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Does uncertainty affect participation in the European Central Bank's Survey of Professional Forecasters?

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Abstract

This paper explores how changes in macroeconomic uncertainty have affected the decision to participate in the European Central Bank's Survey of Professional Forecasters. Two different approaches are employed in order to address this question. First, a time-series analysis explores if changes in measures of uncertainty over time have led to changes in aggregate response rates. And second, a discrete-choice model for panel data is estimated to test if changes in uncertainty measures have had effects on the likelihood to participate by SPF forecasters. The main result of the paper is that higher (lower) uncertainty reduces (increases) participation in the survey. This effect is statistically and economically significant. As participation and uncertainty are found to be negatively correlated, measures of uncertainty from the ECB's SPF could be biased downwards.

Keywords: participation, uncertainty, Survey of Professional Forecasters, European Central Bank.

JEL classification: D81, D84, E66.

Non-technical summary

The European Central Bank's Survey of Professional Forecasters (SPF) is gaining prominence in recent years not only for policy analysis but also for academic research. Despite this interest, there is a surprisingly scarce amount of research on the factors that affect participation in this survey. Some authors have explored the effects on aggregate survey results from changes in the composition of the panel of participants but the participation decision is not investigated.

This paper tries to start analysing the participation process in the SPF by considering the effects of macroeconomic uncertainty on the probability that panellists reply to the survey. More uncertainty could make the production of macroeconomic forecasts more difficult (or costly). This could lower the incentives to participate in the SPF, especially the incentives to submit density forecasts, because most SPF forecasters do not use them for purposes other than the SPF.

Two approaches are employed in this paper to verify whether uncertainty affects participation in the SPF. First, a time-series analysis of aggregate results explores if changes in uncertainty led to changes in the response rates of the survey. And second, a discrete-choice model for panel data is estimated to test whether changes in uncertainty have had effects on the individual likelihood to participate by SPF forecasters.

This research finds that the effect on participation from changes in uncertainty is statistically and economically significant. For instance, the increase in uncertainty that occurred during the first two years of the current financial crisis may have led to declines in the probability of response by SPF participants by more than 10 percentage points for point forecasts and by more than 20 percentage points for density forecasts.

This finding has implications for the information content of the ECB's SPF data. Given that fewer responses are likely to be received when uncertainty surges, the information content of the survey may be eroded during periods of heightened uncertainty, precisely when the information from the survey may be needed the most.

Moreover, the estimated link between uncertainty and participation gives rise to the possibility that uncertainty measures obtained from SPF data could be biased downwards. If the participants that are more uncertain participate less than others, overconfident participants are going to be overrepresented in the SPF panel. A comparison between SPF-based uncertainty measures and some measures of uncertainty from financial markets seems to support this hypothesis.

1. Introduction

The European Central Bank's Survey of Professional Forecasters (SPF) is gaining prominence in recent years not only for policy analysis (e.g., ECB, 2014a and 2014c) but also for research (Bowles, Friz, Genre, Kenny, Meyler and Rautanen, 2010, Conflitti, 2011, Kenny, Kostka and Masera, 2012, and Rich, Song and Tracy, 2012 among many others). The SPF was launched in the first quarter of 1999 and collects expectations of inflation, GDP growth and the unemployment rate in the euro area for different forecasts horizons. These expectations are submitted quarterly by professional forecasters located in the European Union.[2]

The number of forecasts collected by the ECB varies from one quarter to the next. Figure 1 shows the number of participants that submitted a *point* forecast of a variable of interest (inflation, GDP growth or unemployment) for selected forecast horizons (one and two years ahead) in each survey round.[3] Figure 2 shows the same statistics for *density* forecasts. The number of replies is not constant over time because some participants skip some survey rounds, for instance due to holidays.[4] Moreover, some of the respondents to the first waves of the SPF stop participating in later rounds, a feature of panel surveys commonly known as *attrition* (Lindeboom, Rider and Vandenberg, 1994).[5]

Despite the growing interest in the SPF, there is a surprisingly scarce amount of research on the factors that affect participation in this survey. Engelberg, Manski and Williams (2011) and López-Pérez (2014) explored the effects from changes in the composition of the panel of participants on aggregate results from the survey, but the participation decision is not investigated. Furthermore, Engelberg *et al.* (2011) concluded that,

> "*We observed in the Introduction that, in the absence of knowledge of the forecaster recruitment and participation process, the assumption that data are missing completely at random is not refutable. Hence one might argue that this simplifying assumption should be maintained until evidence to the contrary emerges. To forestall endless debate about the validity of this or other simplifying assumptions, we see a strong need for research that sheds light on the forecaster recruitment and participation process. Only then will it become possible to reach consensus on the seriousness of the composition issue in survey response*."

This paper tries to start scratching the surface of the participation process in the ECB's SPF by analysing the effects of macroeconomic uncertainty on the probability that panellists participate in the survey. Theoretically, a higher degree of Knightian

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[2] For a full description of the survey, see http://www.ecb.europa.eu/stats/prices/indic/forecast/html/index.en.html.

[3] The SPF collects two types of forecasts. A *point* forecast is just a number (e.g. inflation in 2015 is expected to be 1.2%). A *density* forecasts is a vector of subjective probabilities over a set of predefined intervals (e.g. there is a 60% probability that inflation in 2015 will be between 1.0% and 1.4% and 40% probability that it will be between 1.5% and 1.9%).

[4] There is a clear seasonal pattern in the number of replies: the ECB systematically receives the lowest number of forecasts in Q3 surveys, which are conducted in the second half of July.

[5] In this context, *attrition* is defined as the gradual reduction over time in the number of participants that remain in the panel of respondents to a survey.

uncertainty (Knight, 1921) could make the production of macroeconomic forecasts more difficult (or costly). This could lower the incentives to participate in the SPF, especially the incentives to submit density forecasts because most SPF forecasters do not use them for purposes other than the SPF (79% of them, according to ECB, 2014b).

Preliminary evidence of the link between uncertainty and participation can already be found in Figures 1 and 2. It is typically assumed in forecasting that uncertainty increases with the forecast horizon. If this were true, and if uncertainty reduced incentives to participate, the number of forecasts submitted by SPF panellists for each macroeconomic variable would decline as the forecast horizon lengthens. And this is what is found in the SPF data: the number of two-year-ahead forecasts on Figures 1 and 2 is consistently below the number of one-year-ahead forecasts.

The finding of significant effects from macroeconomic uncertainty on SPF participation may have implications for policy analysis based on SPF data. First, if fewer responses are received when uncertainty surges, the information content of the survey may be eroded during periods of heightened uncertainty, precisely when the information from the survey may be needed the most.

And second, a negative correlation between participation and uncertainty could make SPF-based estimates of uncertainty biased downwards. If forecasters perceiving more uncertainty are less likely to participate, the estimates of uncertainty based on the data submitted by the remaining panellists may underestimate the overall degree of uncertainty perceived by SPF panellists.

Two approaches are employed in this paper to verify whether uncertainty affects participation in the SPF. First, a time-series analysis of aggregate results explores if changes in uncertainty over time led to changes in response rates. Its results are presented in Section 3. Given the relatively short sample used in this first analysis (the ECB's SPF started in 1999), it may be advisable to pursue a second approach where the panel dimension of the SPF dataset is used. Therefore, a discrete-choice model for panel data is estimated in Section 4 to test whether changes in uncertainty measures have had effects on the individual likelihood to participate by SPF forecasters. Section 5 concludes and outlines directions for future research.

2. The data

Participation data is constructed from the raw survey data available on the ECB's SPF website. Time series of a number of dummy variables are created. These dummies take the value 0 when forecaster i did not submit a forecast of variable j for forecast horizon h in survey round t, and take the value 1 otherwise. Therefore, each forecaster's participation is characterised by 12 dummy variables: three variables of interest (inflation, GDP growth and unemployment) times two types of forecasts (point forecast and density forecasts) times two forecast horizons (one year ahead and two years ahead).[6] Figure 3 shows the values of the 12 time series that characterise the participation of forecaster number 1 from 1999 Q1 to 2013 Q4.

[6] Some forecast horizons in the SPF are constant over survey rounds (the "rolling horizons": one year ahead and two years ahead) while others are not (current calendar year, next calendar year, calendar year after the next and five calendar years ahead). This paper focuses on the former.

Out of 113 forecasters, 13 never submitted a forecast to the ECB. These forecasters were removed from the sample.[7] Moreover, not all 113 forecasters received invitations to participate in the SPF in 1999 Q1, but many of them were invited later on. The survey rounds in which each forecaster was first invited to participate are unknown. Therefore, it is assumed that a participant whose longest non-response spell starts in 1999 Q1 was invited to participate just before her first reply. 26 forecasters are in this situation, and their “zeros” before the assumed invitation date are replaced with “NAs” in their dummy variables of participation.[8]

Finally, the panel of participants is subject to attrition, with the number of participating panellists gradually declining over time. Attrition in the context of the SPF may occur, among other reasons, because the contact person leaves the participating institution and the contact details are not updated, because the participating institution disappears or because the participating institution merges with another participating institution. Attrition results in the absence of replies by some panellists from a particular date until the end of the sample. If the longest non-response spell of a participant is at the end of the sample, it is assumed that she left the panel immediately after her last reply.[9] 34 forecasters meet this condition, and their “zeros” after their last reply are replaced with “NAs” in their dummy variables of participation.[10,11]

Figure 4 shows the resulting response rates (i.e. the number of replies divided by the number of invited, non-attritioned panellists) by variable, type of forecast and forecast horizon. As already discussed in the Introduction, participation declines with the length of the forecast horizon and displays a seasonal behaviour. Participation started high in 1999. Then it fell in 2000-2001 and recovered around 2003-2004, before initiating a downward trend that ended around 2008-2009. Afterwards, participation rates remained at relatively low levels until the end of the sample period.

Turning now to uncertainty measures, the data is obtained from López-Pérez (2014) where several measures of uncertainty are computed from SPF density forecasts. One of those measures of uncertainty, the one built on the Gini index, is used in this paper.

[7] Forecasters 12, 21, 25, 27, 51, 69, 74, 75, 77, 78, 79, 81 and 83.

[8] Forecasters number 8 (first reply: 2007 Q2), 15 (2000 Q1), 22 (2000 Q2), 30 (1999 Q4), 41 (1999 Q2), 58 (2006 Q4), 80 (2001 Q2), 84 (2001 Q2), 96 (2000 Q2), 97 (2004 Q1), 98 (2004 Q3), 99 (2004 Q3), 100 (2006 Q1), 101 (2008 Q2), 102 (2008 Q2), 103 (2008 Q2), 104 (2008 Q2), 105 (2008 Q2), 106 (2009 Q3), 107 (2008 Q2), 108 (2008 Q2), 109 (2010 Q2), 110 (2010 Q4), 111 (2011 Q3), 112 (2011 Q3) and 113 (2011 Q4).

[9] This condition is checked after removing the no-response spell at the beginning of the sample for the panellists whose identification numbers appear in footnote 8.

[10] Forecasters number 9 (last reply: 2007 Q4), 10 (2010 Q3), 11 (2010 Q1), 13 (2000 Q1), 17 (2006 Q2), 18 (2010 Q1), 19 (2011 Q4), 28 (2010 Q4), 33 (2013 Q1), 34 (2001 Q1), 40 (2009 Q4), 43 (2000 Q3), 44 (2000 Q2), 46 (2001Q2), 50 (2009 Q4), 53 (2004 Q1), 55 (2001 Q1), 59 (2011 Q1), 60 (2009 Q2), 61 (2011 Q4), 62 (2007 Q2), 64 (2002 Q4), 65 (2010 Q4), 66 (2004 Q3), 71 (2004 Q3), 73 (2011 Q3), 76 (2008 Q3), 86 (1999 Q1), 87 (2003 Q3), 90 (2011 Q4), 97 (2011 Q2), 100 (2009 Q1), 106 (2013 Q2) and 109 (2012 Q2).

[11] Attrition may also be the outcome of a deliberate decision by a participating institution to discontinue its contribution to the survey because of cost-benefit considerations. If increases in uncertainty augmented the cost of forecasting, the removal of these observations would bias the results presented in this paper *against* any effect from uncertainty on participation.

Borrowed from the literature on income and wealth inequality, the Gini index (Gini, 1955) is based on the Lorenz curve (Lorenz, 1905). This curve is typically used to represent how much wealth is in the hands of the poorest *x*% of the population. The Lorenz curve may also be applied to the analysis of uncertainty with SPF data by representing the cumulative probability allocated to the x% less likely intervals of a density forecast.

If a forecaster faces no uncertainty, her density forecast would have 100% probability in just one interval. In this case, the Lorenz curve would be zero from the first interval to the one before the last and then it would jump to 100% in the last interval. On the contrary, if a forecaster faces maximum uncertainty, her density forecast would have the same probability allocated to every interval. Then, the Lorenz curve would increase in regular steps from the first interval to the last.

From the Lorenz curves derived from each individual density forecast, the calculation of individual Gini indices is straightforward. The Gini index is defined as the distance between the 45-degree line and the Lorenz curve divided by the area below the 45-degree line:

$$G = -\frac{\sum_{i=1}^{n}(x_i - lc_i)}{\sum_{i=1}^{n} x_i} \qquad [1]$$

where n is the number of intervals, x is the $nx1$ vector of ordinates representing the 45-degree line, $(1/n, 2/n, \ldots, 1)'$, and lc is the $nx1$ vector of ordinates from the Lorenz curve. As the original Gini index declines with uncertainty, the sign was changed to turn it into an index that increases with uncertainty.

The aggregation (averaging) of the individual Gini indices across the SPF panellists that participated in two consecutive survey rounds allows for the calculation of a quarterly measure of *percentage changes* in uncertainty from one survey round to the next.[12] Compounding these quarterly changes, a quarterly series representing the percentage change in the aggregate Gini index of uncertainty since 1999 Q1 is obtained for each macroeconomic variable and forecast horizon (Figure 5).[13]

These uncertainty measures show an increase in uncertainty during the period between 2000 and 2002, followed by a mild decline from 2003 to 2008. A big jump in uncertainty occurred around the start of the financial crisis, with a moderate fall in macroeconomic uncertainty since 2010 (the exception being the uncertainty measures for unemployment, which kept on rising).

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[12] These percentage changes are shown on Figure 18 in López-Pérez (2014).

[13] To be precise, if c_{jr} is the percentage change in the uncertainty measure for variable j from round r-1 to round r, the percentage change since 1999 Q1 in the uncertainty measure for variable j in round r, cc_{jr}, is:

$$\frac{cc_{jr}}{100} = \left[\prod_{t=1999Q2}^{t=r}\left(1 + \frac{c_{jr}}{100}\right)\right] - 1 \approx \sum_{t=1999Q2}^{t=r}\frac{c_{jr}}{100} \quad \text{for } r > \text{1999 Q1 and } c_{jr} \text{ sufficiently small}$$

The results of this paper are obtained with the approximation shown on the right side of the equation, as the approximation error turned out to be tiny.

In order to achieve the goal of better understanding the relationship between uncertainty and participation, the effects on participation from other variables need to be taken into account. In other words, there is a need to *control* for other variables to isolate the effect of uncertainty on participation. In particular, for any given level of uncertainty, the participation rate is expected to be higher when respondents have more time to fill in the questionnaire. Therefore, a control variable will be used in the empirical exercise, namely, the number of days given to SPF panellists by the ECB to submit their forecasts during each survey round. This variable can be found in the document "Dates when the SPF has been conducted and published" downloaded from the ECB's SPF webpage.[14] Figure 6 shows the number of days given to SPF participants to submit their forecasts during each survey round.

The evolution of this variable over time resembles somewhat the evolution of the participation rates shown on Figure 4: the number of days started high in 1999. Then it fell in 2001-2002 and recovered around 2003-2004, after which it initiated a downward trend that ended around 2007. From then, the number of days has remained relatively low until the end of the sample period. This co-movement is indicative of the potential relevance of this variable for the analysis of participation in the SPF.

3. Time-series analysis with aggregated data

This section explores the relationship over time between uncertainty and the aggregate response rate by variable and forecast horizon.[15] As a preliminary step, the integration order of the series is checked. Table 1 shows the results of the Elliott, Rothenberg and Stock (1996) Optimal Point unit-root test and the Ng and Perron (2001) unit root tests for the variables of interest.

The results of the unit root tests suggest that a unit root in the uncertainty measures cannot be rejected at conventional significance levels for almost all variables and horizons. Conversely, the test clearly rejects the hypothesis of a unit root in the number of days given to SPF panellists to submit their forecasts to the ECB. The results for the response rates are more mixed, however: with a constant, the null hypothesis of a unit root is generally accepted, especially with the Optimal-Point test; but with a constant and a trend, the tests tend to reject the existence of a unit root.

Therefore, the unit-root tests suggest that the response rates may be either I(0) around a deterministic linear trend or I(1). However, does a linear trend in the response rate make sense? By construction, the response rate is bounded between zero (nobody participates) and one (everybody participates). Hence, the response rate cannot take values below zero or above one. Now, let's assume that the response rate is trend stationary, i.e. it is I(0) around a deterministic linear trend. Then, as a result of the linear trend, response rates would eventually end up below zero (if the trend is negative) or about one (if the trend is positive), which does not make any sense. Rather, it seems much more plausible to think of the response rates as I(1) random processes.

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[14] The link to the document is: http://www.ecb.europa.eu/stats/prices/indic/forecast/shared/files/SPF_rounds_dates.pdf?c9bb678c81c9323ae16618656b178e7e.

[15] The response-rate series used in this section have been seasonally adjusted with TRAMO-SEATS (Gómez and Maravall, 2001).

Since uncertainty measures and response rates may be I(1), they could be cointegrated. In other words, there may be a long run relationship between these variables by which when uncertainty increases (falls) participation falls (increases). More formally, there may be a linear combination of response rates and the uncertainty measure that is I(0). To test for cointegration, the Engle-Granger two-step cointegration test is used (Engle and Granger, 1987). The first step consists on running a regression of the response rate on the uncertainty measure. The second step is a unit-root test of the residuals obtained in the first step. If the first-step residuals are I(0) the response rate and the uncertainty measure are cointegrated. Furthermore, the estimated coefficients obtained in the first step define the cointegration vector.

Why is the more popular Johansen's cointegration trace test (Johansen, 1991) not used instead? First, Johansen's approached is based on a VAR not on a single equation. Since the focus in this paper is on the effects of uncertainty on participation, and not on the effects going in the opposite direction, a single equation approach is preferable.[16] This is especially true given the low number of observations available to run the test.

A second reason for not using Johansen's test is that critical values of the trace statistic are conditional on a normal distribution of the residual process (Sjö, 2008). While the normality assumption is justified asymptotically, it is not likely to hold in the small sample used in this section of the paper.

The third and final reason for not using Johansen's test is that the inclusion of I(0) control variables in the cointegration test, like the number of days in this paper, requires expanding the cointegration vector (Rahbek and Mosconi, 1999). This procedure would likely worsen the small-sample problem identified in the previous paragraph.

Table 2 shows the results of the Engle and Granger two-step cointegration test. Panel *a* reports the results of the unit-root tests of the first-step residuals (i.e. the cointegration tests). Note that the variable "number of days to reply" has also been included in the first-step regression. This is because it is I(0) and thereby, if an I(0) linear combination of response rates, uncertainty and days is found, there must be an I(0) linear combination of response rates and uncertainty by construction. Moreover, by proceeding in this way, the long-run effects from the number of days to reply on the response rates may also be analysed.

The absence of cointegration is rejected in almost all instances at conventional significance levels with the exception of the unemployment rate two years ahead. For all the other combinations of macroeconomic variables and forecast horizons, there is an I(0) linear combination of the response rate, the uncertainty measure and the number of days.

Panel *b* in Table 2 reports the cointegration equations estimated in the first step (without standard errors because they are uninformative due to the presence of I(1) variables). In the long run, response rates decline with uncertainty. To gain some insights on the size of this effect, Table 3 shows the long-run effect on the response rate (in percentage points) from the surge in the uncertainty measures observed at the start of the financial

[16] For illustrations of the effects of changing participation on uncertainty measures, see Engelberg, Manski and Williams (2011) and López-Pérez (2014).

crisis (from the lows around 2007-2008 to the peaks around 2009-2010). The effect is economically important: *ceteris paribus*, response rates may have fallen between 1.4 and 10.0 percentage points in the long run as a result of such an increase in uncertainty. Not surprisingly, submissions of density forecasts seem more sensitive to changes in uncertainty than submissions of point forecasts.

Apart from the effect of uncertainty on the response rates, the number of days to reply has a positive effect on the response rates in the long run (see Table 2, panel *b*): giving one more day to SPF participants raises, *ceteris paribus*, the response rates by between 0.5 percentage points and 1.0 percentage points in the long run.

Once the case for cointegration is justified, an error-correction model may be estimated to quantify how deviations from the long-run cointegration relationship affect the response rates in the short run. The estimated functional form is:

$$\Delta R_t = \alpha_C \, fsr_{t-1} + \beta_R \Delta R_{t-1} + \beta_U \Delta U_{t-1} + \beta_D D_t + \varepsilon_t \qquad [2]$$

where R_t is the response rate for a type of forecast (point or density forecasts), a macroeconomic variable (inflation, GDP growth or unemployment) and a forecast horizon (one or two years ahead) at the SPF round t; Δ is the first difference operator; fsr_t is the residual from the first step of the Engle and Granger two-step cointegration test and measures the short-run deviations from the long-run cointegration relationship; U_t is the uncertainty measure; D_t is the number of days to submit forecasts to the ECB; $\alpha_C, \beta_R, \beta_U$ and β_D are constant parameters and ε_t is an iid random disturbance with zero mean and constant variance.

The least squares estimators of the parameters of the error-correction models are shown on Table 4.[17] The parameter that captures the short-run effect of deviations from the long-run relationship on the response rate, α_C, is always statistically significant and has the expected negative sign. Interestingly, the response rates react relatively quickly to deviations from the long-run relationship: between 37% and 79% of these deviations are absorbed after just one quarter. In other words, uncertainty reduces participation in the SPF in the long run but also in the shorter run.

Given the relatively short sample used in this analysis (the ECB's SPF is quarterly and started in 1999), it may be advisable to pursue a second approach where the panel dimension of the SPF dataset is used. Therefore, the next section will use individual SPF participation data to explore the relationship between uncertainty and the likelihood of participation. It aims to investigate if more uncertainty reduces the probability of individual participation in the ECB's SPF.

[17] Neither the Ljung-Box (1978) autocorrelation test with 4 lags nor the autocorrelation LM test (Johansen, 1995) with 4 lags reject the null hypothesis of no autocorrelation in any of the estimated models. The Jarque-Bera (1987) normality test with Cholesky factorization matrix rejects the null hypothesis of normal residuals for inflation one year ahead (point and density forecasts), for inflation two years ahead (density forecasts only) and for unemployment one year ahead (density forecasts only). These rejections are probably related to the small sample size (57 observations). The White (1980) heteroskedasticity test does not reject the null hypothesis of homoskedasticity of the residuals in any of the estimated models.

4. The relationship between uncertainty and participation at a disaggregated level

4.1 The effects of uncertainty on participation

Participation data at the individual level may yield additional insights that complement the analysis of aggregate data conducted in the previous section. In Section 2, 12 participation dummies that characterised the individual participation by each forecaster in the ECB's SPF were constructed (see Figure 3 again). These variables are binary variables, with "zeros" in the periods when the panellist did not reply and "ones" when she did.[18]

Binary choice models have been developed to study, among other things, the choice of human beings between two alternatives and how this choice is affected by some factors. In the SPF context, the decision each panellist takes each survey round is to send her forecasts to the ECB or not. Note that each panellist may send *some* but not *all* the forecasts requested by the ECB. Therefore, the analysis of participation has to be conducted for each variable and forecast horizon: increases in uncertainty may not have the same effect on the likelihood of submission of forecasts of different variables and forecast horizons.

The binary-choice model for panel data assumes that the dependent variable may take two values only:

$$D_{ijht} = \begin{cases} 1 & if \;\; y^*_{ijht} \geq 0 \\ 0 & if \;\; y^*_{itht} < 0 \end{cases} \qquad [3]$$

where D_{ijht} is a dummy variable that takes the value 0 when forecaster i did not submit a forecast of variable j for forecast horizon h in survey round t, and takes the value 1 otherwise; y^*_{ijht} is an unobservable latent variable which, according to the binary-choice model, depends linearly on a set of independent variables x_{ijht}:

$$y^*_{ijht} = x'_{ijht}\beta + u_{ijh} + \varepsilon_{ijht} \qquad [4]$$

where β is a vector of constant parameters, u_{ijh} accounts for unobserved individual heterogeneity and ε_{ijht} is an iid random disturbance with zero mean and constant variance.[19] Then, the probability that forecaster i submits a forecast of variable j for forecast horizon h at survey round t is:

$$\Pr(D_{ijht} = 1) = \Pr(y^*_{ijht} \geq 0) = \Pr(\varepsilon_{ijht} > -x'_{ijht}\beta - u_{ijh}) = F_{\varepsilon}(-x'_{ijht}\beta - u_{ijh}) \qquad [5]$$

[18] And, as described in Section 2, some periods with "NAs" for forecasters with identification numbers included in footnotes 8 and 10 (due to late invitation and attrition respectively).

[19] The notation makes it clear that the unobserved-heterogeneity variable does not change over time but may take different values for different forecasters (some forecasters may be more committed to participating in the SPF than others, *ceteris paribus*). It also may take different values for forecasts of different variables and forecast horizons *from the same forecaster* (a forecaster may be more willing to submit forecasts of some variables than of others, and also more willing to submit forecasts for some forecast horizons than for others, because, for instance, she does not trust equally all the models she used to compute all her forecasts).

where F_ε is the cumulative distribution function of ε_{ijht}. In the logit model, disturbances are assumed to follow a logistic distribution. Thus:

$$\Pr(D_{ijht}=1)=\Pr(y^*_{ijht}\geq 0)=\Pr(\varepsilon_{ijht}>-x'_{ijht}\beta-u_{ijh})=F_\varepsilon(-x'_{ijht}\beta-u_{ijh})=L(-x'_{ijht}\beta-u_{ijh})$$

[6]

where $L(\cdot)$ is the cumulative distribution function of a logistic random variable whose mean is equal to zero and its standard deviation is equal to one.[20] In this paper, six independent variables are included in the vector x: the measure of uncertainty for variable j and forecast horizon h, the number of days to submit the forecasts to the ECB, and four quarterly dummy variables to capture the seasonal pattern of replies. None of these independent variables exhibit variation across individual forecasters. Therefore, the only variation across panellists comes from the unobserved heterogeneity component, u_{ijh}.

The unobserved individual heterogeneity may or may not be correlated with the independent variables of the model. If it is correlated, the fixed-effects estimator is unbiased, because the model is transformed to get rid of the unobserved heterogeneity before estimation.[21] If the unobserved individual heterogeneity is uncorrelated with the independent variables, however, the fixed-effects estimator is inefficient (although it is still unbiased), while the random-effects estimator is more efficient.

The Hausman test may be used to check which estimator has to be computed.[22] Under the null hypothesis of absence of systematic differences between the fixed-effects and the random-effects estimators, the latter is preferred due to its lower variance. If the null hypothesis is rejected, however, the random-effects estimator is inconsistent. Table 5 shows the p-values of the Hausman test when applied to the random-effects and fixed effects estimators of the logit model of individual participation in the SPF. The null hypothesis is not rejected at conventional significance levels for any variable, any forecast horizon and any type of forecast (point or density forecast). Hence, the random-effects estimator seems preferable under this metric.

The following model is thereby estimated by maximum likelihood:

$$\Pr(D_{ijht}=1)=\frac{1}{1+e^{-(\beta_U U_{jht}+\beta_D D_t+\beta_{Q1}D_{Q1}+\beta_{Q2}D_{Q2}+\beta_{Q3}D_{Q3}+\beta_{Q4}D_{Q4}+u_{ijh}+\varepsilon_{ijht})}} \quad [7]$$

where U_{jht} is the uncertainty measure for variable j and forecast horizon h at round t, D_t is the number of days to reply at round t, D_{Qi} is a seasonal dummy variable that takes the value 1 at quarter i and 0 otherwise, and β_U, β_D, β_{Q1}, β_{Q2}, β_{Q3} and β_{Q4} are constant parameters. Table 6 reports the random-effects estimators of the parameters in the logit

[20] All the results presented in the paper are robust to the use of a Probit model instead. Results are available from the author upon request.

[21] More precisely, each variable in the model is replaced with the difference between that variable and its sample mean. As the fixed effects are invariant across time, they do not appear in the transformed model.

[22] Hausman (1978), Green (2008).

model of participation in the SPF.[23] The uncertainty measure is statistically significant at conventional levels in all the estimated models. As expected, the sign of the coefficients suggests that increases in uncertainty reduced the probability of participation at the individual level. The effect on participation from the number of days to reply is also statistically significant and positive in all the estimated models. Finally, there are substantial seasonal effects on participation, with lower participation in Q3 surveys.

Equation [7] makes it clear that the logit model is not a linear model. Consequently, the estimated coefficients cannot be interpreted as the marginal effects on the dependent variable from changes in the regressors. In general, these marginal effects will vary with the values of the regressors. Table 7 shows the estimated marginal effects on the probability of participation from changes in each regressor when all the regressors are equal to their sample means. The marginal effects on the first row of Table 7 have been divided by 100, to interpret them as the effect on the probability of participation from a 1 percentage-point increase in the uncertainty measure.

Abstracting from the non-linearities for a moment, a 1 percentage-point increase in uncertainty from its sample mean led to an estimated decline in the probability of submission of one-year-ahead inflation point forecasts of 2.1 percentage points. As Figure 7 shows, these marginal effects of uncertainty on the response rates vary very little for different values of uncertainty (see Figure 7). Given that the uncertainty measure for inflation one year ahead increased in the first few years of the financial crisis by more than 5 percentage points (see Table 3), the estimated probability of participation could have declined by more than 10 percentage points.

As expected, even larger marginal effects are obtained for density forecasts than for point forecasts. For instance, the marginal effect of uncertainty on the probability of submitting a density forecast for the unemployment rate one year ahead is -4.1 percentage points. Given that the uncertainty measure for unemployment one year ahead has increased by more than 5 percentage points since 2008, the estimated probability of participation could have declined by more than 20 percentage points.

Turning now to the effects on the probability of participation from an increase in the number of days to reply, its marginal effect is around 1 percentage point for point forecasts and around 2 percentage points for density forecasts. Finally, on average, the probability of participation declined in the surveys conducted during the third quarter of each year by between 10 and 20 percentage points with respect to the surveys conducted during the first quarter.

These results confirm the findings reported in the previous section, i.e. that more uncertainty reduces participation in the ECB's SPF.

4.2 Are SPF-based estimates of macroeconomic uncertainty biased downwards?

Correlation between uncertainty and participation could imply that estimates of uncertainty based on SPF data may be <u>biased</u> downwards. This would be the case if the

[23] The null hypothesis of equal random effects across individuals is clearly rejected for all the estimated models (p-value=0.000).

forecasters that felt higher macroeconomic uncertainty participated less, *ceteris paribus*, than the rest because, for instance, they found the task of forecasting to be relatively more difficult in a more uncertain environment.

For the estimates of uncertainty based on SPF data to remain unbiased, the panellists that did not participate in more uncertain times had to feel on average the same degree of macroeconomic uncertainty than the panellists that participated. This could be the case if, for instance, higher uncertainty forces some of the institutions participating in the SPF to disappear: the panellist stops participating not because it was more difficult to cast her predictions in a more uncertain environment, but because the institution disappeared.

For obvious reasons, the SPF dataset does not allow to test whether participating forecasters were less uncertain than non-participating forecasters, as the latter did not submit any data to the ECB. But some indirect evidence supporting the existence of a downward bias in the aggregate measures of macroeconomic uncertainty obtained from the SPF dataset may be found nevertheless.

Figures 8 and 9 compare the SPF-based uncertainty measures previously shown on Figure 5 with two measures of uncertainty from financial markets: the 12-month and the 24-month VSTOXX indices.[24] For an easier comparison, all series have been standardised and thereby have zero mean and one standard deviation. The SPF-based uncertainty measures track reasonably well the VSTOXX indices, especially at the two-year horizon, with two notable exceptions: the two biggest spikes in uncertainty according to the VSTOXX indices, which occurred from 2001 Q2 to 2003 Q1 and from 2007 Q2 to 2009 Q1. Over these two periods, uncertainty measures based on SPF data increased by much less than the VSTOXX indices.

Table 8 shows the evolution of the standardised uncertainty measures over these two episodes. On the first episode, from 2001 Q2 to 2003 Q1, the VSTOXX indices jumped by 2.59 and 2.70 standard deviations while the SPF-based uncertainty measures increased by much less (by between 0.02 and 1.63 standard deviations). On the second episode, from 2007 Q2 to 2009 Q1, the VSTOXX indices rose by 3.94 and 4.02 standard deviations while the SPF-based uncertainty measures did so by between 0.31 and 1.78 standard deviations only. If we assume that these VSTOXX indices are an accurate indicator of macroeconomic uncertainty in the euro area, this finding is consistent with a downward bias in SPF-based uncertainty measures at times of relatively high uncertainty.[25]

[24] The VSTOXX indices are based on EURO STOXX 50 real-time options prices and are designed to reflect the market expectations of short-term and long-term volatility by measuring the square root of the implied variance across all options of a given time to expiration. The data is obtained from http://www.stoxx.com/download/historical_values/h_vstoxx.txt. The quarterly data shown on Figures 8 and 9 are average daily data over the quarter.

[25] There is a third notable discrepancy between SPF-based uncertainty measures and the VSTOXX indices. It happened during 2012 and 2013, when the SPF measures are clearly above the financial-market measures. This gap may be related to the responses by governments and central banks across the globe to the current financial crisis. These actions have helped many financial markets but their effects on the real economy have been more muted so far.

5. Conclusions

This paper has explored the link between the degree of macroeconomic uncertainty and the decision to participate in the ECB's Survey of Professional Forecasters. Two different approaches are employed in order to address this issue. First, a time-series analysis explores if increases in aggregate measures of uncertainty led to changes in the aggregate response rates of the survey. And second, a discrete-choice model for panel data is estimated to test if changes in uncertainty measures had any effects on the likelihood to participate by SPF forecasters.

The main result of the paper is that higher (lower) uncertainty reduces (increases) participation in the survey. This effect is statistically and economically significant. For instance, the increase in macroeconomic uncertainty witnessed at the start of the financial crisis (2008-2010) reduced the probability of response by SPF participants by more than 10 percentage points for point forecasts and by more than 20 percentage points for density forecasts.

This finding has implications for the information content of ECB's SPF data. Given that fewer responses are likely to be received when uncertainty surges, the information content of the survey may be eroded during periods of heightened uncertainty, precisely when the information from the survey may be needed the most.

Moreover, as participation and uncertainty are found to be negatively correlated, measures of uncertainty from the ECB's SPF could be biased downwards. If forecasters perceiving more uncertainty are less likely to participate, the estimates of uncertainty based on the data submitted by the remaining panellists may underestimate the overall degree of uncertainty perceived by SPF panellists. In this regard, a comparison between SPF-based uncertainty measures and measures of uncertainty from financial markets (the VSTOXX indices) seems to support the hypothesis of a downward bias in SPF-based measures at times of relatively high uncertainty.

Further research will analyse attrition in the panel of the SPF. Attrition has been left out of the analysis conducted in this paper but it may also be endogenous to a number of factors in the economy and in the design of the survey. If attrition turned out to be correlated with some features of the survey design, those features could be fine-tuned to minimise the exit of panellists. And if attrition turned out to be correlated with economic developments, they could induce time-variation in the information content of the survey.

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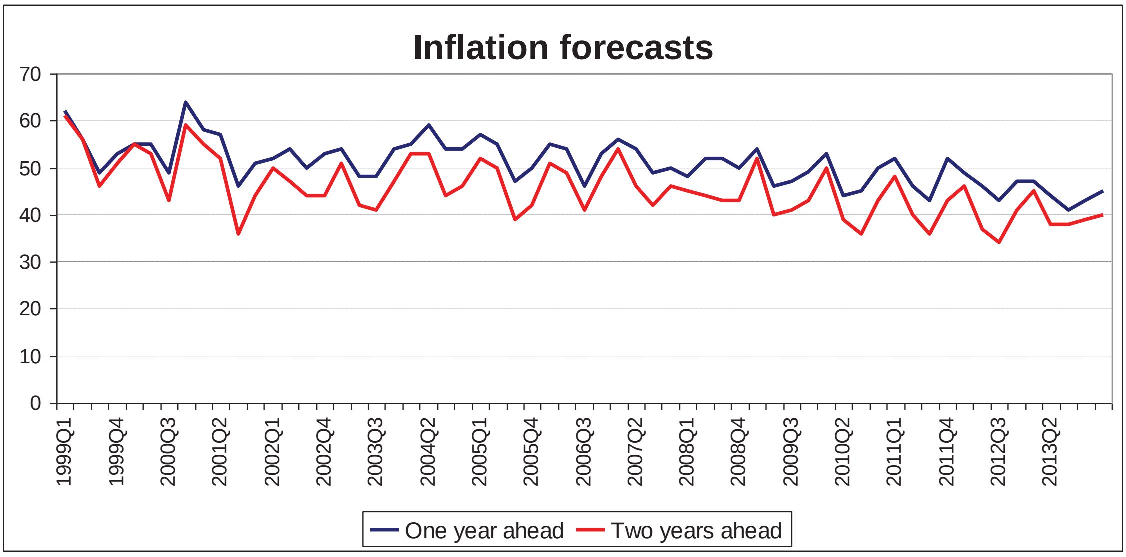
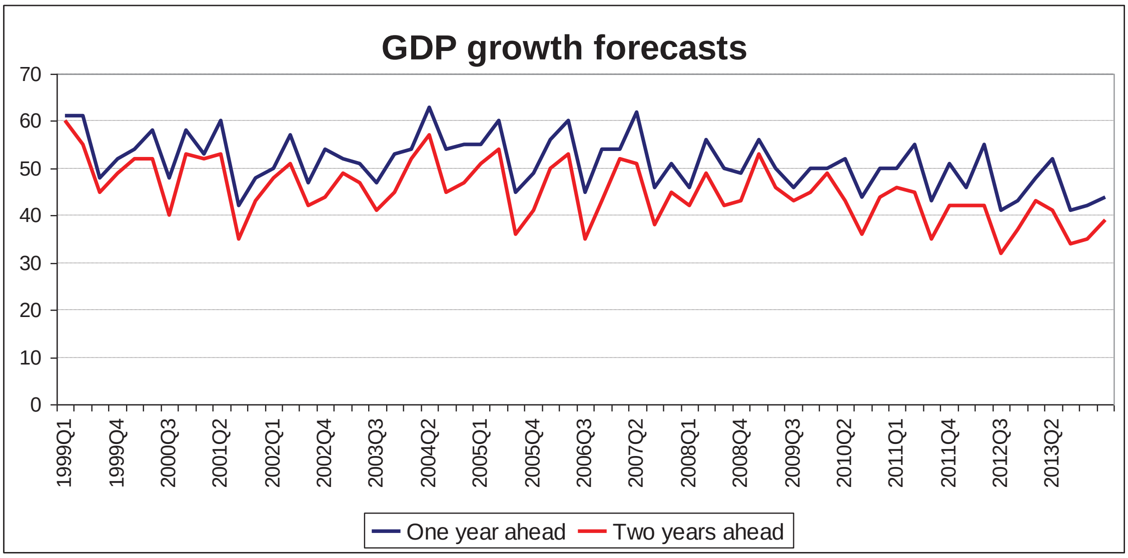
Appendix: Figures and Tables

Figure 1: Number of participants that submitted point forecasts in each survey round.





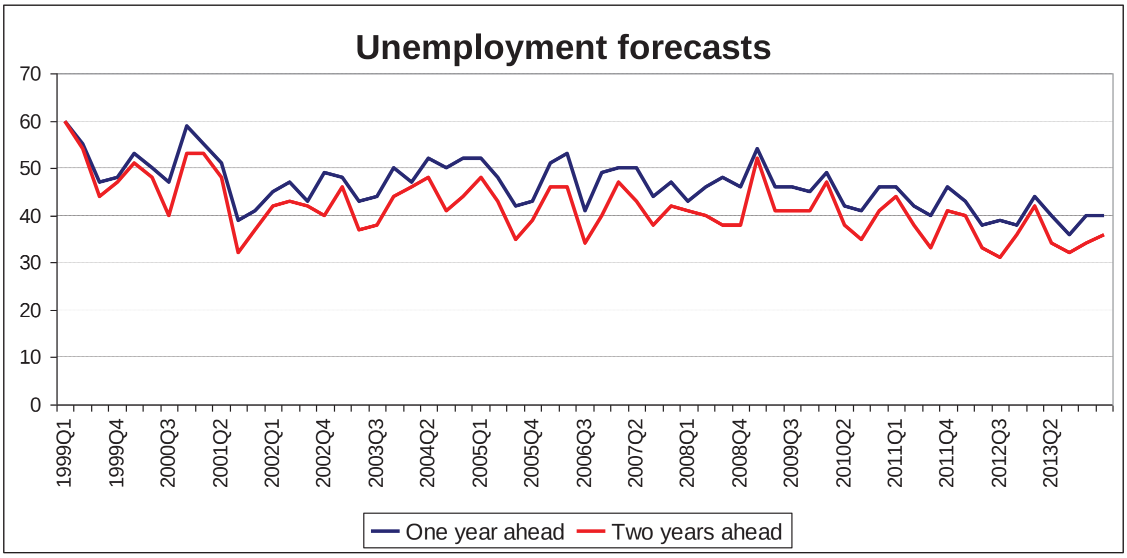


Figure 2: Number of participants that submitted density forecasts in each survey round.

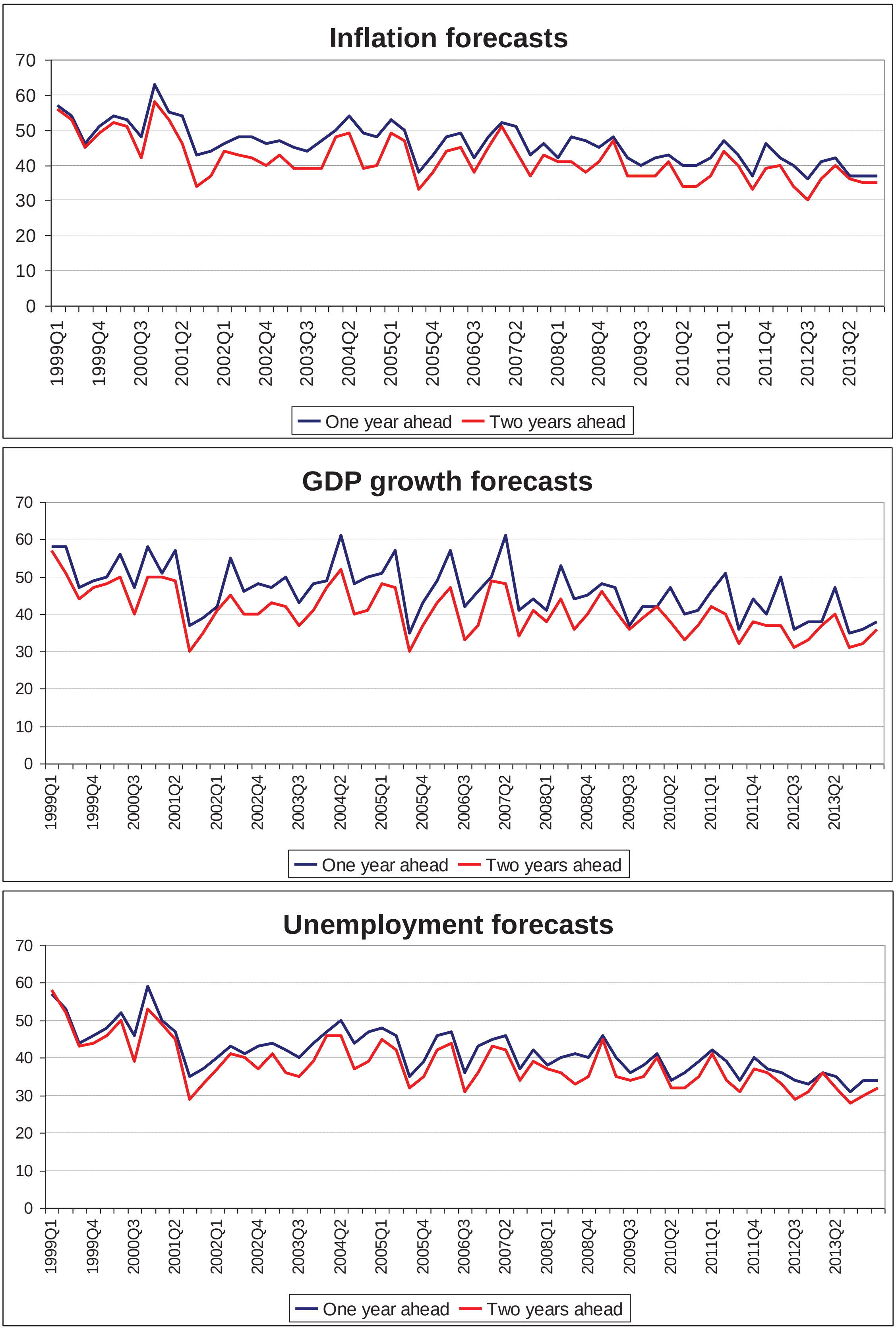


Figure 3: Dummies that characterise participation by forecaster number 1.

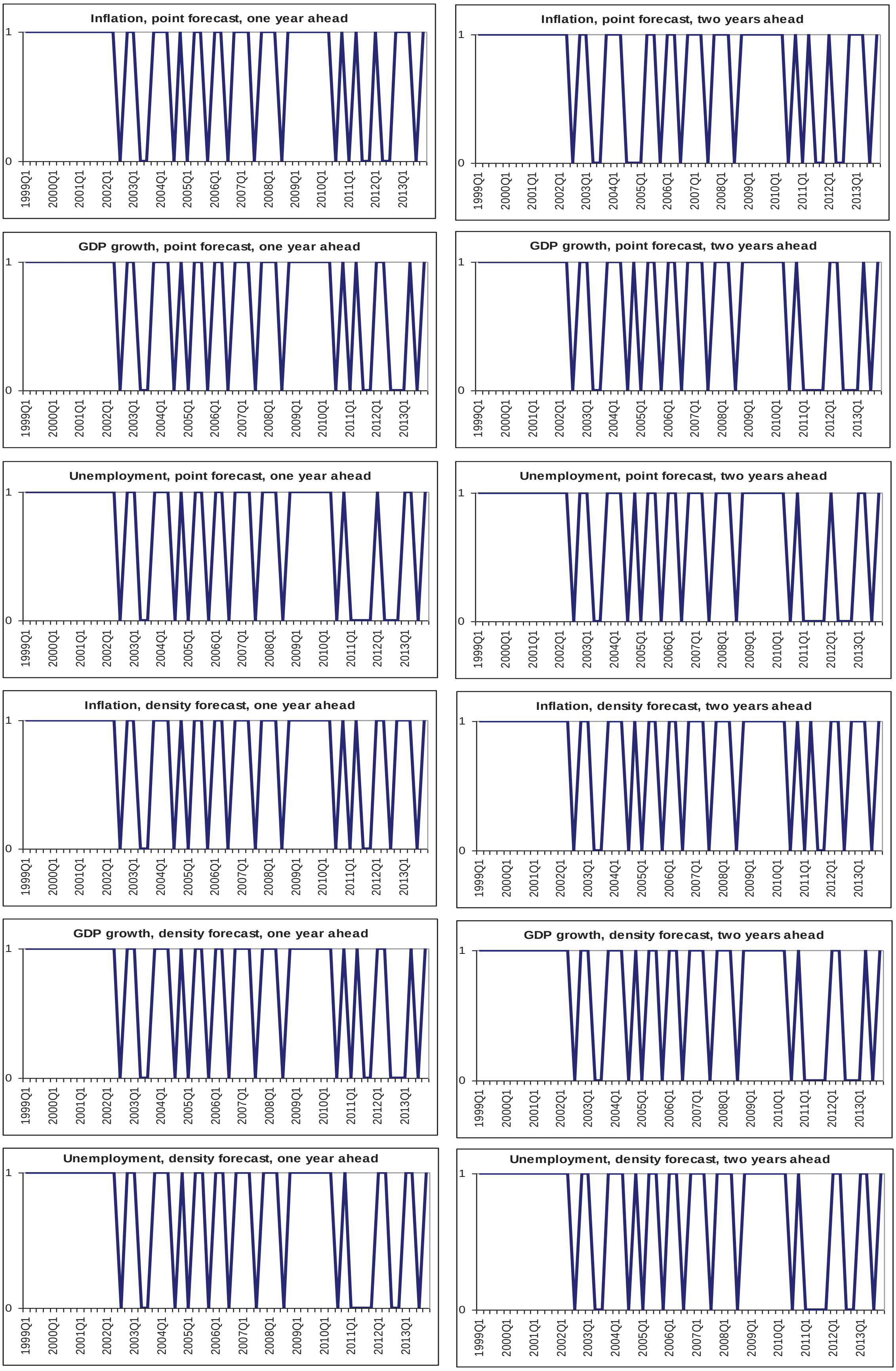


Figure 4: Response rates by variable, type of forecast and forecast horizon.

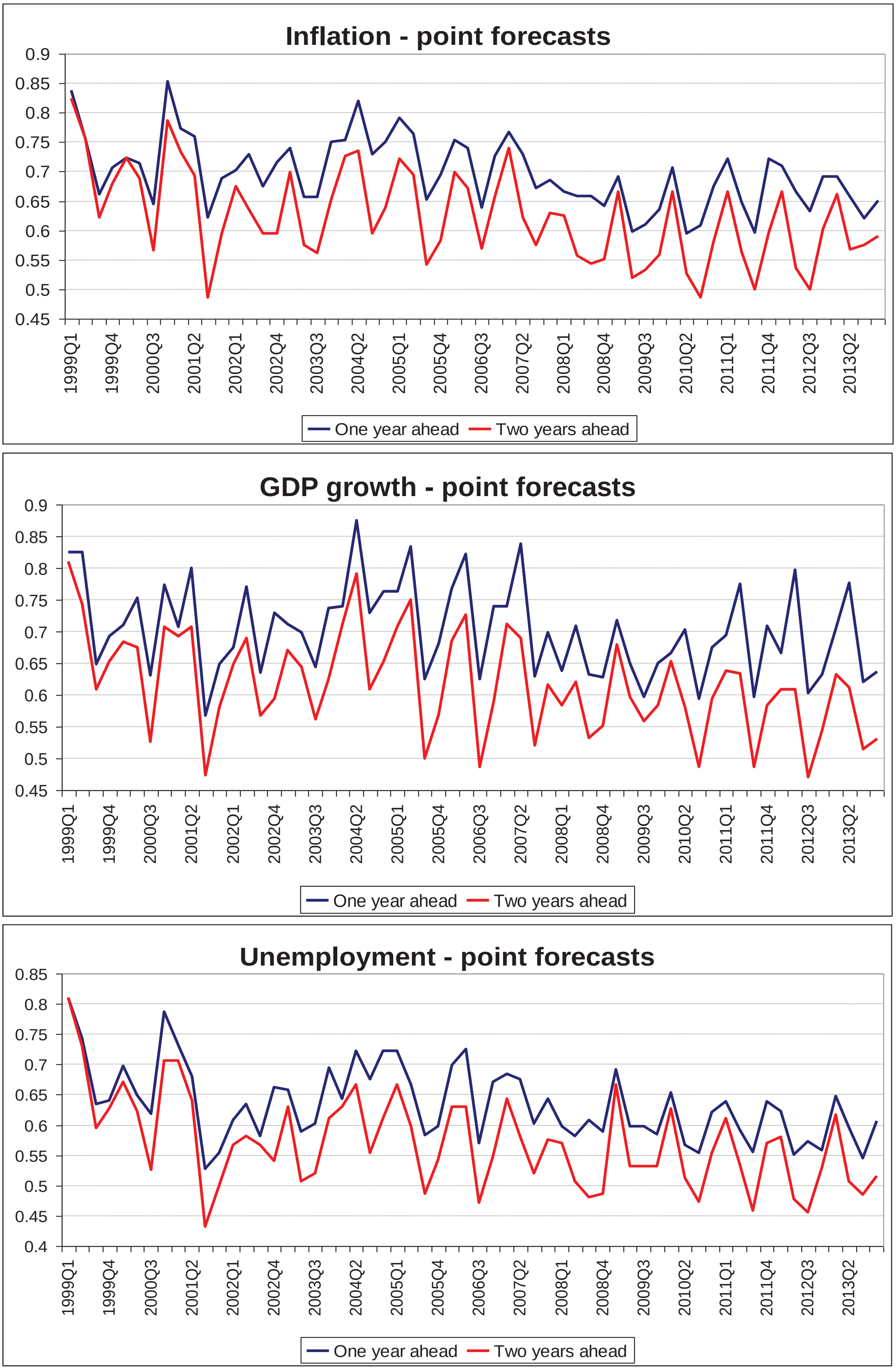
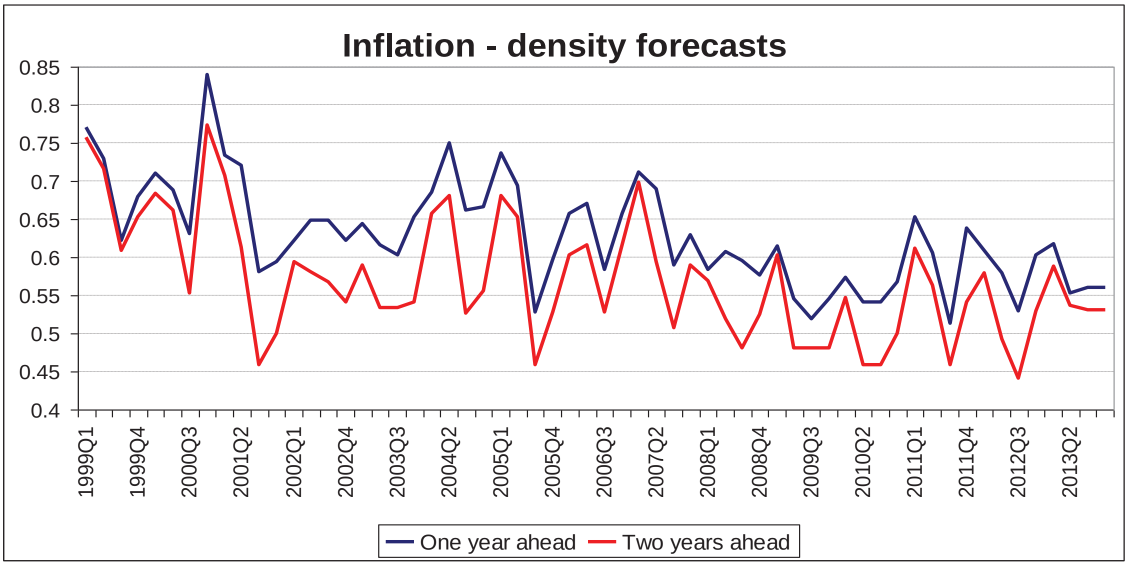
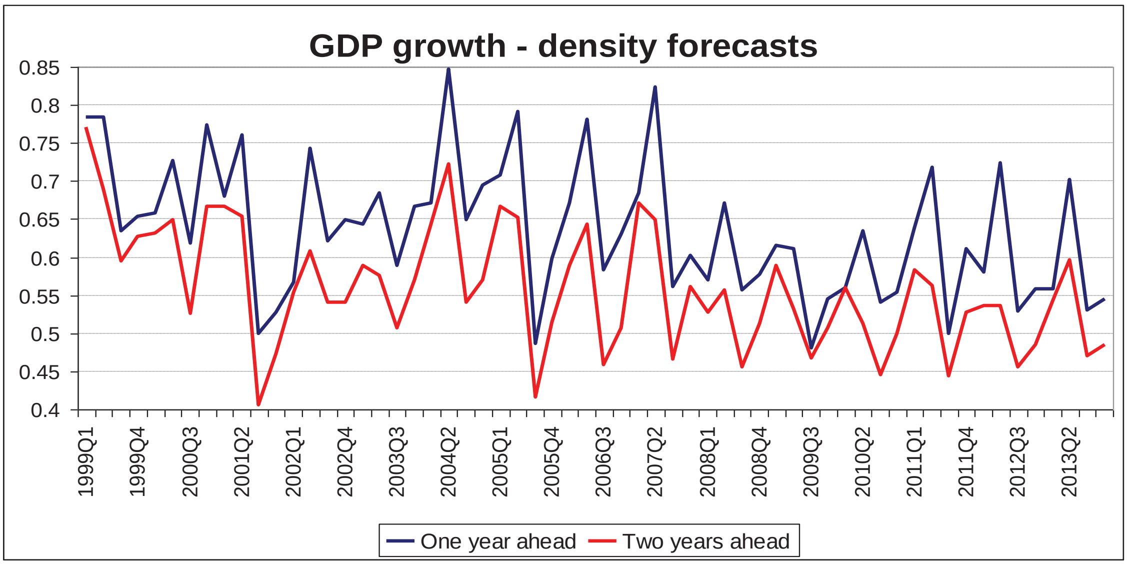


Figure 4 (cont.): Response rates by variable, type of forecast and forecast horizon.





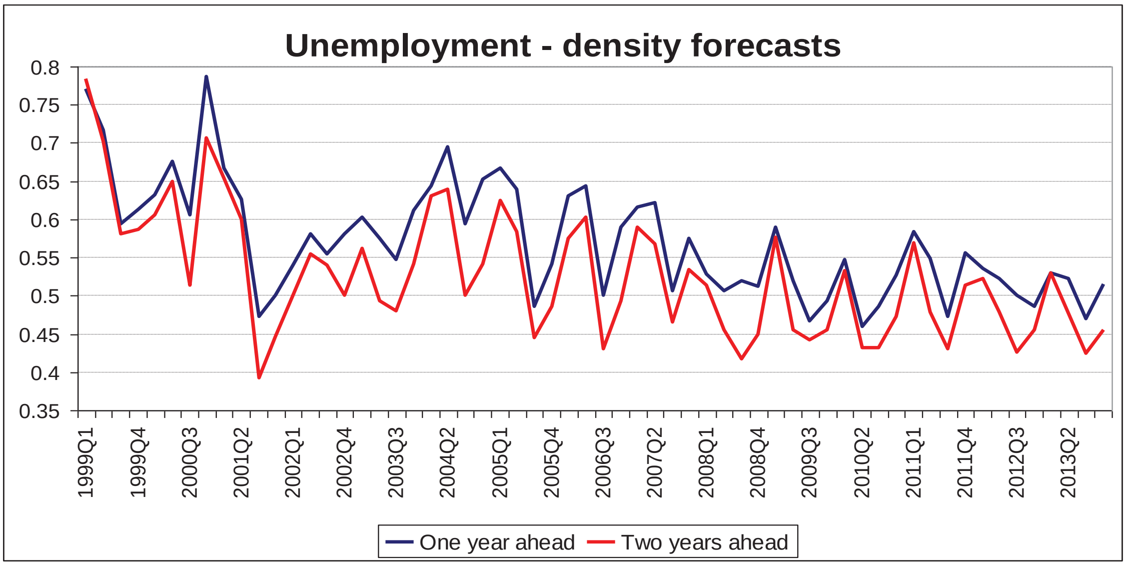
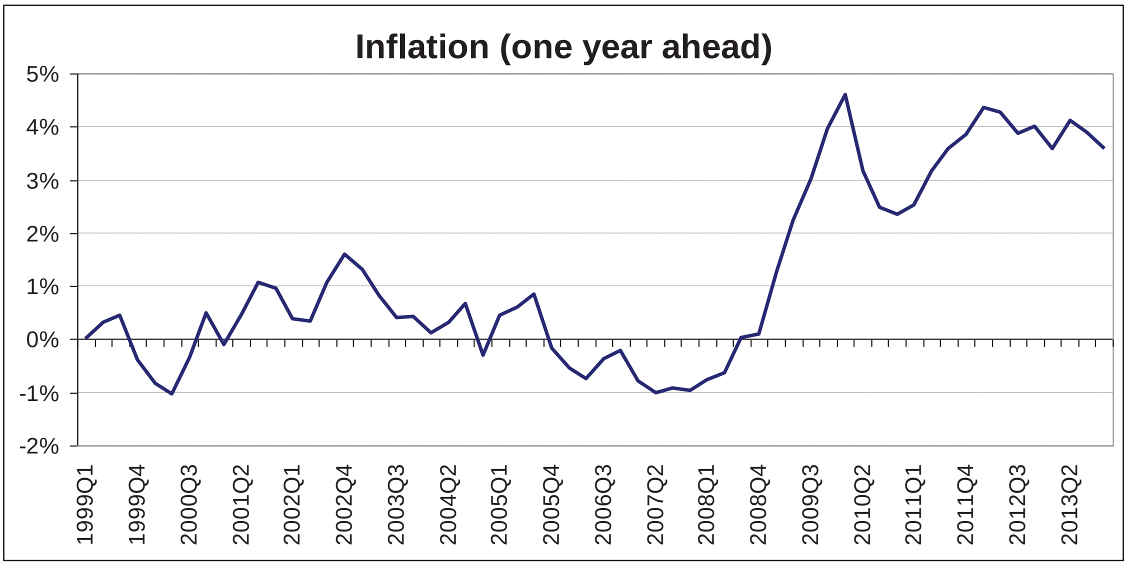
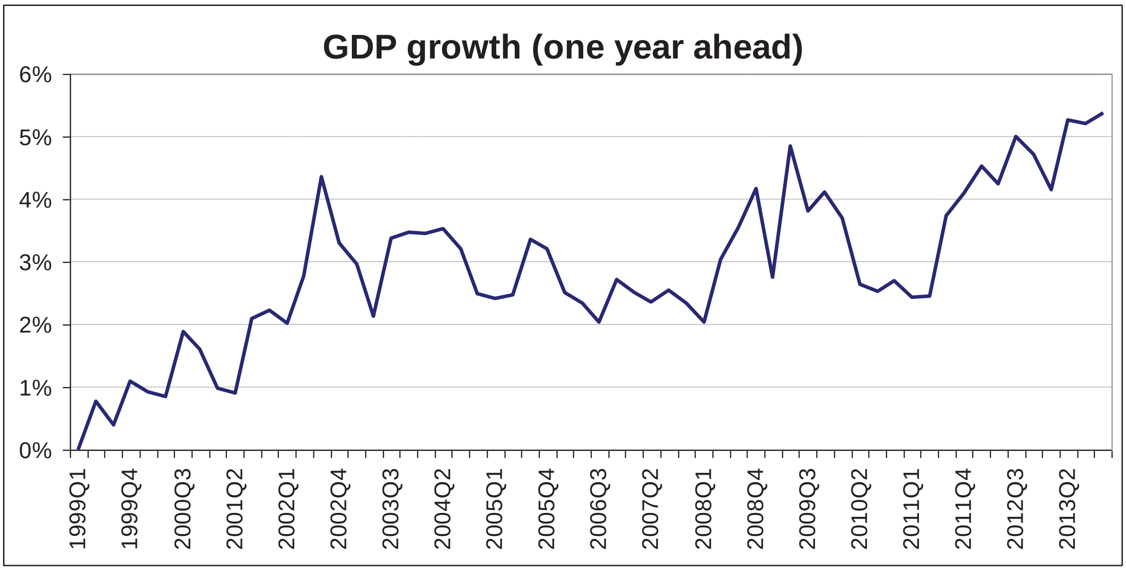


Figure 5: Measures of uncertainty by variable and forecast horizon (percentage change in the aggregate Gini index since 1999 Q1).





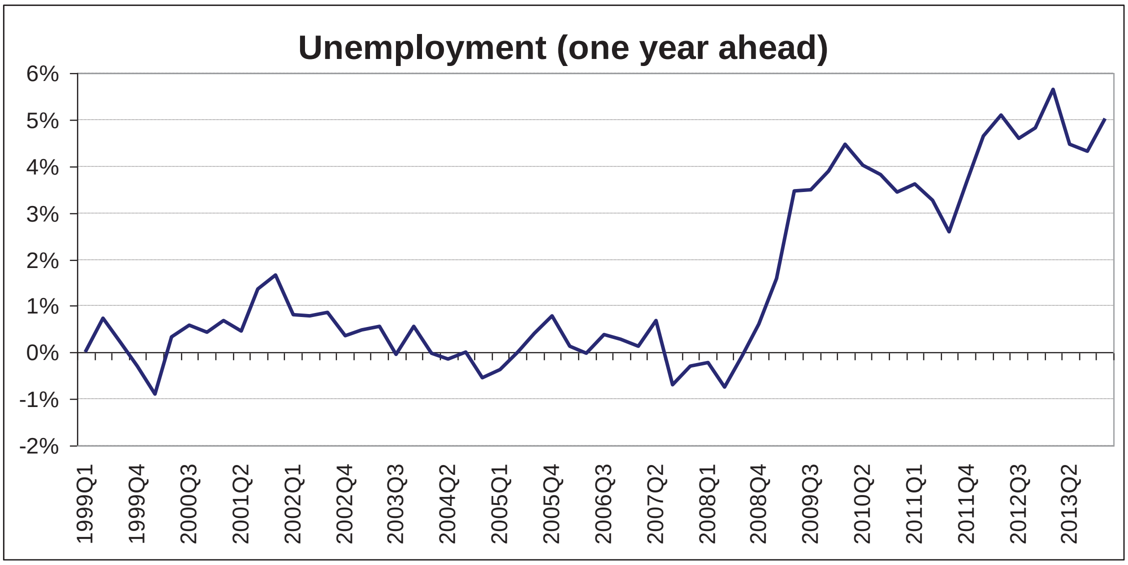
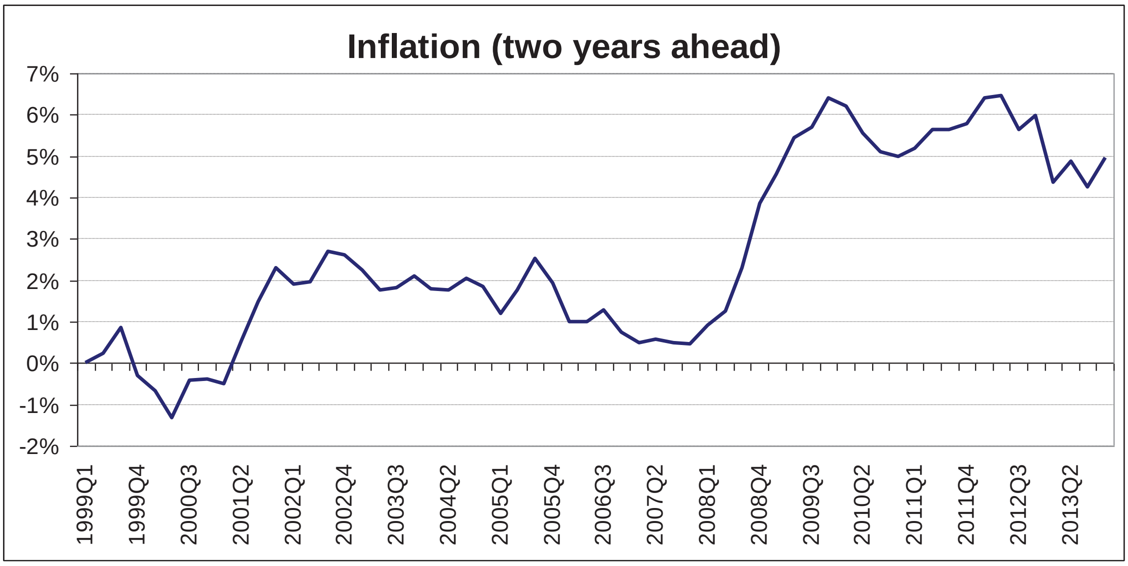
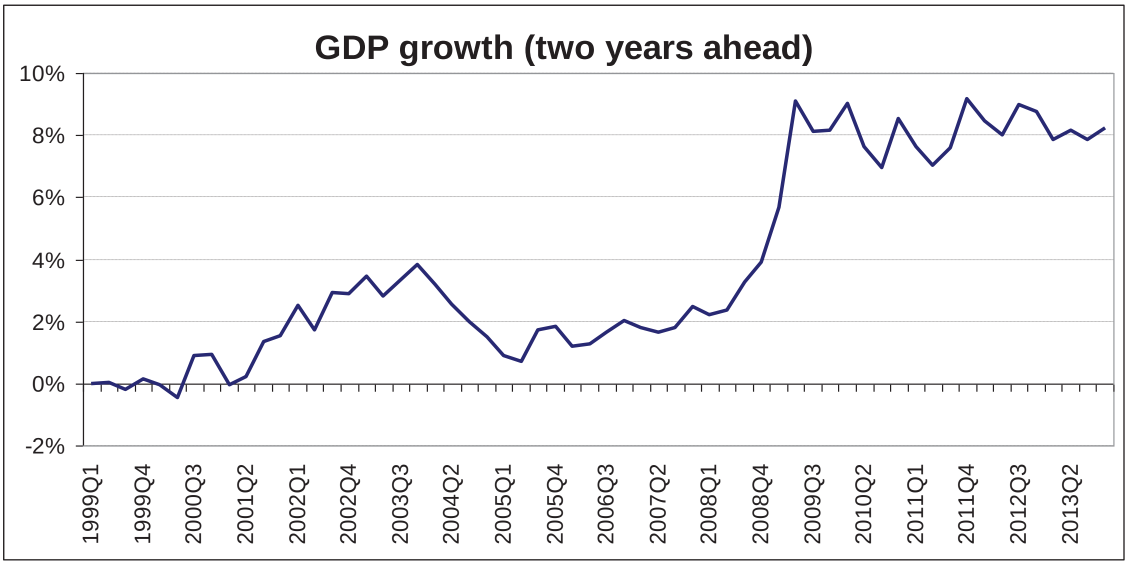


Figure 5 (cont.): Measures of uncertainty by variable and forecast horizon (percentage change in the aggregate Gini index since 1999 Q1).





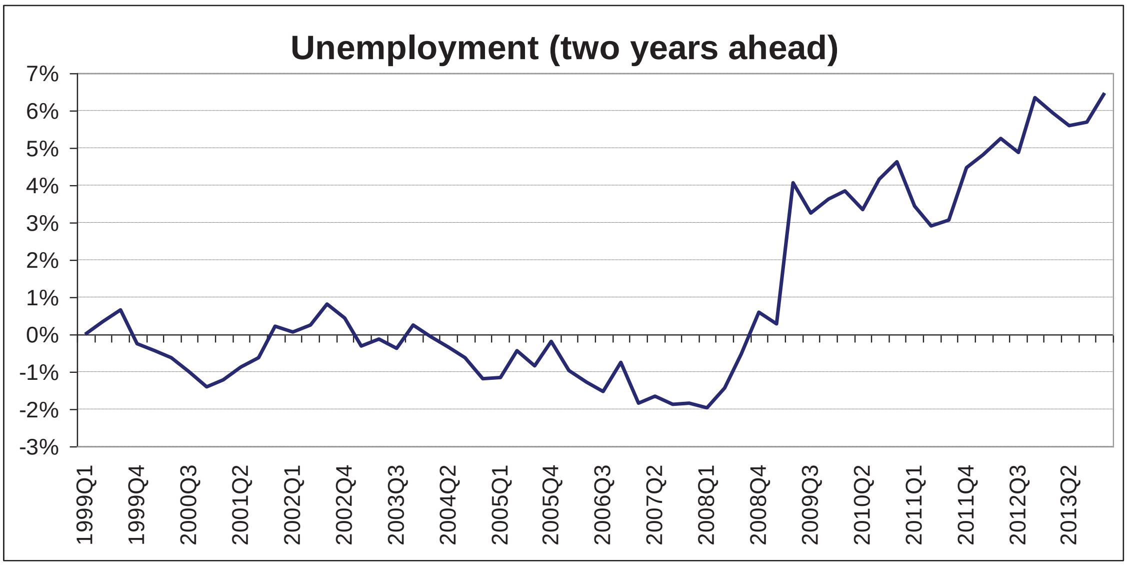


Figure 6: Number of days given to SPF panellists to submit their forecasts to the ECB during each survey round.

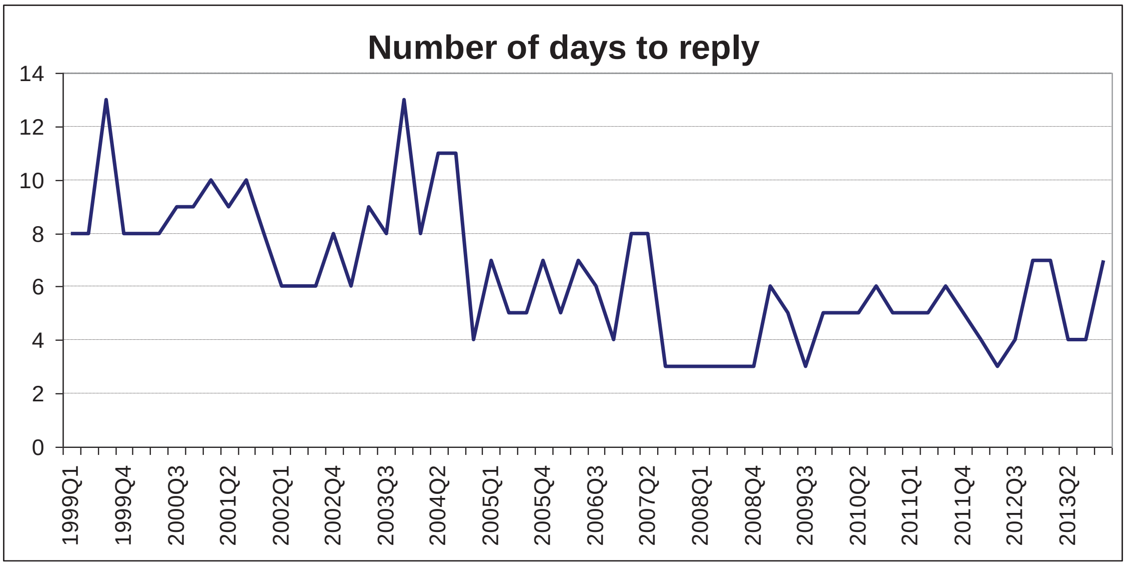


Figure 7: The marginal effect on participation from changes in uncertainty for different values of the uncertainty measure.

a) Point forecasts

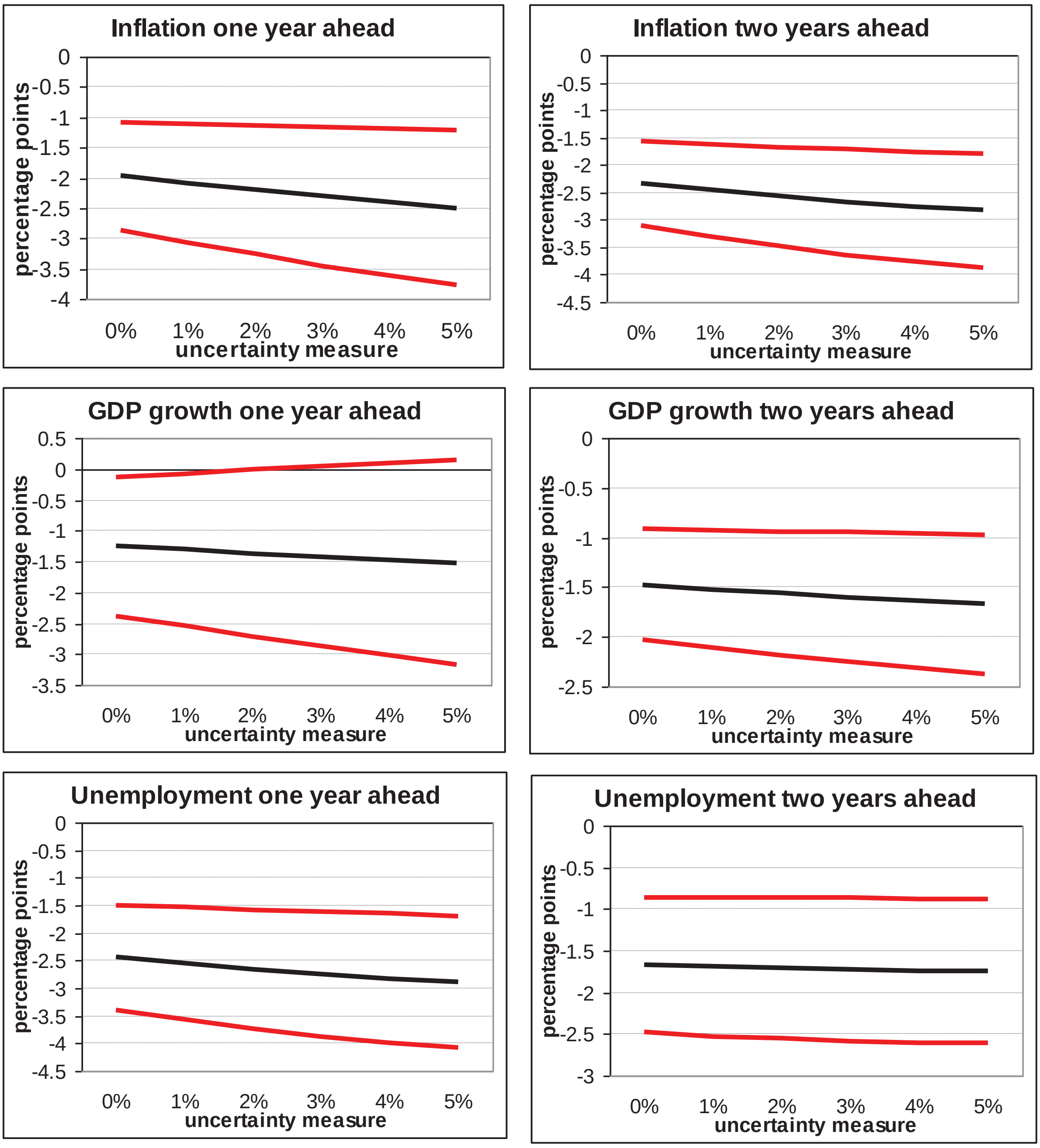


Figure 7 (cont): The marginal effect on participation from changes in uncertainty for different values of the uncertainty measure.

b) Density forecasts

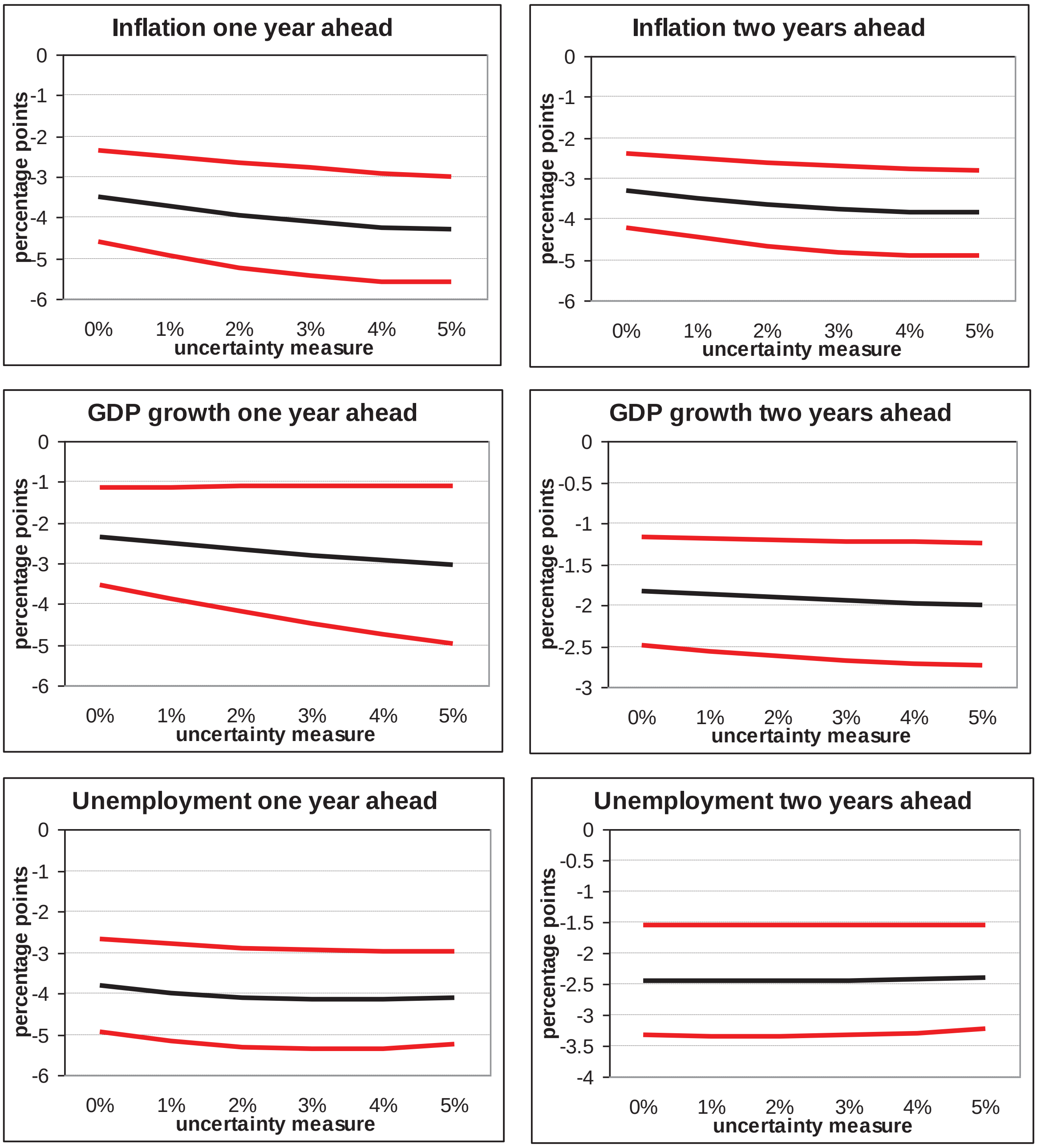


Figure 8: Comparison between the standardised 12-month VSTOXX and the standardised SPF-based uncertainty measures from density forecasts one year ahead.

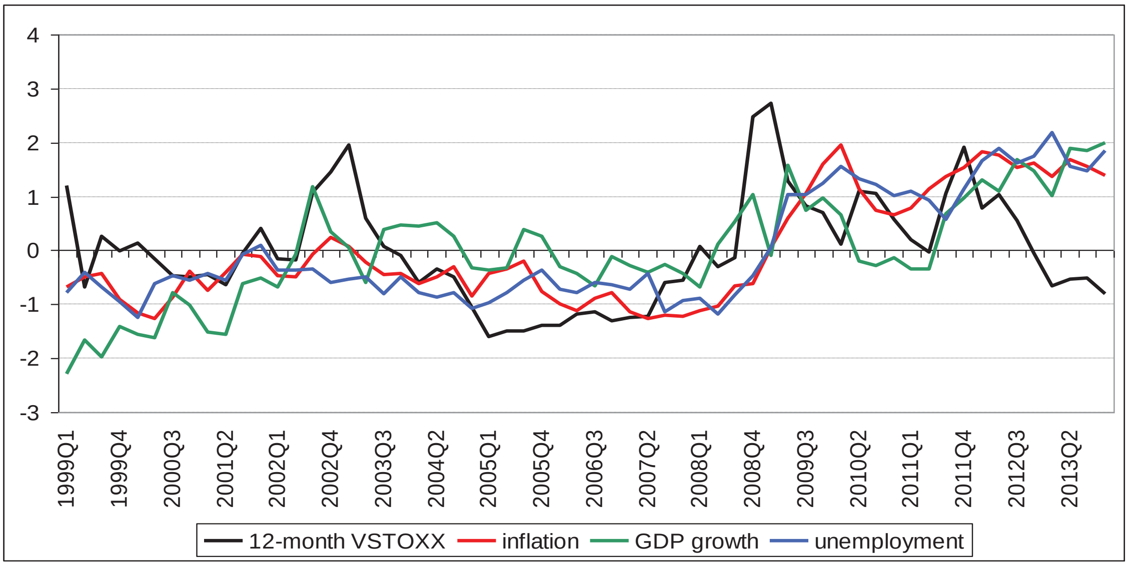


Figure 9: Comparison between the standardised 24-month VSTOXX and the standardised SPF-based uncertainty measures from density forecasts two years ahead.

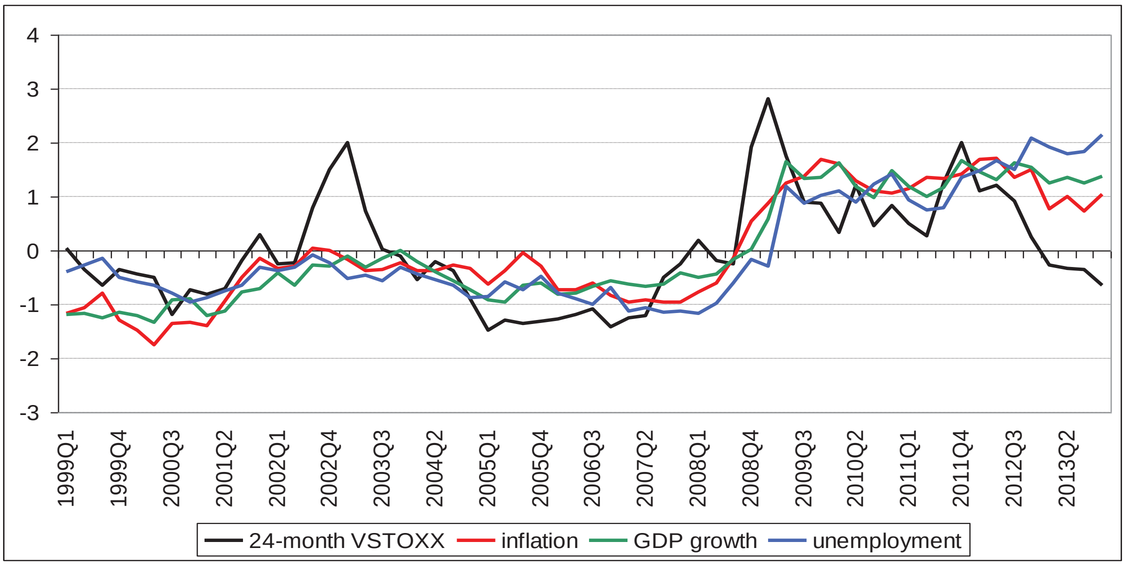


Table 1: Results of the Elliott, Rothenberg and Stock Optimal Point (ERS-OP) unit-root test and the Ng and Perron (NP) unit root tests.

			Constant		Constant + trend	
			ERS-OP	NP	ERS-OP	NP
Response rates	Inflation one year ahead	Point			**	***
		Density		**	***	***
	Inflation two years ahead	Point			**	***
		Density		**	**	**
	GDP growth one year ahead	Point		***	**	**
		Density		*	**	**
	GDP growth two years ahead	Point			**	***
		Density		*	*	**
	Unemployment one year ahead	Point			**	**
		Density			*	**
	Unemployment two years ahead	Point			*	**
		Density				**
Uncertainty measures	Inflation one year ahead					
	Inflation two years ahead					
	GDP growth one year ahead				**	*
	GDP growth two years ahead					
	Unemployment one year ahead					
	Unemployment two years ahead					
Number of days to reply			***	***	***	***

Notes: The null hypothesis of the tests is Ho: there is a unit root in the level of the series. * denotes rejection of the null hypothesis at the 10% level of significance. ** denotes rejection of the null hypothesis at the 5% level of significance. *** denotes rejection of the null hypothesis at the 1% level of significance. "Point" stands for point forecasts. "Density" stands for density forecasts. The ERS-OP test uses the AR spectral OLS estimation method and its lag length is selected according to the Schwarz information criterion with maximum lag length equal to 10. The NP test uses the AR GLS-detrended spectral estimation method and its lag length is selected according the Schwarz information criterion with maximum lag length equal to 10. Sample period: 1999 Q1 – 2013 Q4.

Table 2: Results of the Engle and Granger two-step cointegration tests.

a) Unit root tests of the first-step residuals (cointegration test)

			Constant		Constant + trend	
			ERS-OP	NP	ERS-OP	NP
First-step residuals	Inflation one year ahead	Point	***	***	***	***
		Density	**	***	***	***
	Inflation two years ahead	Point	*	**	**	***
		Density	**		**	***
	GDP growth one year ahead	Point	***	***	***	***
		Density	***	***	***	***
	GDP growth two years ahead	Point	***	***	***	***
		Density	***	***	***	***
	Unemployment one year ahead	Point	*	**	*	**
		Density	*	*	**	*
	Unemployment two years ahead	Point				
		Density			*	**

Notes: See the notes below Table 1.

Table 2: Results of the Engle and Granger two-step cointegration tests (cont.)

b) Cointegration equations:

Inflation one year ahead:

$$\textit{Point forecasts: } R_t = 0.659 - 0.968 * U_t + 0.007 * D_t$$
$$\textit{Density forecasts: } R_t = 0.579 - 1.574 * U_t + 0.010 * D_t$$

Inflation two years ahead:

$$\textit{Point forecasts: } R_t = 0.619 - 1.342 * U_t + 0.006 * D_t$$
$$\textit{Density forecasts: } R_t = 0.576 - 1.673 * U_t + 0.006 * D_t$$

GDP growth one year ahead:

$$\textit{Point forecasts: } R_t = 0.680 - 0.501 * U_t + 0.005 * D_t$$
$$\textit{Density forecasts: } R_t = 0.610 - 1.243 * U_t + 0.009 * D_t$$

GDP growth two years ahead:

$$\textit{Point forecasts: } R_t = 0.602 - 0.651 * U_t + 0.006 * D_t$$
$$\textit{Density forecasts: } R_t = 0.610 - 1.243 * U_t + 0.009 * D_t$$

Unemployment one year ahead:

$$\textit{Point forecasts: } R_t = 0.608 - 1.142 * U_t + 0.006 * D_t$$
$$\textit{Density forecasts: } R_t = 0.526 - 1.578 * U_t + 0.010 * D_t$$

Unemployment two years ahead:

Point forecasts: -
Density forecasts: -

Notes: R_t denotes the response rate, U_t the uncertainty measure and D_t the number of days to reply. Results are not shown for unemployment two years ahead due to the absence of cointegration. Sample period: 1999 Q1 – 2013 Q4.

Table 3: Estimated long-run effects on the response rates from the increase in uncertainty at the start of the financial crisis.

	Change in the uncertainty measure			Effects on response rates	
	From	To	Change	Point	Density
Inflation one year ahead	-0.010063 (2007 Q2)	0.045924 (2010 Q1)	0.055547	-5.4 p.p.	-8.7 p.p.
Inflation two years ahead	0.004649 (2007 Q4)	0.063988 (2009 Q4)	0.059339	-8.0 p.p.	-10.0 p.p.
GDP growth one year ahead	0.020295 (2008 Q1)	0.048535 (2009 Q2)	0.02824	-1.4 p.p.	-3.5 p.p.
GDP growth two years ahead	0.016556 (2007 Q2)	0.090930 (2009 Q2)	0.074374	-4.8 p.p.	-9.2 p.p.
Unemployment one year ahead	-0.007548 (2008 Q2)	0.044722 (2010 Q1)	0.05227	-6.0 p.p.	-8.2 p.p.
Unemployment two years ahead	-	-	-	-	-

Notes: "Point" stands for point forecasts. "Density" stands for density forecasts. The cells report the estimated changes in percentage points in long-run response rates as a result of the increase in uncertainty experienced at the start of the financial crisis. The effect on the response rate for unemployment two years ahead is not reported due to the absence of cointegration.

Table 4: Estimation results of the error-correction models.

$$\Delta R_t = \alpha_C \, fsr_{t-1} + \beta_R \Delta R_{t-1} + \beta_U \Delta U_{t-1} + \beta_D D_t + \varepsilon_t$$

a) Point forecasts

	Inflation one year ahead	Inflation two years ahead	GDP growth one year ahead	GDP growth two years ahead	Unemploy-ment one year ahead	Unemploy-ment two years ahead
α_C	-0.614 (0.000)	-0.638 (0.000)	-0.469 (0.000)	-0.370 (0.004)	-0.788 (0.000)	-
β_R	-0.137 (0.137)	0.395 (0.009)	-0.200 (0.110)	-0.333 (0.000)	-0.035 (0.772)	-
β_U	-0.999 (0.311)	-1.500 (0.005)	1.382 (0.055)	-0.224 (0.750)	-0.990 (0.273)	-
β_D	0.003 (0.083)	0.001 (0.602)	-0.000 (0.915)	-0.000 (0.794)	-0.000 (0.881)	-

Notes: The cells report the least-squares estimated values of the model parameters with p-values in parenthesis. Sample period: 1999 Q1 – 2013 Q4. A lag of D_t has been added to the specification for inflation one and two years ahead to pass the White heteroskedasticity test. An AR(1) error term has been added to the specification for inflation two years ahead to pass the Ljung-Box and LM autocorrelation tests.

b) Density forecasts

	Inflation one year ahead	Inflation two years ahead	GDP growth one year ahead	GDP growth two years ahead	Unemploy-ment one year ahead	Unemploy-ment two years ahead
α_C	-0.639 (0.000)	-0.649 (0.000)	-0.489 (0.002)	-0.722 (0.000)	-0.690 (0.000)	-
β_R	-0.030 (0.770)	0.382 (0.008)	0.094 (0.466)	0.115 (0.325)	0.102 (0.421)	-
β_U	-1.439 (0.187)	-1.607 (0.014)	1.392 (0.108)	-0.423 (0.552)	-1.382 (0.063)	-
β_D	0.000 (0.848)	-0.000 (0.570)	-0.000 (0.830)	-0.000 (0.775)	-0.000 (0.942)	-

Notes: The cells report the least-squares estimated values of the model parameters with p-values in parenthesis. Sample period: 1999 Q1 – 2013 Q4. An AR(1) error term has been added to the specification for inflation two years ahead to pass the LM autocorrelation test. A second lag of the dependent variable has been added to the specification for unemployment one year ahead to pass the LM autocorrelation test.

Table 5: p-values of the Hausman test of random effects vs. fixed effects.

a) Point forecasts

	Inflation one year ahead	Inflation two years ahead	GDP growth one year ahead	GDP growth two years ahead	Unemploy-ment one year ahead	Unemploy-ment two years ahead
p-value	0.258	0.794	0.505	0.466	0.674	0.933

b) Density forecasts

	Inflation one year ahead	Inflation two years ahead	GDP growth one year ahead	GDP growth two years ahead	Unemploy-ment one year ahead	Unemploy-ment two years ahead
p-value	0.156	0.759	0.565	0.702	0.776	0.978

Notes: The cells report the p-values of the Hausman test whose null hypothesis is Ho: there is no systematic difference between the fixed-effects and the random-effects estimators of the Logit model of participation in the ECB's SPF.

Table 6: Estimation results of the Logit models with panel data.

$$\Pr(D_{ijht} = 1) = \frac{1}{1 + e^{-(\beta_U U_{jht} + \beta_D D_t + \beta_{Q1} D_{Q1} + \beta_{Q2} D_{Q2} + \beta_{Q3} D_{Q3} + \beta_{Q4} D_{Q4} + u_{ijh} + \varepsilon_{ijht})}}$$

a) Point forecasts

	Inflation one year ahead	Inflation two years ahead	GDP growth one year ahead	GDP growth two years ahead	Unemployment one year ahead	Unemployment two years ahead
β_U	-11.006 (-4.49)	-11.739 (-5.85)	-7.558 (-1.98)	-7.218 (-5.03)	-11.796 (-5.18)	-6.980 (-4.09)
β_D	0.068 (4.04)	0.044 (3.06)	0.050 (2.84)	0.043 (2.48)	0.057 (3.36)	0.067 (4.04)
β_{Q1}	0.969 (4.47)	1.120 (4.85)	1.019 (4.17)	0.957 (3.95)	0.735 (3.09)	0.391 (1.65)
β_{Q2}	0.768 (3.57)	0.683 (2.98)	1.482 (5.98)	0.969 (4.03)	0.562 (2.37)	0.044 (0.18)
β_{Q3}	0.448 (2.08)	0.271 (1.17)	0.552 (2.17)	0.096 (0.40)	0.227 (0.96)	-0.415 (-1.75)
β_{Q4}	0.832 (3.84)	0.710 (2.54)	0.964 (3.78)	0.559 (2.30)	0.569 (2.40)	-0.006 (-0.03)

b) Density forecasts

	Inflation one year ahead	Inflation two years ahead	GDP growth one year ahead	GDP growth two years ahead	Unemployment one year ahead	Unemployment two years ahead
β_U	-17.228 (-6.82)	-15.410 (-7.34)	-13.007 (-3.39)	-8.062 (-5.40)	-16.699 (-7.02)	-9.814 (-5.44)
β_D	0.091 (5.29)	0.044 (2.48)	0.073 (4.15)	0.059 (3.27)	0.087 (4.97)	0.087 (4.98)
β_{Q1}	0.539 (2.18)	0.865 (3.36)	0.637 (2.45)	0.528 (1.98)	0.224 (0.82)	-0.060 (-0.22)
β_{Q2}	0.450 (1.83)	0.574 (2.24)	1.342 (5.08)	0.578 (2.18)	0.199 (0.73)	-0.230 (-0.84)
β_{Q3}	0.067 (0.27)	0.125 (0.49)	0.255 (0.94)	-0.262 (-0.98)	-0.320 (-1.18)	-0.822 (-3.01)
β_{Q4}	0.387 (1.57)	0.501 (1.94)	0.592 (2.19)	0.147 (0.55)	0.064 (0.23)	-0.438 (-1.60)

Notes: The cells report the maximum-likelihood estimators of the model parameters and their t-statistics in parenthesis. The t-statistic critical values are 1.65 (10%), 1.96 (5%) and 2.58 (1%). Sample period: 1999 Q1 – 2013 Q4. Number of observations: 4317.

Table 7: Estimated marginal effects on the probability of individual participation from changes in the regressors of the Logit model.

a) Point forecasts

	Changes in the probability of participation					
	Inflation one year ahead	Inflation two years ahead	GDP growth one year ahead	GDP growth two years ahead	Unemploy-ment one year ahead	Unemploy-ment two years ahead
Uncertainty	-2.1 p.p. (0.000)	-2.6 p.p. (0.000)	-1.4 p.p. (0.051)	-1.6 p.p. (0.000)	-2.6 p.p. (0.000)	-1.7 p.p. (0.000)
Days	+1.3 p.p. (0.000)	+1.0 p.p. (0.012)	+0.9 p.p. (0.005)	+0.9 p.p. (0.014)	+1.3 p.p. (0.001)	+1.6 p.p. (0.000)
Dummy (Q1)	+23.7 p.p. (0.000)	+28.0 p.p. (0.000)	+25.4 p.p. (0.000)	+23.9 p.p. (0.000)	+18.2 p.p. (0.002)	+9.4 p.p. (0.103)
Dummy (Q2)	+18.7 p.p. (0.001)	+17.1 p.p. (0.003)	+37.0 p.p. (0.000)	+24.2 p.p. (0.000)	+13.9 p.p. (0.019)	+1.1 p.p. (0.854)
Dummy (Q3)	+10.9 p.p. (0.042)	+6.8 p.p. (0.240)	+13.8 p.p. (0.033)	+2.4 p.p. (0.692)	+5.6 p.p. (0.339)	-10.0 p.p. (0.075)
Dummy (Q4)	+20.3 p.p. (0.000)	+17.7 p.p. (0.002)	+24.0 p.p. (0.000)	+14.0 p.p. (0.021)	+14.1 p.p. (0.018)	-0.2 p.p. (0.979)

b) Density forecasts

	Changes in the probability of participation					
	Inflation one year ahead	Inflation two years ahead	GDP growth one year ahead	GDP growth two years ahead	Unemploy-ment one year ahead	Unemploy-ment two years ahead
Uncertainty	-3.8 p.p. (0.000)	-3.7 p.p. (0.000)	-2.8 p.p. (0.001)	-2.0 p.p. (0.000)	-4.1 p.p. (0.000)	-2.5 p.p. (0.000)
Days	+2.0 p.p. (0.000)	+1.1 p.p. (0.014)	+1.6 p.p. (0.000)	+1.4 p.p. (0.001)	+2.1 p.p. (0.000)	+2.2 p.p. (0.000)
Dummy (Q1)	+13.0 p.p. (0.033)	+21.5 p.p. (0.001)	+15.9 p.p. (0.016)	+13.2 p.p. (0.049)	+5.5 p.p. (0.416)	-1.4 p.p. (0.825)
Dummy (Q2)	+10.9 p.p. (0.073)	+14.3 p.p. (0.024)	+33.5 p.p. (0.000)	+14.4 p.p. (0.030)	+4.9 p.p. (0.469)	-5.5 p.p. (0.394)
Dummy (Q3)	+1.6 p.p. (0.786)	+3.1 p.p. (0.627)	+6.4 p.p. (0.349)	-6.6 p.p. (0.324)	-7.8 p.p. (0.235)	-19.5 p.p. (0.002)
Dummy (Q4)	+9.3 p.p. (0.123)	+12.5 p.p. (0.051)	+14.8 p.p. (0.031)	+3.7 p.p. (0.584)	+1.6 p.p. (0.815)	-10.4 p.p. (0.103)

Notes: p-values for the null hypothesis of zero effect are reported in parenthesis.

Table 8: Comparison between changes in the standardised 12-month and 24-month VSTOXX indices and the standardised SPF-based uncertainty measures during two selected episodes.

a) 12-month VSTOXX index and SPF-based uncertainty measures from density forecasts one year ahead

	VSTOXX	SPF		
		Inflation	GDP growth	Unemployment
2001Q2 - 2003Q1	2.59	0.49	1.63	0.02
2007Q2 - 2009Q1	3.94	1.31	0.31	0.47

b) 24-month VSTOXX index and SPF-based uncertainty measures from density forecasts two years ahead

	VSTOXX	SPF		
		Inflation	GDP growth	Unemployment
2001Q2 - 2003Q1	2.70	0.77	1.02	0.22
2007Q2 - 2009Q1	4.02	1.78	1.25	0.77

Notes: The cells in the table show the increase in the different measures of uncertainty over the periods on the first column. All uncertainty measures have been standardised. Therefore, the units are standard deviations of each uncertainty measure.

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