The Measurement and Behavior of Uncertainty: Replication with Evidence from the US Survey of Professional Forecasters

Bachelor Thesis Econometrics and Operations Research

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Abstract

This research concerns the measurement and behavior of uncertainty, based on the point and probability forecasts of the Survey of Professional Forecasters from both the euro area and the United States. Several proxies are proposed to analyze the relationship with a variance- and IQR- based measure of uncertainty. Measures of disagreement and forecast accuracy do not show a meaningful linkage with uncertainty for both surveys. The aggregate point predictions however do show a meaningful linkage with uncertainty for GDP growth (euro area) and inflation (United States). This indicates that expectations of a lower GDP growth in the euro area are accompanied with higher GDP growth uncertainty. In the United States, expectations of a lower inflation rate are followed by higher inflation uncertainty. The results are not influenced by the changing composition of the respondents in the euro area. However, the varying composition of the respondents in the the United States does reduce the explanatory power of the estimated relationships.

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1 Introduction

In many areas of economic behavior, uncertainty plays an important role in understanding expectations and movements in economic time series. Bloom (2014) highlights for example that macroeconomic uncertainty rises during periods of recessions. The increase in uncertainty makes firms more prudent in hiring and investing, which hinders production growth. This is confirmed by Bachman et al. (2013), who notice that high uncertainty may lead to more cautious behavior of firms.

To better understand uncertainty, the construction of relevant measures of uncertainty is required. However, direct measures are relatively rare, so Bloom (2014) suggests that it is important to develop a wider set of uncertainty measures. Surveys provide expectations of economic outcomes, but only a limited amount of surveys report forecasts in the form of probability distributions. These so called 'density forecasts' provide a unique basis from which empirical measures of uncertainty can be derived. Engelberg et al. (2011) state that surveys of professional forecasters, on which is focused in this research, provide important inputs for regulators and financial markets. Moreover, survey derived changes in expectations can affect prices in asset markets and have large influences on policies.

This thesis replicates the research of Abel et al. (2016), by examining the matched point and density forecasts of inflation and output growth from the Survey of Professional Forecasters conducted by the European Central Bank (ECB-SPF). This research is extended with the point and density forecasts of the US Survey of Professional Forecasters (US-SPF), which includes forecasts over a larger time span. Abel et al. (2016) note that their results, using the ECB-SPF data, are heavily influenced by the one recessionary episode in their data: the global financial crisis of 2008. This indicates the need to replicate their research over a larger time span, and compare the results. Furthermore, Sauter (2012) and Beechey et al. (2007) point out that there is hardly any analysis on the expectations and identification of uncertainty via survey based forecasts from both the ECB- and US-SPF yet. Beechey et al. (2007) compare the anchoring of inflation expectations in the euro area and the United States. They argue that the Unites States and the euro area are of comparable size and openness. Moreover, both the Federal Reserve and the European Central Bank have the regulatory power and instruments to preserve price stability. These two central banks however formulate and communicate their policy strategies in different ways, which makes it interesting to compare expectations in the two areas.

The density forecasts of the survey respondents are used to construct two measures of uncertainty: a variance-based and an interquartile range-based measure. These two measures are compared to measures of disagreement and predictive accuracy, to evaluate whether they are reliable proxies for uncertainty. According to Bloom (2014), periods in which professional forecasters hold more diverse opinions are likely to reflect greater uncertainty. Moreover, Giordani & Söderlind (2003) report that disagreement amongst professional forecasters can serve as a reasonable proxy for inflation and GDP uncertainty. Clements (2008) also examines the relationship between output growth uncertainty and disagreement using forecast probabilities, and reports a correlation between 0.32 and 0.52. The relationship between uncertainty and predictive accuracy is explored by Rich & Tracy (2003), but the results do not indicate a strong relation. This conclusion is confirmed by this research for the ECB-SPF data. However, the relation does seem to be somewhat more evident for the US-SPF data.

Next, the relationship between uncertainty and the aggregate point predictions is analyzed, to investigate whether changes in uncertainty may be accompanied by changes in expectations. This relationship is also examined by Rich & Tracy (2010), who find evidence that an increase in expectation is accompanied by heightened uncertainty. Abel et al. (2016) confirm this meaningful co-movement between uncertainty and aggregate point predictions for GDP growth. This research adds to this discussion by re-examining this relation using the US-SPF data, which consists of a considerably larger sample.

Lastly, the compositional effects of the survey data are analyzed, since there is a large variation in the number and composition of respondents in both the US- and ECB-SPF data. This may cause movements in the measures that do not reflect a change in behavior, but indicate a variation in panel respondents. The problem of a changing panel composition is also assessed by Engelberg et al. (2011), who recommend an analyses of sub-panels of fixed composition. This research follows their suggestion, but the analysis of five different sub-panels does not result in significant differences between the results for the ECB-SPF data. For the US-SPF data however, the varying composition of the respondents reduces the explanatory power of the estimated relationships.

The next section of this thesis gives a detailed description of the ECB-SPF and US-SPF data. Section 3 includes the methodology of the construction of the uncertainty measures and the relations between uncertainty and different proxies. Also, the compositional effects are considered. In section 4, the results of the estimated relations and the compositional effects are discussed, and section 5 provides a summarizing conclusion.

2 Data

This research is based on data from the Survey of Professional Forecasters from both the euro area and the United States. In this section, both the ECB-SPF and US-SPF are described in more detail. Also, some differences between the ECB-SPF and US-SPF are illustrated, and required transformations proposed.

2.1 Euro Area

The ECB-SPF is a quarterly survey conducted by the European Central Bank since 1999. The panel consists of about 40 active forecasters per period, who are from financial and non-financial institutions throughout the euro area. The survey includes point and density forecasts for real GDP growth and the harmonized index of consumer price (HICP) inflation. For the density forecasts, respondents are asked to report a probability distribution over a set of intervals. These intervals are provided by the European Central Bank and vary for the different macroeconomic target variables.

The ECB-SPF point and density forecasts are based on a rolling horizon, which means that the length of the horizon remains constant through time. The forecasts include three different horizons: 1-year-ahead, 1-year/1-year forward and a longer-term. However, the realized values of HCIP inflation and GDP growth are published with a lag and at different data frequencies (monthly and quarterly). This results in 1-year-ahead and 1-year/1-year forward forecasts for output growth with a 2-quarter lag and for HCIP inflation with a 1-month lag (see Garcia (2003) for more details). The longer-term horizon is equal to 4 years ahead for surveys that are conducted in the first and second quarter, and 5 years ahead for the surveys conducted in the third and fourth quarter.

The width of the intervals for the density forecasts is equal to 0.4 percentage point for both GDP growth and HCIP inflation, and remains constant through time. There is a gap between the intervals of 0.1 percentage point, which is closed by extending the lower-end and upper-end intervals by 0.05 percentage points. This results in a width of the intervals of 0.5 percentage points. The left-most and right-most exterior intervals do not include end points (open intervals). Since the construction of the measures of uncertainty requires an upper and lower limit of each interval, these open intervals should be closed with some value. I follow the procedure of Andrade et al. (2012), who assume that the the open intervals may have a width of twice the length of the closed intervals (in this case one percentage point).

Although the width of the intervals is fixed, the number of intervals changes over time. Garcia (2003) argues that the open intervals should not receive a significantly high proportion of the probability, and should be more or less ”redundant”. To accomplish this, new intervals should be added over time.

2.2 United States

The US-SPF is a quarterly survey of forecasters' views on key economic variables, conducted since 1968:Q4. The survey panel consist of about 600 professional forecasters, with on average about 40 active forecasters per period. Each respondent is asked to report point and density forecasts of the real GDP growth and GDP price inflation. Note that Abel et al. (2016) consider density forecasts of the CPI inflation. The US-SPF does not provide CPI inflation density forecasts before 2007:Q1, so Andrade et al. (2012) propose the GDP price inflation as a substitute. In this research, I follow their approach, while taking this difference into consideration when interpreting the results.

Apart from the quarterly forecasts, the forecast horizon extends to a 1-year-ahead forecast from 1981:Q3 onwards. Since this research incorporates these 1-year-ahead forecasts, the sample is adjusted to 1981:Q3 until 2016:Q4. Furthermore, from 1981:Q3 to 1991:Q4 the GNP is considered instead of the GDP. This difference is however not taken into account, since fluctuations in both the GDP and GNP are indicative of the state of the business cycle (Rossi et al., 2017).

The forecasters report their probability distribution of the inflation and output growth using a given set of intervals. These intervals evolved over time (see table 7 and 8 of the US-SPF documentation for more information):

Table 1: US-SPF Probability Intervals

	Inflation				GDP Growth		
	1981:Q3 to 1985:Q1	1985:Q2 to 1991:Q4	1992:Q1 to 2013:Q4	2014:Q1 to Present	1981:Q3 to 1991:Q4	1992:Q1 to 2009:Q1	2009:Q2 to Present
Nr of intervals	6	6	10	10	6	10	11
Width of intervals	2%	2%	1%	0.5%	2%	1%	1%
Maximum value	12%	10%	8%	4%	6%	6%	6%
Minimum value	4%	2%	0%	0%	-2%	-2%	-3%

Note that at the beginning of the sample the intervals are wider, which gives the forecasters less opportunities to differentiate among intervals. This difference is taken into account when interpreting the results. For the open intervals, I follow the closing procedure as described above for the ECB-SPF data, based on Andrade et al. (2012). However, the US-SPF intervals have different widths, so the proposed width of the open intervals differs per period.

As mentioned above, the ECB-SPF point and density forecasts are based on a rolling horizon. However, the US-SPF density forecasts are based on a fixed event: the forecasters provide their probability estimates for the current year (the year in which the survey is conducted) and the following year. Since this research aims to compare the ECB- and US-SPF results, it is necessary to transform the US density forecasts to a rolling horizon. Rossi et al. (2017) propose to take a weighted average of the current and next year fixed-event forecasts:

$$\hat{d}^{RH}_{t+4|t} = \frac{k}{4}\hat{d}^{FE}_{t+k|t} + \frac{4-k}{4}\hat{d}^{FE}_{t+k+4|t} \tag{1}$$

where $\hat{d}^{RH}_{t+4|t}$ denotes the four-quarter-ahead rolling horizon density forecasts at time t and k ($k = 1, 2, 3, 4$) refers to the number of quarters till the end of the year at time t. Furthermore, $\hat{d}^{FE}_{t+k|t}$ and $\hat{d}^{FE}_{t+k+4|t}$ are the fixed-event density forecasts for the current and next year, respectively.

Another difference between the ECB-SPF and US-SPF concerns the definition of the point forecasts. The US-SPF point forecasts are forecasts of the target variable for the current quarter, and the four following quarters, whereas the ECB-SPF asks for annual percentage change point forecasts. However, the density forecasts of the US-SPF are defined as the annual average percentage change, instead of the annual percentage change. The US-SPF point forecasts are transformed to match the US-SPF density forecasts. I follow the procedure of Rich & Tracy (2010), where the annual average percentage change is defined as follows:

$$ {}_i f^e_{t,q} = 100 \left[\frac{{}_i P^e_{t,q+1} +_i P^e_{t,q+2} +_i P^e_{t,q+3} +_i P^e_{t,q+4}}{P_{t,q-3} + P_{t,q-2} + P_{t,q-1} +_i P^e_{t,q}} - 1 \right] \tag{2} $$

where ${}_i f^e_{t,q}$ is the point forecast of respondent i, in quarter q of year t. Furthermore, ${}_i P^e_{t,q}$ is respondent i's predicted value of the target variable, and $P_{t,q}$ is the realized value of the target variable, in quarter q of year t. The transformed point forecasts are now consistent with the US-SPF density forecasts, but slightly differ from the ECB-SPF forecasts in the way that these forecasts do not represent an average. However, this difference is beyond the scope of this research.

The former transformation requires the input of realized values of GDP growth and GDP price inflation. The Federal Reserve Bank of Philadelphia provides real-time vintage data of these target variables, where vintage data is defined as a set of data with the latest estimates for each target variable at a particular moment in time. This results in a collection of time series data indexed by the date on which the vintage became available to the public. The availability of this data allows for the transformed forecasts to correspond to the same values that would have been computed at the time the survey was conducted.

3 Methodology

This section describes how the two different measures of uncertainty, disagreement and forecast accuracy are derived from the point and density forecasts. Also, a detailed description of the regression specifications for the following relations is provided: uncertainty and disagreement, uncertainty and forecast accuracy, and the relationship between uncertainty and aggregated point predictions. Finally, compositional effects are discussed.

3.1 Disagreement and Forecast Accuracy

To get more insight in uncertainty and its relations, a definition of uncertainty is required. I consider two different measures of uncertainty. The first measure assumes a uniform probability distribution within each interval of the respondents' density forecast, which follows Zarnowitz & Lambros (1987). The variance of respondent i's density forecast for the survey conducted in quarter q of year t is defined as follows:

$$ {}_i\sigma^2_{q,t} = \Big[\sum_n {}_i p_n \Big(\frac{u_n^3 - l_n^3}{3 * (u_n - l_n)} \Big) \Big] - \Big[\sum_n {}_i p_n \Big(\frac{u_n^2 - l_n^2}{2 * (u_n - l_n)} \Big) \Big]^2 \tag{3} $$

where ${}_i p_n$ is the probability assigned by respondent i to the nth interval, and l_n and u_n are the lower and upper limits of the nth interval, respectively. The uncertainty measure is defined as $\bar{\sigma}^2_{q,t}$, the average of the respondents' variances.

The second measure of uncertainty is based on the interquartile range (IQR) of respondent i's density forecast in quarter q of year t (${}_i\phi_{q,t}^{IQR}$). Here, I again assume a uniform distribution over the intervals. Furthermore, the 25th and 75th percentiles are identified by means of interpolation. The aggregated uncertainty measure is defined as the median of the survey IQR values:

$$\tilde{\phi}_{q,t}^{median} =_{0.50} \tilde{\phi}_{q,t} \tag{4}$$

where $\tilde{\phi}_{q,t}$ denotes an ordered array of the IQR values from a survey in quarter q of year t.

The first proxy of uncertainty is disagreement, and is based on the respondents' point predictions. ${}_if_{q,t}$ refers to respondent i's point prediction of the survey from quarter q of year t. I consider two measures of disagreement, which follow the approach of the two uncertainty measures. The first measure is the cross-sectional variance of the point predictions ($s_{q,t}^2$). The second measure is the IQR of the point predictions ($\tilde{f}_{q,t}^{IQR}$). The linkage between disagreement and uncertainty is measured by means of the following regression:

$$\bar{\sigma}_{q,t}^2 = \alpha + \beta \cdot s_{q,t} + \varepsilon_{q,t} \tag{5}$$

$$\tilde{\phi}_{q,t}^{median} = \alpha + \beta \cdot \tilde{f}_{q,t}^{IQR} + \varepsilon_{q,t} \tag{6}$$

where $\varepsilon_{q,t}$ is random and has a mean equal to zero.

The forecast error variance is the second proxy for uncertainty, which is estimated with time series models of heteroskedasticity. This relates the conditional variance of the target variable ($h_{q,t}^e$) to changes in predictability (η_τ^2). The model is specified as follows:

$$\begin{aligned} X_\tau &= X_{q,t}^e + \eta_\tau \\ \eta_\tau^2 &= h_{q,t}^e + \varepsilon_\tau \end{aligned} \tag{7}$$

Here, X_τ denotes the target variable (inflation or GDP growth), and $X_{q,t}^e$ denotes the mean of this target variable conditional on $I_{q,t}$ (all available information in quarter q of year t). Furthermore, $E[\eta_\tau|I_{q,t}]$ and $E[\varepsilon_\tau|I_{q,t}]$ are equal to zero. By substituting $h_{q,t}^e$ in equation 7 with the two proposed uncertainty measures, the predictive accuracy-uncertainty linkage can be evaluated by means of the following expressions for the conditional variance:

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

$$\eta_\tau^2 = \alpha + \beta \cdot (\tilde{\phi}_{q,t}^{median}) + \varepsilon_\tau \tag{9}$$

where $E[\varepsilon_t|I_{q,t}]$ is equal to zero.

A measure of the forecast error ($\eta_t = X_\tau - X_{q,t}^e$) is required to estimate this regression, where X_τ is the value of the realized target variable. I consider three measures: the unadjusted aggregate forecast error, the bias-adjusted forecast error and the mean/median of the individual forecast errors. The first two measures are based on a summary of the individual prediction errors, whereas the last measure considers the individual prediction errors themselves.

For the unadjusted aggregate forecast error measure, I approximate the conditional mean ($X_{q,t}^e$) with an aggregate of the individual point predictions, such as the mean ($\bar{f}_{q,t}$) or the median ($\tilde{f}_{q,t}^{median}$). The second measure corrects for a bias in the forecasts by means of a two-stage estimation. This bias is examined by Bowles et al. (2007), who statistically test whether the ECB-SPF forecast errors are zero on average. In the first stage, X_τ is regressed on a constant and the aggregate point prediction. The forecast error measure is based on the residuals of this regression. The third forecast error measure is the mean/median of the individual squared forecast errors.

3.2 Aggregate Point Forecasts

Next, the relation between uncertainty and the aggregate point predictions is considered. This gives some insight in the effects of rising inflation/GDP on uncertainty. I examine the linkage between expected output growth and output growth uncertainty, and the relation between expected inflation and inflation uncertainty, for the variance- and IQR-based measures of uncertainty.

$$\bar{\sigma}^2_{q,t} = \alpha + \beta \cdot X^e_{q,t} + \varepsilon_{q,t} \tag{10}$$

$$\tilde{\phi}^{median}_{q,t} = \alpha + \beta \cdot X^e_{q,t} + \varepsilon_{q,t} \tag{11}$$

where $X^e_{q,t}$ denotes the mean of the target variable, conditional on all information available at the time of the survey conducted in quarter q of year t.

3.3 Compositional Effects of Respondents

For the sample period 1999:Q1 to 2013:Q4, the ECB-SPF includes an average of 36 to 46 respondents, after excluding the respondents that did not provide a point and density forecast, or where the density forecasts did not sum up to a probability of more than 99%. More details about the number of invalid responses can be found in Appendix A. The US-SPF includes, after excluding respondents on the same restrictions, an average of 21 to 48 respondents over the same period. This means a frequent exit and entry pattern of respondents, where the variance of average respondents in the US-SPF is even larger than for the ECB-SPF.

Most of the respondents seem infrequent respondents, since the percentage of participating respondents in at least half of the US-surveys is 11%. For the ECB-surveys, this percentage is equal to about 73% percent. This large difference between the US-SPF and ECB-SPF could be due to the difference in time span. Since the composition of the US-SPF respondents is so variable, it is interesting to examine if this has an effect on the results. By varying the panel of respondents, the results can be reviewed for different subsets. These subsets are based on a required minimum of surveys in which each respondent should participate, ranging from 5 to 25. The average number of completed surveys by a respondent is equal to 23 for the US-SPF and 37 for the ECB-SPF. The remaining amount of respondents after restricting the minimum amount of completed surveys to 25 per respondent is equal to 40 for the US- and 34-51 for the ECB-surveys. This seems a sufficiently large group to gain reliable insights in the compositional effects.

4 Results

This section first examines the results of the estimated relationships between uncertainty and disagreement, and uncertainty and forecast accuracy. Next, the relationship between uncertainty and three different measures of aggregated point forecast are considered. Finally, the effects of a changing composition in the forecasters panel is explored. All results are discussed for the target variables inflation and GDP for both the ECB-SPF and US-SPF data.

4.1 Disagreement and Forecast Accuracy

Figure 1 and 2 show the time series of the uncertainty and disagreement measures from the ECB-SPF (left) and the US-SPF (right) for inflation and GDP growth. The top panels represent the variance-based approach, whereas the bottom panels illustrate the IQR-based approach, all based on the one-year-ahead-horizon. The vertical lines in the US-SPF plots indicate a change in interval widths, as described in Table 1.

The behavior of the ECB-SPF uncertainty measure for both inflation and GDP is quite similar for the two approaches, and shows an upward shift from 2007:Q2. The level of the disagreement

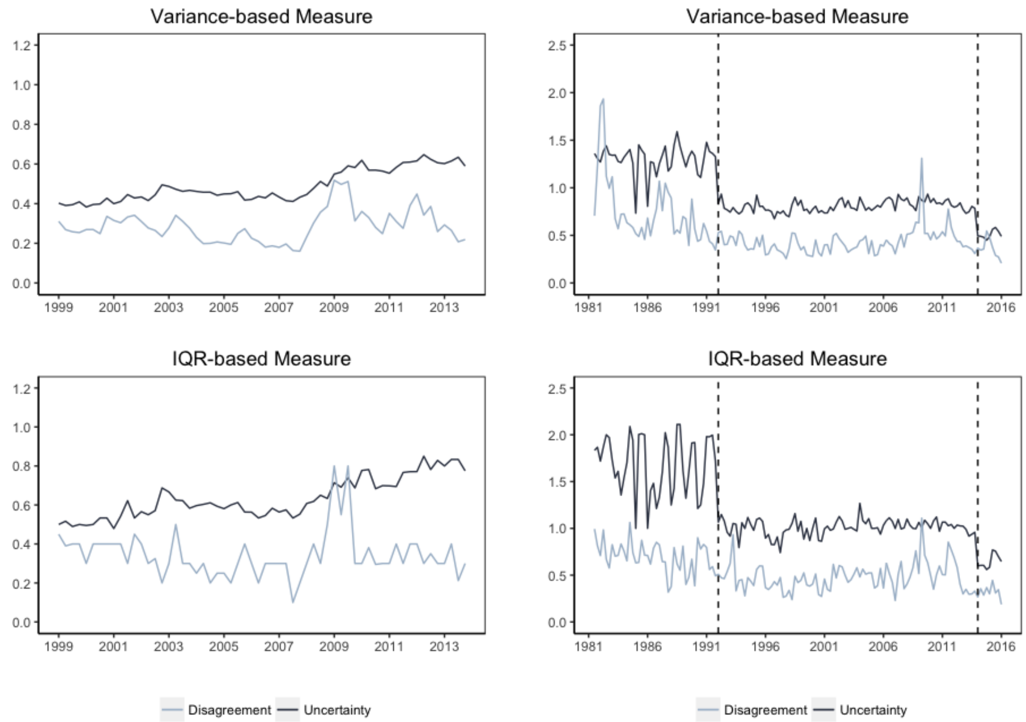

Figure 1: Disagreement and Uncertainty: Inflation one-year-ahead
ECB-SPF (left) - US-SPF (right)

measure is clearly lower, but also comparable for the two approaches, although the IQR-based disagreement measures seems to fluctuate more. A large peak is noticeable around 2009, especially for the GDP growth measures. Abel et al. (2016) argue that the GDP growth forecasts from the survey of 2009:Q1 should be excluded, due to excessive high probabilities in the open-ended intervals of a growth rate of -1% or less. These highly pessimistic forecasts are not incorporated in the survey design, which caused the probabilities to be very concentrated around the lowest intervals. This resulted in a very low value of the uncertainty measure. In this research I follow the approach of Abel et al. (2016) and exclude 2009:Q1 from the ECB-SPF GDP growth forecasts.

The measures based on the US-SPF forecasts result in similar conclusions, with a clearly lower level of the disagreement measure and quite similar patterns of the measures for the two approaches. However, the level of the IQR-based approach uncertainty measure for the GDP growth lies higher. The peaks around 2009 are also very noticeable here. Two peaks of similar size can be seen in the period from 1981 to 1985, which could be due to a recession in the United States in the early 1980s. Furthermore, there seems to be considerably more variation in the measures before 1991, for both inflation and GDP. This change in variation is very likely to be caused by the change in number of intervals. Since 1992:Q2 the number of intervals for both GDP growth and inflation changed from 6 to 10. This gives the respondents the possibility to differentiate more among intervals. This result is in line with Rich & Tracy (2010), who did extensive research on the effects of the change of intervals widths among the density forecasts. The different interval widths lead to clearly lower estimates of their inflation uncertainty measure after 1991:Q4. Another peak in the uncertainty and disagreement measures is visible around 2001, especially for the GDP growth forecasts. This increase in uncertainty could be explained by the collapse of the dot-com bubble (Martin & Ventura (2012)).

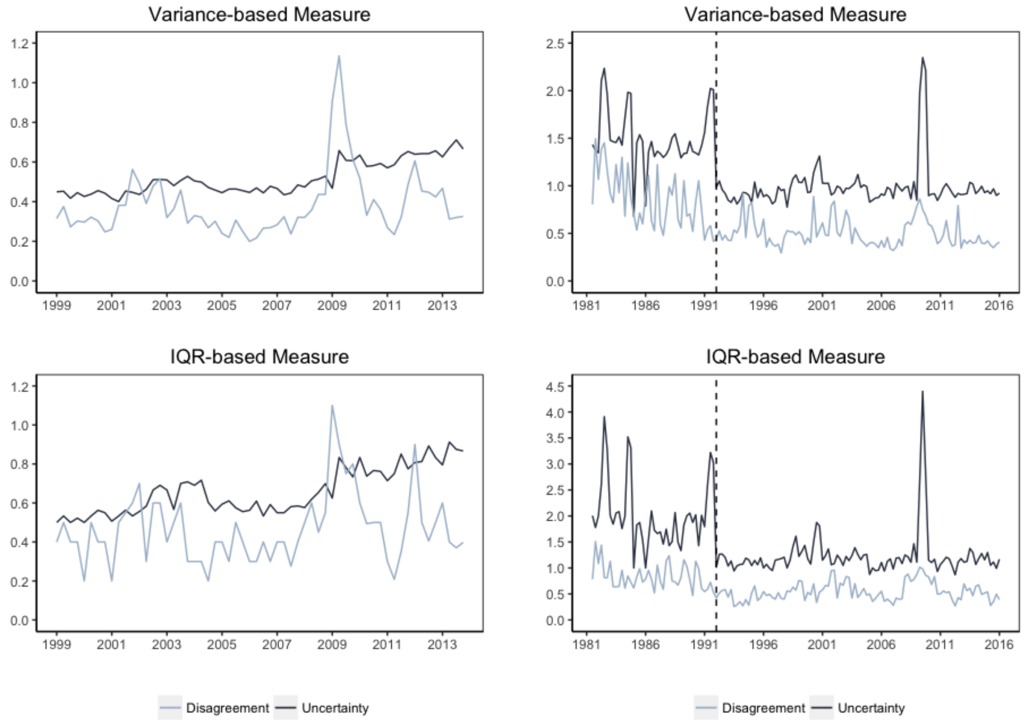

Figure 2: Disagreement and Uncertainty: GDP Growth one-year-ahead
ECB-SPF (left) - US-SPF (right)

Table 2 reports the correlations of the uncertainty and disagreement measures with the GDP growth rate, over different periods. For the ECB-SPF data, the full sample period from 1999:Q1 to 2014:Q4, and a truncated sample period are shown. This truncated sample period excludes post 2007:Q2 data, due to the high volatility during the financial crisis of 2008. For the US-SPF data, the full sample period of the ECB-SPF data is shown for comparison reasons. Next to that, the results of the full sample period from 1981:Q3 to 2016:Q4 are presented. These correlations give more insight in the cyclical properties of the measures. The correlations of the ECB-SPF data are almost all negative and significant for the uncertainty measures, which indicates cyclical behavior. The disagreement measures seem less significant, especially for the truncated sample. The results deviate slightly from the correlations reported by Abel et al. (2016), which could be due to different realized values of the GDP growth rate. The GDP growth rate is published quarterly and the formerly published rates are revised quarterly. This results in a new set of updated GDP growth rates every quarter. For the ECB-SPF data, the latest available data is used, so this could cause a difference. The correlations based on the US-SPF data, which are all insignificant and close to zero, do not seem to display any cyclical behavior.

The results from estimating the relation between uncertainty and disagreement (equations 5 and 6) are shown in Table 3. For the ECB-SPF, the table reports all three horizons for inflation and GDP, over the full sample. For the US-SPF only the one-year-ahead horizon is available, so the results are reported over the ECB-SPF full sample (1999:Q1 to 2013:Q4), and the US-SPF full sample (1981:Q3 to 2016:Q4). The significance of the parameters is based on the standard errors conducted with the Newey & West (1987) variance-covariance estimator, proposed by Abel et al. (2016).

Table 2: Correlations between Uncertainty and Disagreement with GDP Growth Rate

	1999:Q1 to 2013:Q4				1999:Q1 to 2007:Q2			
	Variance-based measures		IQR-based measures		Variance-based measures		IQR-based measures	
ECB-SPF data	$\bar{\sigma}$	s	$\tilde{\phi}^{median}$	$\tilde{f}^{IQR}$	$\bar{\sigma}$	s	$\tilde{\phi}^{median}$	$\tilde{f}^{IQR}$
HICP inflation: horizon								
1-year-ahead	-0.519**	-0.401**	-0.522**	-0.100	-0.432**	-0.254	-0.450**	0.132
1-year/1-year forward	-0.547**	-0.214*	-0.543**	-0.096	-0.508**	-0.064	-0.540**	0.139
Long term	-0.360**	-0.094	-0.333**	0.091	-0.259	-0.123	-0.257	-0.132
GDP growth: horizon								
1-year-ahead	-0.0496**	-0.458**	-0.483**	-0.392**	-0.322*	-0.318*	-0.355*	-0.286*
1-year/1-year forward	-0.515**	-0.361**	-0.504**	-0.297*	-0.470**	-0.091	-0.472**	0.027
Long term	-0.401**	-0.052	-0.332**	0.208	-0.288	0.162	-0.203	0.533**
US-SPF data	1999:Q1 to 2013:Q4				1981:Q3 to 2016:Q4			
Inflation: horizon								
1-year-ahead	-0.095	-0.282	-0.017	-0.014	0.022	-0.001	0.067	-0.001
GDP growth: horizon								
1-year-ahead	0.061	-0.098	0.045	-0.029	0.056	0.062	0.057	-0.005

Notes: The ECB-SPF and US-SPF correlations are shown over the ECB-SPF full sample period from 1999:Q1 to 2013:Q4. Furthermore, the ECB-SPF correlations are displayed for a truncated sample period from 1999:Q1 to 2007:Q1, and the US-SPF correlations for the full sample period from 1981:Q3 to 2016:Q4. Significance levels: ** 1%; * 5%.

Table 3: Uncertainty and Disagreement

	Variance-based measures			IQR-based measures		
	$\bar{\sigma}^2_{q,t} = \alpha + \beta * s_{q,t} + \varepsilon_{q,t}$			$\tilde{\phi}^{median}_{q,t} = \alpha + \beta * \tilde{f}^{IQR}_{q,t} + \varepsilon_{q,t}$		
ECB-SPF data	$\bar{R}^2$	α	β	$\bar{R}^2$	α	β
HICP inflation: horizon						
1-year-ahead	0.182	0.365** (0.033)	0.438** (0.106)	-0.011	0.610** (0.050)	0.070 (0.117)
1-year/1-year forward	0.090	0.457** (0.035)	0.336* (0.149)	0.008	0.644** (0.065)	0.177 (0.243)
Long term	0.035	0.544** (0.050)	0.233 (0.274)	0.136	0.831** (0.063)	-0.414 (0.252)
GDP growth: horizon						
1-year-ahead	0.196	0.424** (0.030)	0.254** (0.059)	0.071	0.556** (0.054)	0.226** (0.085)
1-year/1-year forward	0.124	0.427** (0.057)	0.496** (0.175)	0.101	0.593** (0.053)	0.402** (0.103)
Long term	0.139	0.499** (0.033)	0.576** (0.166)	0.049	0.743** (0.038)	0.279 (0.188)
US-SPF data						
Inflation: horizon						
1-year-ahead	0.118	0.761** (0.024)	0.133** (0.046)	0.038	0.970** (0.035)	0.106* (0.062)
1-year-ahead full sample	0.294	0.643** (0.073)	0.567** (0.116)	0.291	0.602** (0.117)	1.100** (0.230)
GDP growth: horizon						
1-year-ahead	0.147	0.641** (0.185)	0.763* (0.434)	0.156	0.626* (0.284)	1.120* (0.562)
1-year-ahead full sample	0.321	0.676** (0.069)	0.771** (0.114)	0.206	0.717** (0.119)	1.190** (0.226)

Notes: The sample period runs from 1999:Q1 to 2013:Q4. However, the one-year-ahead full sample horizon from the US-SPF data runs from 1981:Q3 to 2016:Q4. The standard errors are based on the Newey & West (1987) variance-covariance matrix estimator. One-tailed statistical significance levels: ** 1%; * 5%.

There is a positive relation between the uncertainty measures and disagreement in all cases, except one. The variance-based measure seems to show a more significant relationship, for both the ECB- and US-SPF data. For the US-SPF, the 1-year-ahead full sample shows a stronger relationship than the 1-year-ahead forecasts for the smaller ECB-SPF horizon. Overall, almost all beta estimates are positive and significant. The adjusted R^2 ($\bar{R}^2$) statistics however, are very low, which indicates little explanatory power. The values are on average equal to about 15%, with the highest explanatory power of 32% for variance-based measure of the US-SPF data. The rest of the $\bar{R}^2$ values seem a little higher for the US-SPF data, especially for the larger full sample. This could be due to the length of the sample period, since the measures are less influenced by one recessionary period as is the case for the ECB-SPF full sample period (financial crisis of 2008).

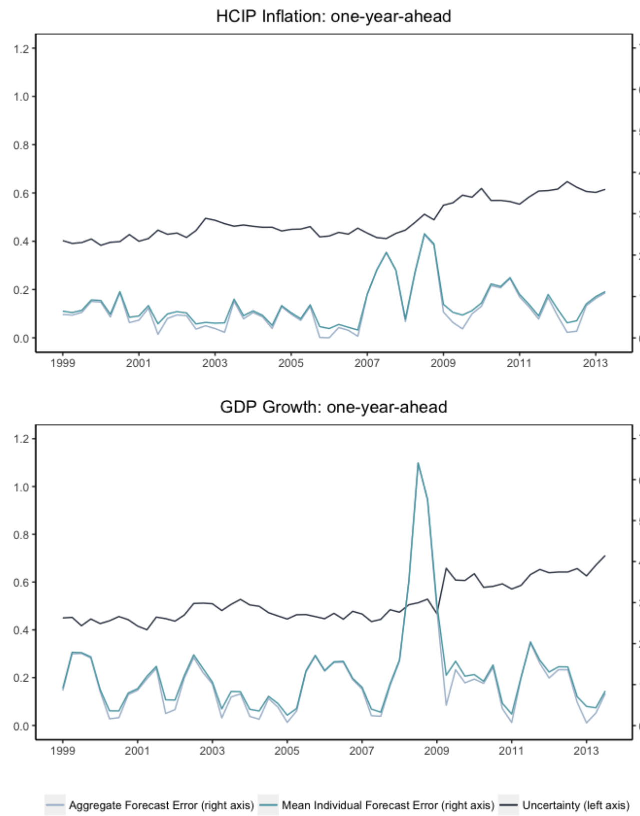

Figure 3: Predictive Accuracy and Uncertainty: ECB-SPF

Figures 3 and 4 show the time series of the variance-based uncertainty measure and two measures for the forecast error: the aggregated forecast error and the mean individual forecast error, for both inflation and GDP at the 1-year-ahead horizon. Figure 3 is based on the ECB-SPF data and covers the period from 1999:Q1 to 2013:Q2, whereas Figure 4 is based on the US-SPF data and covers the larger period of 1981:Q3 to 2016:Q1. The time periods are shorter, due to the lack of availability of real-time data of the target variable inflation and GDP, which is required to construct the forecast error measures. Again, the vertical lines represent a change in interval widths, as described in Table 1.

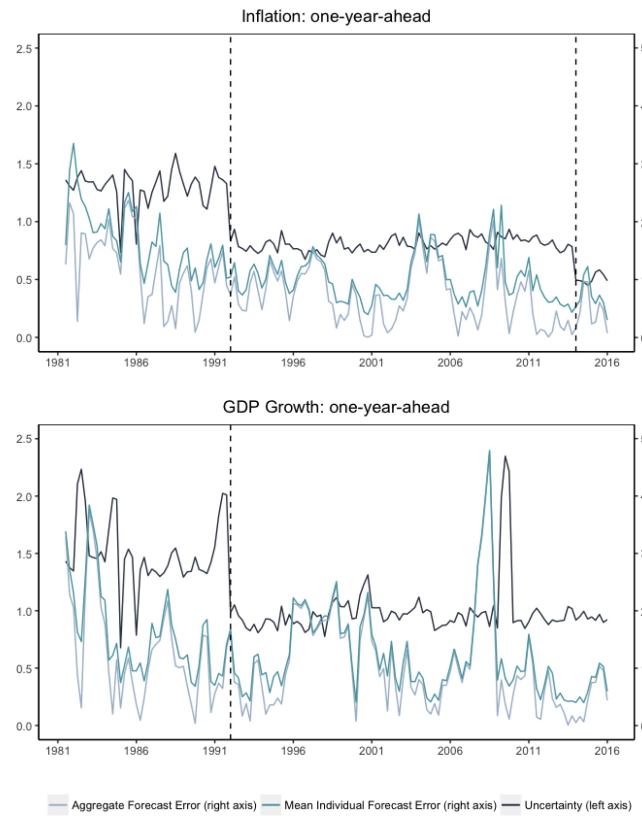

Figure 4: Predictive Accuracy and Uncertainty: US-SPF

For the ECB-SPF data in Figure 3, there is very little difference between the two forecast error measures. Again, there is a big spike around 2009, especially for the GDP growth series. For both inflation and GDP, the forecast error measures have a considerably higher mean value and variance compared to the variance-based uncertainty measure. The US-SPF measures in Figure 4 show a similar pattern, with an even higher variance of the forecast errors compared to the uncertainty measure. The big spike in forecast error around 2009 is also for the US data evidently visible in the GDP growth series. The spike occurs right before the peak in the uncertainty measure, due to the sudden drop of GDP growth values that caused large forecast errors. Around 1983, the forecast error also increases drastically, due to a recession in the United States in the early 1980s.

The results from estimating the relation between uncertainty and predictive accuracy (equations 8 and 9) are shown in Table 4. The table reports the three different measures of forecast accuracy for inflation and GDP growth at the one-year-ahead horizon, over the full sample period (1999:Q1 to 2013:Q4 for the ECB-SPF and 1981:Q3 to 2016:Q4 for the US-SPF). Although most of the β coefficients are positive, almost none seem statistically significant. Also, the $\bar{R}^2$ are all very close to zero, which indicates no relation between the uncertainty measures and predictive accuracy. The US-SPF measures however do show a significant β coefficient for the inflation unadjusted aggregate forecast error and the mean/median of the individual forecast errors, for both the variance- and IQR-based measures. Also, the $\bar{R}^2$ of these regressions are considerably higher, with values around 20%. These results can be explained by the large variance in the forecast accuracy measures, especially in comparison to the much less volatile uncertainty measures. The forecast accuracy measures of the US-SPF data are less volatile (see Figure 4), which explains the higher $\bar{R}^2$ value.

Table 4: Uncertainty and Predictive Accuracy: one-year-ahead horizon

	Variance-based measures			IQR-based measures		
	$\eta_\tau^2 = \alpha + \beta * \bar{\sigma}_{q,t}^2 + \varepsilon_\tau$			$\eta_\tau^2 = \alpha + \beta * (\tilde{\phi}_{q,t}^{median}) + \varepsilon_\tau$		
ECB-SPF data	$\bar{R}^2$	α	β	$\bar{R}^2$	α	β
HICP inflation						
Unadjusted aggregate forecast error	-0.018	0.782 (0.548)	0.041 (1.784)	-0.018	0.813 (0.540)	-0.060 (1.011)
Bias-adjusted aggregate forecast error	-0.014	0.381 (0.594)	0.915 (2.010)	-0.008	0.262 (0.588)	0.845 (1.209)
Mean/median of individual forecast errors	-0.017	0.790 (0.539)	0.371 (1.751)	-0.018	0.810 (0.538)	-0.029 (1.004)
GDP growth						
Unadjusted aggregate forecast error	-0.018	2.658 (1.789)	-0.556 (3.808)	-0.018	2.459* (1.500)	0.052 (2.063)
Bias-adjusted aggregate forecast error	-0.018	2.267 (1.541)	0.196 (3.764)	-0.018	2.129 (1.331)	0.427 (2.110)
Mean/median of individual forecast errors	-0.018	2.591 (1.884)	0.273 (4.235)	-0.018	2.456* (1.497)	0.080 (2.067)
US-SPF data						
Inflation						
Unadjusted aggregate forecast error	0.153	0.110 (0.154)	0.451* (0.194)	0.201	0.098 (0.151)	0.299* (0.127)
Bias-adjusted aggregate forecast error	-0.005	0.317** (0.125)	-0.038 (0.081)	-0.006	0.304** (0.113)	-0.016 (0.037)
Mean/median of individual forecast errors	0.254	0.097 (0.205)	0.806** (0.291)	0.216	0.120 (0.151)	0.305** (0.127)
GDP growth						
Unadjusted aggregate forecast error	-0.007	1.994** (0.726)	0.005 (0.313)	-0.007	2.054** (0.543)	-0.017 (0.085)
Bias-adjusted aggregate forecast error	-0.007	1.992** (0.553)	-0.056 (0.236)	-0.006	2.004** (0.395)	-0.032 (0.065)
Mean/median of individual forecast errors	-0.003	2.102** (0.374)	0.221 (0.374)	-0.007	2.067** (0.542)	-0.009 (0.085)

Notes: The results are based on the full sample period for both the ECB-SPF (1999:Q1 to 2013:Q4) and US-SPF data (1981:Q3 to 2016:Q4). The standard errors are based on the Newey & West (1987) variance-covariance matrix estimator. One-tailed statistical significance levels: ** 1%; * 5%.

4.2 Aggregate Point Forecasts

Table 5 reports the results of the estimated relation between uncertainty and changes in expectations, which are based on the aggregate point predictions (equations 10 and 11). For the ECB-SPF, the table reports all three horizons for inflation and GDP, over the full sample. For the US-SPF the one-year-ahead horizon results are reported over the ECB-SPF full sample (1999:Q1 to 2013:Q4), and the US-SPF full sample (1981:Q3 to 2016:Q4). There is a clear difference between the estimation results for inflation and GDP of the ECB-SPF data. Whereas nearly all inflation regressions have insignificant β coefficients and $\bar{R}^2$ values around zero, the GDP regressions result in significant coefficients for all horizons and much higher $\bar{R}^2$ values of around 55%. This indicates a strong relationship between uncertainty and the aggregated point predictions for GDP growth, so expectations of a lower growth is related to higher growth uncertainty.

For the US-SPF data regressions, the contrary is true. Here, GDP growth shows no significant β coefficients and an explanatory power close to zero. The inflation results however do show a strong relationship between uncertainty and expectations, for the larger US-SPF sample period. These $\bar{R}^2$ values are very comparable with the ECB-SPF data of GDP growth. This suggests that expectations of a lower inflation rate are accompanied with higher inflation uncertainty. The low $\bar{R}^2$ values for GDP growth can be explained by the pattern of the forecast errors in Figure 4. A large jump in the forecast error of GDP growth is visible from 1996 to 2001. This peak is not captured by the uncertainty measure, which has an effect on the weak relationship between the uncertainty and expectations. Furthermore, both the ECB- and US-SPF results show similar results across the two uncertainty measures.

Table 5: Uncertainty and Aggregate Point Predictions

	Variance-based measures			IQR-based measures		
	$\bar{\sigma}^2_{q,t} = \alpha + \beta * X^e_{q,t} + \varepsilon_{q,t}$			$\tilde{\phi}^{median}_{q,t} = \alpha + \beta * X^e_{q,t} + \varepsilon_{q,t}$		
ECB-SPF data	$\bar{R}^2$	α	β	$\bar{R}^2$	α	β
HICP inflation: horizon						
1-year-ahead	0.017	0.592** (0.123)	-0.061 (0.065)	-0.005	0.712** (0.153)	-0.049 (0.082)
1-year/1-year forward	-0.002	0.702* (0.311)	-0.090 (0.166)	-0.017	0.746* (0.442)	-0.031 (0.233)
Long term	0.363	-0.757* (0.336)	0.698** (0.179)	0.131	-0.126 (0.491)	0.453 (0.258)
GDP growth: horizon						
1-year-ahead	0.604	0.622** (0.026)	-0.067** (0.012)	0.566	0.797** (0.034)	-0.092** (0.016)
1-year/1-year forward	0.603	0.863** (0.049)	-0.137** (0.020)	0.611	1.143** (0.058)	-0.195** (0.025)
Long term	0.494	1.009** (0.077)	-0.170** (0.035)	0.437	1.358** (0.118)	-0.254** (0.053)
US-SPF data						
Inflation: horizon						
1-year-ahead	0.007	0.860** (0.060)	-0.022 (0.033)	-0.007	1.056** (0.050)	-0.018 (0.026)
1-year-ahead full sample	0.589	0.497** (0.076)	0.162** (0.029)	0.556	0.597** (0.033)	0.219** (0.033)
GDP growth: horizon						
1-year-ahead	0.028	1.176** (0.162)	-0.056 (0.047)	0.050	1.621** (0.083)	-0.128 (0.083)
1-year-ahead full sample	0.014	1.282** (0.146)	-0.052 (0.056)	0.009	1.683** (0.242)	-0.082 (0.096)

Notes: The sample period runs from 1999:Q1 to 2013:Q4. However, the one-year-ahead full sample horizon from the US-SPF data runs from 1981:Q3 to 2016:Q4. The standard errors are based on the Newey & West (1987) variance-covariance matrix estimator. Statistical significance levels: ** 1%; * 5%.

4.3 Compositional Effects

The composition of both the ECB-SPF and US-SPF panel is not consistent over time, since there is a large in- and outflow of participants. This could affect the results of Tables 2-5, so this section investigates the influence of the changing panel composition. Based on a minimum required number of surveys in which a forecaster participated (ranging from 5 to 25), the data is divided in subsamples. Next, I re-estimate the regressions in Table 2-5, based on these subsamples. The resulting $\bar{R}^2$ values are displayed in Table 6, where the full sample of both the ECB-SPF and the US-SPF data is used. The compositional effects for the uncertainty - predictive accuracy relation are shown for the unadjusted forecast error.

Table 6: Compositional Effects

	Uncertainty and Disagreement: Full sample $\bar{R}^2$							
	Inflation: one-year-ahead				GDP Growth: one-year-ahead			
	ECB-SPF		**US-SPF**		**ECB-SPF**		**US-SPF**	
Required responses	Variance-based	IQR-based	Variance-based	IQR-based	Variance-based	IQR-based	Variance-based	IQR-based
1	0.182	-0.011	0.294	0.291	0.196	0.071	0.321	0.206
5	0.190	-0.008	0.302	0.257	0.188	0.065	0.339	0.191
10	0.223	-0.002	0.295	0.241	0.207	0.079	0.227	0.198
15	0.217	-0.013	0.284	0.269	0.183	0.085	0.210	0.163
20	0.232	-0.010	0.211	0.222	0.160	0.059	0.165	0.134
25	0.266	-0.013	0.234	0.260	0.156	0.060	0.150	0.119
	Uncertainty and Predicitive Accuracy: Full sample $\bar{R}^2$							
1	-0.018	-0.018	0.153	0.201	-0.018	-0.018	-0.007	-0.007
5	-0.018	-0.018	0.149	0.212	-0.018	-0.018	-0.007	-0.007
10	-0.018	-0.018	0.153	0.232	-0.018	-0.018	-0.007	-0.006
15	-0.018	-0.018	0.168	0.224	-0.018	-0.017	-0.007	-0.007
20	-0.018	-0.018	0.124	0.222	-0.018	-0.017	-0.007	-0.007
25	-0.017	-0.018	0.063	0.170	-0.018	-0.017	-0.007	-0.007
	Uncertainty and Aggregate Point Predictions: Full sample $\bar{R}^2$							
1	0.017	-0.005	0.589	0.556	0.604	0.566	0.014	0.009
5	0.015	-0.005	0.590	0.567	0.604	0.565	0.016	0.009
10	0.012	-0.008	0.600	0.581	0.621	0.574	0.009	0.004
15	0.008	-0.014	0.600	0.567	0.637	0.581	0.009	0.006
20	0.006	-0.016	0.579	0.559	0.640	0.555	0.006	0.006
25	0.015	-0.011	0.546	0.517	0.639	0.571	0.002	0.011

Notes: The results are based on the full sample period for both the ECB-SPF (1999:Q1 to 2013:Q4) and US-SPF data (1981:Q3 to 2016:Q4). The $\bar{R}^2$ values of the uncertainty and predictive accuracy relation are based on the unadjusted forecast error.

For the ECB-SPF, the results do not show a large difference between the subsamples. Especially for the uncertainty - predictive accuracy and the uncertainty - aggregate point predictions relation, the $\bar{R}^2$ values remain practically the same. The explanatory power of inflation uncertainty on disagreement increases slightly over the number of required responses, whereas the GDP growth linkage shows a small decline in $\bar{R}^2$ values. This indicates that a change of composition into a more harmonized panel does not have a considerable influence on the estimated relationships based on the ECB-SPF data. The results for the US-SPF show more variation among the subsamples, since the explanatory power decreases for nearly all estimated relationships. The relation between uncertainty and disagreement shows the largest decline, especially for the variance-based measure. The consistent decline in $\bar{R}^2$ values indicates that the varying composition of the US-SPF respondents is indeed of influence on the results, which could be explained by the small amount of frequent respondents.

5 Conclusion

This research concerns the measurement and behavior of uncertainty, based on the point and probability forecasts of both the ECB-SPF and US-SPF data. More specifically, the relation to measures of disagreement and forecast accuracy is examined, to evaluate whether these are reliable proxies for uncertainty. Another proxy is that changes in uncertainty might be accompanied by changes in expectations. This potential relation is explored by examining the linkage between uncertainty and an aggregate of the point forecasts. Lastly, since the panel composition of the two surveys fluctuates over time, the estimated relations are re-examined based on restriction concerning a required minimum of number of surveys, ranging from 5 to 25.

The disagreement measure does not show a consistent relation with the measures of uncertainty for both the ECB-SPF and US-SPF data. The relation with the realized forecast accuracy also does not seem significant. The relation is somewhat more evident for the inflation forecasts from the US-SPF data, due to less volatile forecast accuracy measures. Overall, the proxies disagreement and forecast accuracy do not show a meaningful linkage with uncertainty. However, a significant relationship is observed between uncertainty and aggregate point predictions for GDP growth (ECB-SPF data) and inflation (US-SPF data). This indicates that expectations of lower GDP growth are accompanied with higher GDP growth uncertainty, based on the ECB-SPF data. The US-SPF suggests that expectations of a lower inflation rate are followed by higher inflation uncertainty.

For the ECB-SPF, the re-estimation of the proposed relations to examine the compositional effects does not seem to have a substantial influence on the results. However, for the US-SPF the explanatory power declines for nearly all estimated relationships. This evident influence of the varying composition of the US-SPF respondents could be examined in more detail in further research.

The ECB-SPF and US-SPF results are compared in this research. However, there are some apparent differences between the data, due to the design of the survey and what is requested from the professional forecasters. The data is transformed to match the point and density forecasts of both data sets more closely, but there are still some remaining dissimilarities such as the change of interval widths over time and a slight difference in definition of the forecasts. Nevertheless, these transformations diminish the major differences, so a reliable comparison of the results is possible. Also, the change of interval widths is taken in consideration while interpreting the results.

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Appendix A

Table 7: Number of Total Responses and Invalid Responses

	Total Responses	Invalid Responses
ECB-SPF data		
HICP inflation: horizon		
1-year-ahead	3465	735
1-year/1-year forward	3465	999
Long term	3112	1040
GDP growth: horizon		
1-year-ahead	3465	803
1-year/1-year forward	3465	1034
Long term	3113	1057
US-SPF data		
Inflation: horizon		
1-year-ahead	2458	468
1-year-ahead full sample	5164	976
GDP growth: horizon		
1-year-ahead	2458	453
1-year-ahead full sample	5164	950

Notes: The data covers the period from 1999:Q1 to 2013:Q4. However, the one-year-ahead full sample horizon from the US-SPF data covers the period from 1981:Q3 to 2016:Q4.