Are macroeconomic forecasters optimists or pessimists? A reassessment of survey based forecasts.

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March 2022

Abstract

We examine the issue of macroeconomic uncertainty in the Eurozone Area using forecasts from the European Central Bank's Survey of Professional Forecasters from the inception of the Euro in 1999Q1 to 2020Q2. We provide new insights concerning the optimism or pessimism of the distribution of forecasts by examining the 25^{th} and 75^{th} quartiles of the forecast distribution for each three key macro economic variables, GDP growth, inflation and unemployment. In addition, we examine the over- or under-confidence of forecasters in the survey by deriving the term structure of ex-ante uncertainty for up to 2 years ahead and compare it to ex-post uncertainty, enabling us to make some comparisons with existing US studies. Our results suggest that GDP growth forecasts tend towards optimism, while those for inflation and unemployment tend towards pessimism. In addition, ex-ante uncertainty in forecasts for the Eurozone Area is less than ex-post uncertainty at both the short and longer-term forecasting horizons, for all three variables. This suggests a tendency towards over-confidence on the part of Eurozone forecasters.

JEL classification : E31; E37; C53

Keywords : Macroeconomic uncertainty; ECB Survey of Professional Forecasters; subjective probability distribution; ex-ante uncertainty; ex-post uncertainty; Bayesian decision theory.

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1 Introduction

Macroeconomic uncertainty is a systemic risk which is difficult for most economic agents to quantify. If economic agents face greater uncertainty, it can influence their decision making behaviour resulting in a decrease in consumption, investment and hiring in the labour markets which then translates into reduced economic activity. As such, increased macroeconomic uncertainty, by affecting the economic decisions of both households and companies, ends up ultimately affecting macroeconomic outcomes for key macroeconomic variables, such as, economic growth, inflation and the unemployment rate. Another linkage between greater macroeconomic uncertainty and macroeconomic activity is via its influence on trading volumes and pricing in financial markets. Greater uncertainty can affect the volumes of equities and bonds traded/issued and the price of equities, bonds, commodities and exchange rate parities. Changes in asset prices and macroeconomic activity then have an effect on economic policy decisions made by the authorities which can further influence real economic activity and the financial markets.

We provide a detailed study of forecasts made by professional forecasters on three key macroeconomic series: economic growth, inflation and unemployment for the Eurozone Area. Our study, by using macroeconomic forecasts to extract measures of uncertainty, differs from the strand of literature that extracts measures of uncertainty from financial data such as Bloom (2009) which uses implied volatility estimated from call and put option premiums on the stock markets and currency markets. A shortcoming of the Bloom approach is that, by using the unconditional volatility of returns in stock markets and currencies, it fails to distinguish between expected and unexpected movements.

Most of the existing literature on survey based measures of uncertainty has focused on the likely impacts on economic growth and inflation forecasts such as, Giordani and Söderlind (2003) Engelberg et al. (2009), Clements (2014) and Clements and Galvão (2017) and Glas (2020). In their approach to measure uncertainty, Clements (2014) and Clements and Galvão (2017), use the Federal Reserve Bank of Philadelphia survey of Professional Forecasters (US-SPF) subjective distribution of forecasts of economic growth and inflation combined with individual forecasters point forecasts, to construct the term structure of macroeconomic uncertainty for both economic growth and inflation.

In addition to the US studies, there have been a number of studies looking at the Eurozone Area using data from the European Central Bank's Survey of Professional Forecasters (ECB-

SPF) dataset. Notable contributions here are Bowles et al. (2010)[1], Kenny et al. (2014),[2] Abel et al (2016) and Glas (2020). Recent research by Beckmann et al. (2020) highlights the value of including alternative measures of uncertainty extracted from several economic series rather than focusing on one or two series. They use forecasts from professional forecasters to calculate measures of macroeconomic uncertainty contained in their subjective distribution of forecasts for output growth, inflation, interest rates, exchange rates and the current account to analyze the spillover effects between economies. Beckmann (2021) develops an aggregate measure of exchange rate uncertainty and shows that this uncertainty has systematic effects on the economies of the US and Germany. The latter research builds upon the work of Dovern et al. (2012) who focus on the drivers of disagreement of forecasts for three economic variables for the G7 countries. Abel at al. (2016) use the ECB-SPF to construct three measures of uncertainty and two measures of disagreement.[3] By plotting both measures over time, they find that their two measures of disagreement are not reliable proxies for uncertainty. Along similar lines, Glas (2020) examines the specific issue of the relationship between forecaster disagreement and macroeconomic uncertainty in the Eurozone at three discrete forecasting intervals, one year, two years and five years ahead. He also finds that disagreement is generally a poor proxy for uncertainty.

We make a contribution to the literature on macroeconomic uncertainty by building upon the works of Garcia (2003), Giordani and Söderlind (2003), Engelberg et al. (2009) and Clements (2014) by being the first study to use the ECB-SPF to derive the term structure of ex ante uncertainty (EAU) exhibited in the forecasts from the ECB's SPF from 1 to 8 quarters ahead, we then compare it to measures of ex post uncertainty (EPU). All of which allows us to compare the ECB-SPF to existing US studies in regards to inflation and economic growth. Unlike the Clements (2014) study, we also derive the term structure of macroeconomic uncertainty for unemployment, which is a key macroeconomic variable of interest to economic policy makers.

[1]Bowles et al. (2010) provides important information on the forecast horizons of forecasts, information that is not readily available from standard descriptions of the ECB SPF.

[2]Kenny et al. (2014) use the ECB-SPF but for a much smaller period of time that covers 1999:Q1 to 2011:Q2. We use a much longer period of time of the ECB SPF survey which spans from 1999:Q1 to 2020:Q2 for a total of 21.5 years and 86 surveys.

[3]For two of them they approximate the intervals of the subjective distribution by a uniform distribution. This assumption is used to compute the variance as well as the interquartile range for each forecaster in quarter q of period t; their second measure of uncertainty is the interquartile range using the same approximation. Two aggregate measures of uncertainty are formed by averaging across forecasters in the former and taking the median of the latter. These two measures are compared to two measures of disagreement formed out of the cross-sectional variation of point predictions as well as the interquartile range of point predictions. For more on this see page 536.

Unemployment is examined in the study of Glas (2020), but he deals with forecasts only at the 4, 8 and 20 quarters which does not permit a comparison with the Clements study. Incorporating a study of the unemployment variable permits us to look at the issue of whether macroeconomic uncertainty with respect to unemployment is similar or differs greatly from that for inflation and economic growth. We also differ from Clements (2014) by calculating three measures of the term-structure of EPU, using the median, mean and mode rather than restrict the analysis to the median alone as the consensus forecast.

Another way in which we add a new perspective to the Clements (2014) and Glas (2020) studies is by incorporating some insights from the work of Engelberg et al. (2009) who adopt a non-parametric approach. They attempt to determine whether forecasts are optimistic or pessimistic based upon a small subset of the forecasts. They use the percentages of point forecasts that fall above or below the bounds on the median/mean/mode that are derived from their subjective distribution. As the number of observations that are outside these bounds is usually less than 10%, random chance alone could account for these exceptions. We argue that by looking at the percentages of forecasters' point forecasts that fall within the intervals containing the 25^{th} and 75^{th} quartiles of the forecast's distribution permits a more useful assessment of the optimism or pessimism of forecasters point forecasts and for better inference on possible loss functions employed by forecasters.

The rest of this paper is set out as follows. Section 2 discusses some common approaches to assessing forecasters and whether their point forecasts are optimistic or pessimistic and provides the basis for our later empirical analysis; Section 3 describes the ECB-SPF dataset; Section 4 provides a detailed assessment of the results we produce and these are compared to those of Engelberg et al. (2009) and Clements (2014); Section 5 concludes.

2 How to determine forecaster pessimism or optimism?

To provide the methodology to understand our empirical analysis reported in Section 4, we discuss how forecaster optimism or pessimism has been previously assessed in the literature, our concerns with it and our suggested improvement to the existing methodology. Engelberg et al. (2009) and Clements (2014) view point forecasts as measures of central tendency such as the median, mean and mode. When viewed this way, forecasters' subjective distributions can then be used to construct bounds on them. Engelberg et al. (2009) and others, generally look at whether the forecasts exceed or fall below these bounds to conclude whether forecasters are optimistic or pessimistic. We argue against this approach as it relies upon a relatively small percentage of observations and instead, we propose a refinement to it. We argue that a better approach to determine the optimism or pessimism of forecasters is to examine the distribution of forecasts by examining the bounds for the 25^{th} and 75^{th} quartiles of the forecast distribution for each of three key macro economic variables, GDP growth, inflation and unemployment.

2.1 Using measures of central tendency

In their approach to determine whether forecasters are optimistic or pessimistic about the state of the economy in regard to their point predictions from the US-SPF Engelberg et al. (2009) argue for a non-parametric approach. Almost all of the point predictions of forecasters do not differ significantly from the median/mean/mode but a small percentage do (about 10%). The latter forecasts exhibit an asymmetry which suggests they underestimate inflation and overestimate economic growth. To come to this conclusions, they use the small percentage of forecasts that fall outside of the bounds for the median/mean/mode. They then examine if there is an asymmetry in those forecasts to generate their view on optimism or pessimism. In the case of the GDP growth variable, this subset of forecasts are optimistic if the balance of forecasts are above the relevant bounds for the median/mean/mode rather than below. Whereas, in the case of the inflation variable, forecasts are deemed to be optimistic if the balance of forecasts outside of the three measures of central tendency are below the relevant bounds for these measures rather than above. From this analysis, they find that these forecasters are optimistic with regard to both inflation and economic growth.

A clear problem with the Engelberg et al. (2009) approach is that forecasts may fall outside of the bounds for the mean/mode/medium purely because of the random nature of forecasts or forecasters might on occasion make mistakes when making their point forecasts, or they may use asymmetric loss functions when selecting their optimal forecasts. All three of these can lead to errors in the assessment of whether a forecaster is optimistic or pessimistic. Engelberg et al. report in their overall assessment of these forecasts, that on average forecasters are optimistic. We argue in this paper that all Engelberg et al. can really conclude from their non-parametric analysis is that, on average, forecastors' use point forecasts that are consistent with the median/mean/mode. These measures of central tendency do not allow them to conclude the nature of these forecasts, i.e. whether they on average are pessimistic or optimistic.

Engelberg et al. (2009) approach to classification of optimism or pessimism allows the possibility that forecasters use an asymmetric loss function. In the Bayesian decision theory literature, this is called an asymmetric linear loss function (see Poirier (1995) pages 288-303, for a detailed discussion of optimal Bayesian point estimates under different loss functions). Whether or not forecasters use this loss function indicates their preference for pessimistic or optimistic forecasts because this loss function does not treat positive departures of the forecast from the future value in the same way as negative departures. According to Theorem 6.7.1 of Poirier (1995), the median is the optimal forecast under a symmetric linear loss function; the mean of the distribution is the optimal forecast under a quadratic loss function; whilst the mode is the optimal forecast under an all-or-nothing loss function. However, Poirier (1995) Theorem 6.7.1, states more than this; it allows a forecaster to adopt an asymmetric loss function which allows for different quartiles of a distribution to be optimal forecasts. Forecasters, adopting such loss functions, produce point forecasts that are either larger or smaller than the median. This loss function is given by equation (1):

$$C(\hat{\theta}, \theta) = \begin{cases} c_1|\hat{\theta} - \theta|, & \text{if } \hat{\theta} \leq \theta \\ c_2|\hat{\theta} - \theta|, & \text{if } \hat{\theta} \geq \theta \end{cases} \tag{1}$$

According to Theorem 6.7.1 part c), the optimal prediction is the ηth quantile, q_η, where $\eta = \frac{c_1}{c_1+c_2}$. Set $c_1 = 1$ and $c_2 = 3$, here the optimal forecast is $q_{.25}$.[4]. To understand this loss function, notice when the forecast, $\hat{\theta}$, is larger than the realized value, θ, it is penalized more harshly than a forecast which is smaller than θ. Whether the forecaster is a pessimist or optimist, then depends on the macro-economic time-series. For example, Engelberg et al. (2009, page 31), using the US-SPF, find that forecasts of GDP are more likely to be above the upper bounds of measures of central tendency, whereas inflation forecasts are more often below the lower bound. In this context, they are optimists with respect to both variables. If the converse were reported, then one could infer, forecasters are pessimists.

For our contribution, we deem that if forecasts are consistent with the intervals for 25^{th} or 75^{th} quartiles that we calculate, then we cannot reject the hypothesis they are using an asymmetric loss function. To our knowledge, our research is the first to provide a detailed analysis of the

[4]Our paper is based on the work of Poirier (1995), who uses the asymmetric linear loss function which is a special case of the generalized loss function looked at by Elliott et al. (2005). This model includes the squared and absolute deviation loss function as well as their asymmetrical counterparts, when parameters of this loss function are selected accordingly. This includes the lin-lin loss function which is the asymmetric linear loss function used by Poirier (1995). For more on this, the reader can consult the first paragraph on page 1110 of Elliot et al (2005)

ECB-SPF that includes this possibility. Doing so, allows for a more nuanced analysis on the nature of these forecasts, that is, whether forecasts can be considered optimistic or pessimistic. Our insight is important because the previous literature might wrongly conclude that when a point forecast lies above the bounds of the median that the forecaster is pessimistic but when a larger percentage of forecasts fall above the bound it could indicate a worse outcome, as would be the case for inflation. But using our approach, we are able to look more closely at this conclusion. Our analysis, by using all the forecasts, accommodates the possibility that rational forecasters could be using an asymmetric loss function, such as one from the class of asymmetric linear loss functions discussed in Poirier (1995). As Elliot et al. (2005) point out, if the loss function is asymmetric, then a forecaster can rationally over-predict a variable such as inflation or under-predict a variable such as economic growth due to the relative costs associated with over and under prediction. In the case of GDP growth, one would over-predict economic growth if the relative wights were assigned according to Theorem 6.7.1 of Poirier (1995), with $c_1 = 3$ and $c_2 = 1$. Here the 75^{th} quartile would be the optimal forecast. In the case of inflation, if $c_1 = 1$ and $c_2 = 3$, then the optimal forecasts would be the 25^{th} percentile.

When it comes to forecasters' point forecasts of unemployment, if they also have a larger percentage of point forecasts that lie in the interval for 75^{th} quartile than in the interval for the 25^{th} quartile, this implies forecasters are pessimists when it comes to unemployment. However, when we examine GDP growth, forecasters need to have a larger percentage of point predictions that fall in the interval containing the 25^{th} quartile than for the interval containing the 75^{th} quartile to be classified as pessimistic.

Consequently, when evaluating the overall state of optimism and pessimism for the economy as a whole, we require a larger proportion of the point forecasts for inflation and unemployment to lie in the interval for the 25^{th} quartile than for the interval for the 75^{th} quartile for us to classify forecasters as optimistic. For economic growth, a larger proportion of the point forecasts must fall within the interval containing the 75^{th} quartile than for the interval containing the 25^{th} quartile for us to classify forecasters as optimistic. A key advantage of our procedure to classifying optimism or pessimism is that it uses a much larger percentage of the sample, giving it more validity than the method applied by Engelberg et al. (2009)[5]. Our procedure, by placing

[5] Engelberg et al. (2009) analysis of forecaster optimism begins by calculating bounds on these three measures using forecasters' subjective distribution. These bounds enable them to test the hypothesis that these are consistent with one or more of them. They then look at how the spread of their distributions covers fewer intervals as the forecast horizon shrinks. They then look at the percentage of forecasts that fall above the upper bound than below the lower bound on the measures of central tendency. From this analysis, they determine whether

bounds on the 25^{th} and 75^{th} quartiles, allows us to determine more accurately whether point forecasts are consistent with one or even both of them, and then to conclude whether forecasters are, in general, optimists or pessimists.

2.2 Using Ex-post and ex-ante measures of uncertainty

Following Clements (2014) and Clements and Galvão (2017), we look at two commonly reported measures of uncertainty, referred to as ex-ante uncertainty (EAU) and ex-post uncertainty (EPU). EAU[6] measures average forecaster uncertainty at a given forecast horizon by averaging each individual's forecast uncertainty from their subjective probability distribution. Whereas EPU measures the uncertainty of the consensus forecast once the outcome variable is realized. Each measure is calculated from one to eight quarters ahead permitting us to report on the first quarter to two year term-structure of uncertainty for both EAU and EPU.

Alternative measures of macroeconomic uncertainty have been debated in the literature. For example, Giordani and Söderlind (2003) find the measure of disagreement on the point forecasts can be a better proxy for EAU than theoretically more well-founded ones. While Rossi and Sekhposyan (2015) create an index of macroeconomic uncertainty by comparing the realized h-step-ahead forecast error of an economic time-series with its historical forecast distribution.[7] Effectively, their index of uncertainty comes down to a comparison of the forecast error with the cumulative density of forecast errors. A large or small value of the index indicates greater uncertainty. Engelberg et al. (2009) fit a generalized beta distribution to a forecaster's subjective distributions, however, they provide only a very brief explanation[8] of their procedure. Clements and Galvão (2017)[9] find that fitting a normal distribution to forecaster's subjective distribution is an easier procedure and produces similar results for ex-ante uncertainty measures as the generalized beta distribution. This approach is also used by Giordani and Söderlind (2003) who restrict their analysis to subjective distributions with probabilities assigned to three or more intervals. There is some debate in this literature on whether disagreement, as measured by the standard deviation across forecasters, is an appropriate measure of EAU. For example, Engelberg

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forecasts are optimistic or pessimistic.

[6] It is called ex-ante uncertainty because the forecast is made prior to the realization of the outcome (see section 2 of Clements (2014) for more discussion on this).

[7] See section I, Macroeconomic Uncertainty Index page 651.

[8] See page 38 of Engelberg et al. (2009).

[9] On page 593 of their article, they state *"We calculate the standard deviations of the individual histograms by first fitting normal distribution....(as in Giordani and & Söderlind (2003)")*.

et al. (2009 p.30) states:

"It is possible that forecasters who hold identical probabilistic beliefs provide different point predictions and forecasters with dissimilar beliefs provide identical point predictions. If so, comparison of point predictions across forecasters is problematic. Variation in predictions need not imply disagreement among forecasters, and homogeneity in predictions need not imply agreement"

Moreover, Engelberg et al. (2009 page 31) also warn that the practice of using disagreement to measure ex-ante uncertainty confounds variation in forecaster beliefs with variation in the manner that forecasters make point predictions. Due to this, standard measures of disagreement used in the literature to measure forecaster uncertainty are not used here. For our analysis of the ECB-SPF, we follow the approach of Clements (2014) who reports EAU by averaging the standard deviations obtained by fitting a normal distribution to each forecaster's subjective distribution, at each of the eight horizons. He then averages, for each horizon, across the number of surveys. Consequently, we calculate EAU using the equation of Clements[10] given by equation (2):

$$\overline{\sigma}_{h,eau} = T^{-1} \sum_{t=1}^{T} \left(N_{t,h}^{-1} \sum_{i=1}^{N_{t,h}} \sigma_{i,t|t-h} \right), \tag{2}$$

where $\sigma_{i,t|t-h}$ is the standard deviation for forecaster i for an h step ahead forecast (h=1...,8) derived by fitting a normal distribution to their subjective distributions. We average over individuals and forecast targets (t). T refers to the number of years the survey was applied; $N_{t,h}$ refers to the number of forecasters of target t, for horizon h.

Once fit, the normal distribution yields the standard deviation as an individual forecasters measure of EAU for the appropriate time horizon. In our context, what this means is that the Q1 survey gives the four-quarter-ahead forecasts of year-end economic series; Q2 gives the three-quarter-ahead forecast and so on. Also, from the Q1 survey, one can obtain a measure of EAU of the eight quarter-ahead forecast. Individual forecaster's EAU are averaged for each forecast horizon, one through to eight quarters, to obtain the term structure of EAU for different time horizons. Here, and in what follows, this measure of uncertainty is denoted $\overline{\sigma}_{h,eau}$. Alternative measures of EAU have been used in the literature such as the standard deviation of the aggregate histogram, denoted as σ_h^{agg}. A simple argument based on the decomposition of the variance at

[10]See equation (6) of Clements (2014).

the consensus forecast into the expectation of the conditional variance of the forecast plus the variance of the forecast, indicates that this measure exceeds EAU[11].

Calculation of the measure of EPU is based on a consensus forecast which is often taken to be the median of each of the quarterly forecasts. Rather than use one consensus forecast based on the median, which is used by Clements (2014) and Clements and Galvao (2017), we also calculate EPU using the mean and mode of the respective quarterly forecasts. Using all three measures allows us to show that our term structure is robust to the measure of the consensus forecasts. The EPU is the sample standard deviation of the consensus forecast errors at horizon h (h=1,. . .,8) as given by equation (3):

$$\hat{\sigma}_{h,epu} = \sqrt{T^{-1} \sum_{t} (e_{t|t-h} - e_{h})^{2}}, \tag{3}$$

where $e_{t|t-h} = y_t - y_{t|t-h}$, $e_h = T^{-1} \sum_t e_{t|t-h}$ and $y_{t|t-h}$ is the consensus forecasts of the annual rate of change in calender year t made h quarters earlier.

While the formula used here is the same as Clements (2014), three measures of central tendency, i.e. the median, mean and the mode of the quarterly forecasts, are calculated for each of the three economic series surveyed in the ECB-SPF, namely, GDP growth, inflation and unemployment. Each consensus forecast is then used to construct three measures of EPU for each series. By comparing our measure of EAU to the three EPU measures, permits us to make a more definitive statement on which is larger. This contrasts with research of Clements (2014) and Clements and Galvão (2017) who rely on only one measure of EPU, namely the median. Regarding the relationship between EAU and EPU, Clements (2014) finds, using the US-SPF, EAU exceeds EPU for short-term horizons of one to four quarter-ahead forecasts, but EAU is less than EPU for longer term horizons of five to eight-quarter-ahead forecasts.

As a second departure from the majority of studies that use forecasts of two macro-aggregates, GDP growth and inflation, we follow Abel et al. (2016) and Glas (2020) in also examining the unemployment rate. An analysis of the unemployment rate can potentially provide more useful information on both EAU and EPU, and there is no doubt that it is a key macroeconomic variable that has an influence on the decisions of consumers and firms. It is also of great concern to governments and policy makers. It can be argued that this is an oversight, especially given

[11] This is a technical point where Giordani and Söderline (2003) link three measures of uncertainty as given in their equation (2) which decomposes aggregate uncertainty into a sum of average forecaster uncertainty plus the variance of the forecasts.

the research of Beckmann et al. (2020) who use additional economic aggregates to measure uncertainty. Moreover, forecasts of unemployment provide valuable information on the state of the labour market, the potential for real wage gains or losses and the subjective distribution can also reveal additional information on the optimism or pessimism of forecasters on the overall state of the economy. We, however, differ from Glas (2020) in that we are specifically interested in examining the issue of optimism and pessimism in the forecasts of survey participants in the ECB-SPF rather than the relationship between disagreement among forecasters and the relationship with macroeconomic uncertainty.

3 ECB survey of professional forecasters

The dataset that we employ comes from the European Central Bank (ECB) Survey of Professional Forecasters (ECB-SPF), which contains information on forecasts for real GDP growth, the rate of inflation and unemployment rate in the Eurozone Area over multiple time horizons. The ECB lists some 90 institutions that contribute forecasts to the survey. The survey began in 1999Q1, with the results published four times a year. Point forecasts as well as probability distributions are reported from a panel of forecasters who are experts from European Union (EU) based in financial and non-financial institutions. We use all the surveys from 1999 Q1 till 2020 Q2 for our analysis.

The main purpose for conducting the ECB-SPF is for the ECB to gather macroeconomic forecasts from private sector for the Eurozone Area in an attempt to understand how the private sector gauges key economic indicators. This then serves as an additional part of the information set available to the ECB Governing Council when implementing its monetary policy, especially in relation to its target for price stability.

3.1 Forecast Horizons

The ECB-SPF is carried out four times a year in January, April, July, and October. The questionnaire is delivered to the survey participants and usually conducted in the second half of the first month of each quarter.

Expectations are requested, of year-end macroeconomic variables, for the quarter in which the survey takes place, plus the four-quarter-ahead expectations of the next year's year-end values of these variables. In addition, a two-year ahead forecast of the year-end variables (in the ECB-SPF it is called a year after next forecast), as well as a five year forecast are also requested for each variable.

Further "rolling horizon" forecasts are requested for the month one-year ahead of the latest available release at the time of the survey, which is the previous month for the inflation rate and prior two months for the unemployment rate but the previous two quarters for GDP growth. For example, the 2018Q3 survey had, as the latest available observation of inflation and the unemployment rate, the June 2018 observation for inflation and May 2018 observation for unemployment. The survey asks forecasters to provide expectations for inflation from July 2018 to June 2019 and July 2019 to June 2020, and for the unemployment rate from June 2018 to end of May 2019 and June 2019 to end of May 2020. As for GDP growth, the survey had the latest available observation of GDP growth, the 2018Q1 observation. Forecasters were asked to give expectations for 2019Q1 and 2020Q1. Finally, survey participants were asked to provide a longer-term forecast of five years ahead, for example, the 2018Q3 survey asks for forecasts for the year 2023.

3.2 Description of Variables

Statistical definition of the variables is supplied to the survey participants in the questionnaire for clarity and brevity, along with the latest available data for each of the variables requested. We briefly describe the variables requested in the survey, as well as the point and probability distribution forecasts for each of our three macroeconomic variables of interest: (i) Real GDP growth is defined as the year on year percentage change of real GDP in the Eurozone Area; (ii) Inflation for the Eurozone Area is measured as the annual rate of change of the Harmonised Index of Consumer Prices (HICP), and (iii) The unemployment rate, defined as the number of unemployed as a percentage of the labour force of the Eurozone Area.

For their point forecasts, the participants were asked to give a point estimate for the requested variable for each time horizon. In addition, the survey participants were asked to give a probability distribution of their forecasted outcomes for each of the time horizons. A series of intervals are specified in the survey and it is left to the forecaster to place their probability score out of 100 in these intervals, which must sum to 100. The set of intervals differs across macroeconomic indicators, and revisions of which are possible from time to time, so as to consider economic developments of the Eurozone Area. For example, for the inflation indicator, survey participants to the 2018Q3 were asked to fill in the probabilities that the expected inflation for end-of-year

2018, 2019, 2020 as well as June 2019 and June 2020 would fall in each of the 12 intervals, which were <-1.0%, -1.0 to -0.6%, -0.5 to -0.1%, 0.0 to 0.4%, 0.5-0.9%, 1.0-1.4%, 1.5-1.9%, 2.0-2.4%, 2.5-2.9%, 3.0-3.4%, 3.5-3.9%, and $\geq$ 4.0%. It should be noted that the vast majority of forecasters leave some of the intervals blank or assign a value of zero.

Table 1 shows some summary statistics of our sample data. We have a large sample with 429 unique forecasters over the 21.5 years and observations ranging from 4,805 to 5,075 across three variables. We also report statistics including missing observations for each quarter.[12] We count the observation as missing for the current year if the forecaster does not give a current year point prediction or their current year subjective distribution. Similarly, we count the observation as missing for year 2 if the forecaster does not give a next year point prediction or his/her next year subjective distribution.

TABLE 1 HERE

4 Results

4.1 Medians, Means and Modes in the Bounds

The rationality of the forecasts can be judged in terms of non-parametric statistical theory. Since the ECB-SPF asks forecasters to provide their subjective probability distribution along with their point forecast, it allows us to use the distribution to construct bounds on the relevant median/mean/mode forecasts. We follow Engelberg et al. (2009, section 3.1) who provide a detailed explanation of how to calculate bounds on the median, mean, and mode. Their procedure to obtain bounds for each of the three measures of central tendency are straightforward to produce. In addition, we calculated bounds for the 25^{th} and 75^{th}quartiles. The bounds for the two quartiles are calculated using a similar procedure as the bounds for the median. In summary, the subjective probability distribution is used to locate the intervals where the median/mean/mode and the 25^{th} and 75^{th} quartiles fall.

Our results are detailed in Table 2 which reports on percentages of point forecasts that fall within the intervals for the median/mean/mode computed from the subjective probability distributions and also for predictions that fall within the upper and lower bounds for the 25^{th} and 75^{th} quartiles. We find that a relatively large percentage of forecasts are consistent with the latter

[12] Year 1 columns represent the forecasts for the next year end in the current quarters, while year 2 columns show the statistics on forecasts for the second year-end forecasts in the current quarters.

two intervals. In the cases, where the forecasts fall outside the bound on the median, the median is not an optimal forecast for those forecasters. A similar conclusion would hold, as well, for forecasts that fall outside the bounds on the mean or mode. In what interval the point forecasts fall within, i.e. intervals on the measures of central tendency or the quartiles, will depend on whether or not forecasters penalize more positive or negative deviations of the forecast from the actual value of the series. Since we explicitly tabulate percentages of forecasts that are consistent with these two quartiles, it permits conclusions to be made in this regard. If the forecast is consistent with the 25^{th} quartile then, depending on the forecast variable, the forecaster could be providing either optimistic forecast (in the cases of inflation and unemployment) or pessimistic forecast (in the case of GDP growth) in their forecasts. For example, if the forecast of the inflation rate is consistent with the interval containing the 25^{th} percentile, then in this case, we conclude the forecaster is optimistic. Whereas, if the forecast for GDP growth is consistent with interval containing the 25^{th} percentile, then it is deemed to be pessimistic. When looking at instances when the forecast is consistent with the interval containing the 75^{th} quartile then the reverse applies. In the cases of inflation and unemployment, the forecast is pessimistic; while for GDP growth, such forecasts are optimistic.

TABLE 2 HERE

4.2 Point Prediction Consistency with the Bounds

To begin with, Table 1 provides some useful information on the number of forecasts, missing forecasts as well as the unique number of forecasters. Each of these are recorded from Q1 to Q4 for each of the three macroeconomic series reported in the ECB-SPF. Each column of our table is similar to those of Engelberg et al. (2009),[13] but differs slightly in that we record information on forecasts for year $t + 1$ as well as for year t. [14]

Table 2 reports the percentage of times when the forecaster's point prediction in a given quarter, using only year t point forecasts, falls within the bound for the three measures of central tendency as well as for the percentage of point predictions falling with the intervals for the 25^{th} and 75^{th} quartiles. Examination of the intervals for 25^{th} and 75^{th} quartiles enables us to evaluate whether the forecasters are optimistic or pessimistic. If more forecasters' point predictions are consistent with the interval for the 75^{th} quartile compared to the interval for the 25^{th} quartile of

[13]See Engelberg et al. (2009) Table 1.

[14]Engelberg et al. (2009) state that they "restrict attention to year t point predictions and subjective probability distributions" when producing their Table 1, see section 2.1 last sentence of page 33 of their paper.

their subjection distribution, it implies that forecasters tend to give predictions that are towards the right tail, and therefore optimistic in their GDP growth forecasts but pessimistic in regards to their forecasts for inflation and unemployment rates.

In Table 2, to calculate whether point predictions are consistent with the three measures of central tendency and the intervals for the 25^{th} and 75^{th} quartiles, we count the point predictions within these bounds and then report what percentage of the point predictions lie within the bound for each measure. For example, if the point prediction lies within the bound for the mean, it implies that we cannot reject the hypothesis that the point prediction is the mean. However, if the point prediction does not fall within the bound for the mean, then it implies that we reject that hypothesis. For example, in the upper block of Table 2 for GDP growth, for the first entry starting with Q1, and for the column titled "Median", 86.90% of all GDP growth point predictions for the first quarter fell within the bound computed for the forecasters median. From Table 2, we find that most point predictions fall within the bound for the three measures of central tendency, with all of the reported percentages for the median/mean/mode in Table 2 being above 82%. This implies that most ECB-SPF forecasters point predictions are consistent with their subjective median/mean/mode. Among the three measures of central tendency, the mode has the highest percentages and the mean has the lowest percentages, except for the unemployment variable. This is similar to Engelberg et al. (2009) for the US-SPF. Among the three predicted variables, the inflation rate beats the unemployment rate for the highest percentages of point predictions lying within the three bounds of measures for central tendency, while the GDP growth rate has the lowest percentage.

In addition, the percentages of point predictions falling within the bounds generally increases from the first quarter to the fourth quarter for the median and the mean measures, although not for the mode. This is consistent with the findings of Engelberg et al. (2009) and is reasonable given that the forecast horizon becomes shorter. In other words, forecasters tend to give more accurate predictions near the year end (Q4) compared to in the beginning of the year (Q1). Table 3 confirms this finding, and it reports the cumulative percentages of survey participants whose subjective distributions are concentrated in N or fewer intervals, with N ranging from 1 to 20. For example, For N=2 and for GDP growth, there is only 21.8% of forecasters who have subjective distributions that are concentrated in two or fewer intervals in the first quarter, whereas this percentage increases to 43.56% in quarter 4. Similarly, percentages of concentrated subjective distributions for other macro variables tend to increase as time goes on from quarter 1 to quarter 4.

TABLE 3 HERE

4.3 Pessimistic or Optimistic Forecasters?

Despite high percentages reported in Table 2 showing that most ECB-SPF forecasters have point predictions consistent with their subjective median/mean/mode, there is a small number, less than 10%, of forecasters whose point predictions are inconsistent with the measures of central tendency. For these inconsistent cases, we report percentages in which their point predictions fall above or below the bound in Table 4. It shows, for those 10% of forecasters whose forecasts fall outside on measures of central tendency, their predictions mostly fall above the upper interval of these measures for GDP growth, inflation and unemployment. Specifically, for GDP growth, using the median, 78.76% of forecasters point predictions in comparison with 21.24% gave point predictions that are above the bounds then below. As to the forecasts for unemployment, the results provide conflicting evidence. Most point predictions are above the bounds than below the bounds for median and the mode but not for the mean where the majority of inconsistent forecasts are below the bound.

To determine whether this group of forecasters is pessimistic or optimistic in their predictions, Engelberg et al. (2009) report the percentages of inconsistent cases in which their point predictions lies above or below the bound, as reported in our Table 4 using figures from our study of the ECB-SPF. However, inconsistent cases reported in our Table 4 only account for a small percentage of the total number of survey participants, given most forecasters provide point predictions that are consistent with the measures of central tendency as shown in Table 2. For example, for forecasts of GDP growth using the mean, there are only 530 inconsistent cases report in Table 4 which is 11.03% and in the case of the mode it is only 183 which represents only 3.81% of the forecasts reported in Table 2. Consequently, we argue that, if we make generalizations about the optimism or pessimism of forecasters based on Table 4 using only inconsistent cases, it means that we are assuming all these forecasts are rational, i.e. obtained by minimizing expected loss. Clements (2010) shows that these forecast are more accurate indicators of the first moment than the subjective distributions.[15] Instead, we propose concentrating on Table 2, which reports results using the whole sample of forecasts, instead of the inconsistent cases only reported in Table 4.

[15] See the last paragraph of section 5.

TABLE 4 HERE

For GDP growth, Table 2 shows that there is a larger proportion of forecasters' point predictions consistent with the 75^{th} quartile of their subjective distributions, ranging from 58.82% to 75.92% across four quarters, compared to those consistent with the 25^{th} quartile which ranges from 28.61% to 50.46% across the four quarters. This suggests that forecasters are on balance optimists since their GDP growth predictions are more towards the right tail of their subjective distribution than towards the left tail.

Regarding inflation, Table 2 shows that there are more forecasters with point predictions consistent with the 75^{th} quartile ranging from 55.94% to 81.39% across the four quarters, compared to those consistent with the 25^{th} quartile which ranges from 42.27% to 61.89% across the four quarters of their subjective distributions. This suggests that forecasters are on balance pessimistic by reporting inflation predictions that are more towards the right tail of their subjective distribution than towards the left tail. It also indicates that forecasts of inflation may have been generated from an asymmetric loss function that favours the 75^{th} quartile rather than the 25^{th} one.

As for unemployment, as mentioned previously, Table 4 reports conflicting results, whereas Table 2 based on a far larger percentage of observations, shows that there is a slightly larger proportion of point predictions consistent with the 75^{th} quartile, ranging from 52.33% to 71.05%, than those consistent with the 25^{th} quartile, which ranges from 44.49% to 63.33% across the four quarters. This suggests that ECB-SPF forecasters are in general pessimistic in their predictions for unemployment. However, it could indicate that forecasts of unemployment may have been generated from an asymmetric loss function that favours the 75^{th} quartile rather than the 25^{th} quartile.

Overall, when referring to the state of the economy as a whole, Table 2 makes it difficult to argue that forecasters are optimistic or pessimistic. This is because while GDP growth forecasts tend to be optimistic, those regarding inflation and unemployment indicate pessimism as point forecasts tend to have more of the observations in the interval for 75^{th} quartile rather than the interval for the 25^{th} quartile for those two variables.

4.4 Persistence of Inconsistency

To obtain some insight into the short-term and longer-term persistence of forecasters point predictions in the ECB-SPF survey, we follow the procedure of Engelberg et al. (2009) in their study of the US-SPF, however, we differ from their study since we report results not only for the median but also for the mean and the mode. The ECB-SPF assigns an ID number to each forecaster permitting an analysis of the persistence in the forecasts of the survey participants over different time horizons. Table 5 reports the percentage of point predictions that are above, inside, or below the bounds for the median, mean and mode in adjacent quarters. For GDP growth, we can see that for the measures of the median, forecasters whose point predictions of GDP growth lie above the upper bound in period t are more likely to have point predictions above the upper bound in period $t+1$ (31.63%) than are forecasters whose point predictions are inside (8.22%) or below the bound (6.56%). This short-term persistence is also present for the mean and mode, and for the other two macro variables: inflation and unemployment. In addition, those forecasters that are below the lower bound in period t are more likely to have point predictions below the lower bound for GDP growth in period $t+1$ (14.75%) than are forecasters whose point predictions are inside (2.13%) or above the bound (0.90%). A similar pattern applies to the mean and the mode forecasts for GDP growth.

TABLE 5 HERE

A similar overall pattern of short-term persistence applies to the forecasts for inflation but the persistence is lower than is the case for the GDP forecasts. When it comes to unemployment, the persistence is generally higher than for inflation but lower than GDP growth when it comes to upper bound estimates, but interestingly higher than the GDP estimates when it comes to the below bound estimates.

To examine the issue of the long-term persistence of point predictions in relation to the bounds for the three measures of central tendency, we compare forecasts in period t with those given for one year, two years and three years later as is done in Engelberg et al. (2009), that is for periods $t+4$, $t+8$, and $t+12$. Table 6 reports the results and in general shows evidence of long-term persistence for the median, mean and mode. For instance, looking at the upper block of Table 6, at the measures of central tendency for the median, forecasters whose point predictions of GDP growth lie above the upper bound in quarter t are more likely to have point predictions above the upper bound in quarter $t+4$ (20.32%) than are forecasters whose point predictions are within (10.12%) or below the bound (10.84%). This persistence lasts for quarter $t+8$ in which 15% of forecasters whose point predictions of GDP growth lie above the upper bound in quarter t continue to have point predictions above the upper bound compared to a percentage of 10.34% inside the bound and 8.22% below the bound. When we look further out to t+12, we can observe a similar pattern, with more forecasters whose point predictions of GDP growth lie above the upper bound (15.63%) in quarter t continue to have point predictions above the upper bound compared to those who provide predictions inside (10.67%) or below the bound (10.77%).[16]

TABLE 6 HERE

A similar pattern of persistence exists when looking at the inflation forecasts using the median/mean/mode measures. However, for the unemployment forecasts, the persistence is in general much lower when looking at the predictions for t+4 and t+8. Overall, our results for GDP growth and inflation are similar to those in Engelberg et al. (2009) study of the US-SPF, we cannot, however, make any comparisons with regard to unemployment as this is not included in their study. Overall, short-term persistence at the t+1 forecasts is higher for all three macro variables than for the longer-term persistence measures at t+4, t+8 and t+12 horizons.

4.5 Measures of ex-ante and ex-post uncertainty

Since the outcome variable that is forecasted is not known at the time the forecast is made, much of the existing literature on survey based estimates of forecaster uncertainty calculate them based on the subjective probability distribution of forecasters. When calculated this way they are referred to as EAU given by equation (1).Lahiri and Sheng (2010) provide a mathematical link between EAU and disagreement. Within their model, they decompose EAU into a sum of two variances. The first component due to the cumulative effect of all shocks that occurred from h quarter ahead to the end of the target year t plus a weighted (by the inverse of the number of forecasters) average of idiosyncratic variances (forecaster uncertainty) plus a weighted (1 minus the inverse of the number of forecasters) measure of disagreement. They argue the middle term in that sum is marginal and can be ignored, at least in their sample.[17] As to EPU, Lahiri and Sheng (2010) do not provide much detail on the mathematics but argue that their equation (22) is a good measure of it. That equation measure EPU as the sum of the squared value of the realized time-series at target t minus the consensus forecast plus weighted disagreement (the weight is 1 plus the inverse of the number of forecasters). The latter measure of EPU is larger than EPU employed in this research.

[16] There is a minor inconsistency for some forecasters whose point predictions lie below the bound. However, this does not undermine our conclusion of long-term persistence in forecasting.

[17] For more information on this decomposition see equation (22) of Lahiri and Sheng (2010) and discussion on page 520.

As explained previously, our measure of EPU given by equation (2) is based on a consensus forecast using the median/mean/mode of the time t and $t+1$ forecasts. The EPU is the sample standard deviation of the consensus forecast errors at horizon h. Clements (2014) reports a measure of EPU based on the median as the consensus forecast of time t and $t+1$ forecasts. While we report results using the median, we also report results on EPU that use the mean and the mode as the consensus forecast. With three measures of EPU, each based on a different measure of central tendency, our results are robust compared to those reported by Engelberg et al (2009) or Clements (2014) who do not actually show that their results are robust to the three measures. The term structure of EPU is the sample standard deviation of the consensus forecast errors at horizons $h = 1, \ldots, 8$. Here, as in Clements (2014), these two measures of uncertainty are denoted as $\overline{\sigma}_{h,eau}$ and $\widehat{\sigma}_{h,epu}$.

To calculate these measures of uncertainty, we require forecasters to provide at least five years of forecasts, a requirement which is followed by Clements (2014).[18] This reduces difficulties that arise due to attrition of forecasters, other approaches have been developed in the literature to avoid these problems. Kenny et al (2014) estimate regressions on non-missing forecasts which are then used to estimate the value of missing forecasts. To come up with a corresponding distribution, they re-center last period's subjects probability distribution over the estimate of the missing forecast produced from the regression model.[19] According to Clements (2014), their method is difficult to implement on surveys that span a large number of years. Section 5 of Clements (2014) provides a detailed discussion of this as well as his proposed solution. Clements and Galvão (2017) also use this method which was first used by Giordani and Söderlind (2003).

The existing literature, when measuring EAU and EPU, has largely focused on at most two macroeconomic series, economic growth and inflation. A recent exception is Glas (2020) who also calculates EAU for unemployment but only at time horizons 4, 8 and 20 quarters ahead. Clements (2014) and Clements and Galvão (2017), when calculating EPU, use the median of the quarterly point forecasts as the consensus forecasts but it could just as well have been the mean or the mode. Since our interest is to provide as much information on EPU as possible, we calculate all three consensus forecasts using the median, mean and mode of the h step-ahead point forecasts. As a result, we calculate three measures of EPU, each using one of the three

[18] see Clements (2014) section 5 of their paper

[19] For details on their procedure see section titled "Irregular participation and non-response" on p. 170. In particular, Kennay et al (2014) provide an example how last periods subjective probability distribution is re-centered.

measures of consensus forecasts for each of the three series, economic growth, inflation and unemployment for the Eurozone Area. All told, this gives us a total of nine measures of EPU for our 3 macro variables, which lends more credence to the conclusions we arrive at when compared to those made in the existing literature. Table 7 provides the results from our calculations of uncertainty for the different forecast horizons denoted h in the table.

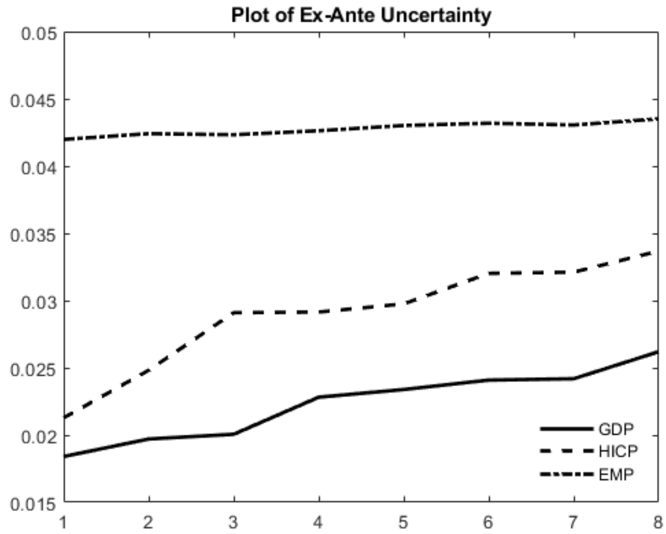
Our estimate of the term structure of EAU for the three series rises as the forecast horizon increases as depicted in Figure 1. In Table 7, these values are located in the column with header $\overline{\sigma}_{h,eau}$. Column S captures the increasing trend in the term structure, as it is the ratio of EAU at horizon i to horizon $h = 8$. It increases with the forecast horizon until it reaches the value of one. This is expected and is consistent with Table 1 of Clements (2014). It is also clear that EAU is lowest for GDP growth, whilst it is generally highest for unemployment which indicates that forecasters' over-confidence is generally highest when it comes to forecasting GDP growth at different time horizons.

TABLE 7 HERE

EAU for the forecast of Eurozone unemployment rate depicted in Table 7 also increases with the forecast horizon but at a far slower rate than in the cases of GDP growth and inflation. As the forecast increases from one to eight quarters ahead EAU increases and the ratio S approaches one. Also with unemployment, there is a higher numerical value than for GDP growth and inflation. Overall, there seems to be considerable EAU in forecasts for unemployment over the period 1999Q1 to 2020Q2. Nonetheless, the EAU is always below EPU for the unemployment variable, suggesting that forecasters are over-confident in their forecasts for this variable.

Turning to our reported EPU measures of uncertainty these are depicted in Figure 2 for economic growth, Figure 3 for inflation and Figure 4 for unemployment. Table 7 reports the values for each of our three measures of EPU for economic growth, inflation and unemployment in the columns with headers $\widehat{\sigma}_{h,epu}^{median}$, $\widehat{\sigma}_{h,epu}^{mean}$ and $\widehat{\sigma}_{h,epu}^{mode}$. The corresponding ratios are in the columns with headers *Smedian*, *Smean* and *Smode*. The rise in uncertainty for EPU for each of the three variables is consistent with the results of Clements (2014). Since, all three measures of central tendency agree, this provides robust support for our interpretations. When we examine uncertainty concerning economic growth, EPU is significantly above EAU suggesting that forecasters are over-confident concerning their forecasts at both the short and longer-term forecast horizons. This result differs from the results of Clements (2014) using the US-SPF who finds that EAU is greater than EPU for the forecasting horizons one to four quarters ahead but

Figure 1: Ex-ante Uncertainty



the reverse happens at horizons five to eight quarters ahead.

When examining the inflation measures of EPU, its term structure also increases with the forecast horizon, but not in such a dramatic fashion as for economic growth or unemployment. EPU, itself, is lower than for both economic growth and output. This result is probably not too surprising, as the ECB has an explicit inflation target of close to but below 2% over the medium-term which helps to reduce the realized variability of this variable as is the success over time of the ECB in achieving its inflation target.

For unemployment, it is clear that EPU also much larger than EAU providing strong support for the notion that forecasters are also over-confident in their forecasts of unemployment. Even though the term structure of unemployment's EAU increases as the forecast horizon increases, the standard deviation of EAU is greater than in the case of inflation and economic growth suggesting more overall EAU with regard to forecasters ability to forecast unemployment at different time horizons.

Our results show a clear relationship between corresponding measures of EAU and EPU for each series. EAU for each series is much smaller than EPU regardless of whether the median/mean/mode is used. This suggests that forecasters are overall over-confident with regard to this measure of their forecasts. This result is consistent with some of the literature from

Figure 2: EPU - Economic Growth

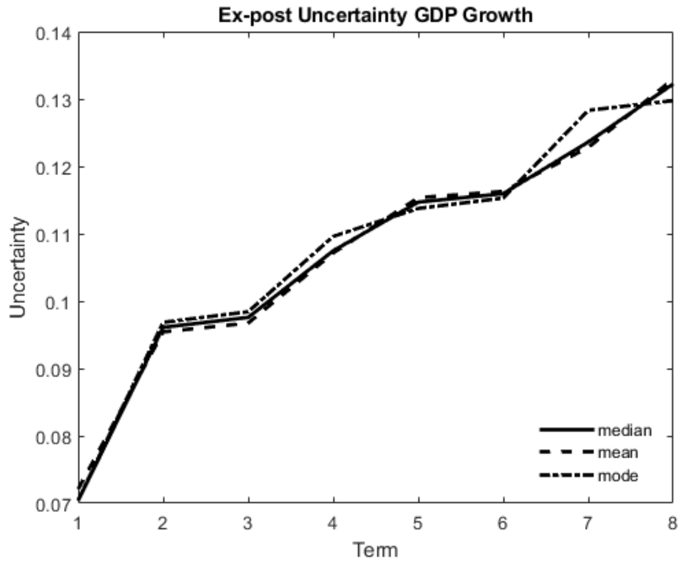


Figure 3: EPU - Inflation

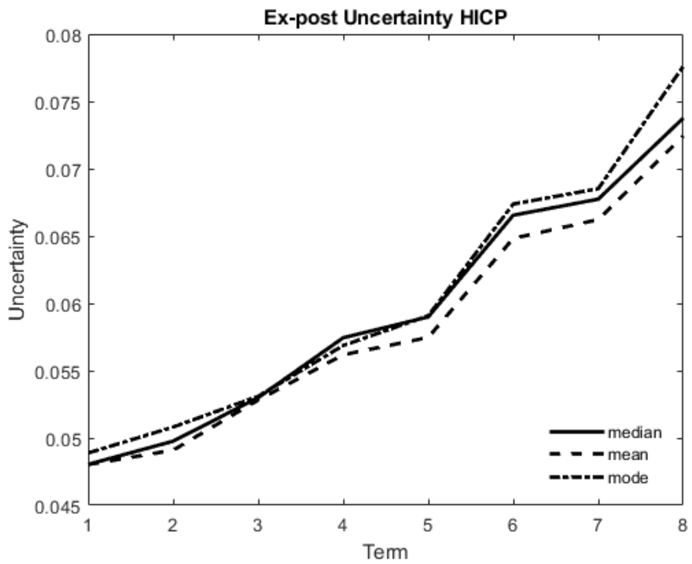
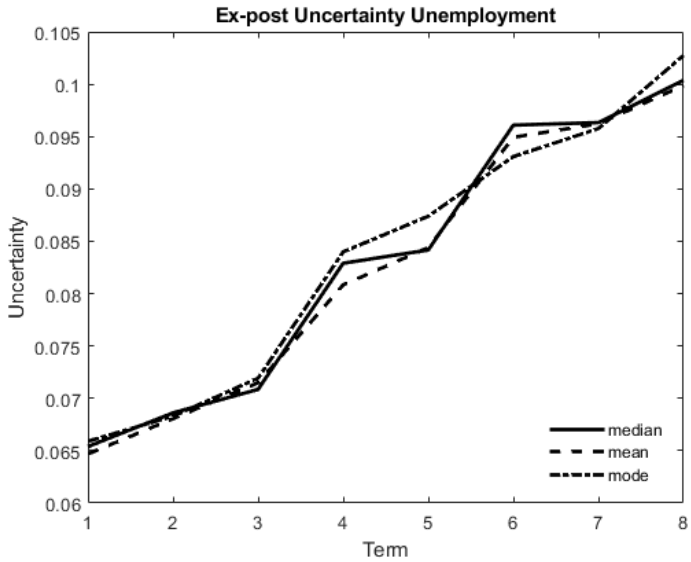


Figure 4: EPU - Unemployment



the US-SPF such as Giordani and Söderlind (2003) who find that EPU is much larger than EAU. Kenny et al (2014) also find this using the ECB-SPF for inflation and growth. However, Clements (2014) finds that, at the five to eight quarters ahead, EPU exceeds EAU in the US-SPF suggesting that US-SPF forecasters are under-confident in their longer-term forecasting ability.

5 Conclusions

Our research expands on the some of the recent literature on survey based measures of macroeconomic uncertainty as well as the rationality of forecasters. It also contributes to understanding of the optimism or pessimism of point forecasts made by participants in the ECB-SPF. To do all this, we employ the ECB-SPF which uses 21.5 years of survey data covering 84 surveys which is the longest time span usage of this survey. We found, just as similar studies using the US-SPF have found, that the median, mean and mode are consistent with a majority of point forecasts made in the ECB-SPF. Unlike other studies, we also consider the possibility that the point forecasts from the ECB-SPF could be consistent with the 25th and 75th quartiles of their subjective distributions. Our results show that many forecasters point forecasts are consistent with these quartiles but the percentages are smaller than those consistent with the median/mean/mode. Our analysis also suggests that forecasters participating in the ECB-SPF have tendency to be optimistic when it comes to economic growth and pessimistic when it comes to inflation and unemployment. As such, no overall inferences can be made concerning their optimism or pessimism on the overall state of the economy.

Unlike Clements, we report the results for EPU using three measures of central tendency as an additional check for the robustness of our results. We find that EAU is less than EPU for all three series over the eight quarters, which contrasts with the results of Clements (2014). The latter author finds that EAU is greater than EPU at short-term time horizons of one to four quarters ahead but over-confident with regard to longer-term forecasting horizons. We also find that the term structure of EAU for the Eurozone unemployment rate does not change as nearly as much as the measures for economic growth or annual inflation. However, the standard deviation of EAU for unemployment is noticeably higher than for either economic growth or inflation.

From a policy perspective, it would be potentially interesting to require individual members of the Federal Reserve Open Markets Committee (FOMC) and members of the Governing Council of the ECB to be asked to provide their point forecasts for key economic variables such as economic growth, inflation and unemployment as well as their subjective probability forecasts for each of these variables. This could provide useful information to economic agents about the likely course of future monetary policy and help them to better evaluate the risks to the upside and downside of the state of the economy. The publication of such individual forecasts would promote transparency while enabling market participants to see the extent of disagreement in the FOMC and ECB Governing Council. It should also assist firms in better anchoring their expectations on the inflation target set by policy makers which should overcome the finding of Coibion et al. (2020) that their inflation expectations tend not follow closely the target.[20] It would also make policy makers more accountable, in that their voting record on interest rate changes and in relation to policies, such as, Quantitative Easing (QE) could be more explicitly linked to their individual forecasts.

[20] Coibion et al (2020) find that firms' inflation expectations are not well anchored.

Table 1: Descriptive Statistics

Year	Quarter	Number of Obs	Missing Observations	Unique Forecasters
GDP growth				
year 1	1	1239	99	105
year 2	1	1239	142	105
year 1	2	1214	90	107
year 2	2	1214	110	107
year 1	3	1127	94	108
year 2	3	1127	106	108
year 1	4	1225	93	109
year 2	4	1225	96	109
total obs	1(also 2)	4805	376	429
Inflation				
year 1	1	1297	115	105
year 2	1	1297	157	105
year 1	2	1269	78	107
year 2	2	1269	97	107
year 1	3	1179	107	108
year 2	3	1179	124	108
year 1	4	1330	130	109
year 2	4	1330	133	109
total obs	1(also 2)	5075	430	429
Unemployment				
year 1	1	1239	145	105
year 2	1	1187	181	105
year 1	2	1214	134	107
year 2	2	1165	153	107
year 1	3	1127	140	108
year 2	3	1087	149	108
year 1	4	1225	151	109
year 2	4	1184	153	109
total obs	1(also 2)	4805	570	429

This table uses the European Central Bank's Survey of Professional Forecasters to summarize the number of unique forecasters (Number of Obs), on each of the three macroeconomics series, who provide forecasts for Q1 to Q4 of the survey year (year 1) and the next year (year 2). The last row of each of the three series totals the number of forecasters (Number of Obs) for Q1 to Q1 of year 1 which also corresponds to the total for the number of forecasters in year 2.

Table 2: Upper bounds on median/mean/mode point predictions and quantiles

Quarter	Median	Mean	Mode	25th quartile	75th quartile
		GDP growth			
Q1	86.90%	82.26%	98.40%	28.61%	58.82%
Q2	86.30%	85.94%	97.17%	35.89%	59.82%
Q3	87.76%	85.96%	94.78%	40.42%	64.19%
Q4	92.31%	88.64%	95.33%	50.46%	75.92%
		Inflation			
Q1	91.55%	90.18%	97.69%	42.27%	55.94%
Q2	93.26%	90.73%	97.46%	48.29%	56.43%
Q3	92.34%	89.63%	95.06%	49.90%	69.48%
Q4	95.28%	91.10%	96.17%	61.89%	81.39%
		Unemployment			
Q1	87.93%	87.22%	94.01%	44.49%	52.33%
Q2	87.59%	88.67%	94.24%	49.64%	53.87%
Q3	89.95%	91.61%	95.54%	58.76%	56.58%
Q4	92.38%	92.19%	95.81%	63.33%	71.05%
		All			
Q1	88.83%	86.61%	96.70%	38.54%	55.66%
Q2	89.10%	88.48%	96.30%	44.69%	56.69%
Q3	90.05%	89.04%	95.12%	49.60%	63.56%
Q4	93.35%	90.63%	95.77%	58.53%	75.23%

This table uses point forecasters recorded by the European Central Bank Survey of Professional Forecasters to summarize the percentage of point forecasts that fall within the bounds calculated from their subjective distribution corresponding to the three measures of central tendency. Columns list percentage by macroeconomic series, while rows list the corresponding quarter of the year: Q1 to Q4. Calculations are based on the surveys for the years 1999Q1 to 2020Q2.

Table 3: Percent of forcasters using N intervals or less

Quarter	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
GDP growth																				
Q1	1.08%	21.80%	53.98%	71.32%	80.93%	85.07%	89.68%	92.22%	93.83%	95.24%	96.11%	96.99%	99.05%	99.16%	99.29%	99.31%	99.44%	99.63%	99.99%	100.00%
Q2	0.95%	25.44%	58.84%	74.57%	83.10%	87.43%	91.22%	93.24%	94.49%	95.87%	96.69%	97.38%	99.10%	99.27%	99.42%	99.64%	99.70%	99.78%	100.00%	100.00%
Q3	2.21%	23.86%	57.35%	74.20%	83.68%	87.65%	90.75%	93.28%	94.94%	97.81%	98.31%	99.90%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
Q4	4.81%	43.56%	73.45%	82.73%	87.17%	90.86%	93.16%	94.38%	95.87%	98.42%	98.88%	99.91%	99.91%	99.91%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
Inflation																				
Q1	0.00%	0.74%	17.32%	45.79%	63.74%	77.56%	84.54%	89.74%	92.19%	96.90%	97.52%	98.05%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
Q2	0.00%	1.52%	22.51%	53.19%	70.26%	81.46%	87.65%	91.86%	94.04%	97.77%	98.57%	99.00%	99.87%	99.89%	99.98%	99.98%	99.98%	99.98%	100.00%	100.00%
Q3	0.00%	2.09%	32.64%	65.97%	80.60%	87.62%	90.93%	94.87%	96.27%	98.63%	99.13%	99.52%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
Q4	0.00%	13.96%	52.81%	81.95%	88.72%	92.96%	94.66%	96.35%	97.21%	99.22%	99.48%	99.60%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
Unemployment																				
Q1	1.13%	22.47%	55.41%	72.75%	82.14%	85.83%	90.21%	92.67%	94.17%	95.31%	96.18%	96.70%	98.96%	99.07%	99.22%	99.24%	99.38%	99.58%	99.98%	100.00%
Q2	0.99%	26.41%	60.45%	75.91%	84.18%	88.15%	91.81%	93.64%	94.79%	95.95%	96.76%	97.17%	99.04%	99.24%	99.40%	99.62%	99.69%	99.77%	100.00%	100.00%
Q3	2.71%	38.80%	69.89%	81.24%	87.42%	90.14%	92.98%	94.26%	95.60%	96.76%	97.50%	98.04%	99.51%	99.59%	99.69%	99.78%	99.78%	99.78%	100.00%	100.00%
Q4	9.55%	56.34%	79.25%	86.48%	90.89%	92.67%	94.42%	95.47%	96.35%	97.08%	97.39%	97.97%	99.65%	99.65%	99.70%	99.70%	99.70%	99.74%	99.97%	100.00%

This table uses the subjective distribution of forecasters recorded by the European Central Bank Survey of Professional Forecasters. It summarizes, by quarter, the percentage of forecasters whose subjective distributions on the three macroeconomic series uses 1 through 20 intervals. The columns header refers to the number of intervals used by forecasters when reporting their subjective distribution in the survey. It used surveys from 1999Q1 to 2020Q2 to tabulate this information.

Table 4: Evidence on the distribution of point predictions

GDP Growth			
	Above bound	Below bound	N
Median	78.76%	21.24%	645
Mean	65.47%	34.53%	530
Mode	64.48%	35.52%	183
25th quartile	97.90%	2.10%	2618
75th quartile	1.38%	98.62%	1526
Inflation			
	Above bound	Below bound	N
Median	83.18%	16.82%	446
Mean	59.20%	40.80%	326
Mode	62.20%	37.80%	164
25th quartile	99.37%	0.63%	2230
75th quartile	1.16%	98.84%	1556
Unemployment			
	Above bound	Below bound	N
Median	71.47%	28.53%	354
Mean	30.98%	69.02%	368
Mode	51.41%	48.59%	142
25th quartile	99.03%	0.97%	1848
75th quartile	1.03%	98.97%	1646

This table uses the European Central Bank Survey of Professional Forecasters to calculate the percentage of forecasts that fall below or above the interval placed on each of the three measures of central tendency. To calculate the table, forecasts for quarters Q1 to Q4 of the survey years 1999Q1 to 2020Q2 were used.

Table 5: Short term persistence

GDP Growth				
		Quarter t+1		
Median				
Quarter t	N	Above bound	Inside Bound	Below Bound
Above bound	332	31.63%	67.47%	0.90%
Inside bound	2299	8.22%	89.65%	2.13%
Below bound	61	6.56%	78.69%	14.75%
Mean				
Quarter t	N	Above bound	Inside Bound	Below Bound
Above bound	250	30.40%	65.60%	4.00%
Inside bound	2264	4.51%	92.54%	2.96%
Below bound	178	6.18%	59.55%	34.27%
Mode				
Quarter t	N	Above bound	Inside Bound	Below Bound
Above bound	73	19.18%	76.71%	4.11%
Inside bound	2544	0.86%	97.68%	1.45%
Below bound	40	12.50%	80.00%	7.50%

Inflation				
		Quarter t+1		
Median				
Quarter t	N	Above bound	Inside Bound	Below Bound
Above bound	228	21.49%	77.63%	0.88%
Inside bound	2410	7.01%	91.70%	1.29%
Below bound	45	6.67%	84.44%	8.89%
Mean				
Quarter t	N	Above bound	Inside Bound	Below Bound
Above bound	143	25.87%	72.03%	2.10%
Inside bound	2451	2.37%	95.92%	1.71%
Below bound	89	5.62%	73.03%	21.35%
Mode				
Quarter t	N	Above bound	Inside Bound	Below Bound
Above bound	63	7.94%	90.48%	1.59%
Inside bound	2539	0.47%	98.35%	1.18%
Below bound	37	5.41%	89.19%	5.41%

continued

Table 5 – continued

Unemployment				
			Quarter t+1	
Median				
Quarter t	N	Above bound	Inside Bound	Below Bound
Above bound	167	26.95%	72.46%	0.60%
Inside bound	2318	4.10%	94.22%	1.68%
Below bound	65	3.08%	76.92%	20.00%
Mean				
Quarter t	N	Above bound	Inside Bound	Below Bound
Above bound	75	24.00%	73.33%	2.67%
Inside bound	2316	1.64%	94.86%	3.50%
Below bound	159	0.63%	61.01%	38.36%
Mode				
Quarter t	N	Above bound	Inside Bound	Below Bound
Above bound	48	16.67%	83.33%	0.00%
Inside bound	2435	0.45%	98.40%	1.15%
Below bound	44	6.82%	81.82%	11.36%

This table uses the European Central Banks Survey of Professional Forecasters to calculate the percentage of forecasts that fall below(above) intervals on the measures of central tendency for adjacent quarters. Forecasters were matched using their unique ID in different surveys for a given year, where the survey spans years 1999Q1 to 2020Q2.

Table 6: Long-term persistence

GDP Growth												
Median												
	Quarter t+4				Quarter $t+8$				Quarter t+12			
Quarter t	N	Above bound	Inside Bound	Below Bound	N	Above bound	Inside Bound	Below Bound	N	Above bound	Inside Bound	Below Bound
Above bound	379	20.32%	77.57%	2.11%	360	15.00%	82.78%	2.22%	320	15.63%	81.56%	2.81%
Inside bound	2904	10.12%	87.78%	2.10%	2621	10.34%	87.75%	1.91%	2400	10.67%	87.46%	1.88%
Below bound	83	10.84%	83.13%	6.02%	73	8.22%	84.93%	6.85%	65	10.77%	81.54%	7.69%
Mean												
Quarter t	N	Above bound	Inside Bound	Below Bound	N	Above bound	Inside Bound	Below Bound	N	Above bound	Inside Bound	Below Bound
Above bound	254	17.32%	75.59%	7.09%	222	12.16%	77.93%	9.91%	195	13.33%	80.00%	6.67%
Inside bound	2894	6.84%	87.91%	5.25%	2635	6.49%	87.44%	6.07%	2404	6.74%	87.56%	5.70%
Below bound	83	10.84%	83.13%	6.02%	197	10.66%	86.29%	3.05%	186	13.44%	74.19%	12.37%
Mode												
Quarter t	N	Above bound	Inside Bound	Below Bound	N	Above bound	Inside Bound	Below Bound	N	Above bound	Inside Bound	Below Bound
Above bound	82	7.32%	87.80%	4.88%	80	3.75%	92.50%	3.75%	71	7.04%	91.55%	1.41%
Inside bound	3178	0.79%	97.67%	1.54%	2884	0.69%	97.88%	1.42%	2642	0.64%	98.11%	1.25%
Below bound	52	3.85%	94.23%	1.92%	41	4.88%	87.80%	7.32%	35	2.86%	91.43%	5.71%
Inflation												
Median												
	Quarter $t + 4$				Quarter $t + 8$				Quarter $t + 12$			
Quarter t	N	Above bound	Inside Bound	Below Bound	N	Above bound	Inside Bound	Below Bound	N	Above bound	Inside Bound	Below Bound
Above bound	281	15.30%	82.56%	2.14%	249	12.85%	85.54%	1.61%	211	15.17%	82.46%	2.37%
Inside bound	2998	7.40%	90.96%	1.63%	2719	8.46%	89.67%	1.88%	2494	8.38%	89.86%	1.76%
Below bound	53	13.21%	84.91%	1.89%	50	14.00%	84.00%	2.00%	45	11.11%	86.67%	2.22%
Mean												
Quarter t	N	Above bound	Inside Bound	Below Bound	N	Above bound	Inside Bound	Below Bound	N	Above bound	Inside Bound	Below Bound
Above bound	142	19.01%	75.35%	5.63%	134	12.69%	78.36%	8.96%	116	12.93%	80.17%	6.90%
Inside bound	3089	3.53%	93.75%	2.72%	2787	3.98%	93.40%	2.62%	2535	4.14%	92.86%	3.00%
Below bound	101	6.93%	84.16%	8.91%	97	9.28%	84.54%	6.19%	99	7.07%	88.89%	4.04%
Mode												
Quarter t	N	Above bound	Inside Bound	Below Bound	N	Above bound	Inside Bound	Below Bound	N	Above bound	Inside Bound	Below Bound
Above bound	73	8.22%	90.41%	1.37%	69	7.25%	92.75%	0.00%	54	3.70%	92.59%	3.70%
Inside bound	3167	0.47%	98.04%	1.48%	2863	0.59%	97.83%	1.57%	2620	0.57%	97.98%	1.45%
Below bound	42	7.14%	90.48%	2.38%	38	13.16%	86.84%	0.00%	37	0.00%	94.59%	5.41%

continued

Table 6 – continued

Unemployment

Median

	Quarter $t+4$				Quarter $t+8$				Quarter $t+12$			
Quarter t	N	Above bound	Inside Bound	Below Bound	N	Above bound	Inside Bound	Below Bound	N	Above bound	Inside Bound	Below Bound
Above bound	188	14.89%	84.04%	1.06%	163	17.18%	76.07%	6.75%	149	11.41%	83.89%	4.70%
Inside bound	2847	4.74%	93.05%	2.21%	2524	6.26%	88.27%	5.47%	2324	5.34%	92.60%	2.07%
Below bound	75	10.67%	82.67%	6.67%	66	10.61%	78.79%	10.61%	63	14.24%	82.54%	3.17%

Mean

	Quarter $t+4$				Quarter $t+8$				Quarter $t+12$			
Quarter t	N	Above bound	Inside Bound	Below Bound	N	Above bound	Inside Bound	Below Bound	N	Above bound	Inside Bound	Below Bound
Above bound	86	11.63%	82.56%	5.81%	73	6.85%	69.86%	23.29%	80	6.25%	80.00%	13.75%
Inside bound	2867	2.23%	92.88%	4.88%	2542	2.68%	87.25%	10.07%	2326	2.49%	92.65%	4.86%
Below bound	75	10.67%	82.67%	6.67%	138	7.97%	73.19%	18.84%	130	8.46%	81.54%	10.00%

Mode

	Quarter $t+4$				Quarter $t+8$				Quarter $t+12$			
Quarter t	N	Above bound	Inside Bound	Below Bound	N	Above bound	Inside Bound	Below Bound	N	Above bound	Inside Bound	Below Bound
Above bound	57	1.75%	98.25%	0.00%	40	7.50%	90.00%	2.50%	44	6.82%	90.91%	2.27%
Inside bound	2973	0.37%	98.05%	1.58%	2611	0.61%	96.13%	3.26%	2423	0.33%	98.14%	1.53%
Below bound	49	2.04%	91.84%	6.12%	45	2.22%	91.11%	6.67%	43	2.33%	93.02%	4.65%

This table uses the ECB's Survey of Professional Forecasters to compare forecasts made by forecasters in Quarter t of a survey year with those made in quarters $t+4$ (one year later) in the same quarter, with those in quarter $t+8$ (two years later) and $t+12$ (three years later) which are in the next survey year. The majority of quarter t forecasts of GDP growth fall within the bounds on the median and mean, and almost all forecasts fall within the bounds on the mode. The percentage of quarter t forecasts above(below) the bounds on the median compared to forecasts one-, two- and three-years later are 20.32%(6.02%), 15.00%(6.85%) and 15.63%(7.69%) respectively. For inflation the percentage of quarter t forecasts above(below) the bounds on the median compared to forecasts one-, two- and three-years later are 13.30%(1.89%), 12.85%(2.00%) and 15.17%(2.22%) respectively. For forecasts of unemployment, the percentage of quarter t forecasts that are above/below the bounds on the median one-, two- and three-years later 14.89%(6.67%), 17.18%(10.61%) and 6.25%(10%).

Table 7: Consensus forecasts - Ex Ante and Ex Post: Euro zone Output Growth, Inflation and Unemployment

h	$\overline{\sigma}_{h,eau}$	S	$\widehat{\sigma}^{median}_{h,epu}$	$\widehat{\sigma}^{mean}_{h,epu}$	$\widehat{\sigma}^{mode}_{h,epu}$	$Smedian$	$Smean$	$Smode$
Annual output growth								
8	0.02615	1.00000	0.13224	0.13297	0.12975	1.00000	1.00000	1.00000
7	0.02415	0.92352	0.12362	0.12280	0.12831	0.93479	0.92352	0.98891
6	0.02402	0.91846	0.11595	0.11629	0.11529	0.87682	0.87453	0.88855
5	0.02332	0.89165	0.11469	0.11535	0.11375	0.86732	0.86748	0.87669
4	0.02276	0.87022	0.10746	0.10714	0.10960	0.81265	0.80573	0.84471
3	0.02001	0.76517	0.09758	0.09674	0.09843	0.73791	0.72752	0.75856
2	0.01961	0.74986	0.09611	0.09543	0.09685	0.72682	0.71771	0.74640
1	0.01840	0.70346	0.07039	0.07208	0.07046	0.53229	0.54211	0.54304
Annual inflation								
8	0.03364	1.00000	0.07376	0.07243	0.07761	1.00000	1.00000	1.00000
7	0.03214	0.95563	0.06774	0.06622	0.06852	0.91836	0.91428	0.88286
6	0.03182	0.94613	0.06654	0.06482	0.06737	0.90218	0.89502	0.86814
5	0.02960	0.87999	0.05899	0.05747	0.05908	0.79977	0.79341	0.76121
4	0.02915	0.86674	0.05744	0.05618	0.05687	0.77878	0.77567	0.73274
3	0.02908	0.86457	0.05299	0.05282	0.05310	0.71848	0.72927	0.68418
2	0.02468	0.73381	0.04976	0.04909	0.05081	0.67465	0.67783	0.65471
1	0.02132	0.63399	0.04804	0.04802	0.04888	0.65127	0.66304	0.62986
Annual unemployment rate								
8	0.04352	1.00000	0.10037	0.09988	0.10275	1.00000	1.00000	1.00000
7	0.04317	0.99175	0.09634	0.09622	0.09576	0.95984	0.96339	0.93197
6	0.04306	0.98929	0.09609	0.09493	0.09309	0.95739	0.95047	0.90593
5	0.04301	0.98809	0.08416	0.08440	0.08739	0.83856	0.84500	0.85054
4	0.04263	0.97941	0.08290	0.08084	0.08398	0.82598	0.80937	0.81736
3	0.04241	0.97289	0.07085	0.07149	0.07193	0.70595	0.71580	0.70003
2	0.04234	0.97448	0.06861	0.06806	0.06829	0.68361	0.68140	0.66461
1	0.04198	0.96449	0.06539	0.06469	0.06590	0.65153	0.64768	0.64135

This table shows the ex-ante and ex-post uncertainty for each of the three macroeconomic variables for time horizons (h=1...,8). There are three measures of ex-post uncertainty using the median, mean and mode. The corresponding ratios of uncertainty in period 1 compared to period 8 are given by the corresponding columns with headers S for ex-ante uncertainty and *Smedian*, *Smean* and *Smode* for ex-post uncertainty.

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