicitly defines regression models in which the difference between the actual and expected values of X as well as the actual and expected squared difference between these terms reflect the influence of random disturbance terms. Moreover, if the consensus point forecast $(\overline{f}^{e})$ from the ECB-SPF is an unbiased estimator of the relevant target variable (X), then we can rewrite the system of equations in (6) as:[21]

$$\begin{aligned} {}^{q,\tau+1}_{q,\tau}X &= {}^{q,\tau+1}_{q,\tau}\overline{f}^{e}_{q,t} + \eta^{q,\tau+1}_{q,\tau} \\ \left(\eta^{q,\tau+1}_{q,\tau}\left[= {}^{q,\tau+1}_{q,\tau}X - {}^{q,\tau+1}_{q,\tau}\overline{f}^{e}_{q,t}\right]\right)^2 &= {}^{q,\tau+1}_{q,\tau}h_{q,t} + \varepsilon^{q,\tau+1}_{q,\tau} \end{aligned} \tag{7}$$

where $E[\eta^{q,\tau+1}_{q,\tau} \mid I_{q,t}] = E[\varepsilon^{q,\tau+1}_{q,\tau} \mid I_{q,t}] = 0.$ As shown, the model inherently links the conditional variance/uncertainty measure $\left({}^{q,\tau+1}_{q,\tau}h_{q,t}\right)$ of ${}^{q,\tau+1}_{q,\tau}X$ to changes in its predictability $\left(\eta^{q,\tau+1}_{q,\tau}\right)^2$.

For the ECB-SPF, a researcher investigating the reliability of heteroskedasticity-based measures of uncertainty might choose to estimate the conditional variance of respondents' forecast errors (h), and then examine the co-movement of the series with the survey-based measures of aggregate uncertainty [$(\overline{\sigma}^2)$ and $(median_{\overline{\phi}})$]. This approach, however, would be an empirical challenge under current circumstances. One reason is that the approach requires a specification for the conditional variance process, as well as imposition of restrictions to ensure that the estimated process is well behaved. More importantly, there is very limited data to undertake estimation of the conditional variance process. This limitation arises not only from the

[21] We will subsequently discuss the issue of unbiasedness of the ECB-SPF consensus forecasts of output growth and inflation.

short sample period, but also from the overlap of forecast horizons that restricts the lags at which information can enter the specification for the conditional variance process.[22]

The previous considerations lead us to an alternative approach to gauge the reliability of heteroskedasticity-based measures of uncertainty. Because this issue centers on the relationship between the conditional variance of respondents' forecast errors and the survey-based measures of aggregate uncertainty, we directly substitute the series $(\bar{\sigma}^2)$ and $(median_{\bar{\phi}})$ for the conditional variance term (h) in the second equation of (7) to obtain:

$$\left(\eta_{q,\tau}^{q,\tau+1}\right)^2 = \alpha + \beta \cdot \left({}_{q,\tau}^{q,\tau+1}\bar{\sigma}_{q,t}^2 \right) + \varepsilon_{q,\tau}^{q,\tau+1} \tag{8}$$

$$\left(\eta_{q,\tau}^{q,\tau+1}\right)^2 = \alpha + \beta \cdot \left({}_{q,\tau}^{q,\tau+1}(median_{\bar{\phi}})_{q,t} \right) + \varepsilon_{q,\tau}^{q,\tau+1} \tag{9}$$

where $E\left[\varepsilon_{q,\tau}^{q,\tau+1} \mid I_{q,t} \right] = 0$ Equations (8) and (9) are easily interpreted as models relating the ex-post predictability and ex-ante uncertainty of the ECB-SPF target variable X. Equations (8) and (9) are also attractive because they circumvent the need to specify and estimate a conditional variance process (h), and also allow for a more direct empirical testing procedure. Following the approach used in the investigation of the relationship between disagreement and uncertainty, we slightly modify equations (8) and (9) to obtain the following linear regression models:

$$\ln\left(\sqrt{\left(\eta_{q,\tau}^{q,\tau+1}\right)^2} \right) = \alpha + \beta \left({}_{q,\tau}^{q,\tau+1}\bar{\sigma}_{q,t} \right) + \varepsilon_{q,\tau}^{q,\tau+1} \tag{10}$$

$$\ln\left(\sqrt{\left(\eta_{q,\tau}^{q,\tau+1}\right)^2} \right) = \alpha + \beta \left({}_{q,\tau}^{q,\tau+1}(median_{\bar{\phi}})_{q,t} \right) + \varepsilon_{q,\tau}^{q,\tau+1} \tag{11}$$

[22] For example, the one-year-ahead horizon only allows for the inclusion of information that is lagged 4 quarters or more, while the one-year/one-year forward horizon only allows for the inclusion of information that is lagged 8 quarters or more. See Rich, Raymond and Butler (1992) and Rich and Butler (1998) for further discussion of this point in the context of the estimation of ARCH models that involve overlapping forecast horizons.

Because our interest again focuses on the issue of a positive relationship between the variables, we conduct a one-sided test of statistical significance for the parameter β.

The analysis currently measures the ex-post predictability of the ECB-SPF target variable by the unadjusted forecast error $(\eta = X - \overline{f}^{e})$.[23] However, other studies [Bowles *et al* (2008, 2010)] have documented bias in the ECB-SPF forecasts. To correct for this feature of the data, we also consider a two-stage estimation procedure where ex-post predictability is based on the residual from a first stage regression of the realized target variable on a constant and the mean forecast $\left[\hat{\eta}_{q,\tau}^{q,\tau+1} = {}_{q,\tau}^{q,\tau+1}X - \hat{\rho}_0 - \hat{\rho}_1\left({}_{q,\tau}^{q,\tau+1}\overline{f}_{q,t}^{e}\right)\right]$. We modify equations (10) and (11) accordingly by using the estimated residual rather than the unadjusted forecast error as the dependent variable:[24]

$$\ln\left(\sqrt{\left(\hat{\eta}_{q,\tau}^{q,\tau+1}\right)^2}\right) = \alpha + \beta\left({}_{q,\tau}^{q,\tau+1}\overline{\sigma}_{q,t}\right) + \varepsilon_{q,\tau}^{q,\tau+1} \tag{12}$$

$$\ln\left(\sqrt{\left(\hat{\eta}_{q,\tau}^{q,\tau+1}\right)^2}\right) = \alpha + \beta\cdot\left({}_{q,\tau}^{q,\tau+1}(median_{\overline{\phi}})_{q,t}\right) + \varepsilon_{q,\tau}^{q,\tau+1} \tag{13}$$

B. Comparison of the Predictive Accuracy and Uncertainty Measures and their Estimated Relationship

Figures 5 and 6 present the time profiles for the ECB survey-based measures of uncertainty and the absolute value of the (unadjusted) forecast error for HICP inflation and GDP growth at the

[23] Drawing upon the discussion in Bowles *et al.* (2010), for the remainder of the paper we use current vintage data on outcomes to construct forecast errors or as the dependent variable in specified regressions. For HICP inflation, the distinction between first and current vintage is not relevant because of the absence of data revisions. For the GDP data, the revisions are primarily related to the move to chain-linking and may mean that current vintage data are closer to what forecasters were trying to forecast.

[24] Although we restrict our attention to a significant positive association between the magnitude of the forecast error and the survey-based uncertainty measures, there is another implication of heteroskedasticity-based measures of uncertainty for equations (10)-(13). Specifically, the survey-based uncertainty measures should be unbiased predictors of the forecast error, implying that $\alpha = 0$ and $\beta = 1$. We do not, however, conduct a joint test of this hypothesis. To preview the results in Table 5, we find an absence of co-movement between the forecast error and the ECB survey-based measures of uncertainty. Consequently, a joint test of this null hypothesis would provide little content because it is unlikely to be rejected due to the imprecision of the estimated relationship.

one-year-ahead horizon, respectively. As before, each figure includes a vertical line at 2007:Q2. The time profile for HICP inflation is from 1999:Q1 through 2011:Q1, while the time profile for GDP growth is from 1999:Q1 through 2011:Q2.[25]

For HICP inflation, the forecast error series displays a higher mean and substantially greater volatility compared to the ECB survey-based measures of uncertainty over the longer sample period. In particular, the standard deviation of the forecast error series is almost seven times larger than that for the survey-based measures. The forecast error series also displays two notable spikes associated with the 2007:Q3 and 2008:Q3-Q4 surveys. The first spike reflects an under prediction of inflation coinciding with the run-up in commodity prices in middle 2008, while the second spike reflects an over prediction of inflation during the Great Recession.

For GDP growth, the forecast error series displays an even higher mean compared to the ECB survey-based measures of uncertainty, and is again characterized by significantly higher volatility - the standard deviation of the forecast error series is now over ten times larger. As in the case of HICP inflation, there is a pronounced spike during the post-2007:Q2 episode. The spike is associated with the 2008:Q2-Q4 surveys which, not surprisingly, reflects an over prediction of growth during the Great Recession.

Although it is not depicted, the adjusted forecast error displays a slightly lower mean and slightly less volatility relative to the unadjusted forecast error. However, the adjusted forecast error still displays a higher mean and substantially greater volatility compared to the ECB survey-based measures of uncertainty over the longer sample period. Because of the large forecast errors observed for HICP inflation and GDP during the latter part of the full sample period, the regression results based on the data through the 2007:Q2 subperiod may offer a more

[25] The different end dates for Figures 5 and 6, as well as for Figures 1-4, reflect the construct of the ex-post forecast error and the availability of realized values for HICP inflation and GDP growth.

reliable assessment of the co-movement between the ex-post accuracy of respondents' forecasts and the ex-ante uncertainty attached to the forecasts.

Tables 4-5 report the results from estimating equations (10)-(13) using the moment-based and IQR-based measures of uncertainty over the full sample period and for the 2007:Q2 subperiod. Table 4 reports the findings for HICP inflation, while Table 5 reports the findings for GDP growth which again excludes the 2009:Q1 observation. We also report the $\bar{R}^2$'s of the regressions as well as Newey-West (1987) corrected standard errors when appropriate.

Taken together, the results uniformly speak to the absence of both an economic and statistically significant relationship between the accuracy and uncertainty of the forecasts – the reported $\bar{R}^2$'s are essentially zero. This holds true regardless of whether the unadjusted or adjusted forecast error is used as the dependent variable of the regression, and there is no example where an estimated β is positive and statistically significant. Moreover, it turns out the evidence using data through 2007:Q2 is actually less, rather than more supportive of the posited linkage between the accuracy and uncertainty of the forecasts. In particular, the estimated $\beta's$ are negative in three out of the four cases for the truncated sample period.

There appears to be a relatively straightforward explanation for the results reported in Tables 4 and 5, and one that has already been touched upon in the earlier discussion. Specifically, the forecast error series is far more volatile than the survey-based uncertainty measures, with the extent of the volatility disparity large enough that the series display no correlation. That is, the results indicate that almost all of the movement in the forecast error series is idiosyncratic and driven by the error term ε. Consequently, our results would seem to raise two concerns for time series models of heteroskedasticity. First, if a conditional variance process for the respondents' forecast errors (h) were to be estimated, then what is its interpretation? Second, and perhaps more importantly, even if there were a meaningful relationship between the conditional variance of respondents' forecast errors (h) and the survey-based measures of aggregate uncertainty [$(\bar{\sigma}^2)$ and $(median_{\bar{\phi}})$], the observed forecast error series would appear to be too noisy to allow an econometrician to uncover a reliable measure of uncertainty.

VI. Uncertainty and the Linkages to Output Growth and Inflation

A. Literature Review

The nature of the relationships between uncertainty and the levels of output growth and inflation is a longstanding question among economists. In his Nobel address, Friedman (1977) argued that higher inflation increases inflation uncertainty, which distorts the effectiveness of the price system in allocating resources efficiently, and thereby creates economic inefficiency and a lower growth rate of output. Since Friedman (1977), economists have proposed potential linkages between uncertainty about inflation or output growth and the average level of inflation or output growth. In particular, the linkages extend to all four possible combinations of the level and type of uncertainty for output growth and inflation.

While it would be desirable to use the survey-based measures of uncertainty to test hypotheses for each case, we will restrict our attention to the output uncertainty-output growth and inflation uncertainty-inflation rate relationships. The reason for these choices is the temporal misalignment between the target variables for output and inflation in the ECB-SPF. As previously discussed, there is a two quarter publication lag for output growth, while there is only a one-month publication lag for HICP inflation. Consequently, there is too much of a disparity in the timing convention across the variables to justify an investigation into the inflation uncertainty-output growth or output uncertainty-inflation relationships using the ECB-SPF data.

With regard to the impact of inflation uncertainty on inflation, Cukierman and Meltzer (1986) and Cukierman (1992) have developed theoretical models in which increases in inflation uncertainty raise the optimal average inflation rate by increasing the incentive of policymakers to create inflation surprises. On the other hand, Holland (1995) claims that an increase in inflation uncertainty associated with a rise in inflation will cause policymakers to slow aggregate demand to eliminate inflation uncertainty. Consequently, Holland argues for an inverse relationship between inflation uncertainty and inflation.

While the possible effect of output uncertainty on output growth has received considerable attention in the theoretical literature, no consensus has emerged on the direction of the effect. Arguments for a positive association have been based on precautionary motives [Sandmo (1970), Mirman (1971)], rewards for risk-taking [Black (1987)] and learning-by-doing [Blackburn (1999)]. Conversely, Pindyck (1991) argues for a negative relationship arising from investment irreversibilities at the firm level, while Blackburn and Pelloni (2005) generate a negative relationship within a stochastic monetary growth model with permanent shocks to technology, preferences and money. Last, Blackburn and Pelloni (2004) again consider a stochastic monetary growth model and find that the relationship is ambiguous – the sign of the relationship will be positive (negative) depending on whether real (nominal) shocks dominate.

B. Regression Model

To investigate the output uncertainty-output growth and inflation uncertainty-inflation rate relationships, we estimate the following regression models:

$$ {}_{q,\tau}^{q,\tau+1}X = \alpha + \beta\left({}_{q,\tau}^{q,\tau+1}\overline{f}_{q,t}^{e}\right) + \delta\left({}_{q,\tau}^{q,\tau+1}\overline{\sigma}_{q,t}\right) + \varepsilon_{q,\tau}^{q,\tau+1} \tag{14} $$

$$ {}_{q,\tau}^{q,\tau+1}X = \alpha + \beta\left({}_{q,\tau}^{q,\tau+1}\overline{f}_{q,t}^{e}\right) + \delta\cdot\left({}_{q,\tau}^{q,\tau+1}(median_{\overline{\phi}})_{q,t}\right) + \varepsilon_{q,\tau}^{q,\tau+1} \tag{15} $$

where ${}_{q,\tau}^{q,\tau+1}X$ denotes the relevant one-year-ahead ECB-SPF target variable, and ${}_{q,\tau}^{q,\tau+1}\overline{f}_{q,t}^{e}$ and ${}_{q,\tau}^{q,\tau+1}\overline{\sigma}_{q,t}$ denote, respectively, the mean forecast and average uncertainty associated with the respondents' predictions from the survey conducted in quarter q of year t.

There are two attractive features of equations (14) and (15). First, the survey-based measure of uncertainty corresponds precisely with the concept underlying the theories discussed above. This is in contrast to other empirical studies to date that have used forecast dispersion among survey respondents, ex-post forecast error variance, or a moving standard deviation of a variable to proxy for uncertainty. We have previously analyzed the potential drawbacks of the first two measures, while the third measure is associated with the concept of variability which need not provide any reliable gauge of the confidence that respondents attach to their forecast.

Secondly, equations (14) and (15) can be interpreted as (G)ARCH-M (ARCH in mean) models that have been widely adopted in recent empirical studies investigating the effect of uncertainty on real activity and inflation.[26] The key feature of the (G)ARCH-M model developed by Engle, Lilien and Robins (1987) is that the conditional mean of a variable is allowed to depend on a set of conditioning variables as well as its time-varying conditional variance. As previously discussed, this class of models estimates a conditional variance process based on the ex-post predictability of the series, with the time-varying residual variance used as a proxy for uncertainty. For our purposes, it is important to note that while equations (14) and (15) are consistent with the (G)ARCH-M testing framework, they do not require the specification of conditioning variables or the incorporation of a (G)ARCH-type estimate of uncertainty. Rather,

[26] These studies include Grier and Perry (1998, 2000), Grier *et al* (2004), Fountas *et al* (2004), Fountas and Karanasos (2007), and Karanasos *et al* (2004). Equations (14)-(15) are also similar to the specification adopted by Andrade, Ghysels and Idier (2012) in their examination of the US-SPF and ECB-SPF and the explanatory content of tails and asymmetries for predicting inflation. We found little evidence that the skew or the degree of probability mass in density forecasts contribute significantly to improvements in predictive accuracy.

the conditional mean of output growth or inflation can be modeled directly using both the reported forecasts and survey-based measures of uncertainty from the ECB-SPF.

Table 6 reports the results from estimating equations (14)-(15) using the mean forecast from the ECB-SPF as well as the moment-based and IQR-based measures of uncertainty. For HICP inflation, the longer sample covers the period 1999:Q1 through 2011:Q1, while the longer sample period for GDP growth is from 1999:Q1 through 2011:Q2 and again excludes the 2009:Q1 observation.[27] We also estimate the regression models using data through the 2007:Q2 subperiod, and report the $\bar{R}^2$'s of the regression models as well as Newey-West (1987) corrected standard errors when appropriate. We conduct two-tailed tests of statistical significance for the parameters α and β. Because of the divergent views concerning the impact of uncertainty on output growth and inflation, we instead conduct one-tailed tests (of either sign) of statistical significance for the parameter δ.

As shown, the HICP regressions provide no evidence of a linkage between movements in one-year-ahead inflation and either expected inflation or inflation uncertainty. The explained variation in inflation is extremely low, and the effect of expected inflation changes from a positive association using data through 2007:Q2 to a negative association over the longer sample period. While uncertainty displays a negative impact in the regressions, the coefficients are very imprecisely estimated and not statistically significant at conventional levels. We recognize, however, that the ECB's inflation targeting regime may bear importantly on the results.

For the one-year-ahead output regressions, there is marked increase in the predictive content of the model. The results also document a highly statistically significant role for expectations of output growth, with estimated coefficients that in all cases are positive and do not

[27] The slightly restricted sample periods are identical to those from the previous section and result from the same considerations concerning the availability of realized values for HICP inflation and GDP growth.

differ statistically from unity. With regard to the effect of uncertainty, the results generally show an inverse relationship. In particular, the IQR-based measure of uncertainty over the truncated sample provides evidence of a statistically significant negative effect. For the other regressions, however, the coefficients on uncertainty are very imprecisely estimated and not statistically significant at conventional levels. While the estimated (G)ARCH-M model for output growth indicates a more economically significant relationship, the evidence suggests a very limited channel of effect of uncertainty on real activity.

VII. Conclusion

The analysis examines matched point and density forecasts of output and inflation from the ECB-SPF. We consider two alternative methodologies to derive measures of forecast uncertainty and find that both methodologies offer little justification for the practice of using forecast dispersion as a proxy for forecast uncertainty. We also study the relationship between the ex-post accuracy and ex-ante uncertainty of respondent's forecasts, with the results offering little justification for the practice of using model-based conditional variance estimates to proxy for forecast uncertainty. Last, we find limited evidence of linkages between uncertainty and levels of output growth and inflation.

We recognize that our analysis and conclusions come with caveats. First, studies have documented that the output and inflation forecasts in the ECB-SPF display evidence of bias. Second, we have assumed that the reported density forecasts provide a reliable way to estimate forecaster uncertainty. Kenny, Kostka and Masera (2012), however, have recently shown that ECB-SPF respondents display overconfidence in their density forecasts, and that the coverage of the histograms is also too narrow in that a higher percentage of actual outcomes fall outside the range of intervals in which respondents place positive probability. Last, there is the issue of sample size and the sample period itself. Because the ECB-SPF was only started in 1999:Q1, the survey instrument has a short-lived history that is impacted even further by the concentration of events and large shocks during the last four years.

To try to temper these concerns, we can appeal to an argument made by Bowles *et al.* (2010). In particular, they note that evidence of possible bias in the ECB-SPF forecasts may dissipate and be overturned as the sample becomes longer and the shocks driving the business cycle lessen in magnitude and become more symmetric. To support their view, Bowles *et al.* cite the findings of Croushore (2009) who shows the properties of survey forecasts can look very different over a long time period compared to shorter periods, and that survey forecasts invariably go through episodes in which they appear to perform poorly. A similar consideration may also apply when gauging the performance of the density forecasts. Consequently, while we acknowledge the need to be cautious when evaluating the information content of the ECB-SPF, our analysis attempts to develop and employ an empirical framework that can address a number of important issues concerning the measurement and behavior of uncertainty as well as its relationship to several key variables of interest.

Table 1

Full Sample – HICP Inflation			Truncated Sample – HICP Inflation		
Moment-Based Uncertainty Measure	Correlation with		IQR-Based Uncertainty Measure	Correlation with	
	Δy_t	UN_t		Δy_t	UN_t
One-Year-Ahead	-0.35	0.57	One-Year-Ahead	-0.33	0.20
One-Year/ One-Year Forward	-0.39	0.55	One-Year/ One-Year Forward	-0.31	-0.02
IQR-Based Uncertainty Measure	Correlation with		IQR-Based Uncertainty Measure	Correlation with	
	Δy_t	UN_t		Δy_t	UN_t
One-Year-Ahead	-0.46	0.54	One-Year-Ahead	-0.63	0.04
One-Year/ One-Year Forward	-0.48	0.57	One-Year/ One-Year Forward	-0.54	0.12

Full Sample – GDP Growth			Truncated Sample – GDP Growth		
Moment-Based Uncertainty Measure	Correlation with		IQR-Based Uncertainty Measure	Correlation with	
	Δy_t	UN_t		Δy_t	UN_t
One-Year-Ahead	-0.34	0.53	One-Year-Ahead	-0.33	0.10
One-Year/ One-Year Forward	-0.37	0.55	One-Year/ One-Year Forward	-0.56	0.09
IQR-Based Uncertainty Measure	Correlation with		IQR-Based Uncertainty Measure	Correlation with	
	Δy_t	UN_t		Δy_t	UN_t
One-Year-Ahead	-0.40	0.58	One-Year-Ahead	-0.37	0.18
One-Year/ One-Year Forward	-0.44	0.53	One-Year/ One-Year Forward	-0.47	0.04

Table 2

Disagreement and Uncertainty: HICP Inflation – Full Sample				
Moment-Based	$\ln(\bar{\sigma}) = \alpha + \beta \cdot (s_f) + \varepsilon$			
Horizon	$r\ (\bar{R}^2)$	α	β	MA correction
One-Year-Ahead	0.46/(0.19)	-1.232** (0.052)	1.026** (0.210)	3
One-Year/ One-Year Forward	0.29/(0.07)	-0.959** (0.076)	0.617 (0.390)	4
IQR-Based	$\ln(median_{\tilde{\phi}}) = \alpha + \beta \cdot (iqr_{\tilde{f}}) + \varepsilon$			
Horizon	$r\ (\bar{R}^2)$	α	β	MA correction
One-Year-Ahead	0.17/(0.01)	-0.573** (0.049)	0.182 (0.147)	3
One-Year/ One-Year Forward	0.14/(0.0)	-0.472** (0.080)	0.193 (0.346)	4

Disagreement and Uncertainty: GDP Growth – Full Sample				
Moment-Based	$\ln(\bar{\sigma}) = \alpha + \beta \cdot (s_f) + \varepsilon$			
Horizon	$r\ (\bar{R}^2)$	α	β	MA correction
One-Year-Ahead	0.13/(0.0)	-0.971** (0.083)	0.162 (0.180)	4
One-Year/ One-Year Forward	0.28/(0.01)	-0.839** (0.104)	0.343 (0.293)	4
IQR-Based	$\ln(median_{\tilde{\phi}}) = \alpha + \beta \cdot (iqr_{\tilde{f}}) + \varepsilon$			
Horizon	$r\ (\bar{R}^2)$	α	β	MA correction
One-Year-Ahead	0.16/(0.09)	-0.622** (0.089)	0.322* (0.175)	4
One-Year/ One-Year Forward	0.35/(0.11)	-0.526** (0.081)	0.484** (0.172)	4

Note: Standard errors are obtained using the Newey-West (1987) variance-covariance matrix estimator. One-tailed test for statistical significance of β.

$H_0 : \beta = 0,\ H_1 : \beta > 0$

** Significant at 1% level
* Significant at 5% level

Table 3

Disagreement and Uncertainty: HICP Inflation – Truncated Sample				
Moment-Based	$\ln(\bar{\sigma}) = \alpha + \beta \cdot (s_f) + \varepsilon$			
Horizon	$r\ (\bar{R}^2)$	α	β	MA correction
One-Year-Ahead	-0.15/(-0.01)	-0.955** (0.080)	-0.320 (0.340)	1
One-Year/ One-Year Forward	-0.37/(0.11)	-0.720** (0.054)	-0.720 (0.245)	0
IQR-Based	$\ln(median_{\tilde{\phi}}) = \alpha + \beta \cdot (iqr_{\tilde{f}}) + \varepsilon$			
Horizon	$r\ (\bar{R}^2)$	α	β	MA correction
One-Year-Ahead	-0.51/(0.24)	-0.386** (0.067)	-0.572 (0.214)	1
One-Year/ One-Year Forward	-0.53/(0.26)	-0.333** (0.047)	-0.543 (0.159)	3

Disagreement and Uncertainty: GDP Growth – Truncated Sample				
Moment-Based	$\ln(\bar{\sigma}) = \alpha + \beta \cdot (s_f) + \varepsilon$			
Horizon	$r\ (\bar{R}^2)$	α	β	MA correction
One-Year-Ahead	0.24/(0.03)	-1.095** (0.062)	0.345* (0.198)	1
One-Year/ One-Year Forward	-0.06/(-0.03)	-0.747** (0.138)	-0.175 (0.491)	3
IQR-Based	$\ln(median_{\tilde{\phi}}) = \alpha + \beta \cdot (iqr_{\tilde{f}}) + \varepsilon$			
Horizon	$r\ (\bar{R}^2)$	α	β	MA correction
One-Year-Ahead	0.04/(-0.03)	-0.563** (0.077)	0.033 (0.164)	3
One-Year/ One-Year Forward	-0.10/(-0.02)	-0.356** (0.078)	-0.173 (0.204)	2

Note: Standard errors are obtained using the Newey-West (1987) variance-covariance matrix estimator. One-tailed test for statistical significance of β.

$H_0 : \beta = 0, H_1 : \beta > 0$

** Significant at 1% level
* Significant at 5% level

Table 4

Ex-post Predictability and Ex-ante Uncertainty: One-Year-Ahead HICP Inflation				
	$\ln\left(\sqrt{\left(\eta^2\right)}\right)=\alpha+\beta\left(\bar{\sigma}\right)+\varepsilon$			
Moment-Based	$\bar{R}^2$	α	β	MA correction
Full sample	-0.01	-1.509 (0.894)	1.936 (2.174)	1
Truncated Sample	0.0	0.586 (1.711)	-4.585 (4.777)	0
	$\ln\left(\sqrt{\left(\eta^2\right)}\right)=\alpha+\beta(median_{\tilde{\phi}})+\varepsilon$			
IQR-Based	$\bar{R}^2$	α	β	MA correction
Full sample	-0.02	-1.271 (1.068)	0.858 (1.761)	1
Truncated Sample	0.03	1.783 (2.014)	-5.010 (3.551)	0
	$\ln\left(\sqrt{\left(\hat{\eta}^2\right)}\right)=\alpha+\beta\left(\bar{\sigma}\right)+\varepsilon$			
Moment-Based	$\bar{R}^2$	α	β	MA correction
Full sample	0.00	-2.316** (0.960)	2.386 (2.518)	3
Truncated Sample	-0.03	-1.650 (2.205)	-0.657 (6.156)	0
	$\ln\left(\sqrt{\left(\hat{\eta}^2\right)}\right)=\alpha+\beta(median_{\tilde{\phi}})+\varepsilon$			
IQR-Based	$\bar{R}^2$	α	β	MA correction
Full sample	0.00	-3.149 (1.664)	2.945 (2.814)	3
Truncated Sample	-0.01	-3.805 (2.615)	3.398 (4.611)	0

Note: Standard errors are obtained using the Newey-West (1987) variance-covariance matrix estimator.
One-tailed test for statistical significance of β.

$H_0:\beta=0,\ H_1:\beta>0$

** Significant at 1% level
* Significant at 5% level

Table 5

Ex-post Predictability and Ex-ante Uncertainty: One-Year-Ahead GDP Growth				
	$\ln\left(\sqrt{(\eta^2)}\right) = \alpha + \beta(\bar{\sigma}) + \varepsilon$			
Moment-Based	$\bar{R}^2$	α	β	MA correction
Full sample	-0.02	-0.375 (1.125)	0.082 (2.769)	0
Truncated Sample	-0.03	0.182 (1.751)	-1.582 (4.611)	0
	$\ln\left(\sqrt{(\eta^2)}\right) = \alpha + \beta(median_{\tilde{\phi}}) + \varepsilon$			
IQR-Based	$\bar{R}^2$	α	β	MA correction
Full sample	-0.02	-0.045 (1.233)	-0.479 (1.971)	0
Truncated Sample	-0.02	0.827 (2.013)	-2.139 (3.449)	0
	$\ln\left(\sqrt{(\hat{\eta}^2)}\right) = \alpha + \beta(\bar{\sigma}) + \varepsilon$			
Moment-Based	$\bar{R}^2$	α	β	MA correction
Full sample	-0.02	-0.415 (0.966)	0.366 (2.379)	0
Truncated Sample	-0.03	-0.379 (1.641)	-0.453 (4.319)	0
	$\ln\left(\sqrt{(\hat{\eta}^2)}\right) = \alpha + \beta(median_{\tilde{\phi}}) + \varepsilon$			
IQR-Based	$\bar{R}^2$	α	β	MA correction
Full sample	-0.01	-0.978 (1.055)	1.145 (1.686)	0
Truncated Sample	-0.01	-1.984 (1.877)	2.471 (3.216)	0

Note: Standard errors are obtained using the Newey-West (1987) variance-covariance matrix estimator.
One-tailed test for statistical significance of β.

$H_0 : \beta = 0, H_1 : \beta > 0$

** Significant at 1% level
* Significant at 5% level

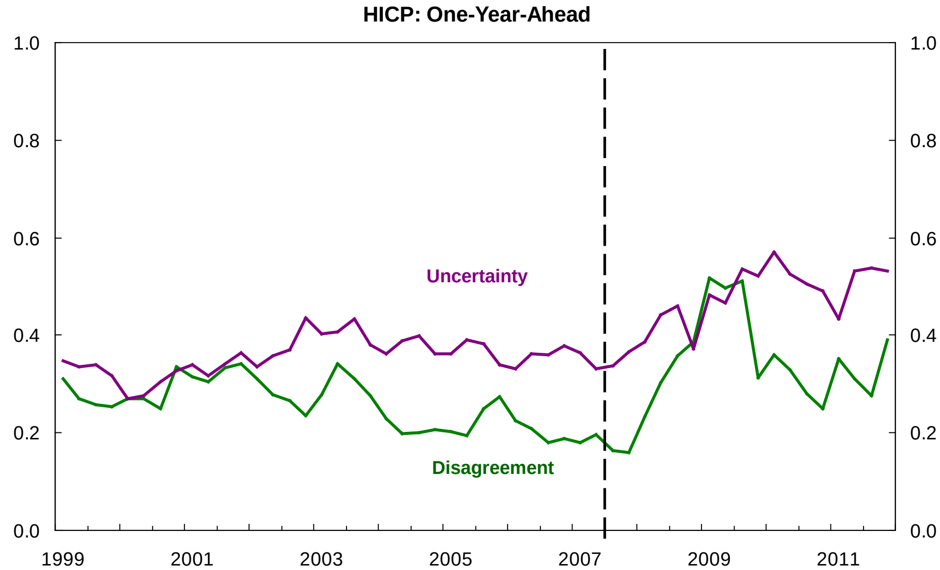
Table 6

(G)ARCH-M Model for One-Year-Ahead HICP Inflation					
	$\pi = \alpha + \beta\left(\overline{f}^{e}\right) + \delta\left(\overline{\sigma}\right) + \varepsilon$				
Moment-Based	$\overline{R}^2$	α	β	δ	MA Correction
Full Sample	0.04	4.264* (1.830)	-0.547 (0.786)	-3.104 (2.070)	1
Truncated Sample	0.06	2.166* (0.821)	0.511 (0.328)	-2.376 (1.704)	0
	$\pi = \alpha + \beta\left(\overline{f}^{e}\right) + \delta(median_{\tilde{\phi}}) + \varepsilon$				
IQR-Based	$\overline{R}^2$	α	β	δ	MA Correction
Full Sample	0.02	4.279* (2.073)	-0.448 (0.808)	-2.331 (1.872)	1
Truncated Sample	0.01	1.727 (0.874)	0.532 (0.342)	-0.786 (1.343)	0

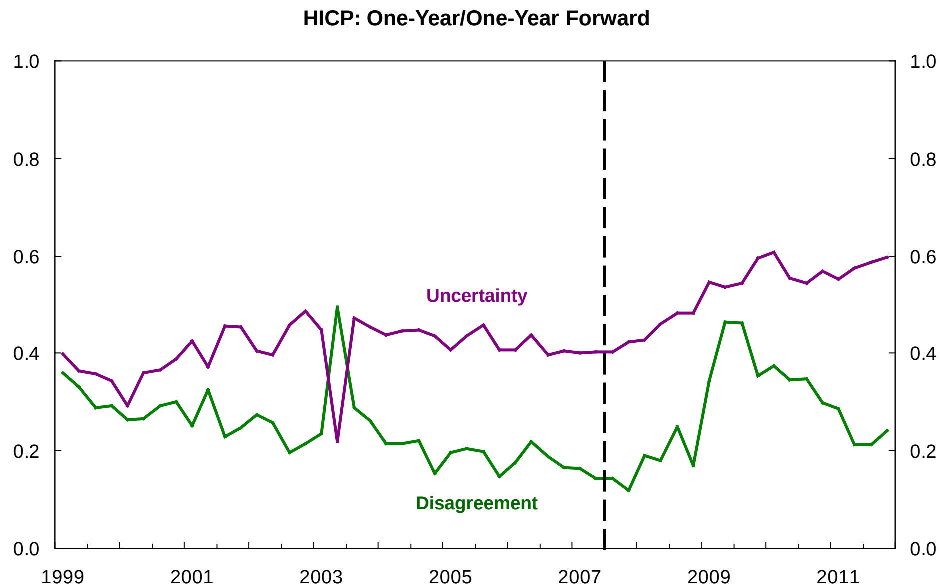
(G)ARCH-M Model for One-Year-Ahead Output Growth					
	$\Delta y = \alpha + \beta\left(\overline{f}^{e}\right) + \delta\left(\overline{\sigma}\right) + \varepsilon$				
Moment-Based	$\overline{R}^2$	α	β	δ	MA Correction
Full Sample	0.42	0.166 (1.801)	1.422** (0.422)	-2.011 (3.316)	1
Truncated Sample	0.39	1.553 (2.889)	1.297** (0.406)	-4.522 (5.943)	2
	$\Delta y = \alpha + \beta\left(\overline{f}^{e}\right) + \delta(median_{\tilde{\phi}}) + \varepsilon$				
	$\overline{R}^2$	α	β	δ	MA Correction
Full Sample	0.42	-1.084 (2.734)	1.517** (0.533)	0.446 (2.997)	1
Truncated Sample	0.46	3.832 (2.426)	1.209** (0.339)	-6.552* (3.499)	1

Note: Standard errors are obtained using the Newey-West (1987) variance-covariance matrix estimator.
** Significant at 1% level
* Significant at 5% level

Figure 1: Moment-based Measures of Disagreement and Uncertainty



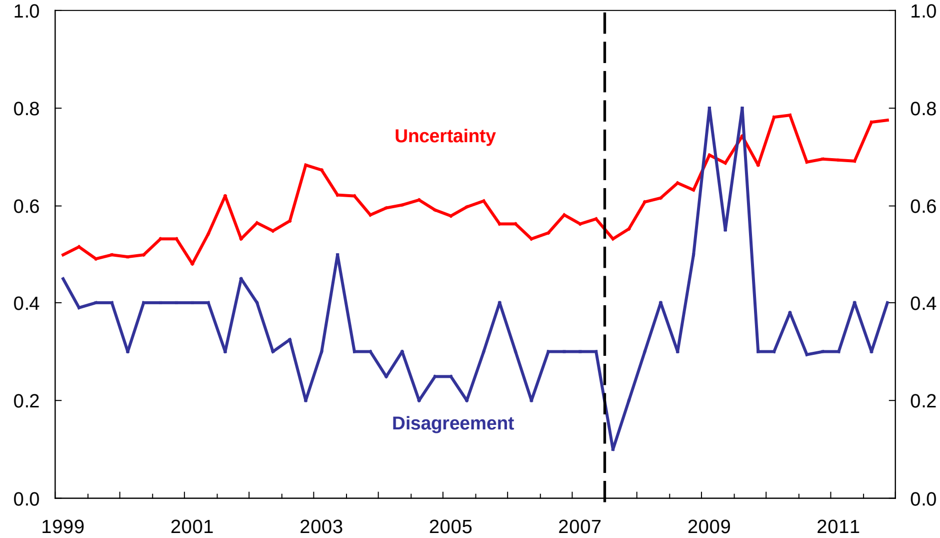
Source: European Central Bank



Source: European Central Bank

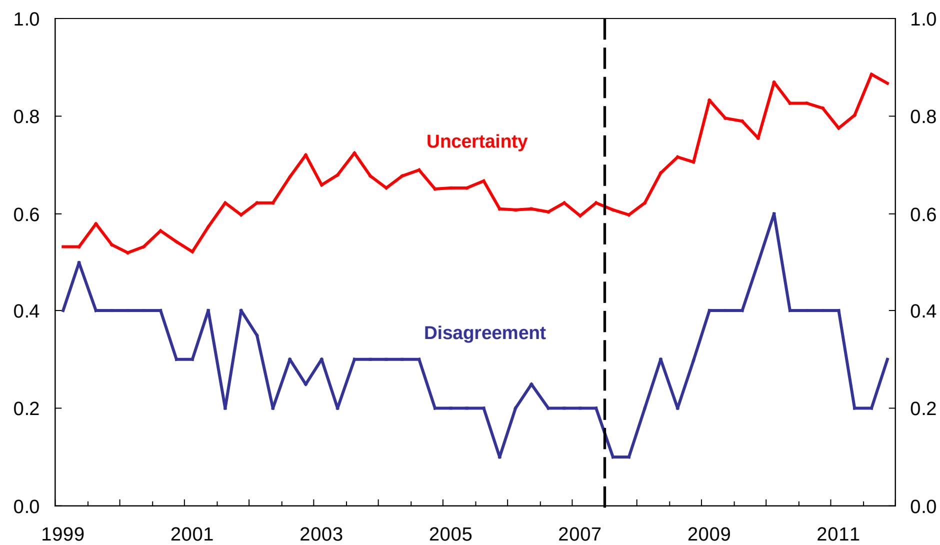
Figure 2: IQR-based Measures of Disagreement and Uncertainty

HICP: One-Year-Ahead



Source: European Central Bank

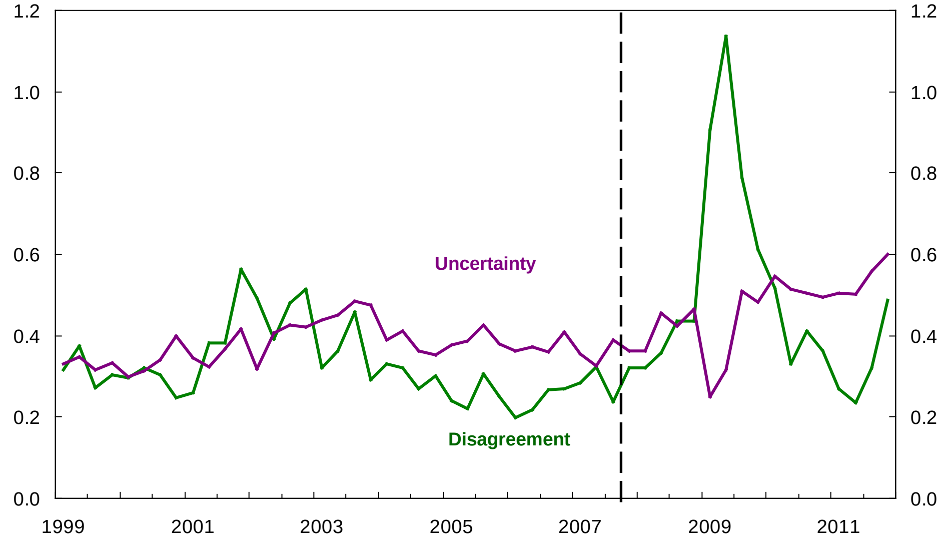
HICP: One-Year/One-Year Forward



Source: European Central Bank

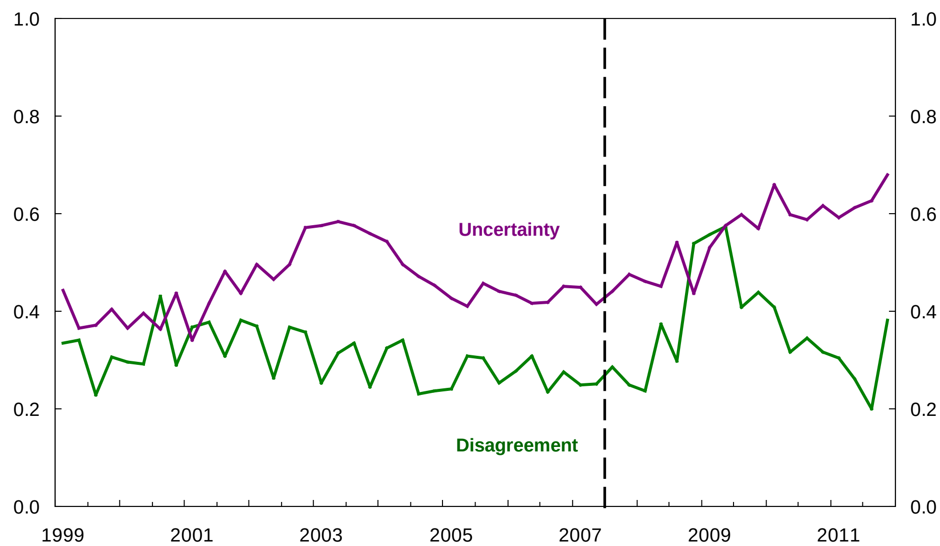
Figure 3: Moment-based Measures of Disagreement and Uncertainty

GDP: One-Year-Ahead



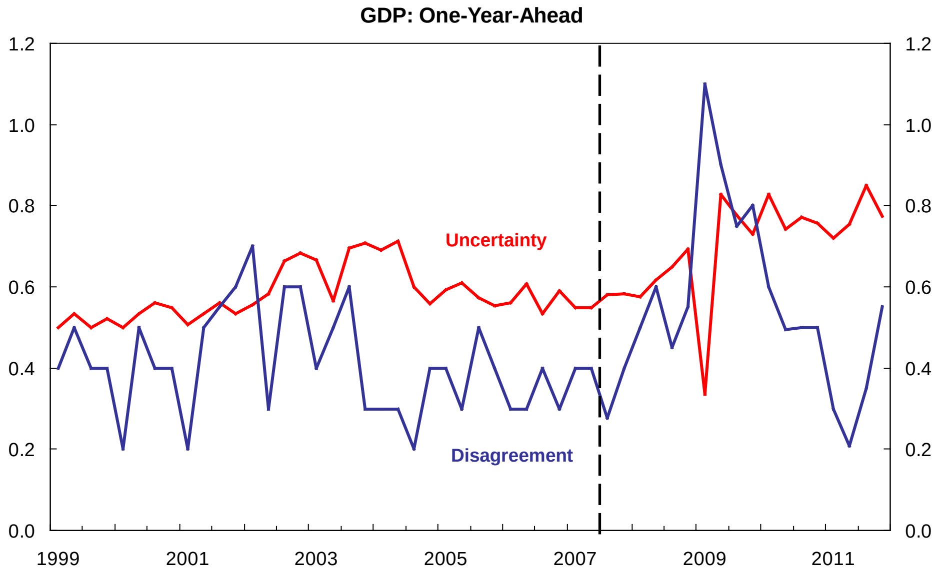
Source: European Central Bank

GDP: One-Year/One-Year Forward

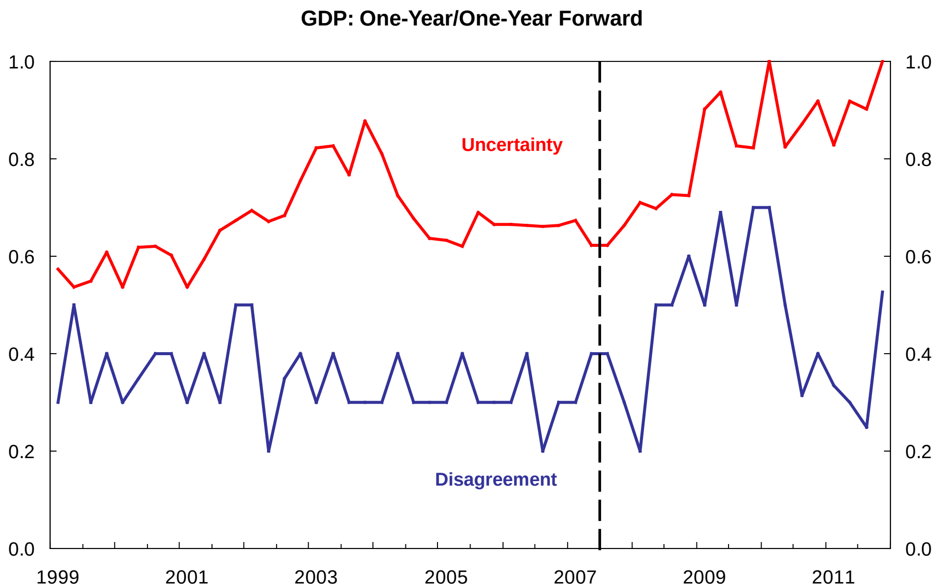


Source: European Central Bank

Figure 4: IQR-based Measures of Disagreement and Uncertainty

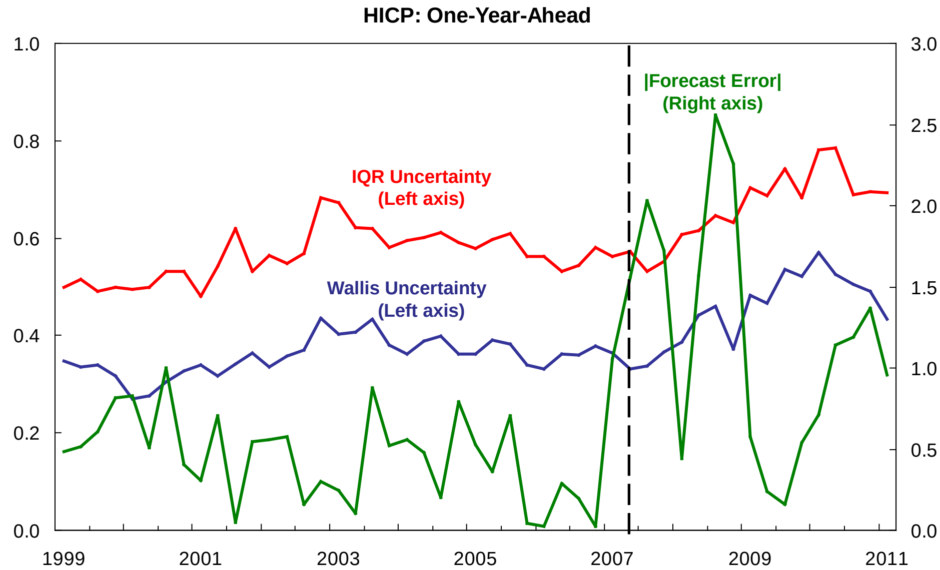


Source: European Central Bank



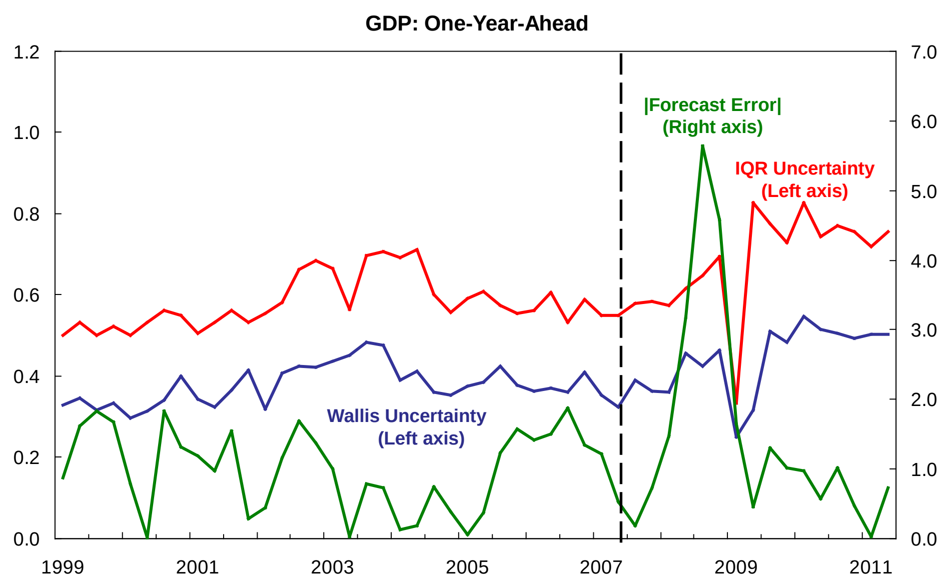
Source: European Central Bank

Figure 5: Ex-post Predictive accuracy and uncertainty



Source: European Central Bank

Figure 6: Ex-post Predictive accuracy and uncertainty



Source: European Central Bank

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