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ECB communication as a stabilization
and coordination device:
evidence from ex-ante
inflation uncertainty

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Abstract

This paper investigates the impact of ECB communication of its assessment of the economic outlook on ex-ante inflation uncertainty and sheds light on how central bank information shocks operate. The paper finds that ECB communication of new outlook information not only reduces professional forecasters' disagreement (i.e., the cross-sectional dispersion of their average point forecasts of inflation) but also makes forecasters less uncertain about their own beliefs, thus reducing ex-ante average individual uncertainty. By combining and exploiting these types of ex-ante inflation uncertainty, results suggest that central bank information acts as a “coordination device” able to influence opinions and actions. Most importantly, it generates a “stabilizer effect” by substantially decreasing the dispersion among the inflation point forecasts, which converge towards their unconditional aggregate mean. The results of this paper not only help to explain the impact of new central bank information, but they are also useful for policymakers to define a communication strategy that attenuates ex-ante inflation uncertainty in the most effective way.

Keywords: central bank communication, ex-ante inflation uncertainty, inflation expectations, euro area

JEL: D83, E52, E58, E65, G14

Non-technical summary

Central bank communication has evolved from a reluctance of central banks to provide precise information on the policy process to become an increasingly important instrument of monetary policy. It plays a central role in steering expectations, which is fundamental to ensuring that the central bank can successfully stabilize aggregate demand and therefore inflation.

While existing studies focus mainly on assessing the impact of central bank information on expectations and on the economy, there has so far been no attempt to understand how news communicated by the central bank affects uncertainty, in particular ex-ante uncertainty about inflation. Ex-ante uncertainty refers to measurements of uncertainty that are estimated before economic events occur, in contrast to ex-post (or realized) uncertainty, which is estimated based on the information available after a certain event has occurred.

Investigating the relationship between central bank communication and ex-ante inflation uncertainty is important because if the latter is exacerbated by communication, it may harm economic activity as well as the effectiveness of monetary policy in maintaining price and/or financial stability. Inflation uncertainty can slow investments and affect wealth allocation, increasing the costs of a contractionary monetary policy or even counteracting an expansionary stimulus. In addition, increasing inflation uncertainty can be a sign of a central bank's weakening credibility.

In this paper, I estimate three ex-ante uncertainty measures (disagreement, individual, and aggregate) using the European Central Bank (ECB) Survey of Professional Forecasters (SPF), which collects information on the expected rates of inflation in the euro area at several horizons. Central bank information shocks are estimated by Jarociński and Karadi (2020) by identifying high-frequency co-movement of interest rates and stock prices in a narrow window around ECB policy announcements. By using local projection methods (Jordà, 2005) based on a sample between 2000 Q2 and 2019 Q2, I find evidence that the ECB information shocks not only reduce disagreement among agents about their inflation projections but also the individual uncertainty of agents about their own projections. Both effects result in a lower aggregate ex-ante inflation uncertainty.

Building upon this evidence that ECB communication affects ex-ante inflation uncertainty, the next question is: how does it happen? In answering this question, this paper also sheds light on the channels through which central bank communication operates. By analyzing the results through the lens of the characteristics of each ex-ante uncertainty measure, I find evidence that central bank communication

shocks act as a public signal that is effective in coordinating opinions and actions and also contributes to strengthening forecasters' confidence in their predictions.

Finally, combining these results with the evidence documented in the literature on the effect of central bank information shocks on inflation expectations, I also conclude that central bank communication generates a “stabilizer effect”. In other words, after a central bank information shock, not only the disagreement across the forecasters decreases, but most importantly, this convergence moves towards the mean, in contrast to the alternative, which would imply a convergence of the point forecasts towards one of the tails. Crucially, this convergence induces a steady consensus among the forecasters that is more in line with the ECB's objectives. Communication shocks therefore act as a powerful device to reduce uncertainty while steering expectations.

Deciphering how each type of ex-ante inflation uncertainty responds to ECB announcements can help policymakers to define a communication strategy that attenuates inflation uncertainty in the most effective way possible. For example, the ECB could tailor its communication to mitigate potential increases in forecast disagreement in volatile times. Communication could also be sharpened to minimize the possibility of different interpretations among the group of forecasters. Likewise, it is important to sharpen communication when further clarifications or reinforcements of previous messages are necessary, as it helps to improve forecaster's confidence about their own assessments.

1. Introduction

In the past decades, central bank communication has gained increasing importance. It has evolved from a reluctance of central banks to provide precise information on the policy process to a facilitator of conventional monetary policy, eventually becoming a new instrument of monetary policy itself (Blinder, 2018; Weidmann, 2018; and Issing, 2019). Central bank communication steers expectations, and the better expectations are aligned with the monetary policy objective, the more likely it is that the central bank will stabilize aggregate demand and therefore inflation (Clarida, Gali and Gertler, 1999).

Recently, a nascent literature has been shifting the attention from quantifying and estimating the implications of several aspects of communication, such as transparency, clarity, and tone,¹ towards the informative nature of central bank communication. By using high-frequency surprises around central bank announcements, recent research seeks to isolate the communication of assessments of the economy from information about monetary policy, which are conveyed simultaneously in policy announcements (see Jarociński and Karadi, 2020; Cieslak and Schrimpf, 2019; Kerssenfischer, 2018; Andrade and Ferroni, 2016).

In this context, there are at least two important gaps in the literature. First, existing studies focus mainly on assessing the impact of central bank information on aggregate measures of expectations and on the economy. While this is consistent with the consensus that disentangling communication about the economic outlook from monetary policy information in central bank communication is important to prevent bias in the estimated effects of monetary policy, there has so far been no attempt to understand the effects of news communicated by the central bank on measures of ex-ante uncertainty about the economy, particularly ex-ante uncertainty about inflation.

Ex-ante uncertainty refers to measurements of uncertainty which does not include the realization of events, in contrast to ex-post (or realized) uncertainty, which does. Investigating the relationship between central bank communication and ex-ante inflation uncertainty is important because if the latter is exacerbated by communication, it may harm economic activity and the effectiveness of monetary policy in maintaining price and/or financial stability. Inflation uncertainty can increase the costs related to a contractionary monetary policy or counteract an expansionary stimulus by, for example, slowing

¹ These elements are typically proxied by indexes or dictionary approaches (see for example, Eijffinger and Geraats, 2006; Minegishi and Cournède, 2009; Jegadeesh and Wu, 2017; Picault and Renault, 2017; Dincer, Geraats, and Eichengreen, 2019).

investments and affecting wealth allocation.² In addition, increasing inflation uncertainty can be a sign of a central bank's weakening credibility. Therefore, assessing whether central bank communication mitigates or exacerbates inflation uncertainty is very important for monetary policy strategy.

Second, the channels through which central bank information shocks operate and how they impact the ex-ante inflation uncertainty are unknown. The closest related discussion in the literature is about how central bank information impacts the economy and expectations, focusing on the levels and first moment of inflation. In particular, the discussion revolves around whether central banks convey new information that directly impacts forecasts or whether their announcements help market participants and forecasters to focus on one particular equilibrium, thereby serving as an impactful coordination device. This debate still remains unresolved.

By making use of the European Central Bank (ECB) Survey of Professional Forecasters (SPF) and the central bank information shocks provided by Jarociński and Karadi (2020), this paper provides a twofold contribution. First, for the first time in the context of the central bank communication literature, the paper disentangles the effects of ECB communication on three different types of ex-ante inflation uncertainty: disagreement, average individual, and aggregate uncertainty.

In particular, by using local projection methods (Jordà, 2005), I find evidence that the ECB's outlook information shocks not only reduce the dispersion across agents' average point forecasts (disagreement), but they also make agents less uncertain about their own beliefs (ex-ante average individual uncertainty). Both effects result in a lower aggregate ex-ante inflation uncertainty. This decomposition across different types of ex-ante uncertainties is possible because, in contrast with other surveys used in the literature, the ECB SPF provides both point (mean) forecasts and their distributions for each individual forecaster.

Second, given that there is evidence that ECB communication affects ex-ante inflation uncertainty, the next question is: how does it happen? In answering this question, this paper also sheds light on the channels through which central bank communication operates. The particularities and the complementarities of each ex-ante uncertainty measure provide unique insights when interpreting the results of the reactions of these measures to central bank information shocks. Most importantly,

² There is substantial evidence in the literature on the negative impact of inflation uncertainty on financial and macroeconomic variables. Inflation uncertainty may induce agents to postpone investment or savings decisions and reduce market efficiency due to an increase in the volatility of both relative prices and risks regarding income streams from nominal financial and wage contracts (Friedman, 1977; Bloom, 2009). Furthermore, inflation uncertainty can lead to shifts in wealth allocation between creditors and debtors (see Fama, 1976; Barnea, Dotan, and Lakonishak, 1979; Grauer and Litzenberger, 1979).

disagreement reflects the dispersion of projections across forecasters but does not provide information about each forecaster's uncertainty regarding their own forecast. In contrast, average individual uncertainty assesses the uncertainty of each individual regarding their own projections, so it is often considered a better proxy for uncertainty (see Abel et al., 2016; Glas and Hartmann, 2016; and Glas, 2020). Some studies even show that disagreement in survey forecasts could be more reflective of differences in opinion than of uncertainty (see Diether, Malloy, and Scherbina, 2002; Mankiw, Reis, and Wolfers, 2004).

Given that central bank information shocks lead agents to disagree less among each other about their inflation projections and also to become less uncertain about their own projections, I find evidence that they act as a public signal, which is effective in coordinating opinions and actions. Furthermore, forecasters are comfortable in incorporating the public signal emitted by the central bank in the assessment of their analysis. This also implies that this signal is valuable and on average it contributes to strengthen their confidence in their predications.

In addition, after a central bank information shock, the point forecasts converge towards their mean. This convergence implies that the central bank communication generates a “stabilizer effect” in which not only the dispersion among the point forecasts decreases, but most importantly, this convergence moves towards the mean. This convergence is very important as it induces a steady consensus among the forecasters more in line with the ECB's objectives, in contrast to the alternative, which would imply a convergence of the point forecasts towards one of the tails.

This paper is organized as follows: Section 2 provides a review of the related literature. Section 3 provides a detailed description of the databases and how uncertainty measures and the central bank communication shocks used in this study are estimated. Section 4 summarizes the estimation methodology using local projections. Section 5 explains the identification strategy for the econometric analysis. Sections 6 and 7 respectively show the results and the robustness checks. Section 8 concludes.

2. Related literature

Typically, empirical studies exploiting the relationship between central bank communication and uncertainty focus on the transparency aspect of central bank communication as the object of study. In most cases, these studies use survey-based data to measure uncertainty as the dispersion of individual forecasts around the average forecast (disagreement) or around the forecast outcome (mean forecast error). Likewise, most of the studies employ panel data for different economies. Within this framework,

the literature provides evidence that greater central bank transparency reduces inflation uncertainty (Ehrmann, Eijffinger, and Fratzscher, 2012;³ Siklos, 2013; Csavas, Erhart, Felcser, and Nazodi, 2016).

This paper is the first to investigate the relationship between the ECB communication and ex-ante inflation uncertainty in the euro area. As explained in Section 3, in order to measure ECB communication, I use the new dataset on central bank information shocks from Jarociński and Karadi (2020), which are estimated using high-frequency data. These shocks ultimately consist of ECB communication about the economy. Furthermore, by following Engelberg, Manski, and Williams (2009) and Kenny and Melo Fernandes (2021), I estimate three ex-ante uncertainty measures using the ECB SPF: disagreement, average individual, and aggregate uncertainty.

Another common approach for estimating inflation uncertainty in the literature is from an ex-post perspective, either by estimating conditional variance using GARCH models (Grier and Perry, 2000; Fountas et al., 2004; Kontonikas, 2004; Conrad and Karanasos, 2005) or stochastic volatility (see Berument, Yalcin, and Yildirim, 2009; and Chan, 2017). To the best of my knowledge, Kliesen and Schmid (2004) is the first paper investigating how ex-post inflation uncertainty reacts to central bank communication. They define inflation uncertainty as the conditional volatility of inflation compensation, i.e., the additional yield that investors require to hold nominal assets that are exposed to inflation risk, and following a common event analysis approach based on Kohn and Sack (2003), they find that Federal Reserve communication reduces ex-post inflation uncertainty.

In contrast to market-based measures, expectations and uncertainty measures derived from survey-based sources do not incorporate any additional compensation for risk and liquidity premia that may cause distortions in the signals and drivers of the measures.⁴ On the other hand, the information content of survey data on inflation expectations is sometimes questioned because these expectations might not correspond to either those on which economic decisions are based or to those that economic agents truly think. In addition, these measures are more subject to mistakes. These arguments are, however, unlikely to apply in the case of professionals who make macroeconomic forecasts as part of their regular duties (see Garcia, 2003). Furthermore, survey-based measures have a clear advantage in that regard as they contain direct estimates of future inflation outcomes. Therefore, ex-ante survey-based inflation

³ In addition to transparency, Ehrmann, Eijffinger, and Fratzscher (2012) also construct a measure of central bank communication based on dummy variables, which specify whether or not a central bank has announced a quantified inflation objective.

⁴ Grothe and Meyler (2015) show that both market-based and survey-based measures have a non-negligible predictive power for inflation developments, as compared to statistical benchmark models.

uncertainty measures are arguably the most appropriate for the purpose of this paper.

The closest study related to this paper is by Jitmaneeroj, Lamla, and Wood (2019), who analyze the impact of central bank transparency on three types of uncertainty: disagreement, aggregate, and common. In contrast to this paper, which focuses on the euro area, they use panel data for 25 economies and provide evidence that greater transparency reduces uncertainty of interest rates and inflation, primarily by reducing common uncertainty rather than disagreement. Rather than estimating a measure for common uncertainty, in this paper I estimate the ex-ante average individual uncertainty. I find that out of three measures, the reduction in disagreement is the most prominent response in terms of magnitude.

More recently, a new strand of literature has emerged focusing on the relevance of central bank communication in non-conventional times and its implications for uncertainty. Coenen et al. (2017) find evidence that announcements of asset purchase programs have lowered market uncertainty (measured by the VSTOXX index), particularly when accompanied by a contextual release of implementation details of the program. Ehermann et al. (2019) find that while forward guidance directly decreases forecast disagreement, the way that it is implemented matters for uncertainty. In particular, the implementation of weak types of forward guidance makes market prices less informative and may increase uncertainty.

Other related studies investigate the effect of central bank communication on other types of uncertainty. Swanson (2006) finds that increased transparency by the US Federal Reserve reduces ex-ante uncertainty about the future course of short-term interest rates. Hüning (2019) shows that Swiss National Bank communications indicating a future rate cut reduce stock market uncertainty, measured as the abnormal stock market variance derived from the Swiss Market Index. In contrast, communication indicating future policy tightening does not affect it.

The main novelty of this paper is that on top of gaining new insights into the implications of the ECB communication on ex-ante inflation uncertainty, it also sheds some light on understanding the channels through which central bank information shocks operate. So far, to the best of my knowledge, the mechanism through which central bank communication impacts ex-ante inflation uncertainty has not yet been explored.

There is, however, a similar debate in the literature about how central bank information shocks affect market expectations and the economy. There are two hypotheses when it comes to addressing this point but no concrete answer has so far been provided on which of them is more plausible. The first hypothesis is based on a Bayesian approach, in which central bank information shocks could contain new information

about how the central bank interprets the state of the economy and/or predicts future economic developments. Once this new information is communicated, financial market participants and forecasters would use this information to update their expectations as long as the central bank analysis is credible.

There are several explanations for the central bank's information advantage in the literature. Romer and Romer (2000) argue that the Fed has an advantage compared to the market in terms of resources and chooses to use more of these inputs than any commercial forecasters find profitable. Therefore, the private sector considers the information provided by the central bank to be valuable, since the forecasts and analyses are conducted by well-trained staff with a high degree of specialization.

Another explanation is that because most central banks function both as supervisors and as liquidity providers, central banks have tighter links with the financial sector in particular after the crisis. This provides a comparative advantage in collecting detailed information about current and recent developments in the economy. Furthermore, the central bank has the knowledge advantage of its own probable policy actions, so it plays some role in determining the variables it is forecasting (see Jung and Uhlig, 2019). Nakamura and Steinsson (2018) and Jarociński and Karadi (2020) suggest that the central bank also simply announces information earlier than other sources. This interpretation implies that if the central bank would not have communicated some specific information, this content would have become known to the market via other sources anyway at a later stage. Nevertheless, their interpretation ultimately suggests that central bank information shocks convey new information and the market learns from it.

The second hypothesis is that central bank information might also contain little or no new information about the current or future state of the economy in terms of hard data. But in a world of possible multiple equilibria, the released information could help market participants and forecasters to focus on one particular equilibrium, supported by the central bank, and therefore serve as an impactful coordination device. This hypothesis thus implies that the public nature of certain signals (in the case of this paper, the communication itself) acts as a signal that can guide expectations and individual decisions even if they contain minimal information, as in Morris and Shin (2002). From this perspective, public signals serve as a coordination device.

Interestingly, Born et al. (2011), when investigating how central bank communication about financial stability influences financial markets, find that it works primarily as coordination device, highlighting that markets also perceive it to contain relevant information.

While the assessment of whether central bank information shocks convey new information about the

economy is beyond the scope of this paper, I provide evidence that they do act a public signal, able to coordinate and influence opinions and actions. I thereby explore how central bank information operates on the second moments, focusing on the role of central bank communication as a coordination device. In addition, I also document that central bank information shocks do not significantly affect inflation expectations, but they do decrease all the three measures of ex-ante inflation uncertainty. More precisely, I show that while central bank information conveys new information to the market, it also aligns opinions across forecasters, generating a “stabilizer” effect as the convergence of these measures is towards their mean.

3. Data description

The research question of this paper centers on four main variables of interest: the three types of ex-ante inflation uncertainty and the central bank communication shocks. Sub-sections 3.1 and 3.2 respectively provide detailed explanations of how these measures and shocks are estimated, but some of the features of the data can already be highlighted here.

To estimate the three measures of ex-ante inflation uncertainty, both the aggregate and the individual histograms of the ECB SPF are exploited. The ECB SPF gathers information on the expected rates of inflation, real GDP growth and unemployment in the euro area at different horizons. These expectations are reported both as point forecasts and as probability distributions. The ECB SPF provides both the aggregate histogram containing the median of the responses of the forecasters as well as the individual histograms contain the anonymized distribution of projections provided by each forecaster. In order to measure central bank communication, I use the central bank information shocks from Jarociński and Karadi (2020) as a proxy.

As the SPF is conducted on a calendar quarter basis, the central bank information shocks which are on a daily basis – are added together to make a quarterly frequency (see for example Jarociński and Karadi, 2020; and Kerssenfischer, 2018). Adding the information shocks is preferable to other methods of aggregation (such as the average) because information accumulates over time and the sum makes sure that there are no losses in terms of content. Given the nature of a shock, which is exogenous and does not anticipate the dependent variable, I assume that ex-ante inflation uncertainty in t is affected by all shocks that occurred since the previous survey in $t-1$. Therefore, these shocks are aggregated on a quarterly basis, always respecting the deadlines to reply to the SPF. As shown in detail in Section 5, this approach assures that all available central bank information is known by the forecasters by the deadline to reply to the survey, that is, when the uncertainty measures are estimated.

The analysis covers the period between 2002 Q1 to 2019 Q1.⁵ The structure of the SPF database allows a clear distinction between the specific horizons over which uncertainty is measured, since the participants are asked to provide their inflation forecasts for one-, two-, and five-year horizons. This paper focuses on forecasts for two years ahead, which is the relevant horizon for monetary policy. In other words, the benchmark analysis evaluates how central bank information shocks affect the current uncertainty of the forecasters about inflation on a two-year horizon.

The remaining variables employed in the analysis reflect the control variables identified in the literature as potential impacting factors on forecast uncertainty and disagreement. They are the quarterly change in crude oil prices, inflation (year-over-year HICP), real GDP, the unemployment rate, the output gap, and the term spread defined as the difference between the euro area ten-year government benchmark bond yield and the Euribor three-month money market rate. Table 1 shows the data used in the analysis, including definitions and sources.

3.1 Estimating ex-ante inflation uncertainties

This section shows how I estimate the three ex-ante uncertainty inflation measures. These measures closely relate to each other, as the ex-ante aggregate inflation uncertainty (EAU in the equations, and from now on referred to as ‘aggregate’ in the text) incorporates both individual uncertainty and disagreement (see, for example, Wallis, 2005). Nonetheless, they carry different meanings and are all estimated separately.

The forecasts are reported in the SPF not only as point forecasts but also as probability distributions. In other words, for each horizon, the forecasters should provide both the estimation of the HICP inflation as a single number and assign probabilities for different pre-defined ranges of possible outcomes for the HICP inflation. I exploit both features to construct the ex-ante inflation uncertainty measures.

Aggregate is the proxy for the overall ex-ante inflation uncertainty. It is the resulting variance after fitting a generalized beta distribution to the aggregate SPF histogram, as in Engelberg, Manski, and Williams (2009) and Kenny and Melo Fernandes (2021). The other two measures are more specific proxies for ex-ante inflation uncertainty. Disagreement d_{t+h} is defined as the variance of the point forecasts of a variable

⁵ The earlier part of the sample dating back to 1999 Q3 is characterized by a relatively low market liquidity, which impacts the reliability of the surprises. This is reflected in the very small and negative correlation between the series of daily shocks aggregated to a quarterly frequency using the SPF deadlines and the monthly shocks aggregated to quarterly frequency not using the SPF deadlines. The correlation becomes high and positive only from 2002 Q1 onwards.

y performed in t for a specific horizon h . In other words, disagreement is the dispersion of the point forecasts, indicating how much the individuals diverge among each other regarding the future values of inflation, as shown in equation (1):

$$d_{t+h} = N^{-1} \sum_{i=1}^N [E_{i,t}[y_{t+h}] - \bar{y}_{t+h}]^2 \quad (1)$$

where $E_{i,t}$ is the expectation of the forecaster i in time t with respect to the variable y for a specific horizon h and $\bar{y}_{t+h}$ is the average forecast of variable y in time t for a specific horizon h .

The average individual uncertainty (AIU) is the average of the individual variances, which can be interpreted as how assured individuals are with respect to their own forecasts:

$$\bar{\sigma}_{t+h} = N^{-1} \sum_{i=1}^N E_{i,t} [(y_{t+h} - E_{i,t}[y_{t+h}])^2] \quad (2)$$

Finally, EAU incorporates both individual uncertainty and disagreement as shown below:

$$EAU_{t+h} = \bar{\sigma}_{t+h} + d_{t+h} \quad (3)$$

Looking at equation (3), one could calculate AIU as simply the residual between EAU and d , as in Abel et al. (2016). However, conditioning the estimation of AIU to disagreement is not ideal. First, the literature documents that disagreement may on its own be a relatively poor proxy for uncertainty as compared to AIU (see the discussion in Section 3.2). Therefore, estimating AIU as the residual of equation (3) might lead to a less accurate measure of AIU compared to using the individual data independently of disagreement. Indeed, as shown in Figure 1, when AIU is calculated as the residual after plugging in aggregate and disagreement in equation (3), it reflects, for example, a point forecast outlier in 2003 Q2.⁶ When subtracting disagreement from the aggregate, this outlier is reflected in both a temporary fall in AIU and a peak in disagreement, which does not make economic sense. Likewise, in situations where disagreement increases more than EAU, the residual AIU falls, which also leads to a misleading measurement of average individual uncertainty.

Therefore, instead of employing equation (3), I compute AIU by first estimating the respective variances using a similar approach to the estimation of aggregate uncertainty. I follow Engelberg, Manski, and

⁶ In that quarter, the average of the forecast for the year-over-year change in inflation for a two-year horizon was 1.7%, while one specific forecaster reported a projection of -1%. Note that this outlier in disagreement was removed before performing the regressions.

Williams (2009) in estimating the measure in three steps. First, I fit distributions in each individual histogram provided by each forecaster. These distributions are determined according to how at many intervals the forecasters place their probabilities. In the second step, I extract the variance of each histogram after fitting these distributions. In the third stage, I take the average of these resulting variances.

When estimating the variances, two different distributions are fitted. When the probabilities are placed in three or more histogram intervals, the assumption is that each subjective distribution has the generalized beta form. Just as in the case of the aggregate histogram, I estimate the variance by using the interval probability data to fit the parameters.

In contrast, when a forecaster assigns probabilities to only one or two intervals, the assumption is that the distribution has the shape of an isosceles triangle. The placement of probabilities in fewer bins can be interpreted as if these forecasters have relatively more conviction about the outcome of the future inflation than those that place their probabilities in more bins. This happens in approximately only 3% of the total cases in the database.⁷ Furthermore, 88% of these cases occur before the Great Financial Crisis.

Finally, in cases where the forecaster is 100% convinced that the outcome of inflation will be within a particular range, the base of the triangle includes the interval correspondent to this range and part of the adjacent interval. In cases where the forecaster places the probabilities in two intervals, they are always adjacent to one another and the base of the triangle includes the entire interval with the greater probability mass and part of the neighboring interval. This assumption gives one parameter to be fit, which fixes the center and height of the triangle.

Despite providing similar outcomes to the residual estimation method, the direct AIU estimation method results in a slightly higher level of AIU and does not reflect potentially noisy observations coming from other estimation sources. Therefore, extracting AIU directly from the histograms leads to a more accurate and cleaner measure of AIU, as shown in Figure 2.

Table 2 shows that the different nature of individual uncertainty and disagreement are reflected in the low correlation between these measures (0.28, 0.37 and 0.09 for the one-, two-, and five-year horizons respectively). In contrast, aggregate uncertainty has a very high correlation with AIU (0.93 for the two-year horizon) and a lower correlation with disagreement (0.61 for the two-years horizon). Indeed, Figure 2 shows that unlike disagreement, both AIU and aggregate uncertainty show a clearer level shift and

⁷ Estimates calculated based on the sample composed by forecasts for one and two-year horizons.

much higher persistence in the period since the Great Financial Crisis. Such differences highlight the importance of variation in uncertainty at the individual level as a key driver of aggregate ex-ante uncertainty. In addition, for all ex-ante uncertainty variables, one can observe that the longer the time horizon, the lower the correlation between all measures. That reflects the relatively higher difficulty in assessing the accuracy of forecasts over longer horizons.

3.2 Central bank information shocks

Central bank announcements simultaneously convey information about monetary policy and the central bank's assessment of the economic outlook. Jarociński and Karadi (2020) distinguish between these two types of information quantitatively and provide a measure of ECB communication by identifying high-frequency co-movement of interest rates and stock prices in a narrow window around ECB policy announcements.

The reasoning behind it is that when interest rates go up, stock prices are expected to go down for two reasons: first, after a policy tightening, investors foresee a relative slowdown in the economy, which discourages the appetite for investments, and second, the discount rate increases with higher real interest rates and rising risk premia (the denominator effect). However, if instead stock prices increase following an increase in interest rates, the authors attribute this unexpected move to the impact of information shocks containing positive economic news. Therefore, central bank information shocks are identified when interest rates and stock prices co-move positively. As the scope of the shocks is limited to communication about economic outlook assessments only, one can exclude any type of direct effect involving forward guidance.⁸

In order to capture these co-movements, Jarociński and Karadi (2020) construct a dataset of euro area high-frequency financial-market surprises,⁹ which are defined as financial asset price changes around the ECB announcements. These announcements are delimited within windows of 30 minutes around press statements and 90 minutes around press conferences, both starting 10 minutes before and ending 10 minutes after the event. The assumption is that within this narrow window only two structural shocks can materialize and systematically influence the financial market surprises: a monetary policy shock, which is defined as the negative co-movement between interest rate and stock price changes, and a central bank information shock, defined as the positive co-movement of interest rates and stock prices. In the euro

⁸ The information shocks by Jarociński and Karadi (2020) carry information about the economy, not about future monetary policy.

⁹ This novel dataset for the euro area is based on Gürkaynak, Sack, and Swanson (2005), who constructed a similar dataset for the US.

area, this is the case for approximately 46% of the data points. The dataset contains more than 300 ECB policy announcements from 1999 to 2019.

In this paper, I use the shocks estimated by Jarociński and Karadi (2020) using the “poor man” sign restrictions method. In a nutshell, the poor man sign restrictions use the interest rate surprises in the days in which announcements resulted in stock price surprises with the same sign as the interest rate change as the proxy for central bank information shocks. Otherwise, the proxy is zero.

The measure used to compute changes in stock valuation is the EuroStoxx50 index. The proxy for interest rates is a combination of different maturities of Eonia swaps. In particular, the measure used as a benchmark in this paper is the first principal component of the Eonia swaps with maturities of one month, three months, six months, one year, and two years. The reason to choose this proxy as a benchmark rather than one single and shorter maturity, is that by including longer maturities one can capture higher volatilities that might occur in the Zero Lower Bond (ZLB) period. Typically, in this period the value of assets with longer maturities changes more than those with shorter maturities.

Kerssenfischer (2018) follows the same standard sign restrictions approach of Jarociński and Karadi (2020) and builds central bank information shocks using two-year German bond yields as a proxy for interest rates and the EuroStoxx50 index as a proxy for stock valuations.¹⁰ Furthermore, he replaces the narrow window by a wider window around the ECB’s press release that also includes the market reaction to the press conference. Table 4 shows all the communication shocks that were employed as robustness checks in Section 7. As explained in Section 5, all shocks were aggregated to quarterly frequency using the dates of the ECB survey deadlines in order to obtain an accurate identification. Figure 3 shows the final aggregation.

4. The empirical model

The primary objective of the analysis is to estimate the impact of central bank information shocks on ex-ante inflation uncertainty. I use local projections (see Jordà, 2005) to estimate the impulse responses. Local projections consist of the estimation of a series of regressions for each variable in each horizon h . Therefore, the linear regression of the benchmark model is designated as follows:

$$\Delta x_{t+h} = \beta_{0,h} + \beta_{1,h} shock_t + \beta_{n,h}(L)y_{n,t-1} + D_t + \varepsilon_{t+h}, \quad \text{for } h=0,1,2,\dots \quad (4)$$

¹⁰ The study encompasses 186 scheduled ECB Governing Council meetings between March 2002 and December 2018.

where Δx_{t+h} is defined as $\frac{x_{t+h}-x_{t-1}}{x_{t-1}}$, that is, the change in the ex-ante inflation uncertainty in $t+h$ with respect to the first period of time of horizon h , $\beta_{0,h}$ is a constant, $\beta_h(L)$ is a polynomial in the lag operator, *shock* is the identified shock, and y is the vector of control variables. D_t is a set of dummies. In the regressions involving average individual and aggregate ex-ante uncertainties, D_t is a set of step dummies as there is a clear upward shift in the level of both measures after the Great Financial Crisis, which remains even after the changes of these variables are computed in each horizon (see Figures 4 and 5). Therefore, in this case $D_t=1$ after 2009 Q1 and $D_t=0$ before 2009 Q1. These structural breaks in the mean were detected and tested using the saturation indicator method available in R. In regressions in which disagreement is the dependent variable, D_t represents two impulse dummies to address the outliers in disagreement in 2009 Q2 and 2009 Q3 (see Figure 6). These quarters coincide with a steep fall in inflation following the Great Crisis, which might have contributed to this unprecedented level of disagreement. In fact, annual HICP change reached -0.6% in July 2009, the lowest level since the beginning of the series in 1999.

The baseline shock is estimated using the poor man sign restrictions method, which ultimately calculates the co-movement between the EuroStoxx50 index and the first principal component of the Eonia swaps with maturities of one month, three months, six months, one year, and two years (see Section 3.3). In essence, they consist of market reactions to unanticipated communications about the state of the economy and are unrelated to other factors likely to influence ex-ante inflation uncertainty in the near term.

The first specification relies on the exogenous nature of these shocks, which leads to a simple regression in which each ex-ante inflation uncertainty measure is regressed on a constant, on the shock, on the lagged ex-ante inflation uncertainty and on the respective dummies.

From this starting point, the model is progressively augmented to include different sets of controls in vector y as well as a variety of lags for robustness check purposes. The control variables and the other specifications are further detailed in Section 6.

In all cases, the coefficients of interest are the sequence $\beta_{1,h}$, which gives the response of x at time $t+h$ to the shock that happened at time t . Hence, the results are presented as impulse responses built on this sequence of $\beta_{1,h}$ estimated by single regressions for each horizon. As central bank communication on economic outlooks is often focused on a short-term period, the horizon of the estimated effects is limited to eight quarters. Furthermore, given the limited number of observations in the sample due to the

relatively short time series (70 quarters in total), I opt for a more parsimonious approach as the higher the number of horizons, the shorter the sample of observations available for estimations in the later horizons.

5. Identification strategy

An important aspect of the identification is that surveyed probabilities used in the estimation of ex-ante inflation uncertainty are on average collected in the middle of the first month of quarter t . Therefore, it is important to make sure that all the information available is known by the forecasters by the deadline to reply to the survey.

The alignment between the timing of the survey deadlines and the timing of the information shocks is made possible by combining the daily dataset of the shocks and the quarterly deadlines to reply to the SPF. This alignment is achieved by summing the shocks that occurred between the deadline to reply to the SPF in the quarter $t-1$ and the deadline to reply to the next survey round in quarter t , thereby ensuring that all shocks that happened within this period have been observed by the forecasters and potentially included in their projections, and are consequently reflected in their replies to the survey in quarter t . In summary, I regress this aggregated sum on the ex-ante inflation uncertainty estimated from the survey of quarter t .

Table 5 shows an example of the timing framework used to aggregate the shocks in Q2 of an illustrative year. In this case, the deadline to reply to the SPF in Q2 is on 12th April. Therefore, only shocks that happened between this date and the deadline to reply in Q1 (i.e., 12th January) were summed. The corresponding days are in bold.

If instead one opted to add the shocks by calendar quarter, ignoring the SPF deadlines, two issues would arise: first, one would miss some information that was released in the following quarter just before the SPF deadline (in this example, the shock on 11th April), and second, one's models would incorporate information that had already been absorbed in the former survey (in this case, the shock on 11th January).

Another relevant point to consider in the identification strategy is the timing of the control variables. Following the same logic described above, I also define the timing of the real variables in the regressions using the SPF deadlines as a reference. I use the Eurostat calendar to extract the latest information of real variables that was available for the forecasters. For example, for inflation I use the latest value released before each survey. The same applies for the change in crude oil prices and unemployment. These variables, which are available at a monthly frequency, are therefore included in $t-1$ when the survey deadline was in t . The most recent release of real GDP information prior to the SPF deadline always

contains the real GDP value for the two previous quarters. Therefore, real GDP is included in the timing $t-2$.

6. Results

Figure 7 summarizes the results of estimating the benchmark specification of equation (4), which includes a constant, the central bank information shock, and the corresponding set of step dummies of each dependent variable on the right side of the equation. It is also important to control for the normal dynamics of ex-ante inflation uncertainty and for several other factors that are likely to be serially correlated and may affect the dependent variable. Hence, the benchmark model also includes the lagged ex-ante inflation uncertainty as a control variable in levels. I adopt the results from this specification as the baseline. Other specifications including different lags and controls are explored in Section 7. In Figure 7, each column shows the cumulative responses for each ex-ante inflation uncertainty measure to a central bank information shock. The estimations rely on 90% confidence bands and are based on Newey-West standard errors to account for serial correlation.

After a central bank information shock, all three types of ex-ante inflation uncertainty fall significantly after one quarter. Two interesting observations can be made based on this result: first, these findings suggest that central bank communication decreases both the average individual uncertainty and the divergence of opinions among the forecasters. Second, the reaction of ex-ante inflation uncertainties systematically happens with a delay. This delay is in line with the findings of Coibion and Gorodnichenko (2012), who document evidence of a delayed response of mean forecasts to macroeconomic shocks for professional forecasters in the US, reflecting information rigidities.

The impact of the central bank information shocks is most prominent on disagreement, which decreases 3.7 percentage points in the second quarter – approximately more than twice the drop of average individual uncertainty. While average individual and aggregate uncertainty retract from their peak in the third quarter, disagreement falls 5.6 percentage points further. Aggregate ex-ante inflation uncertainty decreases 3.5 percentage points after two quarters, with some persistence in the last horizons. Clearly, the results for the aggregate uncertainty are driven by the stronger magnitude and persistence of the reaction of disagreement.

When interpreting these results, the first conclusion is that after analyzing the same new public information provided by a credible central bank, agents become more aligned in their views even as they

also become more certain about their own predictions.¹¹ However, in addition to that, the nature of each ex-ante uncertainty measure can provide interesting insights into the mechanism behind the impact of the central bank information shocks on ex-ante uncertainty.

6.1 The role of disagreement in understanding how central bank information shocks operate

As shown in Section 3.1, disagreement reflects the dispersion of projections across forecasters but does not provide information about each forecaster's uncertainty regarding their own forecast. For example, it could be that each forecaster is extremely uncertain about future events; however, they could still have very similar point estimates. In this case, disagreement fails to accurately capture the actual level of inflation uncertainty.

In fact, although used as a common approach to estimate ex-ante uncertainty in the literature, disagreement survey-based measures have been criticized as a relatively poor proxy for uncertainty.¹² In particular, some studies show that disagreement in survey forecasts could be more reflective of differences in opinion than of uncertainty (see Diether, Malloy, and Scherbina, 2002; Mankiw, Reis, and Wolfers, 2004). Despite being often seen as a criticism, this feature is particularly useful for understanding how central bank information shocks operate in reducing ex-ante uncertainty.

Specifically, the substantial fall in disagreement in response to central bank information shocks implies that these shocks are able to influence forecasters' opinions. In particular, the shocks help opinions to converge. However, it is also important to understand whether these opinions converge in a direction that contributes to market stabilization or whether this convergence goes towards a point that may cause instability. Since central bank communication undoubtedly plays a fundamental role in steering expectations (see Binder et al., 2008), it is important also to understand the response of forecasters' expectations to these shocks in order to answer this question. Interestingly, the literature addressing the effects of central bank information shocks first shows that central bank information shocks generate an increase in inflation expectations; however, this effect is not significant, as shown by Jarociński and Karadi (2020) for the US and Kerssenfischer (2018) for the euro area. I repeat the same exercise using a

¹¹ This is in contrast with the findings of Johnstone (2016), who shows that the best available information can often leave decision makers less certain about future events.

¹² For discussion, see Zarnowitz and Lambros (1987), Grier and Perry (1998, 2000), Giordani and Söderlind (2003), Lahiri and Sheng (2010), Abel, Rich, Song, and Tracy (2016), and Glas and Hartmann (2016). These studies highlight the absence of a theoretical foundation to link disagreement with uncertainty and document empirical deviations between disagreement and ex-ante average individual uncertainty. Lahiri and Sheng (2010) establish a simple relationship connecting forecast uncertainty to disagreement and show that disagreement is found to be a reliable measure for uncertainty in a stable period, but not in periods with a large volatility of aggregate shocks.

similar specification with inflation expectations being the dependent variable to verify its reaction to central bank information shocks.¹³ Figure A.1 in the appendix shows results that are consistent with the literature.

These findings lead to some interesting reflections. First, the muted responses from inflation expectations and the strong decline of disagreement suggest that after being affected by a central bank information shock, agents do not necessarily update their expectations, but they converge towards the mean of the point forecasts. This convergence implies that the central bank communication has a “stabilizer effect” in which not only the dispersion among the point forecasts decreases, but most importantly, this convergence moves towards the mean. This convergence is very important as it induces a steady consensus among the forecasters more in line with the ECB’s objectives; in contrast to the alternative, which would imply a convergence of the point forecasts towards one of the tails. This result is also consistent with the high credibility of the ECB.

It has been shown by some studies that one important reason why professional forecasters disagree is that they may interpret public information in different ways (see Lahiri and Sheng, 2008; and Manzan 2011). The decrease in disagreement after a central bank information shock implies that these shocks help to better align how forecasters interpret public information, providing evidence that the content of the shocks in this case is more related to clarifications or reinforcements of previous messages. Another well-known reason why forecasters disagree is that forecasters are presumed to have asymmetric loss functions (see Capistrán and Timmermann, 2009).

Therefore, the response of disagreement to central bank information shocks indicates that central bank information shocks operate as some sort of public signal able to influence and coordinate forecasters’ opinions. Public signals can often serve as a focal point for the beliefs of market players (Morris and Shin, 2002).

6.2 The role of average individual uncertainty in understanding how central bank information shocks operate

As demonstrated in Section 3.1, average individual uncertainty is the uncertainty of an individual forecaster averaged across all forecasters. In contrast to disagreement, it disregards how forecasters’ projections are positioned in comparison to their peers. This measure is often considered a better proxy

¹³ In contrast to the baseline specification for ex-ante inflation uncertainties, no dummies were included for inflation expectations.

for uncertainty than disagreement in the literature (Abel et al., 2016; Glas and Hartmann, 2016; and Glas, 2020). The responses of both measures are complementary for understanding how central bank information shocks operate.

The decrease of average individual uncertainty after central bank information shocks means that forecasters became more confident about their own projections. This suggests that forecasters are comfortable in incorporating the public signal emitted by the central bank in the assessment of their analysis, which also implies that this signal is valuable and on average it contributes to strengthen the confidence in their predications. This is in line with Morris and Shin's (2002) statement that "when prevailing conventional wisdom or consensus impinge on people's decision-making process, public information may serve to reinforce their impact on individual decisions to the detriment of private information" (Morris and Shin, 2002, p. 1521).

Concerning what we can learn from average individual uncertainty with respect to the content of central bank information, there are the following possibilities: it might consist either of clarifications or reinforcements of previous messages and/or of new information that is incorporated by the forecasters, which helps to improve their confidence about their own assessments. As central bank information shocks induce forecasters to sharpen their own beliefs about possible outcomes, one cannot exclude the possibility that these emitted signals also contain relevant information that ultimately increases the forecasters' confidence in their own forecasts. However, the assessment of whether central bank information shocks convey new information about the economy is beyond the scope of this paper.

7. Robustness

It is important to account for potential remaining information in the estimated residuals that might influence ex-ante inflation uncertainty. Therefore, this section explores the potential sensitivity of the results to other specification choices and to the addition of other controls.

First, I estimate the baseline equation adding different lags of the correspondent dependent variable in levels. Figure 8 shows that the findings for the three types of ex-ante inflation uncertainty are robust to different lag specifications. Although the significant response of disagreement in the second quarter is double the baseline in magnitude when increasing the lag structure to two, it is still aligned with the reasoning of the baseline results.

Next, by closely following Jitmaneeeroj et al. (2019), I augment the baseline specification with control variables that have been identified in the literature as potential real, nominal, and financial impact factors

on forecast uncertainty and disagreement.¹⁴ These variables are the lagged inflation levels year-over-year (HICP), lagged unemployment rate, lagged output gap, and lagged term spread, which is defined as the difference between the euro area ten-year government benchmark bond yield and the Euribor three-month money market rate.

The inclusion of these control variables results in slightly milder responses for all ex-ante uncertainty types. As shown in Figure 9, the confidence bands become narrower for disagreement and are only significant in the second quarter. Interestingly, it has the same drop as the baseline specification (-3.6 percentage points). The same specification is only slightly modified by substituting inflation with changes in crude oil prices, and the responses remain robust (Figure 10).

In addition, I also estimate the baseline specification using other central bank information shocks. Specifically, I compare the benchmark poor man sign restriction shock with two other types of shocks: another version of the central bank information shocks estimated via sign restrictions, also provided by Jarociński and Karadi (2020), and central bank information shocks as estimated by Kerssenfischer (2019). As explained in Section 3.3 and shown in Table 4, different versions of the poor man and sign restriction shocks are estimated by employing Eonia swaps with different maturities. Kerssenfischer (2019) follows the same sign restriction methodology but sticks to the immediate change in two-year German bond yields. The measure used to compute changes in stock valuation is the EuroStoxx50 index for all cases.

Figure 11 shows the comparisons for the different shocks and maturities. The first row shows the comparison between the responses to the short maturity version of the benchmark poor man sign restriction shock and to the sign restrictions shocks, both estimated using the three-month Eonia swap. The second row shows the responses to another version of these shocks, using the first principal component of the Eonia swaps with maturities of one month, three months, six months, and one year. The third row shows the responses to the extended version of these shocks, which includes two-year Eonia swaps in the first principal component and the shocks estimated by Kerssenfischer (2019). The responses of the three ex-ante inflation uncertainty measures are fairly robust to all versions of the shocks. Despite the similarities of the responses, there are still some variations across them.

The responses of ex-ante inflation uncertainties to sign restrictions information shocks are also less prominent and less persistent than to poor man sign restriction shocks. Furthermore, the Kerssenfischer

¹⁴ As listed by Jitmaneeeroj et al. (2019), see Dopke and Fritsche (2006), van der Cruysen and Demertzis (2007), Patton and Timmermann (2010), Dovern et al. (2012), Ehrmann et al. (2012), Lamla and Maag (2012), Hartmann and Roestel (2013), Posso and Tawadros (2013), and Siklos (2013).

information shocks deliver responses that are more similar to the poor man sign restriction shocks. However, in contrast to the delay in the reactions of ex-ante inflation uncertainties to the shocks from Jarociński and Karadi (2020), aggregate and average individual uncertainty immediately fall following a Kerssenfischer information shock.

As a further robustness exercise, it is interesting to see whether these findings hold for different ex-ante inflation uncertainty horizons. As shown in Figure 12, the responses of one- and two-year horizon ex-ante inflation uncertainties behave very similarly, while the responses of both five-year aggregate and average individual uncertainties are notably less prominent in the first quarters. In addition, disagreement and aggregate uncertainty react with a larger delay than the benchmark measure: the first significant reactions appear only after three quarters.

On the one hand, this result is intuitive as the scope of the content of the central bank news is mainly limited to the shorter term, so it should be expected that the impact on longer ex-ante inflation uncertainty horizons is more contained and might take more time to be incorporated than for shorter ex-ante inflation uncertainty horizons. On the other hand, the larger magnitude of the fall in disagreement when compared to the benchmark measure is less straightforward to interpret.

In Appendix B I show the impact of central bank information shocks on ex-ante uncertainty about the other two variables that are also included in the Survey of Professional Forecasters, that is, GDP and unemployment. The results are very similar and discussed in detail in the Appendix.

Finally, the exclusion of the set of step and impulse dummies does not have any relevant impact either on the shape or on the magnitude of the impulse responses (see Figure 13), except for wider confidence intervals, particularly for the disagreement responses.

8. Conclusions

This paper investigates how the ECB communication of its assessment of the economic outlook impacts three types of ex-ante inflation uncertainty in the euro area by making use of the ECB SPF and the central bank information shocks provided by Jarociński and Karadi (2020). In addition, the paper also sheds some light on understanding the channels through which central bank information shocks operate.

The results can be summarized as follows. First, I find evidence that ECB communication of its assessment of the economic outlook reduces the dispersion across agents' average point forecasts (disagreement) and at the same time makes agents less uncertain about their own beliefs (ex-ante average

individual uncertainty). The decrease of disagreement following an ECB information shock suggests that these shocks help opinions to converge, while the reduction of the average individual uncertainty indicates that this signal is valuable and on average it contributes to strengthen the confidence in their predications.

Second, a remarkable aspect of this finding is the direction in which inflation forecasts converge. As the point forecasts move towards the mean instead of towards the tails, one can conclude that ECB communication has a “stabilizer effect” on inflation forecasts. Therefore, this result reinforces the idea that central bank information shocks operate as some sort of public signal that is able to influence and coordinate forecasters’ opinions and might contribute to market stabilization.

Finally, the muted reaction of inflation expectations to central bank information shocks provides evidence that medium-term inflation expectations remain anchored, reinforcing the institutional credibility aspect of the ECB.

Deciphering how each type of ex-ante inflation uncertainty responds to ECB announcements can help policymakers to define a communication strategy that attenuates inflation uncertainty in the most effective way possible. One well-known reason on why forecasters disagree is that forecasters may interpret public information in a different way. Therefore, the ECB could tailor its communication to mitigate potential increases in forecast disagreement in volatile times as well as to minimize the possibility of different interpretations among the group of forecasters. Likewise, it is important to sharpen communication when further clarifications or reinforcements of previous messages are necessary, as it helps to improve the forecasters’ confidence about their own assessments.

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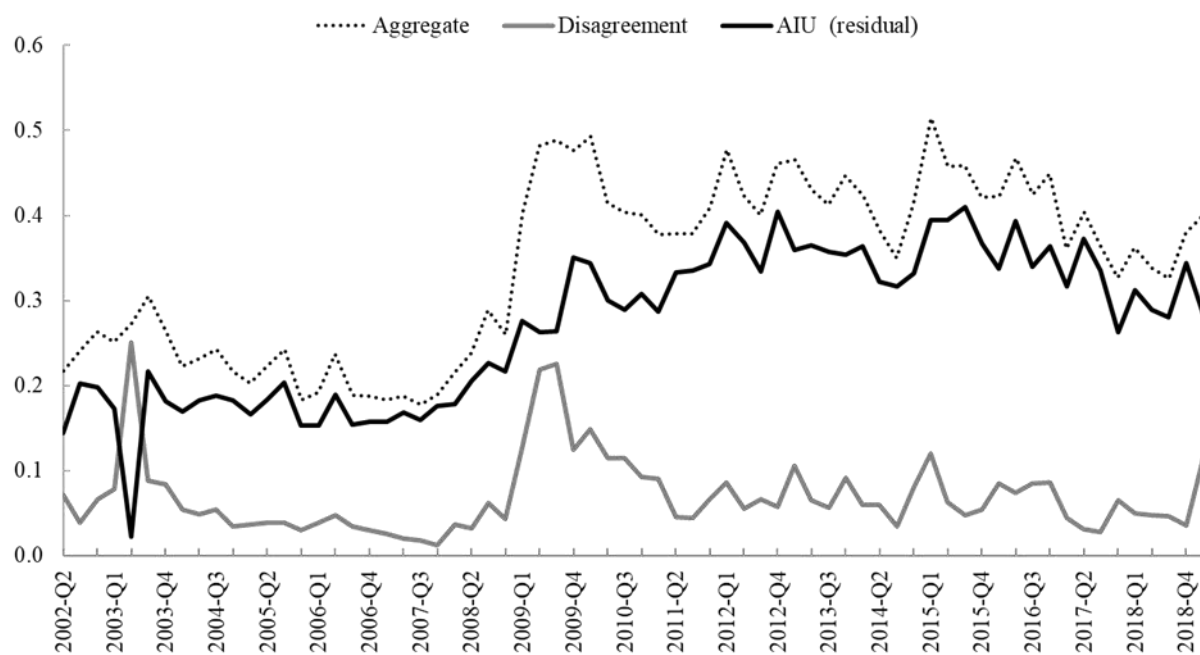
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Figure 1: Ex-ante inflation uncertainties – AIU as residual (two-year horizons)



Note: Ex- ante average individual uncertainty is estimated as the residual between aggregate and disagreement.

Figure 2: Ex-ante inflation uncertainties – AIU estimated (two-year horizons)

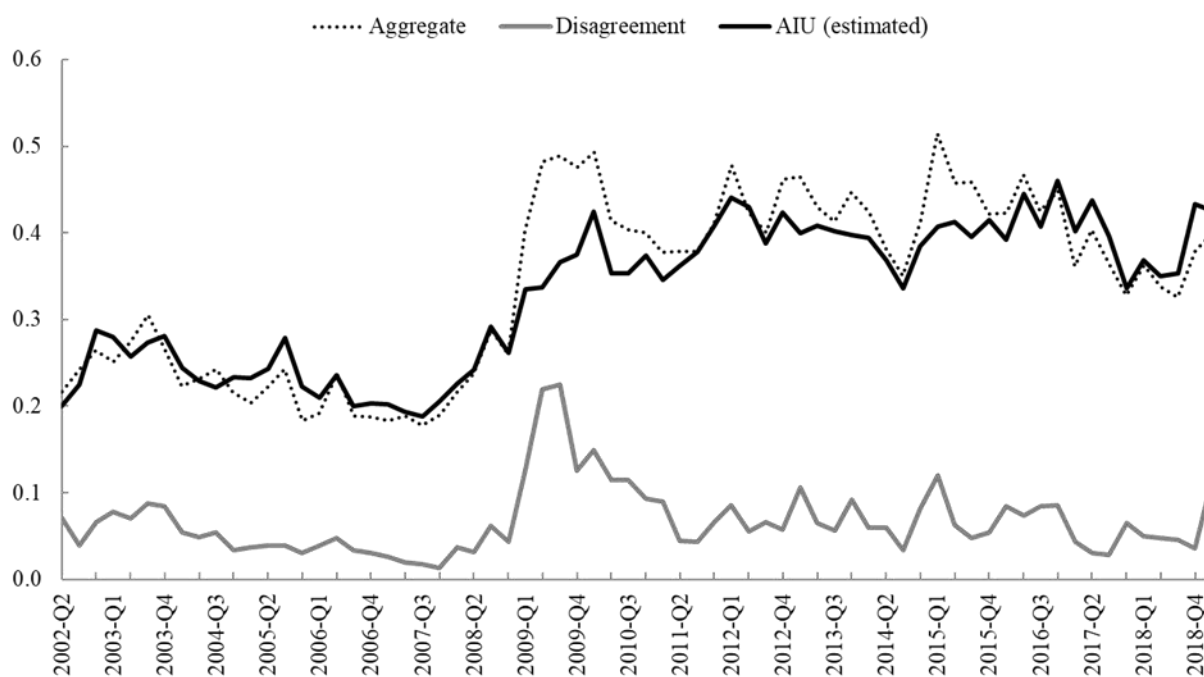
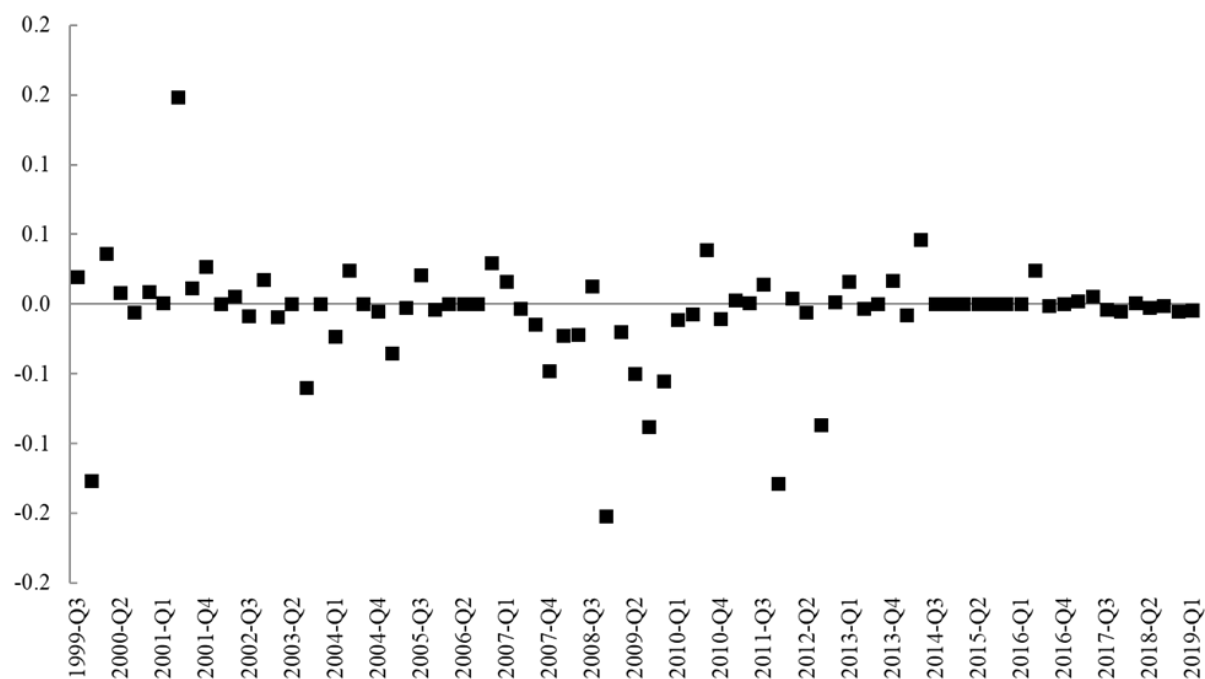


Figure 3: Central bank information shocks (baseline)



Note: Central bank information shocks estimated by Jarociński and Karadi (2019) using the “poorman method”. The measure used to compute changes in stock valuation is the EuroStoxx50 index and the proxy for interest rates is the first principal component of the Eonia swaps with maturities of one month, three months, six months, one year and two years. The daily shocks were aggregated to a quarterly frequency by summing the shocks in between the deadlines to reply to the SPF.

Figure 4: Ex-ante average individual uncertainty: changes by impulse response function horizons

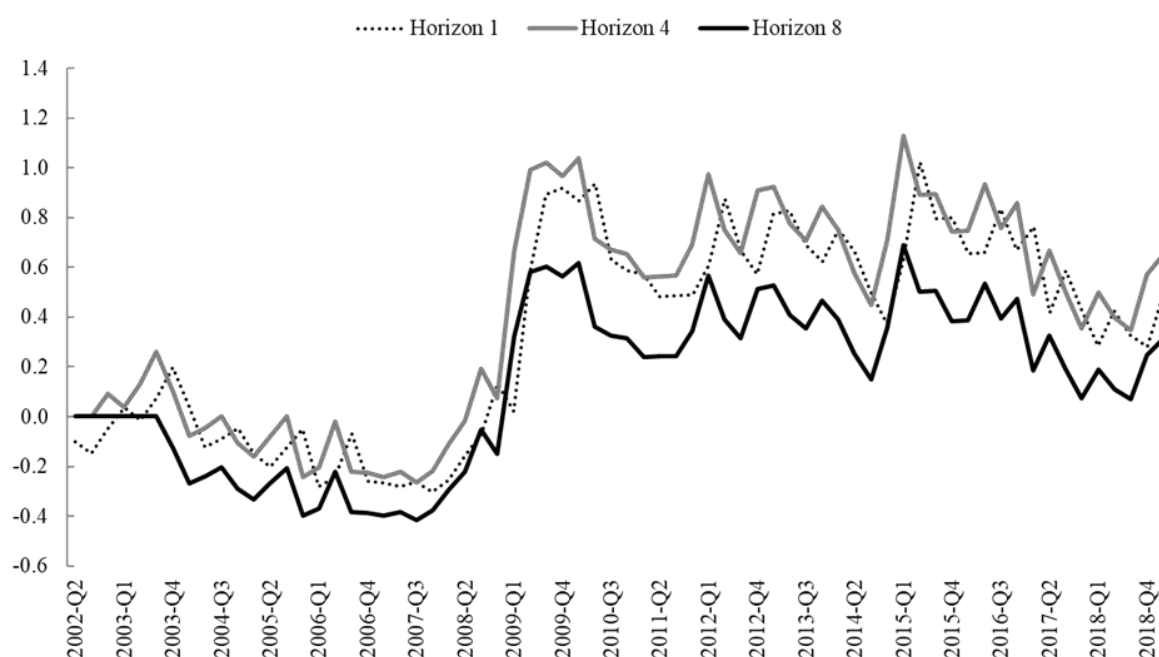


Figure 5: Ex-ante aggregate uncertainty: changes by impulse response function horizons

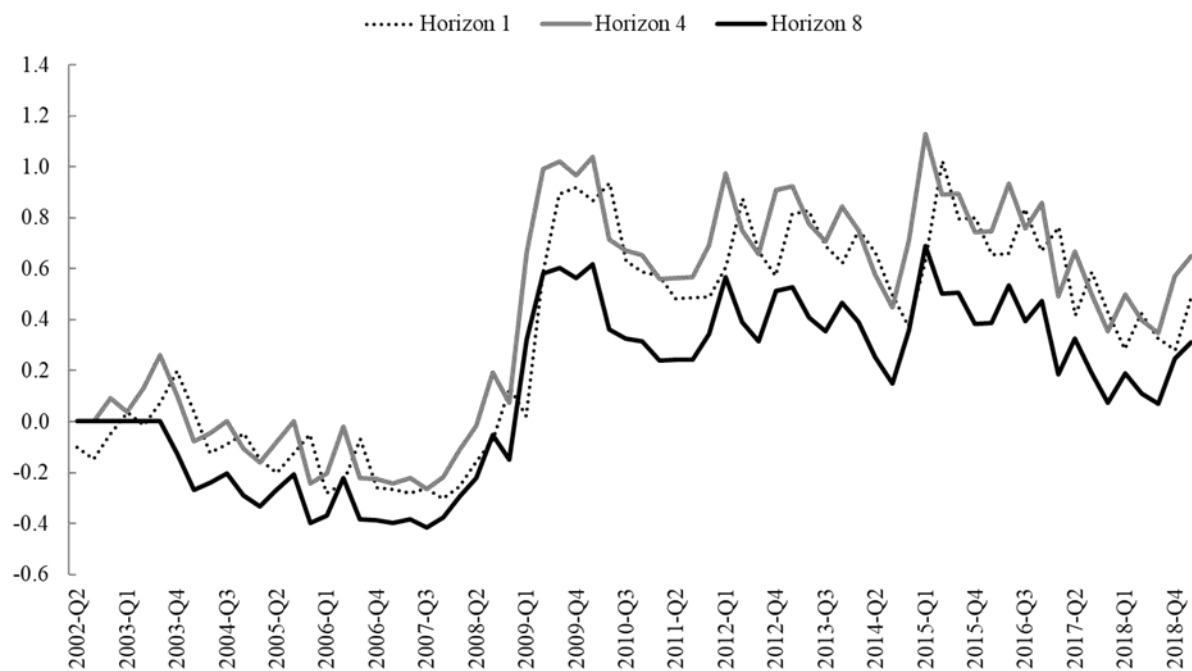


Figure 6: Disagreement: changes by impulse response function horizons

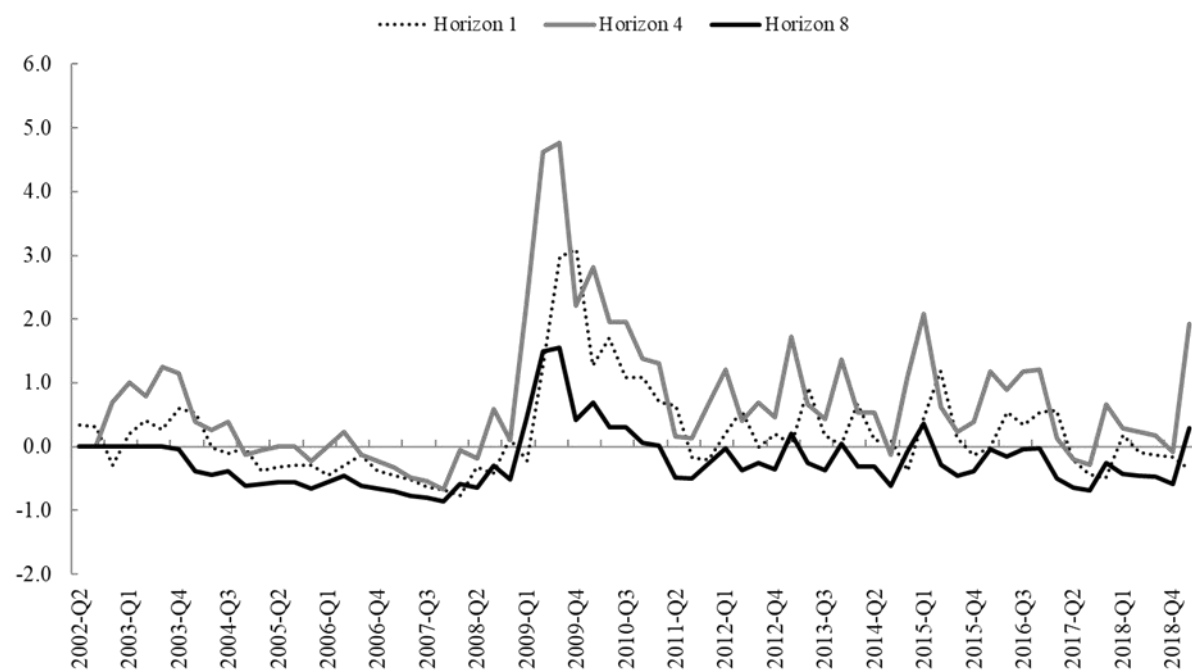
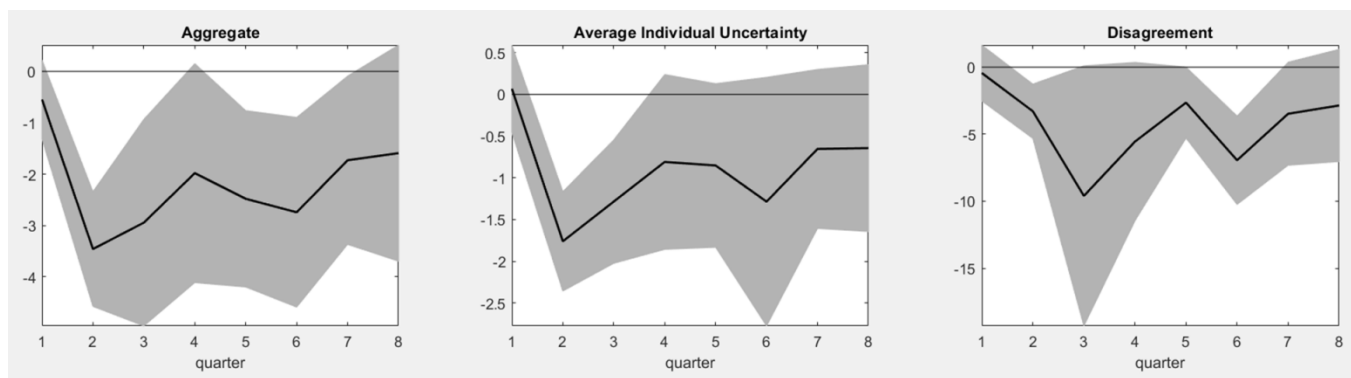
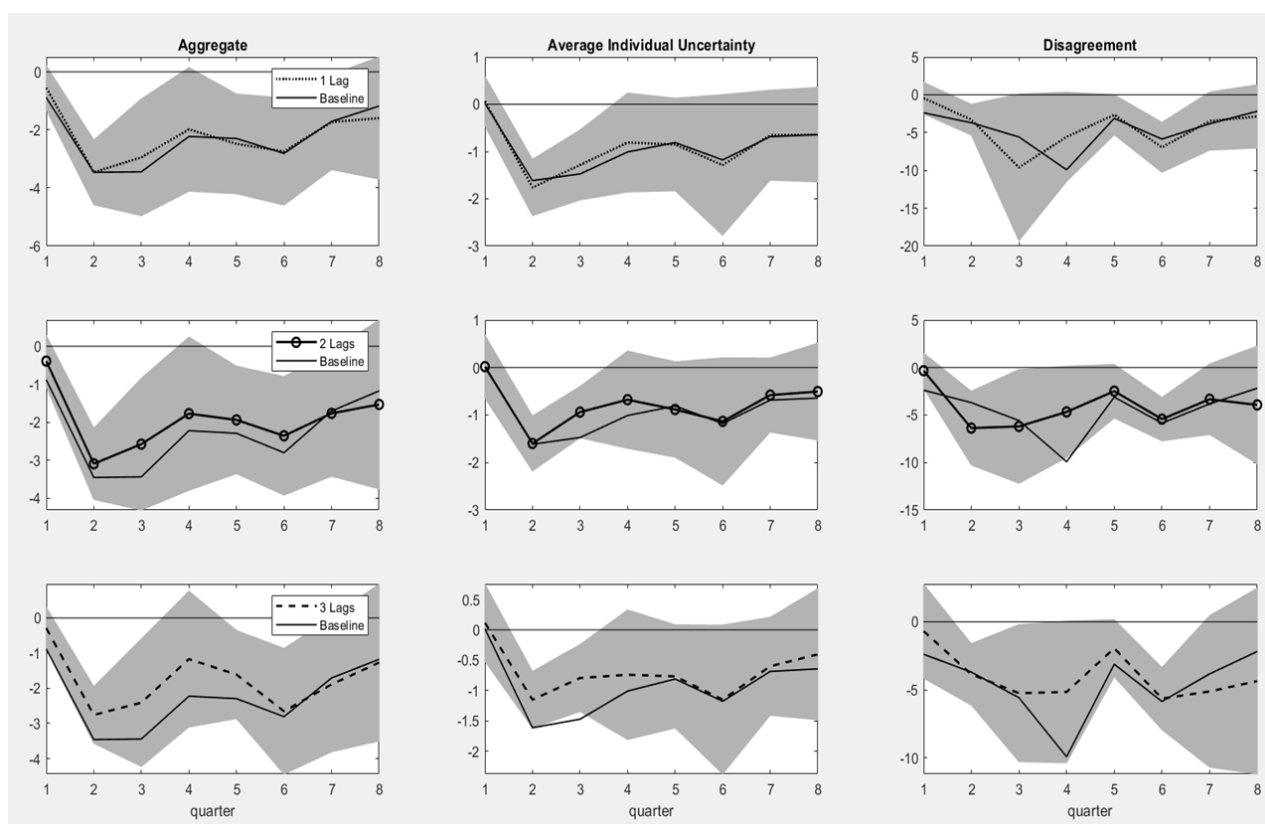


Figure 7: Impulse response functions: baseline specification



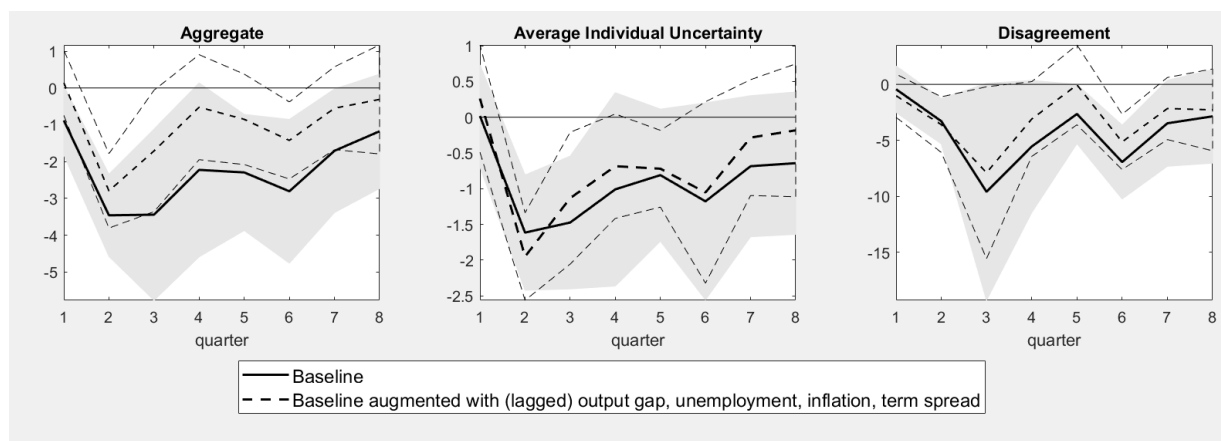
Note: This specification includes constant, the respective dummies (step dummies for aggregate and ex-ante average individual uncertainty and impulse dummies for disagreement) and the lag of ex-ante inflation uncertainty. Shaded region represents 90% confidence bands.

Figure 8: Robustness check - different lags



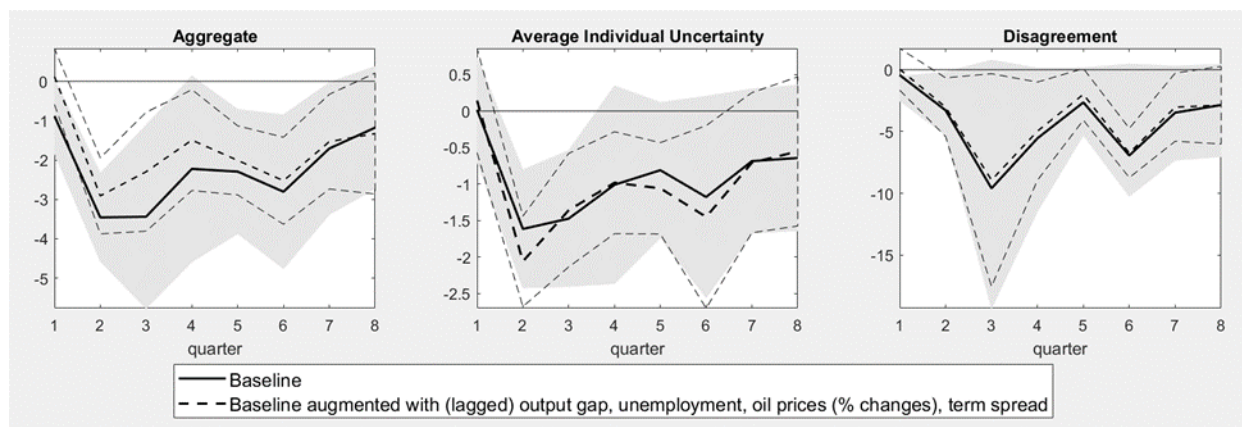
Note: Shaded region represents 90% confidence bands.

Figure 9: Robustness check - different controls (1)



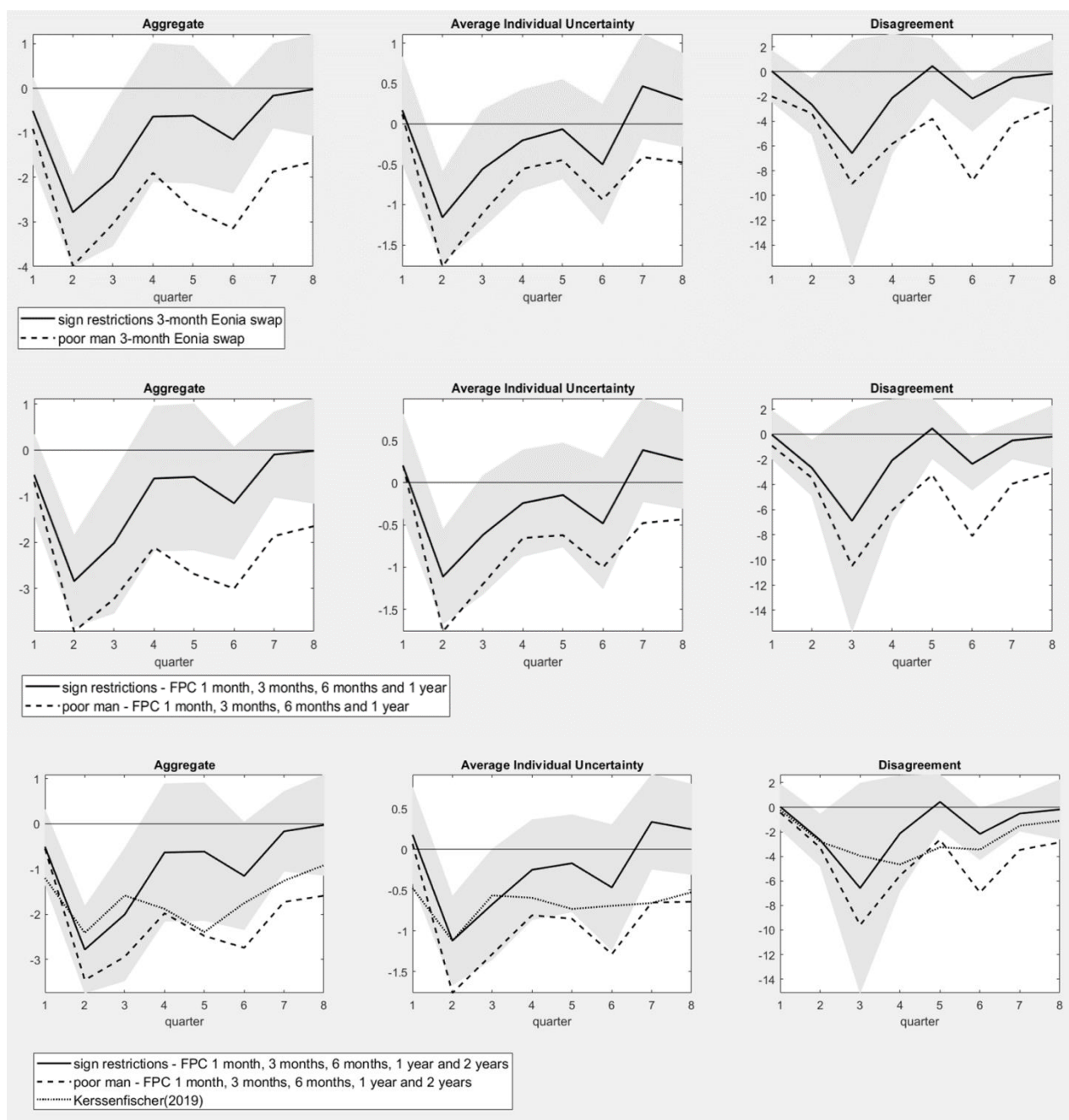
Note: Shaded region represents 90% confidence bands.

Figure 10: Robustness check - different controls (2)



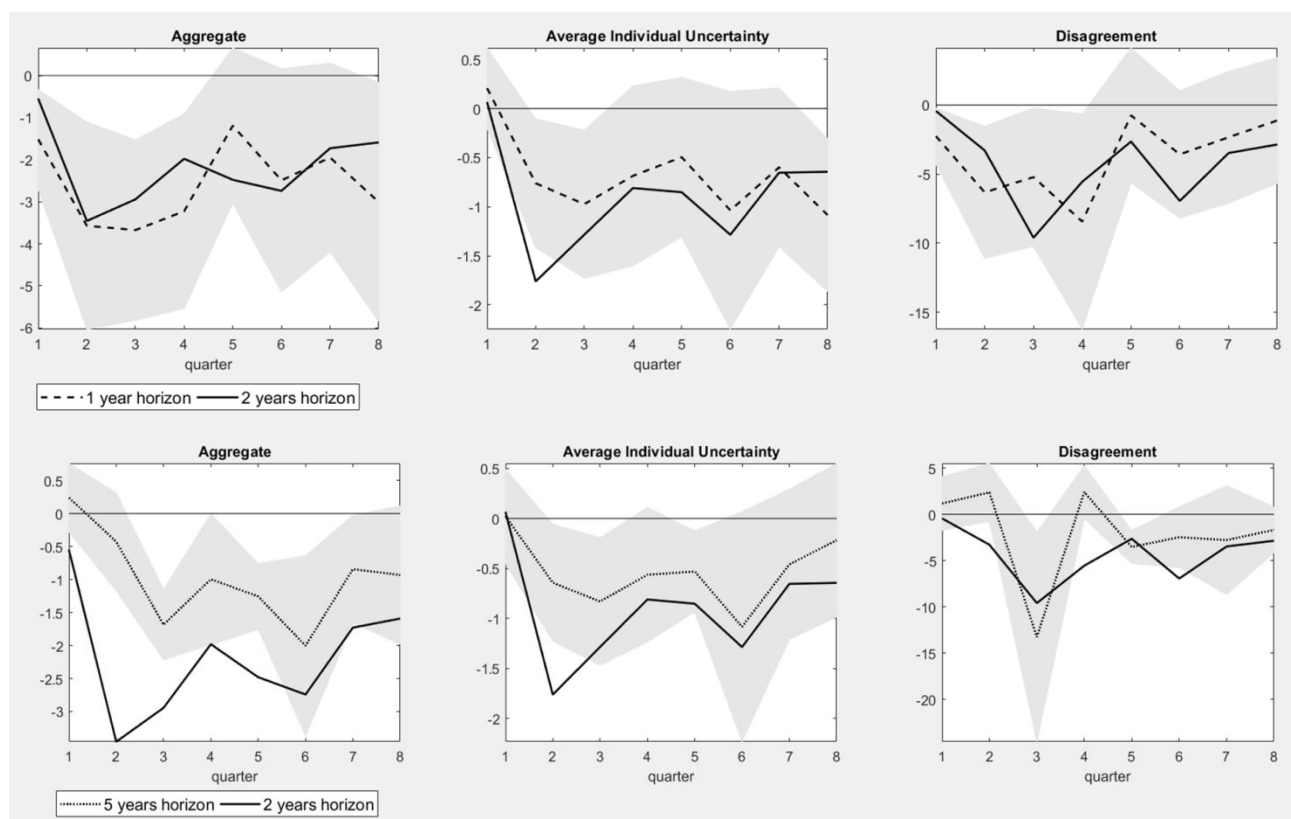
Note: Shaded region represents 90% confidence bands.

Figure 11: Robustness check - different shocks



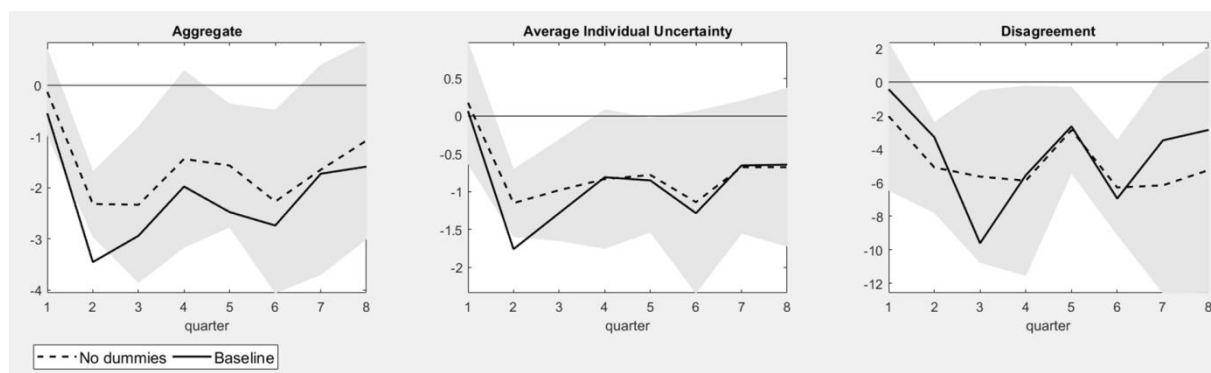
Note: Shaded region represents 90% confidence bands.

Figure 12: Robustness check - different horizons



Note: Shaded region represents 90% confidence bands.

Figure 13: Robustness check - dummies



Note: Shaded region represents 90% confidence bands.

Table 1: Data information

Variable	Units	Definitions	Data Sources
Aggregate uncertainty	Index	Own calculations	ECB SPF ¹
Average individual uncertainty	Index	Own calculations	ECB SPF
Disagreement	Index	Variance of forecasts	ECB SPF
Central bank information shocks (benchmark)	Index	Positive co-movement between EuroStoxx50 and the first principal component of the Eonia swaps with maturities of 1 month, 3 months, 6 months, 1 year and 2 years	Jarociński and Karadi (2020)
Inflation expectations	Percent per annum	Average of point forecasts	ECB SPF
GDP expectations	Percent per annum	Average of point forecasts	ECB SPF
Unemployment expectations	Percent per annum	Average of point forecasts	ECB SPF
Real GDP	Percentage change	Gross domestic product at market prices - annual rate of change	Eurostat
Output gap	Percent	Deviations of actual output from potential output	Estimated based on Hamilton (2018)
Unemployment rate	Percent	Standardized unemployment, total, percentage of labor force	Eurostat
Crude oil prices	Percent per annum	Bloomberg European Dated Brent Forties Oseberg Ekofisk (BFOE) Crude Oil Spot Price	ECB SDW ²
Consumer Prices	Percentage change	Harmonised Index of Consumer prices - annual rate of change	Eurostat
Term spread	Percent per annum	Own calculations - spread between the euro area 10-year government benchmark bond yield and the 3-month Euribor rate	ECB SDW
3-month Euribor rate	Percent per annum	Euro Interbank Offered Rate - Historical close, average of observations through period	ECB SDW
10-year government benchmark bond yield	Percent per annum	Benchmark bond – Yield	ECB SDW

Notes:

¹Survey of Professional Forecasters: <http://www.ecb.europa.eu/stats/prices/indic/forecast/html/index.en.html>²ECB Statistical Data Warehouse: <https://sdw.ecb.europa.eu/>

Table 2: Correlations – Ex-ante inflation uncertainty measures

	Horizons	Disagreement			AIU			Aggregate		
		1-year	2-year	5-year	1-year	2-year	5-year	1-year	2-years	5-years
Disagreement	1-year	1								
	2-years	0.72	1							
	5-years	0.36	0.56	1						
AIU	1-year	0.28	0.36	0.18	1					
	2-years	0.30	0.37	0.18	0.98	1				
	5 years	0.07	0.21	0.09	0.90	0.93	1			
Aggregate	1-year	0.72	0.65	0.31	0.85	0.84	0.65	1		
	2-years	0.50	0.61	0.33	0.92	0.93	0.81	0.92	1	
	5-years	0.14	0.31	0.25	0.91	0.93	0.96	0.70	0.87	1

Table 4: Central bank information shocks information

Shock	Methodology	Interest rate	Stock prices	Data Sources
Benchmark	Poor man's sign restrictions	First principal component of the Eonia swaps with maturities of 1, 3, 6 months, 1 and 2 years	EuroStoxx50	Jarociński and Karadi (2020)
Robustness 1	Sign restrictions	First principal component of the Eonia swaps with maturities of 1, 3, 6 months, 1 and 2 years	EuroStoxx50	Jarociński and Karadi (2020)
Robustness 2	Poor man's sign restrictions	First principal component of the Eonia swaps with maturities of 1, 3, 6 months and 1 year	EuroStoxx50	Jarociński and Karadi (2020)
Robustness 3	Sign restrictions	First principal component of the Eonia swaps with maturities of 1, 3, 6 months and 1 year	EuroStoxx50	Jarociński and Karadi (2020)
Robustness 4	Poor man's sign restrictions	3 months Eonia swaps	EuroStoxx50	Jarociński and Karadi (2020)
Robustness 5	Sign restrictions	3 months Eonia swaps	EuroStoxx50	Jarociński and Karadi (2020)
Robustness 6	Sign restrictions	2-years German bond yields	EuroStoxx50	Kerssenfischer (2018)

Table 5. Representation of the timing for the aggregation of shocks

Quarters	Months	Deadline to reply to SPF (day)	Days in which shocks were recorded
Q1	January		11
	January	12	15
	February		17
	February		19
	March		20
	March		21
	March		22
Q2	April	12	11
	May		15
	June		18

Note: In bold are the days in which shocks were aggregated to build the shocks for Q2.

Appendix A

The Impact of Central Bank Information Shocks on the First Moment

In order to have a precise interpretation of what the results for ex-ante inflation uncertainty mean, it is useful to understand how central bank information shocks affect the changes in the level of inflation expectations. Therefore, I estimate equation (4) under the benchmark specification below:

$$\Delta x_{t+h} = \beta_{0,h} + \beta_{1,h} shock_t + \beta_{n,h}(L)y_{n,t-1} + \varepsilon_{t+h}, \quad \text{for } h=0,1,2,\dots \quad (4)$$

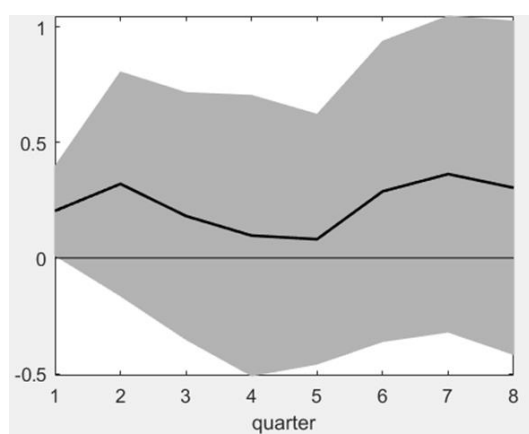
where Δx_{t+h} is defined as $\frac{x_{t+h} - x_{t-1}}{x_{t-1}}$, i.e., the change in inflation expectations in $t + h$ with respect to the first period of time of horizon h , $\beta_{0,h}$ is a constant, $\beta_h(L)$ is a polynomial in the lag operator, *shock* is the identified shock and y is the vector of control variables. In contrast to the baseline specification for ex-ante inflation uncertainties, no dummies were included for inflation expectations. Figure A1 shows inflation expectations in levels.

Figure A1: Inflation expectations – 2 years horizon



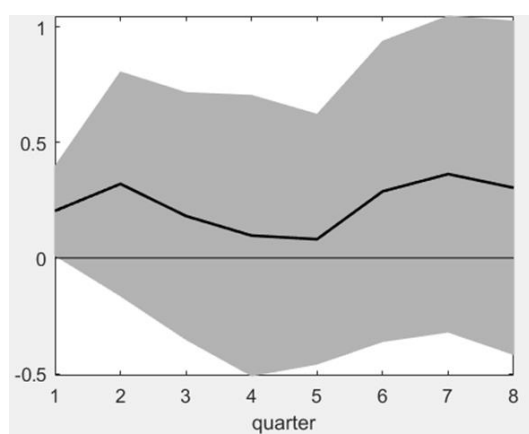
As mentioned in Section 6.2, Figure A2 shows that central bank information shocks generate an increase in inflation expectations; however this effect is not significant, in line with Jarociński and Karadi (2020) for the US and by Kerssenfischer (2018) for the euro area. Figure A3 shows a different specification by including inflation as a control.

Figure A2: Response of inflation expectations to central bank information shocks



Note: Shaded region represents 90% confidence bands.

Figure A3: Response of inflation expectations to central bank information shocks (Robustness)



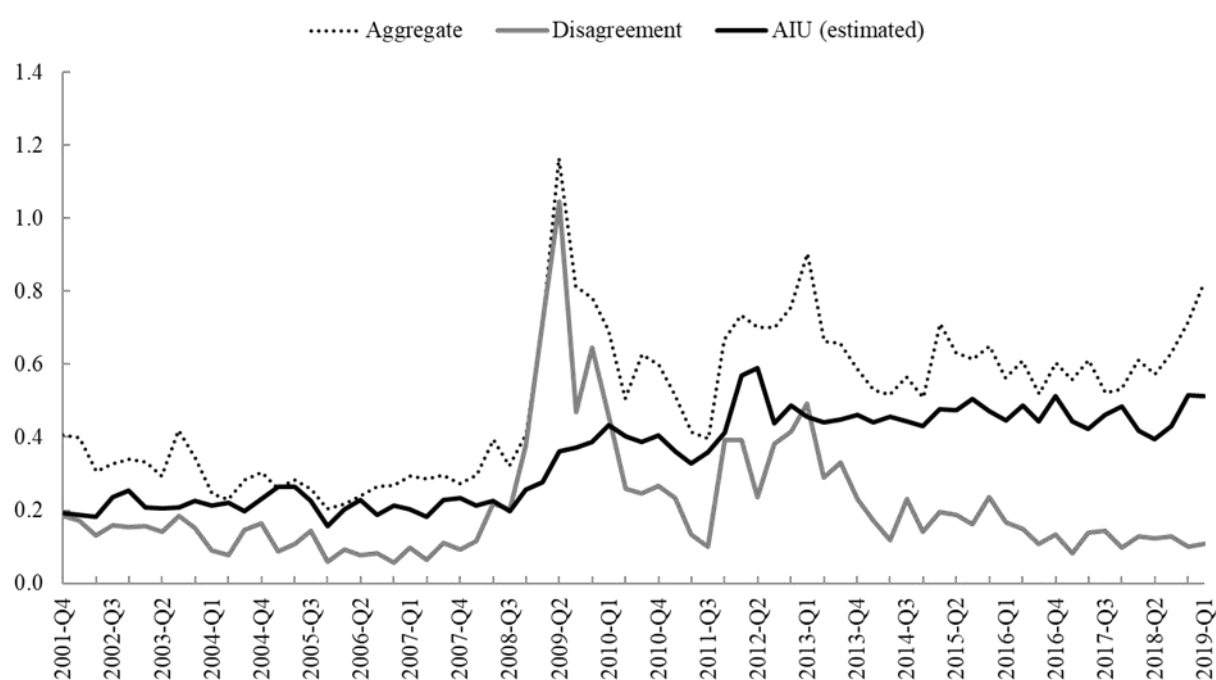
Note: Shaded region represents 90% confidence bands.

Appendix B

Further Robustness Checks

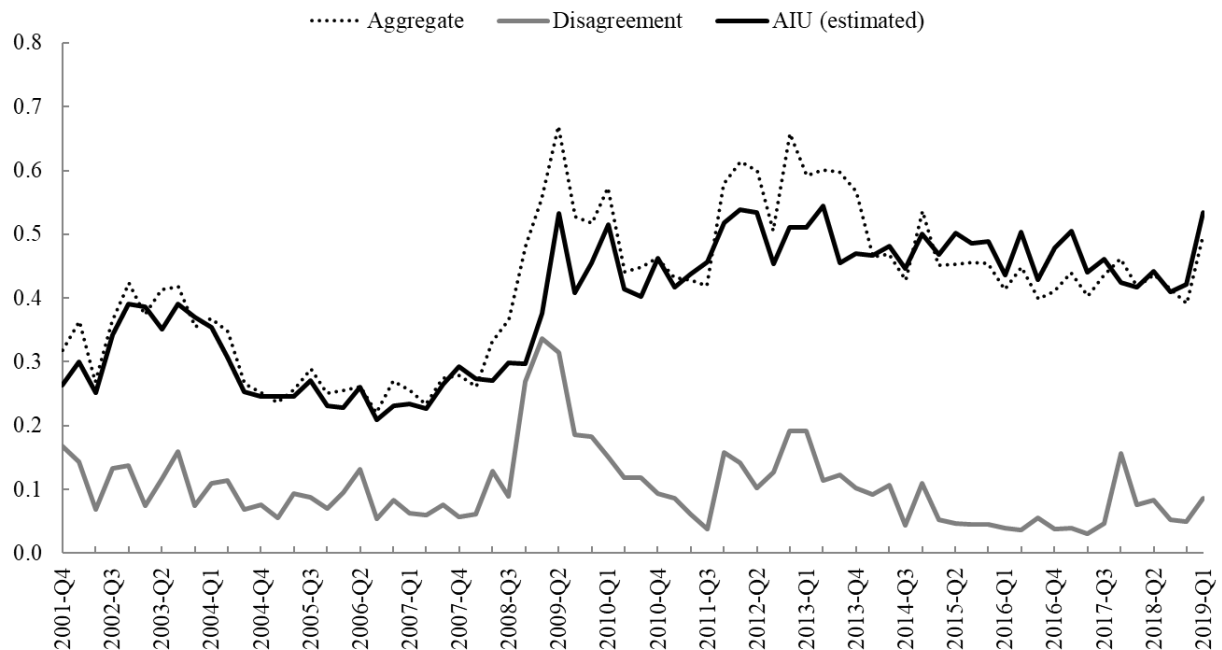
In this appendix, I report in more detail the results related to other variables available in the Survey of Professional Forecasters. Hence, I build the equivalent uncertainty measures for GDP and unemployment¹⁵ for two-year horizon using the same method described in Section in 3.1 (see Figures B.1 and B.2).

Figure B1: Ex-ante unemployment uncertainties - two-year horizon



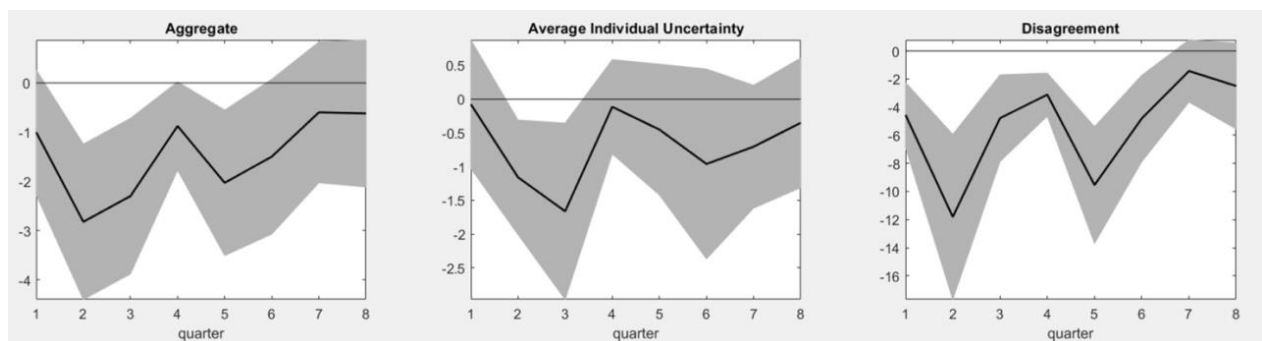
¹⁵ For unemployment average individual uncertainty unemployment, in cases where the forecaster placed probabilities in one or two bins, the simple variance was calculated instead of fitting the triangle distribution.

Figure B2: Ex-ante GDP uncertainties - two-year horizons



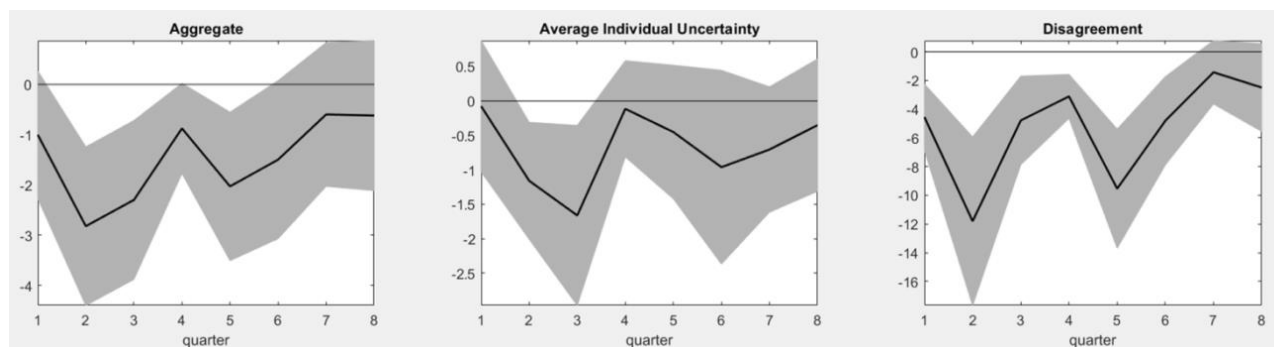
Then, I do the same exercise using local projections as shown in equation (4) to investigate whether the central bank information shocks yield similar results for GDP and unemployment ex-ante uncertainties. Figures B3 and B4 show that they do: following a central bank information shock, all types of uncertainties decrease for both variables.

Figure B3: Response of ex-ante GDP uncertainties to central bank information shocks



Note: Shaded region represents 90% confidence bands.

Figure B4: Response of ex-ante unemployment uncertainties to central bank information shocks



Note: Shaded region represents 90% confidence bands.

In addition, as it is also the case in the analysis for ex-ante inflation uncertainty, both average individual uncertainty and disagreement are reduced, with the effect on disagreement being the most prominent and persistent. The persistent effect of central bank information shocks on both GDP and unemployment disagreement confirms the influence of central bank communication on aligning opinions across forecasters.

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