ECB Communication as a Stabilization and Coordination Device: Evidence from Ex Ante Inflation Uncertainty*

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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 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 toward their aggregate mean. The paper not only helps to explain the impact of central bank information but is also useful for policymakers to define a communication strategy that attenuates ex ante inflation uncertainty.

JEL Codes: D83, E52, E58, E65, G14.

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; Issing 2019). Central bank communication steers expectations, and the better expectations are aligned with the monetary policy

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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] toward 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 Andrade and Ferroni 2016; Cieslak and Schrimpf 2019; Kerssenfischer 2019; Jarociński and Karadi 2020).

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,

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

for example, slowing 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 affect the ex ante inflation uncertainty are unknown. The closest related discussion in the literature is about how central bank information affects 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 affects forecasts or whether their announcements help market participants and forecasters 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 uncertainty, 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 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

[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).

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, 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; 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 with 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 contributes to strengthen their confidence in their predications.

In addition, after a central bank information shock, the point forecasts converge toward their mean. This convergence implies that the central bank communication generates a "stabilizer effect" in which the dispersion among the point forecasts decreases and, most importantly, this convergence moves toward 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 toward 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; Naszodi et al. 2016).

This paper is the first to investigate the relationship between the ECB communication and ex ante inflation uncertainty in the euro area using survey-based measures of inflation uncertainty. As explained in Section 3, in order to measure ECB communication, I use the new data set 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 Melo Fernandes and Kenny (2024), I estimate three ex ante uncertainty measures using the ECB SPF: disagreement, average individual uncertainty, and aggregate uncertainty.

Another common approach for estimating inflation uncertainty in the literature is from an ex post perspective, either by

[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.

estimating conditional variance using generalized autoregressive conditional heteroskedasticity (GARCH) models (Grier and Perry 2000; Fountas, Ioannidis, and Karanasos 2004; Kontonikas 2004; Conrad and Karanasos 2005) or stochastic volatility (see Berument, Yalcin, and Yildirim 2009; Chan 2017). To the best of my knowledge, the paper by Kliesen and Schmid (2004) is the first to investigate 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 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 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 uncertainty, and common uncertainty. 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

[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 with statistical benchmark models.

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, of the 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. Ehrmann 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 U.S. Federal Reserve reduces ex ante uncertainty about the future course of short-term interest rates. Hüning (2017) 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, in addition to gaining new insights into the implications of the ECB communication on ex ante inflation uncertainty, it 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 affects 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 Federal Reserve has an advantage compared with 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, Ehrmann, and Fratzscher (2011), when investigating how central bank communication about financial stability influences financial markets, find that it works primarily as a 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 as 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 three measures of ex ante inflation uncertainty. More precisely, these shocks help to align opinions across forecasters, generating a "stabilizer effect," as the convergence of these measures is toward 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. Subsections 3.1 and 3.2, respectively, provide detailed explanations of how these measures and shocks are estimated.

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 gross domestic product (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 and the individual histograms containing 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, Kerssenfischer 2019; Jarociński and Karadi 2020). 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 publicly 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 and 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 influencing factors on forecast uncertainty and disagreement. They are the quarterly change in crude oil prices, inflation (year-over-year Harmonised Index of Consumer Prices, HICP), real GDP, the unemployment rate, the output gap, and the term spread defined as the difference between the euro-area 10-year government benchmark bond yield

[5]The earlier part of the sample dating back to 1999:Q3 is characterized by a relatively low market liquidity, which affects 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.

and the euro interbank offered rate (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. Table 2 presents the key statistics for each of the three measures.

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 the estimation of the HICP inflation as a single number and assign probabilities for different predefined 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 Melo Fernandes and Kenny (2024). 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 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):

$$d_{t+h} = \mathrm{N}^{-1} \sum_{\mathrm{i}=1}^{\mathrm{N}} \left[\mathrm{E}_{\mathrm{i},t}\left[\mathrm{y}_{t+\mathrm{h}}\right] - \overline{\mathrm{y}}_{t+\mathrm{h}}\right]^2, \tag{1}$$

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

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 EuroStoxx 50 and the first principal component of the EONIA swaps with maturities of one month, three months, six months, one year, and two 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

(continued)

Table 1. (Continued)

Variable	Units	Definitions	Data Sources
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 three-month EURIBOR rate	ECB SDW
Three-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

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

Table 2. Summary Statistics: Ex Ante Inflation Uncertainty Measures

Horizon	Measure	Mean	St. Deviation	Skewness	Kurtosis
One-Year Horizon	Aggregate	0.30	0.11	0.19	2.01
	AIU	0.27	0.07	–0.18	1.64
	Disagreement	0.09	0.06	1.79	6.55
Two-Year Horizon	Aggregate	0.34	0.10	–0.18	1.61
	AIU	0.32	0.08	–0.29	1.61
	Disagreement	0.06	0.04	1.87	7.64
Five-Year Horizon	Aggregate	0.36	0.09	–0.37	1.7
	AIU	0.38	0.08	–0.19	1.82
	Disagreement	0.05	0.04	5.05	35.7

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:

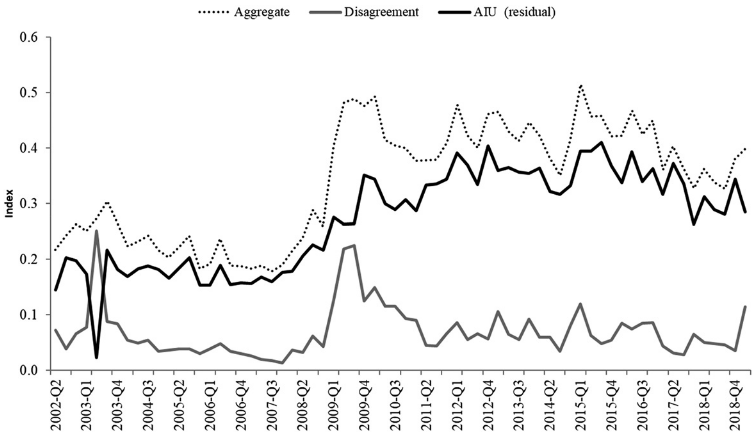
$$\overline{\sigma}_{t+h} = \mathrm{N}^{-1} \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{E}_{\mathrm{i,t}} \left[(\mathrm{y}_{\mathrm{t+h}} - \mathrm{E}_{\mathrm{i,t}} [\mathrm{y}_{\mathrm{t+h}}])^2 \right]. \tag{2}$$

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

$$\mathrm{EAU}_{t+h} = \overline{\sigma}_{t+h} + d_{t+h}. \tag{3}$$

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 with AIU (see further discussion in Section 6.1). Therefore, estimating AIU as the residual of Equation (3) might lead to a less accurate measure of AIU compared with 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

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.

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 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 the intervals at which the forecasters place their probabilities. In the second step, I extract the variance of each histogram after fitting these

[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 percent, while one specific forecaster reported a projection of −1 percent. Note that this outlier in disagreement was removed before performing the regressions.

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 places probabilities in 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 percent of the total cases in the database.[7] Furthermore, 88 percent of these cases occur before the Great Financial Crisis.

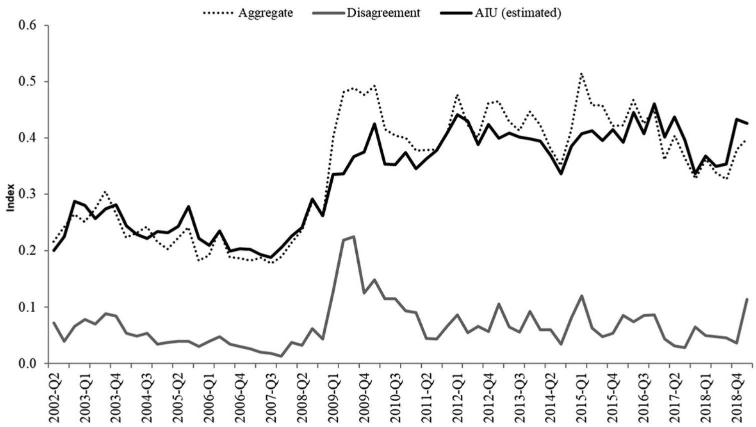
Finally, in cases where the forecaster is 100 percent convinced that the outcome of inflation will be within a particular range, the base of the triangle includes the interval correspondent to this range and part of the adjacent interval. In cases where the forecaster places the probabilities in two 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 (see Figure 2).

Table 3 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

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

Figure 2. Ex Ante Inflation Uncertainties—AIU Estimated (Two-Year Horizons)



lower correlation with disagreement (0.61 for the two-year horizon). Indeed, Figure 2 shows that unlike disagreement, both AIU and aggregate uncertainty show a clearer level shift and 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 might reflect the fact that given the relatively high degree of persistence in inflation, shorter horizons are more influenced by data realizations on which forecasters agree, while the impact of present developments fades away over longer-term projections.

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

Table 3. Correlation: Ex Ante Inflation Uncertainty Measures

		Disagreement			AIU			Aggregate		
	Horizons	**One Year**	**Two Years**	**Five Years**	**One Year**	**Two Years**	**Five Years**	**One Year**	**Two Years**	**Five Years**
Disagreement	One Year	1								
	Two Years	0.72	1							
	Five Years	0.36	0.56	1						
AIU	One Year	0.28	0.36	0.18	1					
	Two Years	0.30	0.37	0.18	0.98	1				
	Five Years	0.07	0.21	0.09	0.90	0.93	1			
Aggregate	One Year	0.72	0.65	0.31	0.85	0.84	0.65	1		
	Two Years	0.50	0.61	0.33	0.92	0.93	0.81	0.92	1	
	Five Years	0.14	0.31	0.25	0.91	0.93	0.96	0.70	0.87	1

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 data set 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 area, this is the case for approximately 46 percent of the data points. The data set 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's" sign restrictions method. In

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

[9]This novel data set for the euro area is based on Gürkaynak, Sack, and Swanson (2005), who constructed a similar data set for the United States.

a nutshell, the poor man's 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 EuroStoxx 50 index. The proxy for interest rates is a combination of different maturities of euro overnight index average (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 bound period. Typically, in this period the value of assets with longer maturities changes more than those with shorter maturities.

Kerssenfischer (2019) 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 EuroStoxx 50 index as a proxy for stock valuations.[10] Furthermore, he replaces the narrow window with 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

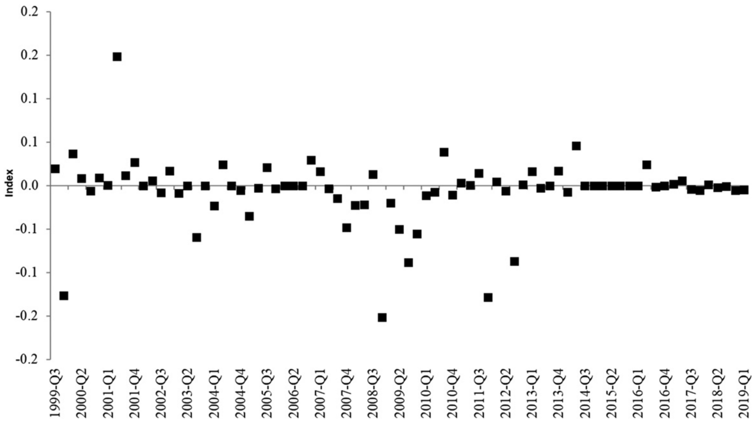
The primary objective of the analysis is to estimate the impact of central bank information shocks on ex ante inflation uncertainty. I use local projections (see Jordà 2005) to estimate the

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

Table 4. Central Bank Information Shocks Information

Shock	Methodology	Definition of Interest Rate	Definition of Stock Prices	Data Sources
Benchmark Shock	Poor Man's Sign Restrictions	First principal component of the EONIA swaps with maturities of one month, three months, six months, one year, and two years	EuroStoxx 50 Index	Jarociński and Karadi (2020)
Robustness 1	Sign Restrictions	First principal component of the EONIA swaps with maturities of one month, three months, six months, one year, and two years	EuroStoxx 50 Index	Jarociński and Karadi (2020)
Robustness 2	Poor Man's Sign Restrictions	First principal component of the EONIA swaps with maturities of one month, three months, six months, one year, and two years	EuroStoxx 50 Index	Jarociński and Karadi (2020)
Robustness 3	Sign Restrictions	First principal component of the EONIA swaps with maturities of one month, three months, six months, one year, and two years	EuroStoxx 50 Index	Jarociński and Karadi (2020)
Robustness 4	Poor Man's Sign Restrictions	Three-month EONIA swaps	EuroStoxx 50 Index	Jarociński and Karadi (2020)
Robustness 5	Sign Restrictions	Three-month EONIA swaps	EuroStoxx 50 Index	Jarociński and Karadi (2020)
Robustness 6	Sign Restrictions	Two-year German bond yields	EuroStoxx 50 Index	Kerssenfischer (2019)

Figure 3. Central Bank Information Shocks (Baseline)



Note: Central bank information shocks estimated by Jarociński and Karadi (2020) using the "poor man's method." The measure used to compute changes in stock valuation is the EuroStoxx 50 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.

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:

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

where $\triangle x_{t+h}$ is defined as $x_{t+h} - x_{t-1}$, where x_{t+h} and x_{t-1} are in logs. The changes for each ex ante uncertainty type are shown in Figures 4, 5, and 6. $\beta_{0,h}$ 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. The coefficient $\beta_{1,h}$ gives the response of the changes in x at time $t + h$ with respect to $t - 1$ to the shock that happens at time t. This calculation ensures that the direct impact of the shock is isolated, enabling the analysis to focus on the net change that has occurred over that time span.

Figure 4. Ex Ante Average Individual Uncertainty: Changes by Impulse Response Function Horizons

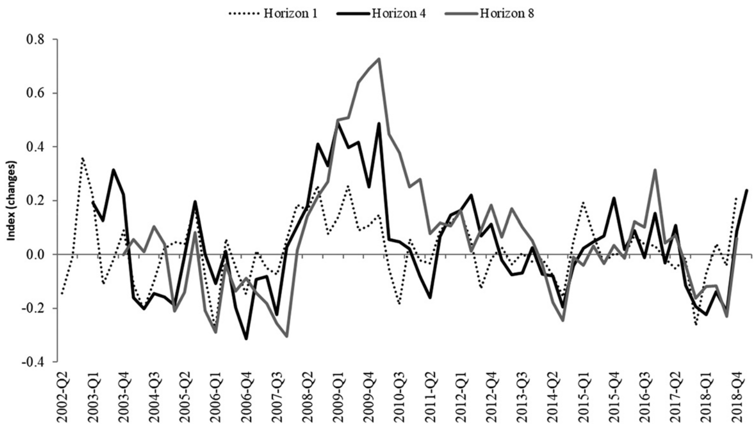
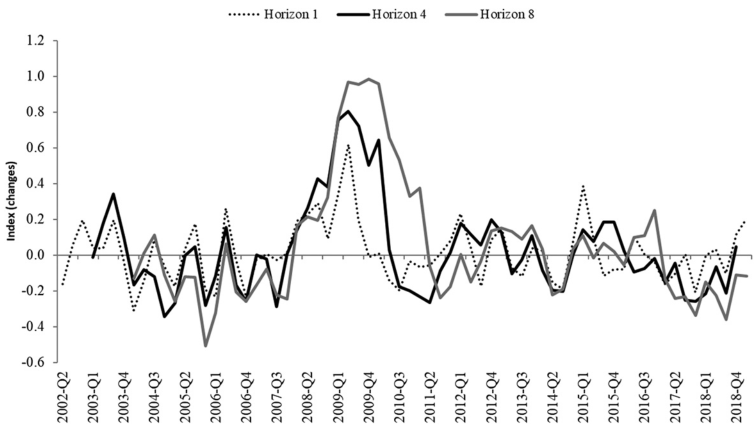
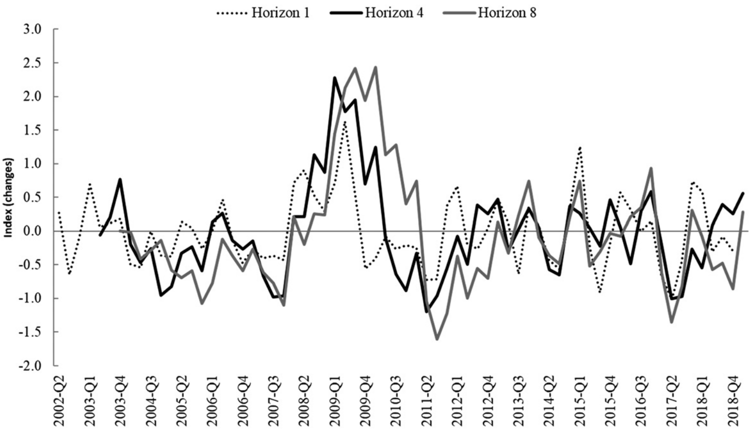


Figure 5. Ex Ante Aggregate Uncertainty: Changes by Impulse Response Function Horizons



The baseline shock is estimated using the poor man's sign restrictions method, which ultimately calculates the co-movement between the EuroStoxx 50 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

Figure 6. Disagreement: Changes by Impulse Response Function Horizons



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, and on the lagged ex ante inflation uncertainty.

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.

Table 5. Representation of the Timing for the Aggregation of Shocks

Quarters	Months	Deadline to Reply to SPF (Day)	Date in Which Shocks Were Recorded (Day of the Month)
Q2	April		4
	April	19	—
	May		**2**
	June		**6**
Q3	July		**4**
	July	19	—

Note: This table illustrates a case in which the deadline to reply to the SPF in 2013:Q3 was on July 19, 2013. Therefore, only shocks that happened between the deadline to reply to the SPF in Q2 (i.e., April 19) and July 19 were summed. The dates of the days in which shocks were aggregated to build the shocks for Q3 are highlighted in bold.

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 data set 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 2013:Q3. In this case, the deadline to reply to the

SPF in Q3 was on July 19. Therefore, only shocks that happened between the deadline to reply in Q2 (i.e., April 19) and July 19 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 July 4), and second, one's models would incorporate information that had already been absorbed in the former survey (in this case, the shock on April 4).

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 $t-2$.

Finally, the approach used to calculate the changes in the dependent variable as shown in Equation (4)—in which the changes on the measures of uncertainty in time to $t+h$ are always with respect to $t-1$ in response to a shock that happens at time t—ensures consistency between the timing of the survey data collection and the aggregation of the shocks. This rationale is elucidated through the illustrative example provided in Table 5. The survey deadline for 2013:Q3 (time t) was on July 19, meaning that the estimation for uncertainty in 2013:Q3 was produced in the beginning of that quarter. Meanwhile, the shocks for 2013:Q3 were aggregated using central bank information that started to be collected right after the survey deadline for 2013:Q2 (time $t-1$), with most of the information being collected still in this quarter. In light of this dynamic, in order to measure the effect of the shock in 2013:Q3 (time t) on the subsequent horizons, it becomes crucial to utilize the uncertainty data preceding the shock as the foundational reference for computing changes. This entails employing 2013:Q2 (time $t-1$) as the benchmark for such calculations.

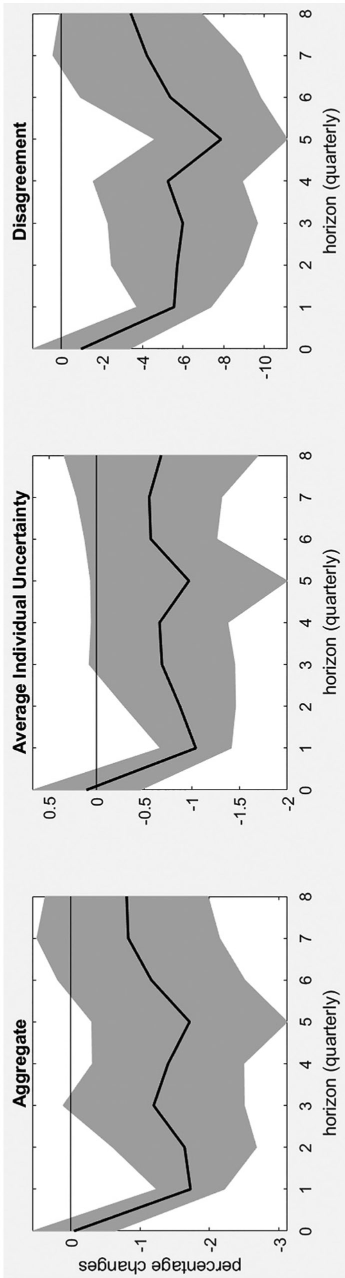
6. Results

Figure 7 summarizes the results of estimating the benchmark specification of Equation (4), which includes a constant and the central bank information shock 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. 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 percent 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 United States, reflecting information rigidities.

The impact of the central bank information shocks is most prominent on disagreement, which decreases 5.5 percentage points in the first quarter—approximately more than five times the drop of average individual uncertainty. While average individual and aggregate uncertainty retract from their peak in the third quarter, disagreement falls nearly half a percentage point further. Aggregate ex ante inflation uncertainty decreases 1.7 percentage points in the first quarter, with some persistence in the last horizons. Clearly, the

Figure 7. Impulse Response Functions: Baseline Specification



Note: This specification includes constant and the lag of ex ante inflation uncertainty.

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

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

[12] For discussion, see Zarnowitz and Lambros (1987), Grier and Perry (1998, 2000), Giordani and Söderlind (2006), Lahiri and Sheng (2010), Abel et al. (2016), Glas and Hartmann (2016), and Clements, Rich, and Tracy (2023). 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.

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—i.e., whether these opinions converge to the mean, leading to a "stabilizer effect"—or whether this convergence goes toward a point that may cause instability. For example, if after a central bank communication shock the opinions converged toward one of the tails of the distribution of inflation expectations rather than toward the mean—which is aligned with the ECB objective of 2 percent inflation in the medium term—that could be a detrimental outcome given the risk of de-anchorage of inflation expectations. Since central bank communication undoubtedly plays a fundamental role in steering expectations (see Blinder 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 United States and Kerssenfischer (2019) for the euro area.

Therefore, 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. Thus, I repeat the exercise using the baseline specification with inflation expectations being the dependent variable to verify how it reacts to central bank information shocks.[13] Figure 8 shows inflation expectations in levels. Figures 9 and 10 depict the resulting impulse response functions, illustrating the effect of central bank information shocks on inflation expectations. It is noteworthy that this effect lacks statistical significance, aligning with previous findings in the literature.

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

Figure 8. Inflation Expectations—Two-Year Horizon

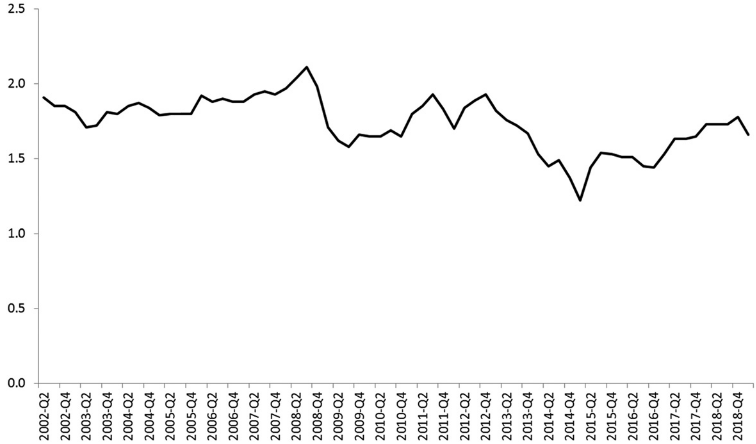
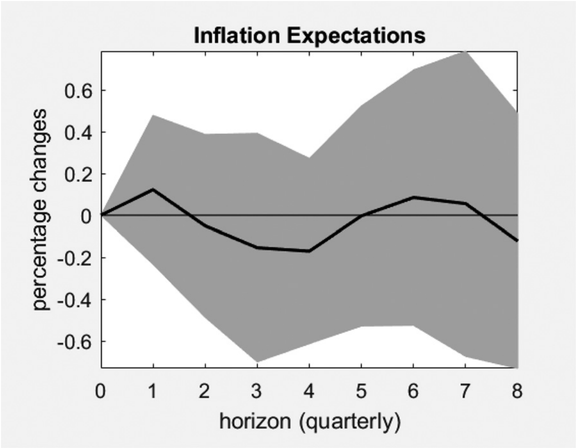


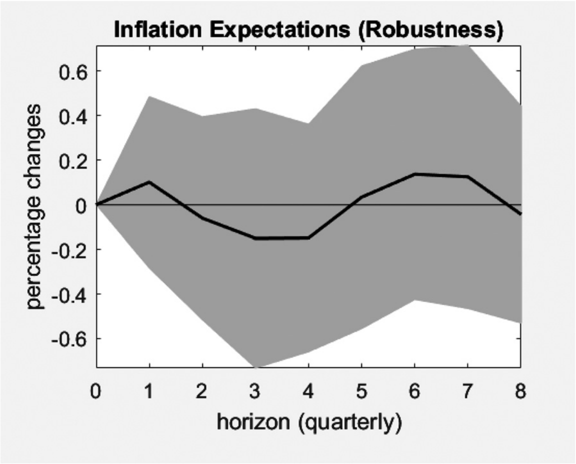
Figure 9. Response of Inflation Expectations to Central Bank Information Shocks



Note: This figure shows the response of inflation expectations for the two-year horizon measured as the average of point forecasts to central bank information shocks. As the figure shows, the effect of central bank information shocks on inflation expectations is not significant.

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

Figure 10. Response of Inflation Expectations to Central Bank Information Shocks (Robustness)



Note: This figure shows the response of inflation expectations for the two-year horizon measured as the average of point forecasts to central bank information shocks. The specification also includes inflation as a control variable for a robustness check. The result also shows that the effect of central bank information shocks on inflation expectations is not significant.

information shock, agents do not necessarily update their expectations, but they converge toward the mean of the point forecasts, which remains close to the ECB objective of 2 percent inflation over the medium term. This convergence implies that the central bank communication has a "stabilizer effect" in which the dispersion among the point forecasts decreases and, most importantly, this convergence moves toward the mean. This convergence is very important, as it induces a steady consensus among the forecasters more in line with the ECB's objective of price stability. In contrast, if the point forecasts responded significantly with a steep increase or decrease to central bank communication shocks, that would indicate that inflation expectations could converge toward one of the tails, which could ultimately lead to the de-anchorage of inflation expectations, undermining the ECB's price stability goals. 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; 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 with their peers. This measure is often considered a better proxy for uncertainty than disagreement in the literature (Abel et al. 2016; Glas and Hartmann 2016; 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 with 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 contributes to strengthen the confidence in their predications. This is in line with Morris and Shin's (2002, p. 1521) 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."

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 indeed convey new information about the economy to the agents requires further empirical exercises and is beyond the scope of this paper.

7. Robustness

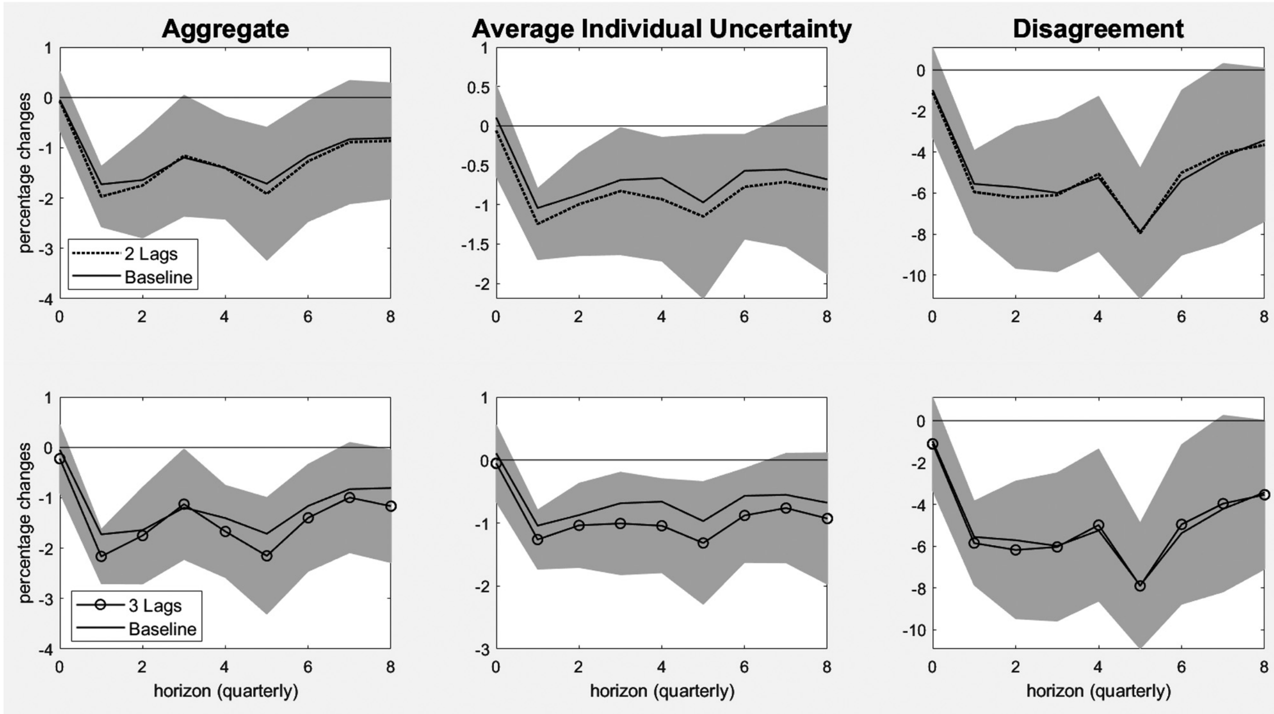
It is important to account for potential remaining information in the estimated residuals that might influence ex ante inflation uncertainty. Therefore, this section explores the potential sensitivity of the results to other specification choices and to the addition of other controls.

First, I estimate the baseline equation adding different lags of the correspondent dependent variable in levels. Figure 11 shows that the findings for the three types of ex ante inflation uncertainty are robust to different lag specifications and therefore aligned with the reasoning of the baseline results.

Next, by closely following Jitmaneeroj, Lamla, and Wood (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

[14] As listed by Jitmaneeroj, Lamla, and Wood (2019), see Döpke and Fritsche (2006), van der Cruijsen and Demertzis (2007), Patton and Timmermann (2010), Dovern, Fritsche, and Slacalek (2012), Ehrmann, Eijffinger, and Fratzscher (2012), Lamla and Maag (2012), Hartmann and Roestel (2013), Posso and Tawadros (2013), and Siklos (2013).

Figure 11. Robustness Check—Different Lags



Note: The confidence intervals correspond to the impulse responses of the series employed as a robustness check.

term spread, which is defined as the difference between the euro-area 10-year government benchmark bond yield and the EURIBOR three-month money market rate.

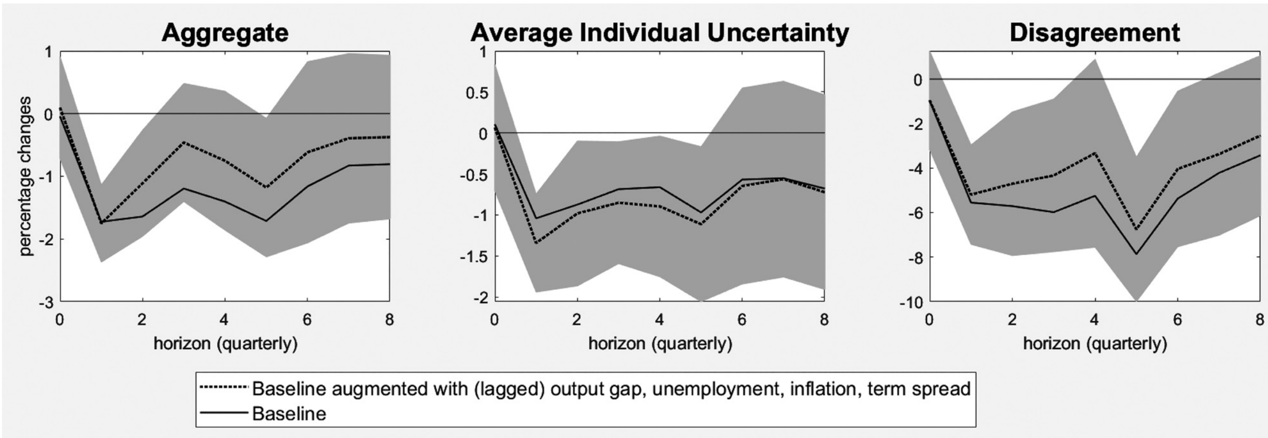
The inclusion of these control variables results in slightly milder responses for aggregate uncertainty and disagreement, while it is marginally more pronounced for average individual uncertainty, though it remains closely aligned with the baseline. As shown in Figure 12, interestingly, disagreement has the same drop as the baseline specification in the first quarter (−5.5 percentage points). The same specification is only slightly modified by replacing inflation with changes in crude oil prices, and the responses remain robust (Figure 13).

In addition, I estimate the baseline specification using other central bank information shocks. Specifically, I compare different versions of the poor man's shocks from 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's 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 EuroStoxx 50 index for all cases.

Figure 14 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's sign restriction shock to the baseline shock, 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 shocks estimated by Kerssenfischer (2019). The responses of the three ex ante inflation uncertainty measures are fairly robust to all versions of the shocks.

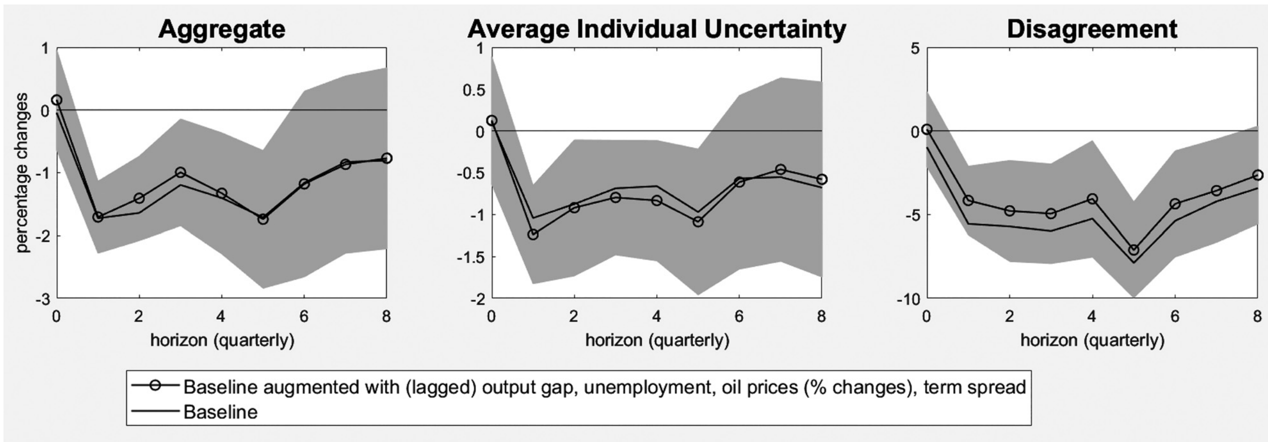
As a further robustness exercise, it is interesting to see whether these findings hold for different ex ante inflation uncertainty horizons. As shown in Figure 15, the responses of one-year horizon ex ante inflation uncertainties are in general milder but still similar to the baseline, while the response of five-year aggregate is notably

Figure 12. Robustness Check—Different Controls (1)



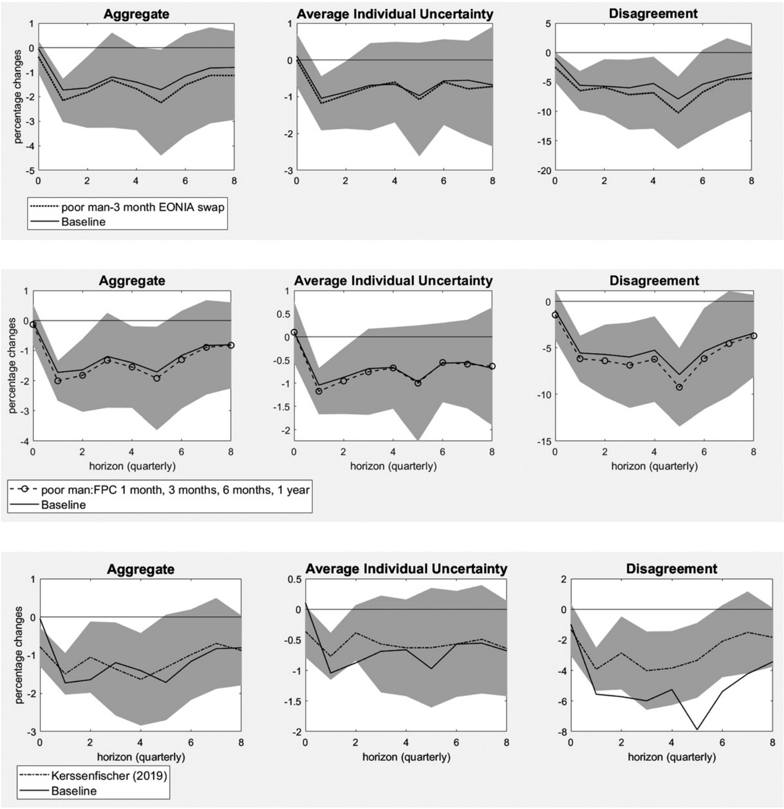
Note: The confidence intervals correspond to the impulse responses of the series employed as a robustness check.

Figure 13. Robustness Check—Different Controls (2)



Note: The confidence intervals correspond to the impulse responses of the series employed as a robustness check.

Figure 14. Robustness Check—Different Shocks

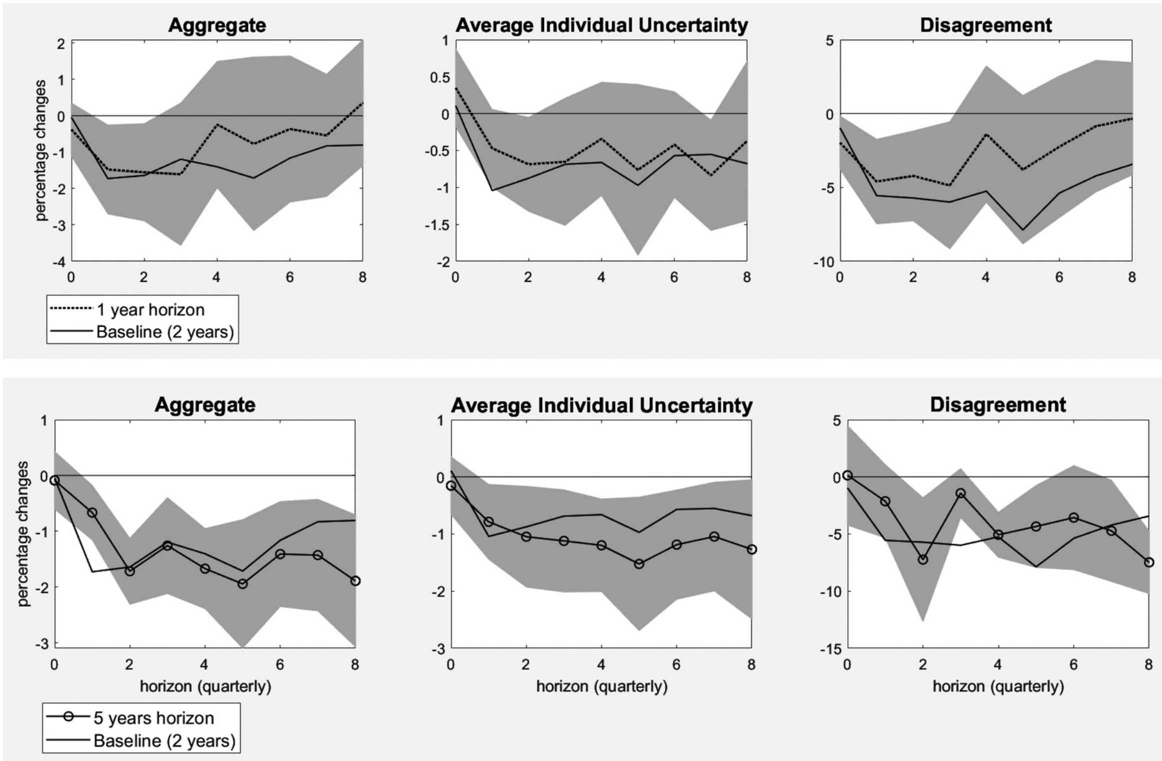


Note: The confidence intervals correspond to the impulse responses of the series employed as a robustness check.

less prominent in the first quarter, becoming larger than the benchmark in the following quarters, a trend also present in the response of average individual uncertainty. In addition, disagreement reacts with a larger delay than the benchmark measure: the first significant reactions appear only after two quarters. These results also provide reassurance regarding the robustness of the benchmark estimation.

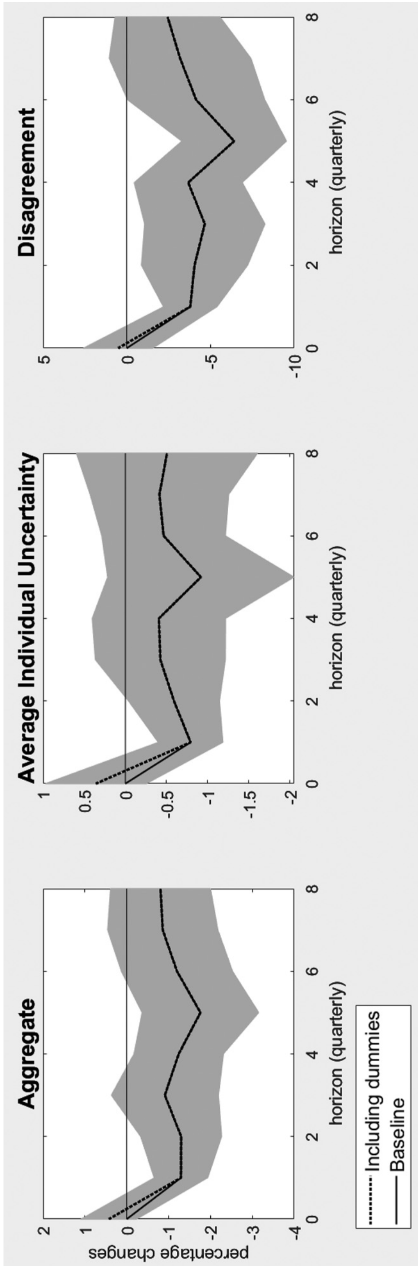
In the appendix I show the impact of central bank information shocks on ex ante uncertainty about the other two variables that are also included in the Survey of Professional Forecasters, that is, GDP

Figure 15. Robustness Check—Different Horizons



Note: The confidence intervals correspond to the impulse responses of the series employed as a robustness check.

Figure 16. Robustness Check—Dummies



Note: The confidence intervals correspond to the impulse responses of the series employed as a robustness check.

and unemployment. The results are aligned with the uncertainties about inflation and discussed in detail in the appendix.

Finally, I include a set of dummies from 2009:Q1 to 2009:Q4 to account for the effect of the Great Financial Crisis, as the changes computed during that period gain more prominence in each horizon (see Figures 4, 5, and 6). Following the Great Financial Crisis, there was a steep fall in inflation, which contributed to an upward shift in aggregate and average individual uncertainty after 2008:Q4 and resulted in an unprecedent level of disagreement in 2009:Q3. In fact, annual HICP change reached –0.6 percent in July 2009, the lowest level since the beginning of the series in 1999. The inclusion of dummies does not have any relevant impact either on the shape or on the magnitude of the impulse responses (see Figure 16).

8. Conclusions

This paper investigates how the ECB communication of its assessment of the economic outlook affects 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 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 toward the mean instead of toward 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 define a communication strategy that attenuates inflation uncertainty in the most effective way possible. One well-known reason for 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.

Appendix. 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 unemployment[15] for the two-year horizon using the same method described in Section 3.1 (see Figures A.1 and A.2).

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 A.3 and A.4 show that they do: following a central bank information shock, all types of uncertainties decrease for both variables.

In addition, as is also the case in the analysis for ex ante inflation uncertainty, both average individual uncertainty and disagreement

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

Figure A.1. Ex Ante Unemployment Uncertainties—Two-Year Horizon

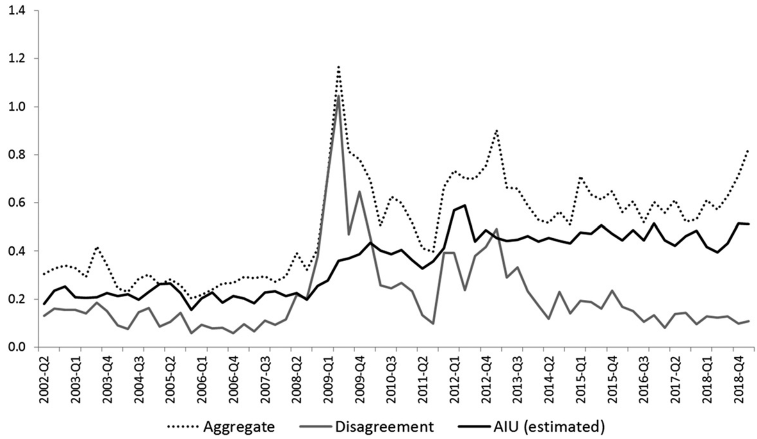
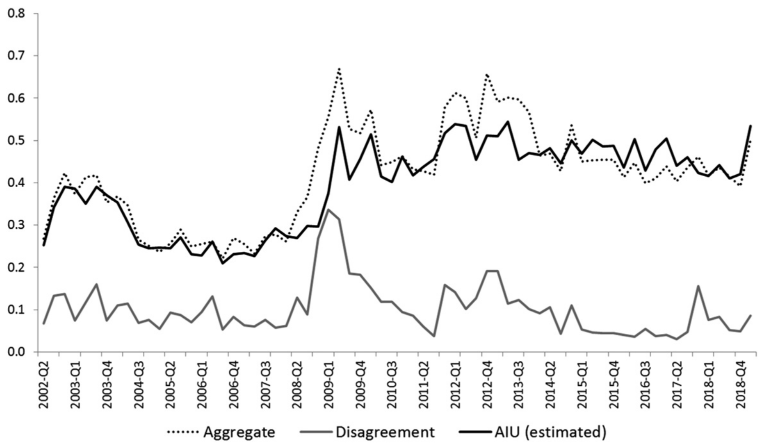


Figure A.2. Ex Ante GDP Uncertainties—Two-Year Horizons



are reduced, with the effect on disagreement being the most prominent, persistent, and immediate. 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.

Figure A.3. Response of Ex Ante GDP Uncertainties to Central Bank Information Shocks

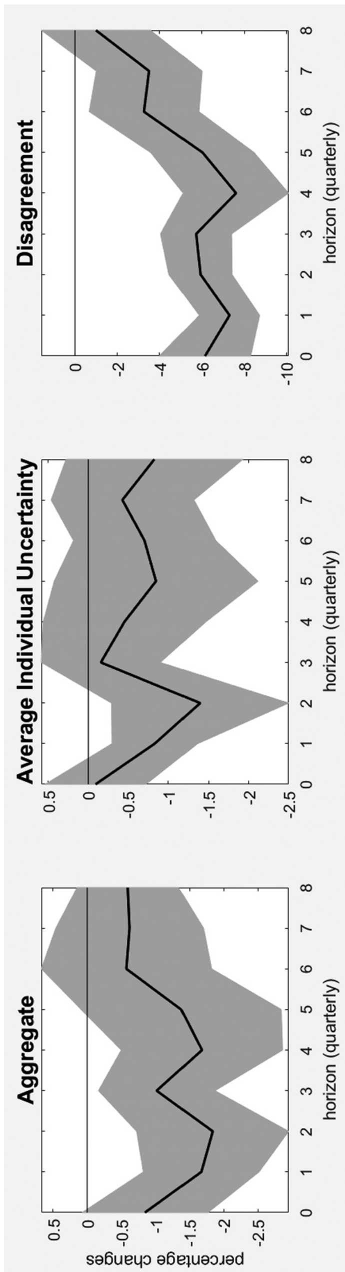
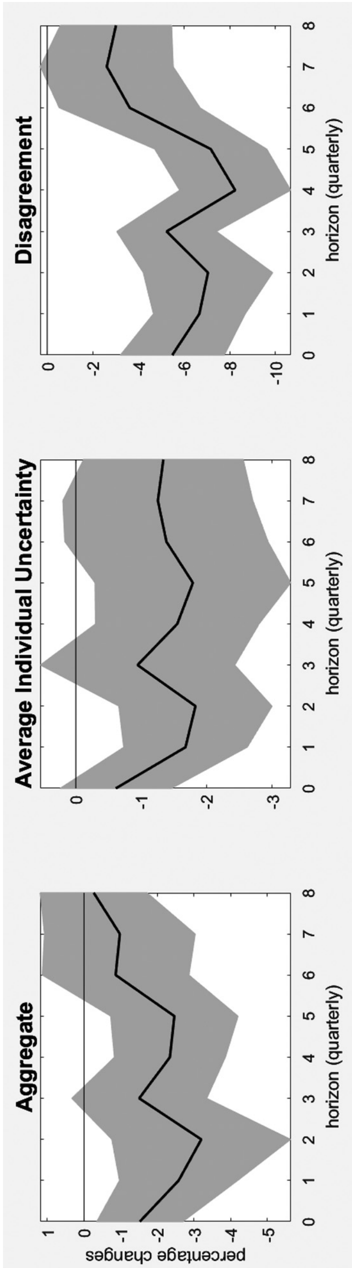


Figure A.4. Response of Ex Ante Unemployment Uncertainties to Central Bank Information Shocks



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