Ex-Ante Uncertainty and the Euro Area Business Cycle†

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Abstract
We propose a new survey-based measure of aggregate ex-ante uncertainty for the euro area to assess the relevance of uncertainty shocks at business cycle frequencies. The proposed measure combines information about the disagreement concerning future outcomes for key macro variables with information on their expected conditional volatilities as perceived by individual forecasters. We then exploit information delays and the timing of the survey to identify an exogenous uncertainty shock in a medium-sized Bayesian Vector Auto Regression (BVAR) and trace out the transmission of these shocks via both real and financial sector variables. The relevance of uncertainty shocks during the Great Recession and subsequent sovereign debt crisis in the euro area is then assessed both in sample and in terms of out-of-sample prediction. We find a strong role for our identified ex-ante uncertainty shock as a driver of euro area business cycles, with the financial sector response playing an important role in the propagation of such shocks. Also, a real time out-of-sample forecasting evaluation highlights the relevance of ex-ante uncertainty measures in improving the predictions of credit dynamics as well as bank lending and corporate bond spreads.

Keywords: Uncertainty Shocks, Great Recession, Euro Area

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Non-Technical Summary

In this paper, we present a new measure of macroeconomic uncertainty for the euro area economy and analyse its transmission to both real and financial sector variables. Our proposed measure is constructed from the probabilistic assessments of panellists in the ECB’s Survey of Professional Forecasters. It combines information about real variables like GDP growth and future unemployment with information about inflation and has a number of attractive conceptual features. Firstly, it takes a forward looking or ex-ante perspective which directly links the measurement of uncertainty to the perceived predictability of economic outcomes. Second, our proposed measure takes into account information about forecaster disagreement about the predictable component of a given variable as well as the expected volatilities that are estimated by each forecaster. Third, reflecting its survey origins, our proposed measure lends itself conveniently to identify the effects of uncertainty shocks on the macroeconomy.

Our proposed measure and identification strategy deliver a range of important new empirical results of relevance to euro area business cycle analysis. In the first instance, our results highlight the importance of uncertainty shocks for the understanding of business cycle fluctuations in the euro area economy. A typical shock to our proposed measure of uncertainty is associated with a drop in GDP and its components, most notably private consumption and investment. Also, higher uncertainty leads to a deterioration in labour market conditions and is reflected in a substantial and persistent rise in the unemployment rate. Our results also highlight the importance of the response of the financial sector in the transmission of uncertainty shocks: a positive shock to ex-ante uncertainty is associated with a rise in credit spreads, a drop in equity prices and a persistent reduction in private sector credit. At the same time, our results suggest that much of the fluctuations in euro area GDP over the sample period and particularly during the Great Recession should be attributed to other real and financial sector shocks and not to uncertainty shocks per se. Over the period of the Great recession, as defined by the CEPR’s business cycle dating committee, approximately 1/6th of the drop in the level of euro area GDP is explained by the rise in uncertainty. Although certainly economically significant, this contrasts with results for the US economy suggesting that uncertainty shocks
may have played more significant role in relative terms. An important feature of this historical analysis is how uncertainty shocks contributed to the expansion in the economy also before the financial crisis. These expansionary or “negative uncertainty shocks” can partly be interpreted as excess confidence about the future evolution of the economy.

Finally, we also show how our proposed measure of aggregate ex-ante uncertainty can contribute to out-of-sample prediction compared with a reference model which does not contain any uncertainty measures. Most notably, using a real time simulated forecasting exercise, we find an important role for uncertainty in helping to forecast real and, particularly, financial variables such as bank credit and risk premia. We also find that to achieve these improvements in predictive performance it is sufficient to focus on our proposed measure of aggregate uncertainty, rather than focussing on separately modelling the transmission of uncertainty related to specific macroeconomic variables or to specific prediction horizons. Also, compared with some of the other proxies for uncertainty that are commonly used in the literature, it is the proposed aggregate measures of ex-ante uncertainty extracted from the aggregate probability distributions that yields the most important gains in quantitative terms. Overall, therefore, measures of aggregate uncertainty extracted from expert probability forecasts of the type that we have analysed appear to offer a conceptually well-grounded measure of uncertainty for business cycle analysis that is empirically relevant.
1. Introduction
Since the global financial crisis of 2007, a growing body of theoretical and empirical research in economics has emphasised the role of uncertainty as a fundamental determinant of macroeconomic fluctuations at business cycle frequencies - see, for example, Bloom (2014) for a related survey article. The importance of uncertainty shocks has been linked both to the extent of the drop in activity during the downturn as well as to the relative sluggishness of the subsequent recovery in aggregate demand, in investment and hiring decisions. For example, the study by Bloom, Floetotto, Jaimovich, Saporta-Eksten and Terry (2014) using macroeconomic data suggests that uncertainty shocks may have reduced US GDP by about 3.0% during the great recession, implying that uncertainty can explain close to 1/3rd of the crisis-related drop in US GDP. Using more microeconomic sources of data, Stein and Stone (2012) reach similar conclusions on the fundamental role of uncertainty as a driver of US business cycles.¹

In this paper we contribute to the empirical literature on uncertainty shocks with a particular focus on the euro area during the recent great recession and subsequent sovereign debt crisis. Our analysis brings forward several important contributions both with regard to the measurement of uncertainty and the assessment of its macroeconomic impact and relevance for forecasting. In line with recent work of Clements (2013), Rossi and Sekhposyan (2015) and Jurado, Ludvigson and Ng (2015), we develop a statistically and economically well-grounded concept of uncertainty that is linked to the ex-ante predictability of economic outcomes. By exploiting the predictive densities from the ECB Survey of Professional Forecasters (SPF), our measure has several advantages compared with other commonly-used proxies such as implied stock market volatility, forecaster disagreement or indicators based on textual analysis of media commentary. Most notably, it can be directly linked to the variance of the aggregate forecast distribution for key

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¹ A survey of some recent commentaries by policy makers gives much prominence to the importance of the uncertainty narrative both in the United States and in the Euro area. For example, Lagarde (2012) states “There is a level of uncertainty which is hampering decision makers from investing and from creating jobs” while ECB (2016) makes a similar argument “... elevated uncertainty ..., is an important factor hampering business investment in the present environment”. Indeed, while such statements highlight the importance of uncertainty as a factor influencing private sector decisions, uncertainty has also been given a prominent role in explaining the timing of policy: For example, Yellen (2015) notes “... in light of the heightened uncertainties abroad and the slightly softer than expected path for inflation, the committee judged it appropriate to wait for more evidence.”
macroeconomic variables, such as GDP, inflation and unemployment. As such, it combines information about the average conditional volatility of future economic outcomes as perceived by individual forecasters along with information about how much forecasters disagree about the most likely or mean outcome. Such a composite uncertainty indicator captures well the uncertainty faced in actual decision making where, for example, policy makers or private agents will often be confronted with multiple forecasts each of which has its own probability distribution. A second attractive feature of our measure is that it can distinguish the specific horizon over which uncertainty is measured – a feature which enables an empirical comparison of the effects of uncertainty shocks depending on the horizon to which they relate (e.g. the effects of long term uncertainty shocks compared with shocks to short term uncertainty). Third, the real-time nature of the SPF densities and the beginning-of-quarter timing of the SPF surveys can be used to motivate restrictions on the contemporaneous interactions of uncertainty with other real and financial variables. This helps us to identify an exogenous innovation to uncertainty.\(^2\) In particular, because they are unobserved at the time the survey is carried out, shocks to other real and financial sector variables should have no contemporaneous impact on ex-ante uncertainty. This natural identification strategy using survey data helps ensure that our assessment of the contribution of uncertainty is not simply reflecting an endogenous reaction to other economic phenomena but rather may capture a fundamental source of business cycle dynamics. Exploiting this strategy, we employ a medium-sized Bayesian Vector Autoregression (BVAR) to trace out the effects on both real and financial-sector variables associated with these “structural” innovations in uncertainty. Moreover, we can exploit the same BVAR to conduct an out-of-sample evaluation of the relative contribution of ex-ante uncertainty for forecasting other real and financial variables and compare that contribution with that of the other main uncertainty proxies used in the literature.

\(^2\) Inoue, Kilian, and Kiraz (2009) also motivate such restrictions with information delays linked to the timing of SPF forecasts. They observe that Survey of Professional Forecasters (SPF) inflation forecasts for the current quarter are formed before the interest rate for the current quarter is set (reflecting their release in the middle of the preceding quarter), while household survey expectations of the real interest rate are formed after observing the nominal interest rate at the beginning of the quarter. The authors then use this reasoning to motivate a recursive structure with the SPF forecast ordered first, followed by the interest rate and households' real interest rate expectations.
Our results show that aggregate ex-ante uncertainty is highly relevant for understanding the evolution of the euro area economy. Following a positive shock to ex-ante uncertainty GDP falls, investment is weaker and the unemployment rate is higher. Also, such effects are highly persistent. Our results also suggest that the adjustment of financial variables is central to the transmission of uncertainty shocks. In particular, a positive shock to uncertainty is associated with a rise in both corporate bond and lending rate spreads and a contraction in the overall supply of credit to the private sector of the economy. In line with this, we find that a substantial share of macroeconomic fluctuations associated with the Great Recession and subsequent sovereign debt crisis in the euro area can be attributed directly to the impact of uncertainty shocks that are orthogonal to other real and financial sector shocks. Lastly, we also find that our measure of ex-ante uncertainty is relevant for out-of-sample forecasting in the sense that its inclusion improves the predictive performance of the BVAR for many real and, especially for financial sector variables. These results mirror recent findings in Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2016) for the US economy, suggesting a much stronger and more fundamental role for uncertainty as a source of euro area business cycle fluctuations. Lastly, we show that these results are very robust across both the parametric and non-parametric methods that can be used to measure ex-ante uncertainty.

The remainder of the paper is organised as follows. In Section 2, we describe the parametric methods that can be used to derive measures of ex-ante uncertainty from the euro area SPF. In Section 3, we explore the contribution of these uncertainty measures to the euro area business cycles in terms of in-sample explanatory power, including an assessment of their historical contribution to the Great Recession and the recent euro area sovereign debt crisis. In Sector 4 we report the results of a real time out-of-sample forecasting evaluation to assess the empirical relevance of uncertainty indicators for economic prediction in the euro area. Finally Section 5 concludes.
2. Measuring aggregate ex-ante uncertainty

In this Section, in line with the approaches of Clements (2014), Jurado et al. (2015) and Rossi and Sekhposyan (2015), we propose a measure of macroeconomic uncertainty that directly links to the ex-ante predictability of economic outcomes. As in Jurado et al. (2015), for a given prediction horizon $h$, we consider a measure of Ex-Ante Uncertainty (EAU) to be the conditional volatility of a time series once its predictable component has been removed, i.e. $\text{EAU} = E_t[(y_{t+h} - E_t[y_{t+h}])^2]$, where expectations are taken with respect to the period $t$ information set. To measure EAU at the level of the macroeconomy, Jurado et al. (2015) construct a representative uncertainty index as a weighted average of ex-ante uncertainty measures from a large cross-section of economic variables. Although we focus on only a few variables, our proposed measure takes a similar track but allows for the fact that in reality both decision makers and economic agents are confronted with multiple forecasts for a given economic variable. In the absence of a single rational forecast on which all agents would agree, there is no single measure of the predictable component, $E_t[y_{t+h}]$, that can be removed. Instead, decision makers and the public are confronted with a range of such forecasts $E_{it}[y_{t+h}]$ for each forecaster $i = 1, \ldots, N$. Clearly, however, disagreement about the predictable component of a variable represents an additional layer of uncertainty that is likely to impact on decision making and economic outcomes. Indeed, such disagreement has often been put forward in its own right as a plausible proxy for overall uncertainty.\(^3\)

Wallis (2005) considered the case of multiple forecasts and showed how the variance of a mixture distribution $\bar{f}(y_{t+h})$ that is constructed as a weighted average of individual density forecasts, i.e. $\bar{f}(y_{t+h}) = N^{-1} \sum_{i=1}^{N} f_i(y_{t+h})$, can represent a tractable approach to the measurement of uncertainty in this case.\(^4\) Our proposed measure of EAU draws on these ideas and represents uncertainty as the variance of such an aggregate or average distribution. As shown in Wallis (2005), this variance is the sum of two

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\(^3\) See, for example, Abel, Rich, Song and Tracy. (2016) and references cited therein.

\(^4\) See also the recent papers by Clements (2013) and Boero, Smith and Wallis (2014).
parts. A first part, which we denote by \( \bar{\sigma}(y_{t+h}) \), reflects the average across forecasters of the individual conditional volatilities after removing the predictable component as estimated by each individual forecaster. A second part, denoted by \( d(y_{t+h}) \), captures the cross-sectional dispersion of individual forecasts around the mean, or consensus, forecast. As shown in Wallis (2005), EAU is then given by the sum of these two components:

\[
\text{EAU} = \bar{\sigma}_{t+h} + d_{t+h}
\]  

where \( \bar{\sigma}_{t+h} = N^{-1} \sum_{i=1}^{N} E_{i,t} \left[(y_{t+h} - E_{i,t}[y_{t+h}])^2\right] \), \( d_{t+h} = N^{-1} \sum_{i=1}^{N} [E_{i,t}[y_{t+h}] - \bar{y}_{t+h}]^2 \) and \( \bar{y}_{t+h} = N^{-1} \sum_{i=1}^{N} E_{i,t}[y_{t+h}] \). Importantly, as discussed in Boero et al. (2014), expression (1) holds irrespective of the form of the underlying individual density forecasts \( f_i(y_{t+h}) \). To estimate EAU according to (1) above, we fit a flexible parametric distribution to the average density forecasts from the ECB Survey of Professional Forecasters (SPF). The estimated standard deviation of this average distribution provides a direct measure of EAU for three variables: GDP growth, inflation and the euro area unemployment rate. We then construct a combined measure of macroeconomic uncertainty as the first principal component of these variable-specific measures.

### 2.1 Survey data

To measure uncertainty we exploit the surveyed probability forecasts from the ECB SPF collected over the period 1999Q1 to 2017Q3. These probabilities represent the replies of individual forecasters who each assign a probability to the event that a particular economic variable will take on a future value that falls

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5 See also, Clements (2013) for a discussion of the variance of this average distribution.

6 In Appendix C we present an alternative non-parametric estimate and check the robustness of the paper’s main results with respect to this measurement choice.

7 Appendix A details the SPF and other data sources used in the paper.
within a range of possible outcomes defined by the survey (so-called survey “bins”). As such they represent density forecasts at an individual level. The variables covered by the ECB SPF are annual GDP growth, the unemployment rate and the rate of consumer price inflation in the euro area. An important feature of the euro area SPF data is that it is conducted quarterly and is systematically carried out in the middle of the first month of each quarter (see ECB, 2014).

As we discuss further in Section 3 below, this beginning of quarter timing of the survey provides a strong justification for the use of contemporaneous impact restrictions to identify structural innovations to uncertainty in our BVAR model.

A large statistical literature considers how to model such probabilistic agent opinion and how it can be optimally exploited for decision making. In macroeconomics, extensive efforts have also been devoted to study the key properties and predictive power of these probabilities. We use $p_{i,t+h}^k$ to denote the surveyed probability for forecaster $i$ ($i = 1, ..., N$) as reported in survey round $t$. Each probability relates to the possible outcome for $y_{t+h}$ with the range of possible future outcomes indexed over $k$ ($k = 1, ..., K$). In the survey’s design, the intervals at the lower and upper extremities ($k=1$ and $k=K$) are set to be open whereas the interior intervals are closed. This ensures that the probabilities will sum to unity and that when plotted as histograms, the probabilities can be interpreted as a probability distribution function. Our analysis focuses on the simple cross-sectional average of these reported individual probabilities at each point in time, i.e. $p_{t+h}^k = N^{-1} \sum_{i=1}^{N} p_{i,t+h}^k$. The set of these average probabilities delivers an estimate of the finite mixture distribution discussed in Wallis (2005), with the variance of this average distribution given by equation (1). In practice, $N$ and, hence, the equal weights used to construct this mixture are not fixed but vary from survey to survey depending on the number of responses collected. We use $F(y_k) = \ldots$
\[ \text{Prob}[y_{t+h} \leq y_k] \] to denote the cumulative distribution function for this average density forecast. In practice, the cumulative distribution function can be evaluated only for the discrete points associated with the surveyed outcomes ranges, e.g. with \( y_k \) taking on values associated with the rightmost endpoint of interval \( k \). An example of the underlying probabilistic data is provided in Figure 1, which depicts the average of the individual probability forecasts relating to GDP growth in the euro area. The probabilities were collected in the surveys conducted in the third quarters of 2007, 2008 and 2009, i.e. periods strongly influenced by the onset of the global financial crisis, and relate, respectively, to the future outcome for GDP growth in the first quarter of 2009, 2010 and 2011. We focus on this 2 year horizon as we think it is perhaps most relevant from a business cycle perspective, though the shorter 1-year horizon yields very similar information.\(^{11}\) Comparing the survey conducted in 2007 with that conducted in 2009, one can observe a clear increase in the spread of the resulting probability distribution. Hence, at first pass, the survey suggests a clear augmentation of ex-ante uncertainty about the future and an associated reduction in the perceived predictability of the economy.

### 2.2 Parametric estimates

As discussed in Clements (2013), Abel et al. (2016) and Boero et al. (2014), a natural measure of ex-ante uncertainty is obtained by estimating the expected forecast error variance that is implicit in the SPF histograms. Engelberg et al. (2009) discuss both parametric and non-parametric approaches to this estimation for the case of probabilistic forecasts such as those obtained from the SPF. Under the non-parametric approach, the moments of the underlying distributions are estimated without making any assumption about the form of the subjective density function underpinning the survey replies. Under the parametric approach, a flexible parametric functional form is fitted to the SPF histograms. We proceed by

\(^{11}\) The ECB SPF provides the surveyed probability distributions for three fixed-length horizons that are set to be 1-year, 2-years and 5-years ahead of the most recently observed value for the target variable in question. Due to differences in the timing of statistical releases this means that the precise horizon will differ marginally across variables. In our subsequent empirical analysis below we exploit measures of uncertainty derived for each of these three horizons in order to examine empirically if the effects of uncertainty shocks depend on the horizon over which uncertainty is measured.
using the parametric approach as outlined below. The parametric approach seems particularly suited to the average distributions such as those depicted in Figure 1: in particular, as we can observe multiple intervals to which a positive probability mass is assigned, it is possible to fit a flexible functional form to the discrete survey outcomes.\textsuperscript{12} However, in Appendix C of the paper, we demonstrate that our estimated uncertainty measures, their key properties and our paper’s main results are very robust with respect to using an alternative non-parametric estimate.

Following Engelberg et al. (2009), the parametric approach focusses on fitting the generalised beta distribution to the cross-sectional average of the individual probabilities. We then use the standard deviation of this fitted distribution as an estimate of ex-ante uncertainty. In line with equation (1) above, the variance of this fitted distribution is equivalent to the sum of disagreement (cross-sectional variation in point forecasts amongst respondents) and the average uncertainty at the individual level (as measured by the variance of each individual’s reported histogram). Unique estimates of the parameters of this distribution can be obtained when there are at least three bins in a surveyed histogram. Fortunately, when working with the average histogram this is always the case (while at the individual level respondents can often chose to report probabilities for two or even only a single interval). The generalized beta distribution has a very flexible functional form with finite empirical support and thus seems well suited to model the surveyed probabilities. The cumulative beta distribution has support over \( l \) and \( r \) and is given by:

\[
Beta (y; a, b, l, r) = \begin{cases} 
0 & \text{if } y < l \\
\frac{1}{B(a,b)} \int_{l}^{y} \frac{(x-l)^{a-1}(r-x)^{b-1}}{(r-l)^{a+b-1}} \, dx & \text{if } l \leq y \leq r \\
1 & \text{if } y > r
\end{cases}
\]  
(2)

\textsuperscript{12} In contrast, at the individual level, survey respondents often use three or less intervals which can prohibit the fitting of a flexible functional form. For these cases Engelberg et al. (2009) have proposed the use of a triangular distribution.
while the parameter constraints $a > 1$ and $b > 1$ enforce unimodality (see Engelberg et al., 2009) and the standard deviation is given as $\sigma = \left[ d^2 \frac{ab}{(a+b)^2(a+b+1)} \right]^{\frac{1}{2}}$, where $d$ is a scaling parameter, defined as the difference between the rightmost and the leftmost endpoints $(r - l)$. The fitting procedure chooses the shape parameters of the beta function to minimize the squared deviations between the beta’s cumulative distribution function and the corresponding observed survey distribution $F(y_k)$.

$$\text{Min}_{a>1,b>1} \sum_{k=1}^{K}[Beta(y_k; a, b, l, r) - F(y_k)]^2 \quad (3)$$

In our practical implementation, open intervals are treated as closed intervals of equivalent width and this effectively defines the support parameters $l$ and $r$. This assumption would seem justifiable for most survey rounds where the amount of probability mass assigned to the open intervals is trivial. However, as highlighted in Abel et al. (2016), this is not always the case. For example, for the three survey rounds conducted between 2008Q3 and 2009Q1, i.e. in the midst of the Great Recession, there was a non-trivial piling up of probability mass in the open intervals for some variables at both the one- and two-year horizons. This reflected the fact that the range of plausible future outcomes included in the survey questionnaire was not adjusted sufficiently in response to the large deterioration in economic prospects. One solution to this measurement problem could be to exclude the data from these quarters from our analysis. However such an approach is unattractive given our focus on the measurement and transmission of uncertainty shocks during the Great Recession. As described further in Appendix A, we have therefore opted for a different approach and used information from the surveys before and after the effected quarters to interpolate the estimated uncertainty for the effected survey rounds. The use of interpolation to estimate the variance in this particular survey round reflects the assumption that the variance is most likely to have risen between the surveys in 2008Q3 and 2009Q1. This assumption appears justified given that uncertainty had already started to rise in 2008Q1 and 2008Q2. In contrast, due to the piling up of probability mass in some open intervals, a mechanical fitting of the beta distribution suggests that the variance for GDP growth
at the one-year horizon declined in the 2008Q3 survey. Table A1.1 in the appendix shows the detailed results of this interpolation procedure.\textsuperscript{13}

### 2.3 Ex-ante uncertainty: Key features

Figure 2 plots the estimated measures of ex-ante uncertainty for GDP, inflation and the euro area unemployment rate computed according to the parametric method outlined above. The estimates relate to the surveys conducted over the period 1999Q1 to 2017Q4 and are derived from the SPF probability distributions at the 2-year horizon. In the figure, the recessions of 2008 and 2011 reflecting the Great recession and the euro area sovereign debt crisis and as identified by the CEPR business cycle dating committee are indicated as shaded regions. In addition, a third shaded region identifies the period of “growth pause” in 2002 – 2003, which although not corresponding to a recession in a classical sense was identified by the CEPR committee as a period of unusually slow growth.\textsuperscript{14} From Figure 2, a countercyclical pattern in all three uncertainty indicators is visible. This is most clearly evident for uncertainty about GDP and the unemployment rate which both rose during the two recessions and the earlier growth pause. Nonetheless, it is clear from the chart that uncertainty is highly correlated across the three variables considered with pairwise correlations ranging between 0.8 and 0.9. Given these high correlations, it is natural to focus on the common component driving all three indicators. This is computed as the first principal component of the three time series which captures 94% of the variation in all three series. It is depicted by the dark solid line in Figure 2. When considering this common factor driving the three variable-specific uncertainty measures, a clear insight to emerge from the graph is the highly persistent nature of the upward shift in EAU that occurred in the course of 2008. EAU increased sharply during the Great Recession (2008-2009) and subsequently during the period associated with the sovereign debt crisis in the euro area (2011-2013).

\textsuperscript{13} In Section 4, we report the results of an out-of-sample forecast evaluation. However, the evaluation sample covers the period since 2012Q2 and hence the evaluation is not effected by the interpolated uncertainty series.

\textsuperscript{14} The committee has identified two recessions since 2000. The first was in the context of the recent financial crisis (2008Q1-2009Q2), and the second in connection with the European sovereign debt crisis (2011Q3-2013Q1). See http://cepr.org/content/euro-area-business-cycle-dating-committee.
Also, although it has tended to follow a downward trajectory after a peak in the first half of 2009, EAU has not returned to its pre-2007 mean by the end of the sample.

Figure 3 plots our measure of EAU along with three other commonly used proxies from the literature, i.e. implied stock market volatility, disagreement among point forecasts and the euro area Economic Policy Uncertainty (EPU) index from Baker, Bloom and Davis (2016). Table 1 reports some basic summary statistics for these other uncertainty proxies along with our proposed EAU measure. From Figure 3, EAU appears positively correlated with all three proxies considered. It has the highest correlation (0.65) with the measure of disagreement. Such a result is not surprising given that, according to equation (1), disagreement about point forecasts represents a fundamental component of EAU. However, unlike disagreement, EAU shows a clearer level shift and much higher persistence in the period since the great recession. Such differences highlight the importance of variation in uncertainty at the individual level as a key driver of aggregate ex-ante uncertainty. It is also in line with the common finding that disagreement may – on its own - be a relatively poor proxy for uncertainty (see, for example, Abel et al. (2016) as well as Glas and Hartmann (2016)). The overall correlation with economic policy uncertainty based on media reporting is also relatively high at 0.59, while the correlation with implied stock market volatility (VSTOXX) is weaker (0.52). EAU also exhibits the highest persistence compared with the other uncertainty proxies, as reflected in a relatively high co-efficient on its first own lag in a simple auto regression (see Table 1).

In line with the evidence in Figure 3, Table 1 also highlights the evidence of a break in the mean of EAU following the great recession, with the post 2007 mean being always higher than its pre-2007 level (see last column of Table 1). This level shift in uncertainty is also shared by other measures, most notably the EPU

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15 To construct a comparable measure of disagreement, we compute the cross-sectional dispersion in the individual point forecasts for GDP growth, inflation and the unemployment rate forecasts in each survey round and we then take the first principal component of these three disagreement measures.

16 Mumtaz and Musso (2018) construct a common measure of macroeconomic uncertainty for 11 countries in the euro area using a dynamic factor model with time-varying parameters and stochastic volatility. Their measure appears to have markedly different dynamics compared to the EPU and VSTOXX.
index. All four measures generally exhibit a greater likelihood of observing relatively high outcomes above the mean as reflected in the positive skewness measures reported in Table 1. Most measures also exhibit a degree of excess kurtosis implying a stronger likelihood of observing values at the extremities of the distribution compared with a Gaussian distribution. This is, however, not true of the EAU measure which has an average value for kurtosis that is below the value of 3.0 obtained for a Gaussian distribution. This finding is in line with other studies which have pointed to the tendency of expert forecasters to exhibit excessive confidence in reporting their estimated probabilities, and to assign generally low probabilities to the tails of the distribution (see, for example, Kenny et al. (2015)). Finally, for the case of GDP at the 2-year horizon, Figure 4 plots the decomposition according to equation (1) of aggregate EAU into its two components capturing disagreement about point forecasts and average individual uncertainty. An interesting insight from this decomposition is that the persistent increase in the level of uncertainty following the Great Recession appears mainly driven by a persistent rise in average individual uncertainty. In contrast, although disagreement about point forecasts rose significantly in the early stages of the Great Recession (2008-2009), it very quickly reverted to its pre-recession levels. Conversely, average individual uncertainty rose persistently from 2008 until 2012 and remained at these more elevated levels throughout much of the post Great Recession sub-sample. Also, disagreement on its own did not capture the rise in uncertainty during the earlier period of the Growth pause identified by the CEPR business cycle dating committee in 2002-2003, while our measure of EAU shows a significant rise in uncertainty during this period reflected an increase in average individual uncertainty across forecasters in the SPF panel. Overall, the graphical evidence suggests that our proposed measure of EAU which integrates both sources of uncertainty may better capture important medium term and business cycle shifts that cannot be captured by disagreement-based measures on their own.

17 Although not reported, the equivalent decompositions at the two year horizon for the unemployment and inflation measures of EAU yield a broadly similar pattern to that for GDP.
3. Macroeconomic Transmission of Uncertainty Shocks

In this Section, we present a medium-sized Bayesian Vector Autoregressive (BVAR) model to assess the contribution of uncertainty shocks to the euro area business cycle. Building on earlier work by Doan, Litterman and Sims (1984) and Litterman (1986), BVARS have been shown to offer a flexible and tractable approach for forecasting and data-driven policy analysis with, as discussed in Banbura et al. (2010) and Koop (2011), the methods increasingly extended to medium and, even, large-scale cross-sections of time series data. In particular, we estimate a BVAR to analyse the business cycle impact of innovations to the measure of EAU derived in Section 2. To identify the innovations in uncertainty, we exploit the intrinsic real time nature of survey forecasts and the beginning of quarter timing of the survey. As explained in further detail below, the timing of the survey implies that within quarters, shocks to other real and financial variables should not impact the survey responses contemporaneously. We then study the response of both real and financial variables to this identified uncertainty shock.

3.1 A medium-sized BVAR

Our analysis exploits the structural representation of the BVAR, where identification of an uncertainty shock is achieved by placing restrictions on the systems contemporaneous impact matrix. Our baseline model includes the EAU indicator estimated in Section 2, measured as the first principal component extracted from GDP uncertainty, unemployment uncertainty and inflation uncertainty, a block of five real sector variables (GDP, private consumption, consumer prices, unemployment, private investment) and a block of six financial sector variables (short-term interest rates, private sector credit volumes, bank lending spreads over short term rates, corporate bond spreads over short-term rates, long-term government bond yields and equity prices). Lenza, Pill and Reichlin (2010) and, more recently, Altavilla, Giannone and Lenza (2015) present a similar real-financial VAR for, respectively, the assessment of euro area monetary policy during the Great Recession and to study the effects of the ECB’s announcement of outright monetary

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18 Robertson and Tallman (1999) provide an overview of the practical use of BVAR methods for forecasting.
transactions. Table A.1.2 in Appendix A summarises the data sources, definitions and any transformations used in the estimation of the BVAR. In general, we try to work with the log level, seasonally adjusted series for most trending variables while for variables which are expressed as a percentage or in percentage points (interest rate spreads) we do not take logs. The use of log levels of the data preserves as much information as possible and, as discussed further below, also motivates the use of a prior that allows for possible cointegration among non-stationary variables. Collecting these 12 time series together in the \( n \)-dimensional vector \( \mathbf{y}_t = (y_{1t}, y_{2t}, \ldots, y_{nt}) \) the BVAR’s structural form is given in (4):

\[
A_0 \mathbf{y}_t = A_c + A_1 \mathbf{y}_{t-1} + A_2 \mathbf{y}_{t-2} + \ldots + A_p \mathbf{y}_{t-p} + \mathbf{u}_t
\]  \hspace{1cm} (4)

where \( \mathbf{u}_t \sim iid \mathcal{N}(0, \Omega) \) and \( \Omega \) is a diagonal matrix such that each element of \( \mathbf{u}_t = (u_{1t}, u_{2t}, \ldots, u_{nt}) \) is uncorrelated and, hence, can be given a structural interpretation. The corresponding reduced form of the BVAR is given in (5):

\[
\mathbf{y}_t = \Phi_c + \Phi_1 \mathbf{y}_{t-1} + \Phi_2 \mathbf{y}_{t-2} + \ldots + \Phi_p \mathbf{y}_{t-p} + \mathbf{\varepsilon}_t
\]  \hspace{1cm} (5)

where \( \mathbf{\varepsilon}_t = (\varepsilon_{1t}, \varepsilon_{2t}, \ldots, \varepsilon_{nt}) \) is a vector of correlated 1-step ahead prediction errors. Hence \( \mathbf{\varepsilon}_t \sim iid \mathcal{N}(0, \Sigma) \) and \( \Sigma \) is a symmetric matrix such that it’s diagonal elements provide estimates of the variance of each \( \varepsilon_{nt} \) and its off-diagonal elements provide estimates of the contemporaneous covariance between each \( \varepsilon_{nt} \). Identification of the model’s structural shocks is achieved using a Choleski factorization of the \( \Sigma \) matrix such that \( \mathbf{D} \mathbf{D}' = \Sigma \) and by setting \( \mathbf{D} = A_0^{-1} \). To motivate these restrictions, we can exploit the beginning of quarter timing of the SPF survey. As illustrated in Figure 5, the surveyed probabilities used in the estimation of EAU for GDP growth, the unemployment rate and inflation relate to the outcome in periods of between 6 and 7 quarters ahead of the survey quarter \( t \). Moreover, these probabilities are on average collected in the middle of the first month of quarter \( t \) which implies that the survey variables should not
respond (or anticipate) shocks to other real or financial variables in that quarter. The timing of the SPF survey therefore provides a strong justification for the zero impact restrictions implied by the Choleski factorization.

The survey timing above helps motivate the zero impact restrictions of real and financial variables on EAU. To motivate the interrelations between the real and financial variables in the VAR we invoke additional recursive arguments. In the first instance, financial sector variables should be the most responsive to news about uncertainty and the real economy. Therefore we order the block of financial variables last in the BVAR such that there is no restriction on their contemporaneous responses to real variables and uncertainty shocks. However, we would expect some delay in the transmission of financial shocks to real sector variables. Therefore we order the block of real variables before the block of financial sector variables. Identification of the models shocks via Choleski factorisation also requires choices of the ordering of the variables within each of the three blocks. Our benchmark model is based on the following ordering within each block:

**Real Sector Block:** GDP, private consumption, consumer prices, unemployment rate and private investment.

**Financial Sector Block:** short-term interest rate, credit to private sector, bank lending spreads, corporate bond spreads, long-term government bonds yields, equity prices.

Clearly, economic theory provides less of a guide for the contemporaneous relations among the variables within each block. Placing short-term interest rates after real sector variables but before other financial sector variables, as we also do, has been proposed as a means to help with the identification of a

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19 While that is always the case for real variables, some high frequency financial data may be available to SPF respondents in the first days of the quarter. Therefore, it cannot be excluded that some of this information can still be incorporated in their answers until the deadline to reply the survey.

20 Christiano, Eichenbaum and Evans (1999) discuss the recursive approach and its application in a monetary policy context.
conventional monetary policy shock (see, for example, Altavilla et al. 2015). Analogous to the reasoning above, this strategy reflects the idea that unanticipated changes in the short-term interest rate are transmitted to the real sector with a delay but the policy instrument can respond immediately to current quarter real sector developments. This strategy also has the plausible feature that it allows the financial sector respond contemporaneously to a short-term interest rate shock.

Following the early work by Doan et al. (1984) and Sims (1993), the estimation of the BVAR’s reduced form is undertaken using the sum of coefficients Normal-Wishart prior. Table 3 summarises the main features of the BVAR estimation and the hyperparameter selection. Under the Normal Wishart prior, the prior distribution of the model co-efficients is normal while the prior distribution of $\Sigma$ is inverse Wishart. Estimation of the BVAR requires specification of the hyperparameters capturing the mean of the first autoregressive co-efficient and its variance parameter ($\lambda_1$) which determines the overall tightness of the system. The prior also requires a hyperparameter controlling for lag decay ($\lambda_3$) determining the speed at which coefficients for lags greater than unity converge to zero. As the model includes an exogenous constant on which there is no strong prior information, we also specify a relatively large variance parameter for its tightness ($\lambda_4$). The sum of coefficients prior allows for the inexact restriction that the sum of the coefficients on a variable’s own lags equals unity and the sum of coefficients on the lags of other variables equals zero. This is implemented as in Doan et al. (1984) by adding a set of initial dummy observations to the data set. The tightness of the prior is then regulated by attaching a weight ($\lambda_6$) to these initial dummy observations.

The prior specification also allows for the possibility of stable long-run relationships between the levels of the series again implemented by introducing additional dummy observations corresponding to the assumption of co-integration, implying that the model is stationary despite the stochastic trends in the levels.

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21 The implementation is conducted using the BEAR Toolbox for Matlab developed in Dieppe, Legrand van Roye (2016).
of the time series. As with the sum-of-coefficients, this prior is modified by assigning a weight ($\lambda_7$) on these dummy observations. As $\lambda_7$ grows large the estimation puts increasingly more weight on a model that involves a single stochastic trend and a zero intercept. The posterior distributions for the model’s parameters are estimated numerically using direct sampling with 15,000 iterations. The estimation sample is 2000Q1 to 2017Q3 using five lags for each of the variables included in the system. When setting the priors, we initially implemented the hyperparameter values suggested by Sims and Zha (1998). However, we are able to obtain more stable estimation results by simultaneously tightening the prior on the sum-of-coefficients and the one unit root dummy observations, increasing them both by a factor of 2.5 (see Table 2).

### 3.2 Real sector transmission

There is a growing consensus in the empirical literature that uncertainty shocks play an important role either as a fundamental source of business cycles fluctuations or as a key element influencing the propagation of other real and financial shocks. There are different channels through which a rise in uncertainty in the economy may impact macroeconomic variables. Below, we explore these potential channels by analysing the impulse responses of the real variables included in the BVAR system following an exogenous shock to EAU.

Figure 6 plots the impulse response functions which depict the dynamic response of each variable in the system following a one-standard deviation or typical shock to EAU. In each chart, the shaded region represents 68% confidence bands constructed from the model’s posterior distribution. Following a typical shock to EAU, uncertainty rises and remains above baseline levels for close to 12 quarters. This is very much in line with the evidence reported Section 2 which pointed to relatively high persistence in EAU. The responses also highlight the contractionary effects of a positive uncertainty shock, in line with the existing empirical literature on the role of uncertainty shocks as a fundamental source of business cycle fluctuations (e.g. Bloom, 2009; Bloom et al. 2014; Barrero, Bloom and Wright, 2017; Jo and Sekkel, 2016; Alexopoulos
and Cohen, 2009; Gieseck and Largent, 2016; Mumtaz and Musso, 2018). According to our findings, GDP falls with the peak impact occurring after about 8 quarters following the initial shock. The response of other variables shows that both consumption and private investment contribute to the drop in GDP. However, while the effects on the level of investment are larger and materialise more quickly than the effects on consumption, the overall contribution of consumption to the drop in GDP is equally important given its considerably larger share in domestic activity. Our results are in line with other empirical studies which have highlighted the impact of uncertainty on investment and aggregate demand across several countries; see, for example, Bloom, Bond and Van Reenen (2007), Denis and Kannan (2013), Meinen and Röhe (2016), Moore (2017) and Mumtaz and Surico (2018). Importantly, the time profile of the negative effects on investment that we find is not fully consistent with the “wait-and-see” mechanism that is often discussed in this literature. In particular, this mechanism is more often associated with a short-lived investment downturn that is followed by a subsequent rebound and overshoot as pent-up investment demand is suddenly released. In our case, perhaps reflecting the strong weight given to the Great Recession in our estimation sample and the very persistent nature of the identified uncertainty shock, the effects are much more protracted and persistent.

The estimated impulse response functions in Figure 6 also highlight the importance of the household sector and the labour market in the transmission of uncertainty shocks, e.g. because uncertainty may lead to an increase in precautionary savings and lower consumption spending – an effect which may be stronger when the economy is subject to nominal rigidities. Most notably, an unanticipated shock to EAU is followed by a rise in unemployment which is highly persistent. This suggests that firms respond to greater aggregate uncertainty by scaling back or postponing their hiring decisions in tandem with reduced investment

\footnote{22 Other studies such as Bachmann and Bayer (2013) and Bachmann et al. (2013) find that the effects of uncertainty shocks are too small to make the ‘wait-and-see’ mechanism matter for the business cycle.}

\footnote{23 Carroll and Samwick (1998) highlight how uncertainty may lead to an increase in precautionary savings (e.g. which can negatively affect consumption spending. Basu and Bundick (2017) and Fernandez-Villaverde et al. (2015) both highlight how this mechanism may be stronger when the economy is subject to nominal rigidities.}
spending. Our results for EAU are therefore in line with Bloom (2009) who suggests that in a context of high uncertainty, firms also become more cautious in their hiring and firing decisions. Schaal (2017) also shows how, as hiring involves considerable costs, uncertainty can give rise to a decrease in the number of vacancies and in the job finding rate, ultimately resulting in a rise in unemployment. Similarly, Leduc and Liu (2015) employ both a BVAR and a DSGE model and show - in line with our findings - that an increase in uncertainty raises US unemployment considerably. In particular, they show how higher uncertainty gives rise to fewer vacancies and more unemployment. In their model, the associated drop in household income reinforces the initial decline in aggregate demand and further amplifies the recessionary effects of higher uncertainty.

Amongst the variables in the real sector block, the only variable which appears unaffected by a shock to EAU is the consumer price index. Although there is some evidence that there is a marginal downward impact on prices, according to the estimated confidence bands the impact is not significant. Given the more significant effects on the real economy and labour market variables, the negligible effect on consumer prices is somewhat puzzling. For example, Leduc and Liu (2015) have argued that uncertainty shocks operate in much the same way as any other shock to aggregate demand, i.e. with an increase in uncertainty pushing down both output and prices simultaneously. One possible rationalisation for the more negligible effects on prices that we identify may therefore be that uncertainty shifts both aggregate demand and aggregate supply simultaneously such that the overall degree of economic slack is unaffected, or at least, considerably less affected. An alternative explanation is that uncertainty shocks are also associated with a flattening of the slope of the Philips curve, such that a given the associated change in slack has a diminished impact on aggregate prices.

Figure 7 compares the impulse responses for our proposed measure of EAU with the responses for other proxies commonly used in the literature. For each of these proxies, we estimate an equivalent BVAR but replace EAU with the different proxies. To ensure a comparable basis with the impulse responses for EAU,
in re-estimating the BVAR we extract the level of each of the proxies in the first month of each quarter and then order each of them first in the BVAR. In this way, all other variables in the system can be assumed not to impact contemporaneously on the uncertainty proxies in the same way that EAU in our baseline model is unaffected by current quarter shocks to other variables. From the chart, one can see that a typical shock to EAU is relatively close in magnitude to a typical shock to disagreement and the VSTOXX, although it is considerably smaller than a typical shock to the EPU measure. In line with the results for EAU, all other proxies exhibit a negligible effect on consumer prices. Also, although the qualitative direction of the effects on the real economy is generally very similar across the different measures, the real economic effects of an EAU shock appears to be stronger than for all three of the other proxies. For example, despite their similar size, both forecaster disagreement and implied stock market volatility shocks have generally much smaller impacts on both consumption and investment. Also, the impact of forecaster disagreement on the unemployment rate is negligible.

3.2 Financial sector transmission

In the wake of the financial and sovereign debt crises, a lot of the recent literature has focused on the importance of financial frictions and financial markets for the transmission of uncertainty shocks. For example, Alfaro, Bloom and Lin (2018) find that higher uncertainty accompanied by financial frictions induces the standard real-options effects on investment and hiring, and also leads firms to hoard cash, further reducing investment and hiring. Buch et al. (2015) show how refinancing in interbank markets and credit supply might become more challenging in the wake of an increase in uncertainty. Also, Valencia (2017), Bonciani and Van Roye (2015), Arellano et al. (2016) and Gilchrist et al. (2014) all emphasise how

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24 As for the Ex Ante Uncertainty, forecast disagreement is also extracted from the SPF based on the point forecasts collected in the first month of quarter t.

25 Another strand in the literature has emphasised instead the importance of financial shocks per se. For example, Jermann and Quadrini (2012) highlight the importance of financial shocks which show up as a tightening of firms financial conditions and how this contributed to the Great Recession in the US. Also, Furlanetto, Ravazzolo and Saferez (2017) highlight the relevance of financial shocks identified with sign restrictions in a VAR. Smets and Popescu (2010) find that financial risk aversion shocks have a protracted and large negative impact on the economy and are more important in driving business cycles than uncertainty shocks.
uncertainty shocks may be associated with heightened risk premia on various financial assets. For example, the probability that both banks and non-financial firms are hit by large shocks increases when uncertainty is higher and, as a result, investors will tend to demand a higher external funding premia. Also, if elevated levels of uncertainty are associated with heightened risk aversion, this may be associated with a drop in asset values. Furthermore, Ludvigson, Ma and Ng (2015) find that uncertainty about financial markets is a likely source of output fluctuations while Popp and Zhang (2016) highlight the importance of the financial channel in the transmission of uncertainty shocks and that they have a more prominent role during recessions.

In line with the above studies, the impulse responses in Figure 7 lend strong support to the relevance of the financial sector in the transmission of uncertainty shocks. Following a shock to uncertainty, there is a decline in short-term interest rates. This can most likely be interpreted as reflecting the systematic response of monetary policy to the associated deterioration in economic prospects. In contrast, the spread of bank lending rates and corporate bond rates over the short-term interest rate both increase. The transmission is swiftest to the more market-based source of financing with the peak effect being observed about 5 quarters after the initial shock, while bank lending rate spreads exhibit more inertia with the peak effect observed at close to 8 quarters. The rise in corporate bond spreads is in line with recent work by Bali and Wen (2017) who show that uncertainty is priced in a cross-section of corporate bond returns implying an economically and statistically significant uncertainty premium in the corporate bond market. In line with the increase in risk premia, the BVAR also highlights an initial increase in Government bond yields and a decline in equity prices – although the rise in government bond yields is not significant. Most notable, however, is the highly persistent deterioration in the level of credit to the private sector that is associated with a shock to

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26 Another relevant study is Bael et al. (2014) who use a large cross section of countries and identify that liquidity deteriorates on flight to safety days both in the bond and equity markets.

27 The insignificant impact on average euro area bond yields may mask some impact of aggregate uncertainty on bond yields in individual countries. Regarding equity prices, the drop is in line with work by Pastor and Veronesi (2012) who found that by raising risk premia, political uncertainty destroys market value, especially during times when the economy is weak.
EAU. Following the initial rise in uncertainty, credit to the private sector declines steadily and remains on a declining path almost 12 quarters later. Of course, the drop in credit may reflect both credit supply aspects linked to a change in bank behaviour and credit demand aspects linked to weaker demand for loans by firms and households.

Figure 8 also plots the responses of financial variables associated with our proposed EAU measure along with the responses for the other proxies discussed previously. As with the real sector transmission, EAU shocks generally give rise to stronger effects on private sector credit and risk premia compared with other proxies. The impact of EAU shocks on credit appears closest to the effects of Economic Policy Uncertainty, while the corresponding effects on credit from shocks to forecaster disagreement and implied stock market volatility are both very weak. In contrast to the other uncertainty measures, forecaster disagreement has only a muted impact on bank lending spreads and is actually associated with a rise in equity prices. Overall, compared with the other proxies, our proposed measure of EAU appears associated with a stronger and more persistent transmission of uncertainty shocks via financial markets.

3.3 Historical importance of EAU shocks

The impulse responses discussed in section 3.2 and 3.3 provide insights into the effects of an average shock to uncertainty implied by our BVAR specification. It is interesting however to also examine the actual contribution of uncertainty and other shocks to euro area business cycle developments over the period analysed and, in particular, during the Great recession and subsequent sovereign debt crises. Such contributions will reflect not just the structural parameters of the BVAR representation but also the actual magnitude of the different shocks identified using the models recursive scheme. To shed light on this aspect, we also report the historical decompositions implied by the BVAR and partition the dynamics of a specific variable $y_t$ into contributions from the different shocks to the system over time. More specifically, and as discussed in Dieppe et al (2016), each variable in the BVAR can be separated into two parts. A first
component reflects the deterministic and exogenous variables included in the system as well as the initial starting values, which are collected together in $D^{(t)}$. A second and more interesting component reflects the contribution of unpredictable structural disturbances over the history of the estimation sample. The historical decomposition in (6) thus reveals the cumulative effect of each structural shock at every given point in time:

$$y_t = D^{(t)} + \sum_{j=0}^{t-1} \tilde{\psi}_j u_{t-j}$$  (6)

As we are applying the Bayesian approach, we incorporate the uncertainty with respect to the VAR coefficients by carrying out the historical decomposition in the same model specified in Section 3.1, again estimating the posterior distributions for the model’s parameters numerically using direct sampling with 15,000 iterations. The substantial number of draws helps to ensure convergence. At each iteration we obtain random draws from posterior distributions and these are used to compute impulse response functions, the VAR residuals and the structural disturbances $u_t$. Using these elements, the historical contribution of each shock is calculated according to equation (6).

Figure 8 depicts the historical decomposition of euro area GDP into contributions from the three different blocks included in our model: i) shocks to EAU ii) real sector shocks and iii) financial sector shocks. The decomposition is normalised around the level of GDP which would have persisted in the absence of any shocks. It highlights how during the Great Recession in 2008 we observe a complete reversal in the sign of the contribution of real sector shocks. Also, financial sector shocks which had generally contributed positively in the run up to the Great Recession also switched to a more negative contribution from end 2008 onwards. Similarly, shocks to EAU had supported the evolution of euro area GDP up until the end of 2008 but thereafter their contribution became increasingly negative. Importantly, although much of the fluctuations in euro area GDP over the sample period can be attributed to real and financial sector shocks,
the contribution of shocks to EAU uncertainty remains important. Indeed over the period of the Great recession, approximately 1.0 percentage point of the 6.0% drop in the level of GDP is explained by a collapse of the previous strong positive contribution from uncertainty that came before.28 In contrast, shocks to real and financial sector variables which are orthogonal to our uncertainty shocks contributed the residual 4.0 and 2.0 percentage points respectively. Hence compared with the empirical results for the US from Bloom et al. (2014) or Stein and Stone (2012), uncertainty shocks may play a more modest role compared with other real and financial shocks during the Great recession in the euro area. An important feature of the historical decompositions is how uncertainty shocks contributed to the expansion in GDP before the financial crisis. These expansionary or “negative uncertainty shocks” can be partly interpreted as excess confidence about the future evolution of the economy. Also, EAU can help explain the sluggish nature of the recovery, with euro area GDP remaining below its equilibrium level implied by the absence of shocks up to and including the end of the sample period in 2017Q3.29

3.4 Variable- and horizon-specific uncertainty shocks

So far we have considered the effects of an aggregate measure of EAU measured over a forecast horizon of approximately 2 years. However, as highlighted previously in the discussion in Section 2, the SPF data facilitate the analysis of variable specific measures of EAU for GDP, the unemployment rate and inflation (as depicted also earlier in Figure 2 for the 2-year horizon). Hence, it is interesting to assess whether the transmission may differ depending on the underlying variable to which the measure of EAU relates. Moreover, it is possible to construct aggregate EAU measures but for different horizons. For example, we can estimate a measure of short-run aggregate uncertainty by extracting the first principal component for the uncertainty measures for each variable when measured over a 1-year horizon. Equivalently, a measure

28 This computation relies on the definition of the Great Recession from the CEPR business cycle dating committee. In particular the contribution of EAU is computed over the period between 2008Q1 and 2009Q2 by expressing the change in the contribution of uncertainty shocks over this period as a fraction of the total change in GDP over the same period.

29 The historical decompositions for the other real variables show very similar results also regarding magnitude. Uncertainty also plays a highly relevant role for the historical fluctuations of financial variables, in particular for credit to the private sector.
of long-run aggregate EAU can be constructed as the common component of each variable-specific measure when measured over the longer 5-year horizon available in the SPF dataset. In Appendix B, we report impulse response functions for these variable- and horizon-specific uncertainty measures and analyse in more detail the evidence for any differences in their transmission. In particular we analyse the transmission of uncertainty in two additional BVARs. A first (BVAR-VS), includes the three variable-specific uncertainty measure at the 2-year horizon, with uncertainty for GDP ordered first, followed by the equivalent EAU measures for the unemployment rate uncertainty and then inflation. A second (BVAR-HS) includes estimates of aggregate EAU at long, medium and short-run horizons in that order. For both BVAR-VS and BVAR-HS, the ordering of the three uncertainty measures is harder to motivate and hence identification of the individual uncertainty shocks is less well-grounded. Nonetheless, the analysis reported in Appendix B offers some preliminary insights, although we would see this as a very promising area for future empirical research.

In general, we find that the impact of all three variable-specific uncertainty shocks is quite consistent across the range of economic and financial variables included in the BVAR. GDP, private consumption and investment all decline in response to a positive shock to GDP uncertainty, unemployment uncertainty and inflation uncertainty, while the unemployment rate rises. Also, credit and both bank-lending and corporate bond spreads tend to rise. In terms of the magnitude of the impact, it is the measure of GDP uncertainty that appears to have the strongest and most immediate impact on most of the variables included in the model (e.g. on the unemployment rate or on credit spreads). Similarly, the impulse response functions related to the horizon-specific uncertainty reported in Appendix B also highlight that the transmission is quite consistent across the different horizons. Comparing the effects, it is the shock to our reference EAU measure at the medium-term 2-year horizon that has the strongest negative impact on GDP, consumption, investment and the unemployment rate. Also, the negative impact on private sector credit, bank and corporate bond spreads and equity prices is stronger compared with the uncertainty shocks at both the shorter 1-year horizon and at the longer-term 5-year horizon.
4. Role of ex-ante uncertainty in out-of-sample prediction

The analysis of EAU conducted in Section 3 focusses primarily on in-sample evidence. In this section we consider the relevance of EAU in terms of out-of-sample prediction. To investigate the out-of-sample role of uncertainty, we compare the real-time forecasting performance of our BVAR models including the different proxies for uncertainty with the forecast performance of an alternative model which excludes the uncertainty variables altogether. This comparison helps gauge the marginal predictive content of uncertainty variables for forecasting the real and financial variables included in the BVAR model. The estimated BVAR’s reduced form given by equation (5) is ideally suited to produce forecasts for all variables included in the model at different horizons. In the comparison we consider the relative predictive value of the uncertainty indicators at horizons of 1 and 4-quarters ahead.

To run the out of sample experiment, we split our data into an initial estimation period (1999Q1-2011Q4) and a hold-out sample (2012Q1-2016Q4) that is used for evaluation. To produce forecasts, we then re-estimate the BVARs recursively for each quarter of the hold out sample using the vintages of data that would have been available in the quarter for which the model is being estimated. This is particularly relevant for variables such as GDP, inflation, private consumption, private investment, unemployment and credit to the private sector that are subjected to revision and/or significant publication lags. The real time data sources are described in more detail in Appendix A. For other mainly financial variables such as short term interest rates, long-term government bond yields, equity prices, corporate bond yields, implied stock market volatility as well as the media-based EPU indicator, data revisions are not relevant. Also, the SPF survey data are not revised: they are all real-time by construction, i.e. they reflect the information that was available at the time each survey round was conducted.

Table 3 reports the Mean Squared Error (MSE) for the model including uncertainty relative to the model which excludes uncertainty. Hence a relative MSE < 1.0 indicates that the inclusion of the uncertainty
indicators in the BVAR contributes to lowering the MSE and, hence, an improvement in predictive performance for the variables in question. For the trending variables in levels (i.e. GDP, consumption, investment, prices, credit) in computing the MSEs we transform the BVAR level forecasts to quarterly growth rate forecasts one and four quarters ahead. For the non-trending variables we just use the direct BVAR forecasts at the one- and four-quarter ahead horizons. Table 3 also includes the equivalent relative MSE for the variable-specific (BVAR-VS) and horizon specific (BVAR-HS) models. Relative to the baseline BVAR with only a single uncertainty indicator, the out of sample results for these models shed light on whether or not the separate transmission of variable-specific and horizon-specific uncertainty measures is useful in a forecasting context. For the series that are subject to revision, the out-of-sample experiment also requires us to select the vintage of the outcome series used in the computation of the MSEs. For this we use the 1st official statistical release for the series in question and ignore any subsequent revisions in the second and/or subsequent releases.

Panel (a) of Table 3 reports the out-of-sample evaluation results for three models: the baseline BVAR as well as the variable –specific (BVAR-VS) and the horizon specific (BVAR-HS) models. Overall, the results suggest that the inclusion of EAU measures can help improve the out-of-sample forecasting performance of the BVAR significantly compared with a model that does not include them. We would highlight in particular three main results that are evident from the comparison. Firstly, most of the predictive gains are achieved not at very short 1-quarter horizons but more at the longer 4-quarter horizon. Such a result is perhaps not surprising given the strong persistence in ex-ante uncertainty noted earlier and the relatively sluggish transmission of uncertainty shocks to other variables. A second clear feature of our results is that it is the prediction of key financial variables that is improved more - in relative terms- compared with the prediction of real variables. Most notably, across all three specifications, we observe significant improvements in the prediction of private sector credit and corporate bond spreads at the 4-quarter-ahead...

30 As we exploit the reduced form BVAR for forecasting purposes, the identification challenge associated with these models is less relevant.
horizon. For example, in the case of private credit, the relative MSE ranges from 0.76 to 0.81 for the different BVAR specifications considered, implying significant gains of close to 20% compared with the BVAR which excludes all uncertainty measures. In contrast, the results imply quantitatively less relevant gains for the prediction of real variables, though we do observe some significant though more modest improvements for GDP, for the unemployment rate and, in particular – for investment (again only at the longer 4-quarter horizon). Third, the gains from the inclusion of uncertainty do not change substantially when we compare variable-specific, horizon-specific models with the model which only focusses on an aggregate measure. Hence, our results suggest that - for forecasting purposes – it may suffice to focus on an overall aggregate index rather than attempting to model the effects of uncertainty relating to particular variables or by distinguishing the different horizons to which the uncertainty measure relates. The lower panel (b) of Table 3 reports the equivalent comparisons but using the three other uncertainty proxies discussed previously in the paper. Compared with our ex-ante measure, the relative improvements with the other proxies appears smaller. For example, neither the VSTOXX nor forecaster disagreement yield a significant improvement in predictive performance for any of the real variables included in the system. A notable exception is the EPU index which helps improve the forecasts for the unemployment rate at the longer 4-quarter horizon. Also, in the case of financial variables, the improvements are considerably smaller compared with all ex-ante measures highlighted in panel (a). Both the VSTOXX and the EPU index yield quantitatively modest improvements for the prediction of credit and the bank lending rates, while the results suggest that forecaster disagreement can improve the prediction of long-term government bond yields at the 4-quarter horizon.

Overall, the results of this out-of-sample experiment point to some notable role for uncertainty in helping to forecast real and, particularly, financial variables in the euro area. The improvement in performance is most evident at the longer 4-quarter horizon. Also, compared with other proxies, it is the measures of ex-ante uncertainty extracted from the aggregate probability distributions that yields the most important gains in quantitative terms.
4. Discussion and conclusions

In this paper, we present a new measure of ex-ante macroeconomic uncertainty for the euro area economy and analyse empirically its transmission to both real and financial sector variables. Our proposed measure is constructed from the average probability distribution of panellists in the ECB’s Survey of Professional Forecasters. It combines information about real variables like GDP growth and future unemployment with information about inflation and has a number of attractive conceptual features. Firstly, in line with the recent work of Clements (2013), Jurado et al. (2015) and Rossi and Sekhposyan (2015) it takes a forward looking or ex-ante perspective which directly links the measurement of uncertainty to the perceived predictability of economic outcomes. Second, as the variance of a mixture of individual distributions, our proposed measure takes into account information about forecaster disagreement about the predictable component of a given variable as well as the expected conditional volatilities that are estimated by each forecaster. Third, reflecting its survey origins, our proposed measure lends itself conveniently to a natural recursive identification of uncertainty shocks. In particular, because the survey is conducted at the beginning of each quarter, we can exploit information delays to motivate identifying restrictions which can help us trace out the transmission of uncertainty shocks via the real and financial sectors of the economy. We then implement this natural identification strategy in a medium-sized Bayesian Vector Auto Regressive model which includes a range of important real and financial variables in order to be able to parse out the relative contributions of uncertainty shocks from other real- and financial-sector shocks driving economic fluctuations.

Our proposed measure and identification strategy delivers a range of important new empirical results of relevance to euro area business cycle analysis. In the first instance, our results highlight the importance of aggregate ex-ante uncertainty shocks for the understanding of business cycle fluctuations in the euro area economy. A typical shock to our proposed measure of uncertainty is associated with a drop in GDP and its
components, most notably private consumption and investment. Also, higher uncertainty leads to a deterioration in labour market conditions and is reflected in a substantial and persistent rise in the unemployment rate. Our results also highlight the importance of the response of the financial sector in the transmission of uncertainty shocks: a positive shock to ex-ante uncertainty is associated with a rise in credit spreads, a drop in equity prices and a persistent reduction in private sector credit. Second, and at the same time, our results suggest that much of the fluctuations in euro area GDP over the sample period and particularly during the Great Recession should be attributed to other real and financial sector shocks and not to uncertainty *per se*. Over the period of the Great recession, as defined by the CEPR’s business cycle dating committee, approximately 1/6th of the drop in the level of euro area GDP is explained by the rise in uncertainty. Although certainly economically significant, this contrasts with results for the US economy such as those reported in Bloom et al. (2014) or Stein and Stone (2012), suggesting that uncertainty shocks may have played more significant role in relative terms. An important feature of this historical analysis is how uncertainty shocks contributed to the expansion in the economy also before the financial crisis. These expansionary or “negative uncertainty shocks” can partly be interpreted as excess confidence about the future evolution of the economy.

Finally, we also show how our proposed measure of aggregate ex-ante uncertainty can contribute to out-of-sample prediction compared with a reference model which does not contain any uncertainty measures. Most notably we find an important role for uncertainty in helping to forecast real and, particularly, financial variables such as bank credit and risk premia. We also find that to achieve these improvements in predictive performance it is sufficient to focus on an aggregate measure of uncertainty, rather than focussing on separately modelling the transmission of uncertainty related to specific macroeconomic variables or to specific prediction horizons. Also, compared with other proxies for uncertainty that are commonly used in the literature, it is the aggregate measures of ex-ante uncertainty extracted from the aggregate probability distributions that yields the most important gains in quantitative terms.
Overall, therefore, measures of aggregate uncertainty extracted from expert probability forecasts of the type that we have analysed appear to offer a conceptually well-grounded measure of uncertainty for business cycle analysis that is empirically relevant. A promising area for future research with such measures is clearly the possibility that they may enable the identification of the term-structure of uncertainty shocks related to different horizons. Also, in the future, it is clearly of interest to further examine the identification of separate uncertainty shocks originating in the labour market, from those impacting aggregate real activity and/or inflation.
References


Figure 1: SPF probability forecasts for GDP Growth (2 years horizon)

Note: The probability forecasts were collected 6 quarters prior to the indicated outcome date, i.e. in 2006Q4 for 2008Q1, in 2007Q4 for 2009Q1 and in 2008Q4 for 2010Q1.

Figure 2: Parametric ex-ante uncertainty estimates – 2 years horizon

Note: Shaded areas show business cycle phases identified by the CEPR business cycle dating committee. The committee has identified two recessions since 2000. The first was in the context of the recent financial crisis (2008Q1-2009Q2), and the second in connection with the European sovereign debt crisis (2011Q3 -2013Q1). The period between 2002Q2 and 2003Q4 was identified as a growth pause. See http://cepr.org/content/euro-area-business-cycle-dating-committee.
Figure 3: Ex-ante economic uncertainty and other proxies

Note: Shaded areas denote recessions and growth pause identified by the CEPR business cycle dating committee (see also note to Figure 1).

Figure 4: Decomposition of Aggregate Ex-ante uncertainty about GDP growth (2 years horizon)

Note: Shaded areas denote recessions and growth pause identified by the CEPR business cycle dating committee (see also note to Figure 1).
Figure 5: Survey timing and uncertainty horizons

Note: $\text{EAU}_T^\gamma$, $\text{EAU}_T^\eta$, $\text{EAU}_T^\pi$: represent ex-ante uncertainty about GDP growth, the unemployment rate and inflation respectively. The horizontal axis depicts the uncertainty horizon for a survey round conducted in quarter $t$. 

Note: 

Survey rounds are conducted in the beginning of the quarter.

- $\text{EAU}_T^\gamma_{t-6q}$
- $\text{EAU}_T^\eta_{t-2m}$
- $\text{EAU}_T^\pi_{t-2m}$

Real Variables, Financial Variables

$\text{First Principal Component}$

t+6q  t+7q
Figure 6: Impulse response functions: Ex-ante uncertainty shock

Note: Shaded areas represent 60% confidence bands from the BVAR model.
Figure 7: Impulse response functions: Comparison across proxies
Figure 8: Historical Decomposition: euro area GDP

Table 1: Summary Statistics – Ex-ante uncertainty measures and other uncertainty proxies

<table>
<thead>
<tr>
<th></th>
<th>Volatility</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>α1</th>
<th>α2</th>
<th>α3</th>
<th>Mean pre-crisis</th>
<th>Mean post-crisis</th>
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</thead>
<tbody>
<tr>
<td>EAU</td>
<td>0.20</td>
<td>0.22</td>
<td>1.90</td>
<td>0.91</td>
<td>-0.10</td>
<td>0.15</td>
<td>0.00</td>
<td>-0.17</td>
</tr>
<tr>
<td>EAU^Y</td>
<td>0.10</td>
<td>0.14</td>
<td>1.95</td>
<td>0.89</td>
<td>0.15</td>
<td>-0.02</td>
<td>0.62</td>
<td>0.54</td>
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<tr>
<td>EAU^u</td>
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<td>0.35</td>
<td>2.44</td>
<td>0.86</td>
<td>-0.02</td>
<td>0.14</td>
<td>0.66</td>
<td>0.54</td>
</tr>
<tr>
<td>EAU^p</td>
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<td>0.09</td>
<td>1.47</td>
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<td>0.10</td>
<td>0.56</td>
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<tr>
<td>Disagreement</td>
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<td>10.66</td>
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<td>-0.08</td>
<td>0.02</td>
<td>0.14</td>
<td>0.10</td>
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<td>VSTOXX*</td>
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<td>3.40</td>
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<td>EPU</td>
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<td>-0.09</td>
<td>1.39</td>
<td>0.97</td>
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</table>

Note: The entries in the table denote: $\alpha_k$ = partial autocorrelation at lag k; EAU: Ex-ante Uncertainty: GDP, u: unemployment, p: inflation.
*Original series VSTOXX were divided by 100. EPU refers to the Economic Policy Uncertainty index from Bloom, Baker and Davis (2016).

Table 2: BVAR Hyperparameters

<table>
<thead>
<tr>
<th>BVAR hyperparameters</th>
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<tbody>
<tr>
<td>Autoregressive coefficient</td>
</tr>
<tr>
<td>Overall tightness ($\lambda_1$)</td>
</tr>
<tr>
<td>Lag decay ($\lambda_3$)</td>
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<tr>
<td>Exogenous variable tightness ($\lambda_i$)</td>
</tr>
<tr>
<td>Sum-of-coefficients tightness ($\lambda_6$)</td>
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<tr>
<td>Dummy initial observation tightness ($\lambda_7$)</td>
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<table>
<thead>
<tr>
<th>Further Specifications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of iterations</td>
</tr>
<tr>
<td>Prior</td>
</tr>
<tr>
<td>Number of lags</td>
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Table 3: Forecast Performance of BVAR model with and without uncertainty indicators

<table>
<thead>
<tr>
<th>Panel (a)</th>
<th>Variable specific</th>
<th>Horizon specific</th>
<th>EAU Aggregate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real Variables</td>
<td>H=1</td>
<td>H=4</td>
<td>H=1</td>
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<tr>
<td>GDP</td>
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<td>0.99</td>
<td>1.00</td>
</tr>
<tr>
<td>Private Consumption</td>
<td>1.00</td>
<td>0.99</td>
<td>1.00</td>
</tr>
<tr>
<td>Consumer Prices</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Unemployment</td>
<td>1.05</td>
<td>0.95</td>
<td>1.08*</td>
</tr>
<tr>
<td>Private Investment</td>
<td>0.99</td>
<td>0.98</td>
<td>1.00</td>
</tr>
<tr>
<td>Financial Variables</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Short term interest rate</td>
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<td>0.84</td>
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<tr>
<td>Credit</td>
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<td>0.78***</td>
<td>0.94</td>
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<td>Bank lending rate</td>
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<td>0.95</td>
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<td>Corporate bonds</td>
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<td>0.97</td>
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<tr>
<td>Long term gov. bonds</td>
<td>1.05*</td>
<td>1.00</td>
<td>0.98</td>
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<tr>
<td>Equity Prices</td>
<td>0.95</td>
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<table>
<thead>
<tr>
<th>Panel (b)</th>
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<th>VSTOXX</th>
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<tr>
<td>Real Variables</td>
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<td>H=4</td>
<td>H=1</td>
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<td>1.02</td>
<td>1.00</td>
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<td>Private Consumption</td>
<td>1.00</td>
<td>1.01</td>
<td>1.00</td>
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<tr>
<td>Consumer Prices</td>
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<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Unemployment</td>
<td>1.02</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>Private Investment</td>
<td>1.01</td>
<td>1.02</td>
<td>1.00</td>
</tr>
<tr>
<td>Financial Variables</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Short term interest rate</td>
<td>0.95</td>
<td>0.98</td>
<td>1.01</td>
</tr>
<tr>
<td>Credit</td>
<td>0.99</td>
<td>1.03</td>
<td>1.00</td>
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<tr>
<td>Bank lending rate</td>
<td>1.01</td>
<td>1.04**</td>
<td>1.00</td>
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<td>Corporate bonds</td>
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<td>1.15</td>
<td>1.01</td>
</tr>
<tr>
<td>Long term gov. bonds</td>
<td>0.99</td>
<td>0.94**</td>
<td>1.00</td>
</tr>
<tr>
<td>Equity Prices</td>
<td>1.01</td>
<td>1.04*</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Notes: Values less than 0.95 are highlighted in grey. In bold, values that are significant according to the (adjusted) Diebold-Mariano test, where * indicates significance at 10%, ** indicates significance at 5% and *** indicates significance at 1%. The adjustment of the test follows Harvey, Leybourne, and Newbold (1997). They suggest a bias correction to the DM test statistic, and rather than using the standard normal statistic, they compare the corrected statistic with a Student-t distribution with (T-1) degrees of freedom.
Appendix A

Data Sources, Transformations and Treatment of Survey Measurement Problems

In this appendix, we summarise our main data sources and detail the treatment of measurement problems that impacted on the estimation of SPF uncertainty measures during some specific survey rounds.

SPF Data: The Survey of Professional Forecasters (SPF) is a quarterly survey of macroeconomic expectations, conducted by the European Central Bank (ECB). The SPF panel of point and probability forecasts for euro area GDP, HICP inflation and the unemployment rate at long, medium, and short horizons were obtained from the ECB website.31

As discussed in Section 2, we focus on the aggregate or average probabilities in measuring ex-ante uncertainty. Also as highlighted in Section 2, we need to account for the measurement error associated with the pilling up of probabilities in the open intervals of the survey questionnaire in the 2008Q3, 2008Q4 and 2009Q1 survey rounds. Table A1 shows both the original and the new interpolated values (highlighted in grey) after applying the linear interpolation method for the following 1 and 2 years horizons parametric ex-ante uncertainty series. At the 2-year horizon for GDP, no interpolation was needed as there was no pilling up of probability mass in the open intervals.

Table A1: Interpolations

<table>
<thead>
<tr>
<th>Quarter</th>
<th>EAU^Y</th>
<th>EAU^n</th>
<th>EAU^u</th>
<th>EAU^Y</th>
<th>EAU^n</th>
<th>EAU^u</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008Q2</td>
<td>0.57</td>
<td>0.50</td>
<td>0.53</td>
<td>0.58</td>
<td>0.63</td>
<td>0.49</td>
</tr>
<tr>
<td>2008Q3</td>
<td>0.59</td>
<td>0.50</td>
<td>0.57</td>
<td>0.61</td>
<td>0.63</td>
<td>0.54</td>
</tr>
<tr>
<td>2008Q4</td>
<td>0.62</td>
<td>0.51</td>
<td>0.63</td>
<td>0.69</td>
<td>0.64</td>
<td>0.59</td>
</tr>
<tr>
<td>2009Q1</td>
<td>0.92</td>
<td>0.67</td>
<td>0.69</td>
<td>0.75</td>
<td>0.85</td>
<td>0.63</td>
</tr>
<tr>
<td>2009Q2</td>
<td>1.23</td>
<td>0.90</td>
<td>0.70</td>
<td>0.82</td>
<td>1.08</td>
<td>0.69</td>
</tr>
<tr>
<td>Values before interpolation</td>
<td>0.38</td>
<td>0.48</td>
<td>0.56</td>
<td></td>
<td>0.57</td>
<td>0.51</td>
</tr>
</tbody>
</table>

Notes: The entries in the table EAU^Y, EAU^n, EAU^u: represent ex-ante uncertainty about GDP growth, the unemployment rate and inflation respectively. Shaded entries represent the interpolated data.

---

**Other Data:** Table A2 summarises the other data sources used in the BVAR analysis, including definitions, sources and any transformations used.

**Real-time Data:** The series to estimate the real time out-of-sample forecast exercise were extracted from the Euro Area Real-Time Database (RTDB), available at the Statistical Data Warehouse from the European Central Bank.\(^3^2\) This dataset consists of vintages, or snapshots, of time series of several variables, based on series reported in the ECB’s Monthly Bulletin. From 2015 onwards the RTDB reflects the new release schedule of the Economic Bulletin, the first issue of which was published on February 2015.

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\(^{32}\) Available at: https://sdw.ecb.europa.eu/browseSelection.do?node=9689716
<table>
<thead>
<tr>
<th>Variable</th>
<th>Units</th>
<th>Definitions/Data Sources</th>
<th>Transformations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real GDP</td>
<td>Euro, Chain linked volume</td>
<td>Gross domestic product at market prices/Eurostat</td>
<td>sa log</td>
</tr>
<tr>
<td>Private consumption</td>
<td>Euro, Chain linked volume</td>
<td>Individual consumption expenditure/Eurostat</td>
<td>sa log</td>
</tr>
<tr>
<td>Consumer Prices</td>
<td>Index</td>
<td>HICP/Eurostat</td>
<td>sa log</td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>percent</td>
<td>Standardised unemployment, Total, percentage of civilian workforce/Eurostat</td>
<td>sa log</td>
</tr>
<tr>
<td>Private Investment</td>
<td>Euro, Chain linked volume</td>
<td>Gross fixed capital formation/Eurostat</td>
<td>sa log</td>
</tr>
<tr>
<td>Short term interest rate</td>
<td>percent</td>
<td>3 month Euribor rate/ECB SDW</td>
<td></td>
</tr>
<tr>
<td>Credit</td>
<td>Millions of Euro</td>
<td>Loans to non-financial corporation sector - Outstanding amounts at the end of the period (stocks)/ECB SDW</td>
<td>log</td>
</tr>
<tr>
<td>Bank lending rate</td>
<td>percent</td>
<td>spread over 3 month Euribor rate/ECB SDW, own calculations</td>
<td></td>
</tr>
<tr>
<td>Corporate bonds</td>
<td>percent</td>
<td>spread over 3 month Euribor rate/ECB SDW, own calculations</td>
<td></td>
</tr>
<tr>
<td>Long term government bonds</td>
<td>percent</td>
<td>10-year Government benchmark bond yield/ECB SDW</td>
<td></td>
</tr>
<tr>
<td>Equity prices</td>
<td>index</td>
<td>Dow Jones Euro Stoxx Price Index/ECB SDW, provided by DataStream</td>
<td>log</td>
</tr>
<tr>
<td>Ex-ante uncertainty (EAU)</td>
<td>percentage points</td>
<td>Ex-ante uncertainty - Parametric estimation/ECB - Survey of Professional Forecasts¹</td>
<td>First principal component, 2 years horizon.</td>
</tr>
<tr>
<td>Disagreement</td>
<td>percentage points</td>
<td>Variance of SPF forecasts - target period ends 21 months after survey cycle begins (2 years horizon)/ECB - Survey of Professional Forecasts</td>
<td>Average across forecast disagreement on GDP, unemployment and inflation</td>
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<tr>
<td>Policy uncertainty</td>
<td>index</td>
<td>Economic Policy Uncertainty/EPU website² - see Bloom, Baker and Davis (2016)</td>
<td>log, first month of each quarter</td>
</tr>
<tr>
<td>VSTOXX</td>
<td>index</td>
<td>Stock market volatility 24 months ahead/Bloomberg</td>
<td>log, first month of each quarter</td>
</tr>
</tbody>
</table>

Notes: sa: seasonally adjusted

²See http://www.policyuncertainty.com/
Appendix B

Variable- and Horizon-Specific Uncertainty Shocks

In this appendix, we report in more detail the results related to the variable- and horizon-specific BVARs discussed in section 3.4, i.e. BVAR-VS and BVAR-HS. In particular, we analyse the transmission of these variable- and horizon-specific uncertainty measures individually as a way to assess the extent to which either the variable to which uncertainty relates or the length of the horizon over which uncertainty is measured impact materially on our results.

As our variable specific measures, we use the three 2-year horizon uncertainty measures for GDP growth, the unemployment rate and inflation that underlie the first principal component used in the baseline BVAR model (see Figure 2 in the main text). To construct three horizon-specific measures we compute the first principal component across the GDP, inflation and unemployment rate uncertainty measures for each of the 1, 2 and 5 year horizons used in the SPF questionnaire (Figure B1). We then estimate two separate BVARs. A first contains, the three variable-specific measures, while a second contains the three horizon-specific measures. Each of these BVARs employs the same hyperparameter choices as documented in Table 2. Also, as with the benchmark version of our model, the uncertainty measures are ordered first in the BVAR reflecting their beginning of quarter timing. For the variable-specific BVAR, the GDP uncertainty measure is ordered first, followed by the unemployment rate and then the inflation rate. In the BVAR with the three horizon-specific uncertainty measures, we order long-run uncertainty first followed by uncertainty at a two year horizon and then uncertainty one year ahead.

Figures B2 and B3 report the impulse response functions for the variable and horizon specific uncertainty shocks discussed above. In general, the impact of all three variable-specific uncertainty shocks is quite consistent across the range of economic and financial variables included in the BVAR. GDP, private consumption and investment all decline in response to a positive shock to GDP uncertainty, unemployment
uncertainty and inflation uncertainty, while the unemployment rate rises. Also, credit and both bank-lending and corporate bond spreads tend to rise. In terms of the main differences, it is real uncertainty associated with GDP and the unemployment rate that impacts consumptions most strongly while the effect of inflation uncertainty is more muted. Also, it is the measure of GDP uncertainty that has the strongest and most immediate impact on most of the variables included in the model (e.g. on the unemployment rate or on credit spreads). The impulse response functions related to the horizon-specific uncertainty (reported in Figure B3) also highlight that the transmission is quite consistent across the different horizons. Comparing the effects, it is the shock to uncertainty at the medium-term 2-year horizon that has the strongest negative impact on GDP, consumption, investment and the unemployment rate. Also, the negative impact on private sector credit, bank and corporate bond spreads and equity prices is stronger compared with the uncertainty shocks at the shorter 1-year horizon or at the long-term 5-year horizon. In line with the baseline results Figure 6, uncertainty shocks for all three horizons have a consistently very muted or negligible impact on consumer prices.

Figure B1: Horizon-specific uncertainty measures

*Shaded areas represent recession periods identified by CEPR **2001Q4-2003Q4: Period identified as “Growth Pause”

---

1 year horizon  2 years horizon  5 years horizon
Figure B2: Impulse response functions: Variable-specific uncertainty shocks
Figure B3: Impulse response functions: Horizon-specific uncertainty shocks

---

Short run Uncertainty  Medium term Uncertainty  Long run Uncertainty
Appendix C

Comparing Parametric and Non-parametric Estimates of EAU

The fitting of a specific functional form like the generalised Beta distribution to the SPF histograms offers a useful way to summarise the respondents’ views on the predictability of economic outcomes. However, it is subject to the caveat that we do not have a good basis to judge the functional form of the density that may (or may not) underpin the reported histograms. A very simple alternative approach to estimating the variance of the average distribution is to treat it as a discrete distribution and to estimate its moments non-parametrically. In this Appendix we report the results of such a non-parametric approach.

To implement the non-parametric approach we follow Kenny et al. (2015) and assume that all the probability mass in a given bin $k$ is assigned to the midpoint of that bin $y_k$. In addition, in line with the parametric approach above, the open intervals at the upper and lower ends of the distribution are treated as closed intervals of the same width as the other intervals in the histogram. Using $K_t$ to denote the number of bins used in the survey conducted at time $t$, an estimate of the variance is given by the second centered moment, which is computed as the probability weighted averages:

$$EAU = \sum_{k=1}^{K_t} p_{i,t+h}^k [y_k - E_{t}[y_{t+h}]]^2$$  \hspace{1cm} (C1)

where the mean forecast $E_{t}[y_{t+h}]$ is estimated as the probability weighted sum of the mid-point of each interval, $y_k$, i.e.

$$E_{t}[y_{t+h}] = \sum_{k=1}^{K_t} p_{i,t+h}^k y_k$$  \hspace{1cm} (C2)

Figure C1 below plots the estimates of EAU using the non-parametric approach above and compares them with the estimates derived parametrically by fitting the generalised Beta distribution. As with the parametric approach, the EAU measure is derived as the first principal component from the estimate for GDP growth,
the unemployment rate and euro area inflation at a two-year horizon. From the chart it is clear that both parametric and non-parametric approaches yield very similar estimates. In particular, the non-parametric estimate exhibits the same countercyclical pattern for the three CEPR “recessions” and exhibits a sharp and highly persistent rise in the wake of the Great Recession.

Figure C1: Parametric vs. Non-parametric estimates of Ex-Ante Uncertainty

Figure C2 compares the impulse response functions depicting the transmission of an uncertainty shock using both parametric and non-parametric estimates. In deriving these responses we exploit the same contemporaneous impact restrictions motivated by the beginning of quarter timing of the survey data. The chart highlight that the broad conclusions on the transmission of an EAU shock to the euro area economy are robust with respect to both parametric and non-parametric estimates. In particular, following an uncertainty shock we observe a persistent deterioration in financial conditions as reflected in a rise in interest rate spreads for both bank and non-bank based finance, a rise in long-term government bond yields and a drop in equity values as well as an overall contraction in the supply of credit to the private sector. We also observe a substantial transmission of the uncertainty shock to the real economy with persistent negative effects on consumption, investment and the labour market outcomes. In line with the parametric estimates reported in the main text of the paper, the response of inflation appears more muted and the associated confidence bands imply that a shock to uncertainty has no significant impact on inflation. As discussed
earlier, a plausible explanation for this result is that an uncertainty shock has both demand and supply-side effects with the overall level of economic slack being less affected.

Table C3 reports the results of our out-of-sample forecast performance evaluation whilst comparing the BVAR models with both parametric and non-parametric estimates of uncertainty. As in the main body of the paper, we report results for the BVAR using the macro measure of ex-ante uncertainty extracted as the first principal component, along with the equivalent parametric and non-parametric measures for the BVAR-VS and the BVAR-HS. In general, the results of the out-of-sample experiment are not affected by the choice of either the parametric or non-parametric estimation method. Both approaches yield evidence that the inclusion of EAU in a BVAR is associated with a significant improvement in out-of-sample forecast performance. These gains are generally most relevant for the prediction of financial variables and appear more relevant at the longer 4-quarter horizon.
Figure C2: Non-parametric Estimates: Impulse response functions
Table C3: Forecast Performance of BVAR model: Parametric vs. non-parametric estimates

### Panel (a) Aggregate EAU

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### Panel (b) Variable-Specific Models and Horizon Specific Models

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<th>Horizon Specific Models</th>
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**Notes:** Values less than 0.95 are highlighted in grey. In bold, values that are significant according to the (adjusted) Diebold-Mariano test, where * indicates significance at 10%, ** indicates significance at 5% and *** indicates significance at 1%. 

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