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UNCERTAINTY, DATA DEPENDENCE AND INTEREST RATE VOLATILITY

by Vincenzo Cuciniello*, Giuseppe Ferrero*, Alessandro Notarpietro* and Sergio Santoro*

Abstract

We study how central bank communication about the uncertainty surrounding its assessment of macroeconomic developments shapes financial market reactions to economic news. Using euro-area evidence, we show that when markets perceive the central bank to be operating in a "high-learning" regime – marked by high uncertainty and repeated forecast errors – the pass-through of inflation surprises to interest rates is amplified, resulting in greater volatility. To interpret these findings, we develop a model of imperfect information in which the private sector updates its beliefs about the persistent component of inflation using both realized inflation and the central bank's projections. In this setting, the central bank's projections are viewed act as noisy signals, and their perceived precision determines how much weight the private sector places on the central bank's macroeconomic assessment relative to incoming data.

The model predicts that when projections are viewed as more precise, expectations become more anchored and interest rates respond less to news. Overall, the empirical and theoretical results highlight that communicating the confidence surrounding central bank projections is not a neutral act of transparency but an active policy instrument.

JEL Classification: D83, D84, E32, E37, E52, E44, E58.

Keywords: monetary policy, data dependence, imperfect information, financial market expectations.

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1. Introduction[1]

The expression "data dependence" might appear self-explanatory in the context of monetary policy, suggesting that central banks condition their decisions on observed economic data to attain specified macroeconomic objectives. Incoming data shape the central bank's assessment of macroeconomic developments. Since central banks are tasked to safeguard macroeconomic stability – typically in terms of inflation only, in some cases also with regards to economic growth and employment – this assessment is central to the setting of the monetary policy stance.

In practice, however, the term has been invoked by central banks in distinct contexts and with different purposes.[2] One usage arises in the context of forward guidance, where *data dependence* conveys that future policy decisions will respond to the evolution of economic conditions rather than follow a predetermined path.[3] In this sense, the notion emphasizes policy flexibility and state contingency, and carries a purely forward-looking connotation.

A conceptually distinct usage – on which this paper focuses – emerges during periods of heightened uncertainty about the economic environment. Under such circumstances, central banks often operate in what Lane (2024) has described as a "high learning" regime, in which "*an unusually wide set of possible inflation and growth trajectories must be envisaged such that Bayesian updating on the basis of incoming data would be an essential element in a disciplined approach to policy calibration*". Similarly, Clarida (2020) stresses that "*incoming data contain signals*", meaning that new information is employed to update internal model estimates through signal extraction and iterative learning from past forecast errors.[4] This perspective frames *data dependence* as relatively backward-looking, emphasizing the continuous reassessment of how shocks are transmitted through the economy in light of newly available data.[5]

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[2] See Appendix 1 for a discussion on the use of data dependence in the communication strategies of the European Central Bank (ECB) and the Federal Reserve.

[3] In September 2014, The FOMC participants agreed that the timing of the first increase in the federal funds rate and the appropriate path of the policy rate thereafter would depend on incoming economic data and their implications for the outlook. It was observed that "*the reference to 'considerable time' in the current forward guidance could be misinterpreted as a commitment rather than as data-dependent*" (FOMC, 2014a).

[4] See Clarida (2020): "*Monetary policy, however, also needs to be data dependent in the second sense—that incoming data contain signals—that can enable the central bank to update its estimates of r* and u* in order to obtain its best estimate of the destination to which the economy is heading*".

[5] More precisely, under this second usage agents still form expectations about future macroeconomic developments (or "*trajectories* [that] *must be envisaged*"), but they do so in a backward-looking way, by continuously updating their prior beliefs based on new data.

These two notions of data dependence – state-contingent-forward-guidance and learning-signal-extraction – differ not only in their implications for monetary policy but also in how financial markets interpret and react to incoming news. They exert different effects on the sensitivity of market interest rates to data releases and to the central bank communication about its assessment of macroeconomic developments, and hence on the volatility of those rates.

Two considerations are particularly relevant in the case of the euro area. First, the ECB has used the term *data dependence* in the second sense, associated with a high-uncertainty macroeconomic environment. Second, prior to 2022, during earlier episodes of heightened uncertainty, the ECB emphasized the role of incoming data in revising projections and reassessing unobservable variables, even if the specific expression "*data dependence"* was not employed.

A central bank can share its assessment of economic conditions through several channels. It can publish projections, include guidance in policy statements, speak during press conferences, or offer views in speeches and testimonies. During episodes of elevated uncertainty, the central bank's communication of the uncertainty surrounding its macroeconomic assessment becomes particularly important, as it clarifies the reliability of baseline projections (for example) relative to alternative sources of information on the inflation outlook.[6] Indeed, the recent experience of exceptionally high uncertainty and repeated forecast errors has spurred a debate on how major central banks should improve the tools they employ to measure and communicate uncertainty in their macroeconomic assessment (Adrian et al., 2025; ECB, 2025).

The contribution of this paper is twofold.

First, on the empirical side, it examines how financial markets react to macroeconomic news and to central bank communication about its assessment of macroeconomic developments under varying degrees of perceived central bank's confidence in its own assessment. Using euro-area surveys and high-frequency data, we document that when markets perceive the central bank to be operating in a "high learning" regime they exhibit stronger reactions to macroeconomic news and weaker to central bank's own assessment, where the latter is captured by central bank information shocks. This impact on sensitivity translates into an impact on volatility of market interest rates, shedding light on the interaction between monetary policy communication and financial market volatility.

[6] Moreover, the communication of uncertainty also helps the public understand the policy-making process, as risk and uncertainty may become integral elements of monetary decisions. For example, in its July 2025 Monetary Policy Statement, the ECB clarified that, among the criteria guiding its policy decisions, it now explicitly includes the assessment of the risks surrounding the inflation outlook ("*In particular, the Governing Council's interest rate decisions will be based on its assessment of the inflation outlook and the risks surrounding it, in light of the incoming economic and financial data, as well as the dynamics of underlying inflation and the strength of monetary policy transmission.*")

Second, on the theoretical side, we develop a framework of imperfect information and Bayesian learning in which, upon observing an inflation release, neither the central bank nor the private sector can perfectly disentangle the persistent component of inflation from the transitory, more volatile one. The central bank filters these components to generate and publish inflation projections.[7] The private sector updates its beliefs about the persistent component using both incoming data and the central bank's projections. Our analysis shows that the greater the uncertainty surrounding the central bank's projections, as perceived by the private sector, the less these projections affect market interest rates, and the stronger the interest rates sensitivity to macroeconomic news. Put differently, the less reliable the projections are considered as a signal, the less the private sector takes them into account when forming its own inflation expectations, and the more it resorts to new data releases and the less to central bank projections.[8]

The main policy implication concerns the central bank's communication. The model highlights that communication regarding the confidence attached to projections is not merely an issue of transparency but constitutes an active policy instrument. In our framework, the perceived precision of the central bank's macroeconomic assessment is a key determinant of market expectations and interest rate volatility. A perception that the assessment is highly precise implies that the published projections are considered less noisy and therefore more informative. When the central bank faces elevated uncertainty, communicating a highly precise signal may induce private agents to place excessive weight on central bank projections and to adjust insufficiently to fundamentals, thereby risking the entrenchment of misguided expectations. By the same token, when the central bank signals low confidence in its projections during periods of relative stability, this may also be counterproductive, as it could induce unnecessary volatility by undermining the anchoring role of its forecasts.

Although the optimal calibration of communication precision lies beyond the scope of this paper, our analysis points to important normative questions that warrant further investigation.

Related literature. This paper connects with and contributes to several strands of the literature.

First, it relates to recent studies that examine how financial markets incorporate macroeconomic news (Cieslak et al. 2024; Bauer et al. 2024; Bocola et al. 2024; Cuciniello 2024; Kroner 2025; di Pace et al. 2025). These works document that the

[7] In this respect, the central bank's approach is aligned with the ECB's conduct during 2023–2024, as characterised by President Lagarde in her 2024 Sintra address, in which she noted that "*looking at current data allowed us to identify the persistent components of inflation and account for structural changes that might have been missing from our forecast models*", Lagarde (2024).
[8] In what follows, we use "central bank projections" and "central bank signal" interchangeably, thus restricting the set of possible communication tools to the publication of macroeconomic projections.

sensitivity of interest rates to macroeconomic surprises varies over time, reflecting shifts in investor attention (Kroner 2025), uncertainty about the central bank's reaction function (Cieslak et al. 2024), or changes in the perceived monetary policy rule (Bauer et al. 2024; Bocola et al. 2024; Cuciniello 2024; di Pace et al. 2025). In line with this evidence, our paper contributes to the literature by highlighting the time-varying market responsiveness to news and emphasizing central bank communication as a key informational channel of the monetary policy transmission.

Second, the paper contributes to the literature on central bank communication and its impact on market interest rates. Closely related studies include Melosi (2017), Gardner et al. (2022), Ehrmann et al. (2019), Hansen et al. (2019) and Poli and Venturi (2025).

Melosi (2017) develops a general equilibrium model in which the central bank uses the policy rate to signal its views about macroeconomic developments to price setters, and studies the signalling effects of monetary policy on inflation expectations. We consider central bank information shocks – that do not necessarily coincide with movements in the policy rate – and focus on the implied market interest rate volatility.

Gardner et al. (2022) develop a sentiment index that captures descriptions of the state of the economy as reported by the Federal Open Market Committee and find that macroeconomic news has a bigger (smaller) effect on equity prices during bad (good) times as described by such sentiment index. Our analysis considers communication by the ECB that provides the markets with indications on how confident the central bank is on its own macroeconomic assessment.

Ehrmann et al. (2019) show that the sensitivity of sovereign bond yields to macroeconomic news is in general attenuated by forward guidance, although calendar-based guidance can have an amplifying effect. They rationalize these findings within a Bayesian learning framework, where the inflation coefficient in the interest rate rule influences the prior volatility of interest rates. Our analysis departs from their setting by focusing on a distinct policy environment – characterized by data dependence rather than forward guidance – and by introducing a central bank signal whose precision critically affects the responsiveness of market interest rates to macroeconomic news.

The role of central bank communication regarding economic uncertainty in influencing long-term interest rates via the term premium is explored in Hansen et al. (2019). In contrast, we investigate how central bank communication about the uncertainty around its own projections shapes the response of nominal interest rates to macroeconomic news.

Turning to the case of ECB data-dependence, Poli and Venturi (2025) analyse euro-area interest rates’ responses to US macroeconomic surprises, showing that market reaction was dampened during the ECB’s forward guidance phase, but became more pronounced once the ECB shifted to a data-dependent policy. They also find that monetary policy uncertainty, proxied by the dispersion in market rates, amplifies the impact of economic surprises. While related, our analysis focuses on euro-area macroeconomic news and provides a formal framework to assess how central bank communication shapes market responses to macroeconomic news.

Finally, our model is related to recent work on learning and monetary policy. Eusepi et al. (2025) and Crump et al. (2025), among others, study environments in which private agents learn about a drifting trend in inflation without full knowledge of the underlying structural model. As in our setting, agents rely on reduced-form approximations that may be misspecified, leading to learning dynamics that affect the transmission of monetary policy signals.

Closely related to our paper is Gáti and Handlan (2025), which models how a central bank communicates its noisy forecasts while taking into account its own uncertainty and the public's perception of the bank's uncertainty. We take a more positive approach, and study how central bank communication of its own uncertainty affects market interest rates reactions to news.

Outline. The structure of the paper is as follows. Section 2 presents motivating empirical evidence, documenting stylised facts on inflation projection errors, perceived inflation uncertainty, and the responsiveness of interest rate to inflation. Section 3 provides empirical results on the sensitivity of market interest rates to inflation news and explores the relationship between inflation uncertainty and central bank communication strategies. Section 4 introduces the theoretical framework, developing a stylised model to illustrate how data dependence affects market-implied interest rate volatility. Section 5 concludes.

1. Stylized facts

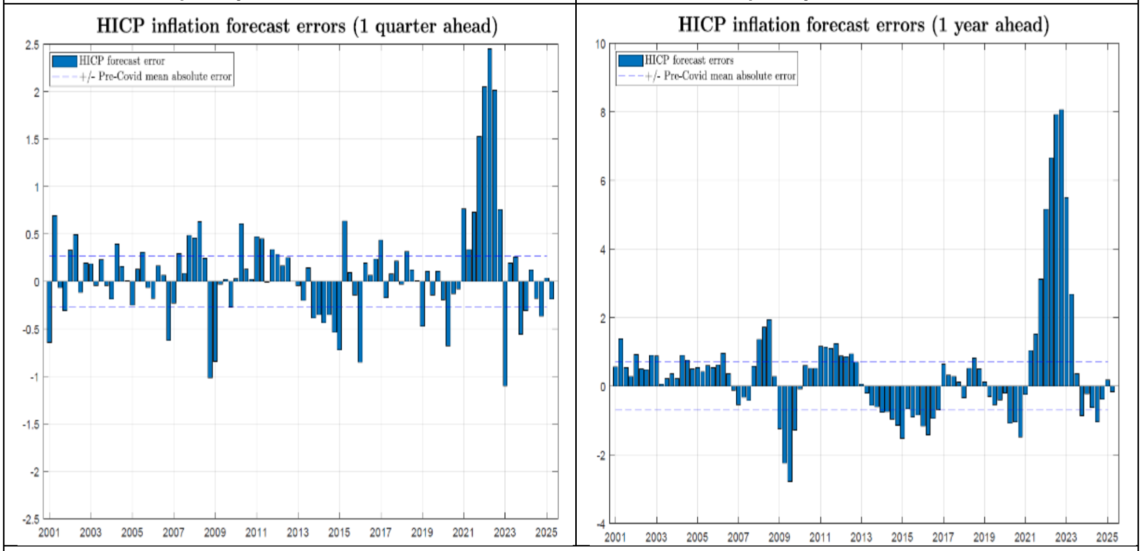
Inflation forecast errors**.** Before 2021, the ECB operated in an environment where short-term inflation forecast errors were generally small and showed no systemic bias (Figure 1). At longer horizons, forecast errors were at times more persistent, but their magnitude remained limited. Since early 2021, the ECB, like other international institutions and private forecasters, repeatedly underestimated inflation. These forecast errors reflected both mistaken assumptions about exogenous variables used in the projections – such as energy prices which turned out to be far above projections – and possible shifts in the underlying economic relationships – such as large and rapid shocks altering the slope of the Phillips curve (Benigno and Eggertsson 2023). Together, these factors increased uncertainty about key economic parameters and led the ECB to place more weight on learning from incoming data and past forecast errors (ECB, 2024b; Lane, 2024).

Since early 2023, the accuracy of the ECB's inflation assessments has improved markedly. Forecast errors became smaller in magnitude and no longer displayed the persistent bias observed in 2021-22, instead resembling an approximately i.i.d. process.

This improvement likely reflected the unwinding of the large and unusual shocks that had driven earlier forecast mistakes, together with the incorporation of updated information on energy prices, supply bottlenecks, and wage dynamics, which restored the reliability of the conditioning assumptions underpinning the projections.[9]

Figure 1: HICP inflation forecast errors of Eurosystem/ECB staff projections

a) 1-quarter horizon	**b) 4-quarter horizon**



Sources: authors' calculations, based on ECB Statistical Data Warehouse data. Latest observation: June 2025

Perceived inflation uncertainty and interest rate volatility. The rise in inflation since 2022 is reflected in the increasing uncertainty around individual inflation forecasts. Panel a of Figure 2 documents this development by presenting the mean of individual respondents' standard deviations in the ECB's quarterly Survey of Professional Forecasters (SPF) at the 1-year ahead horizons.[10]

This perceived inflation uncertainty is reflected in the responsiveness of market interest rates to inflation news. Panel b of Figure 2 documents the absolute daily change in 1-year OIS rates on German HICP release days[11]. These high-frequency rate movements isolate how markets update policy expectations in response to news,

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[9] See ECB (2024a).

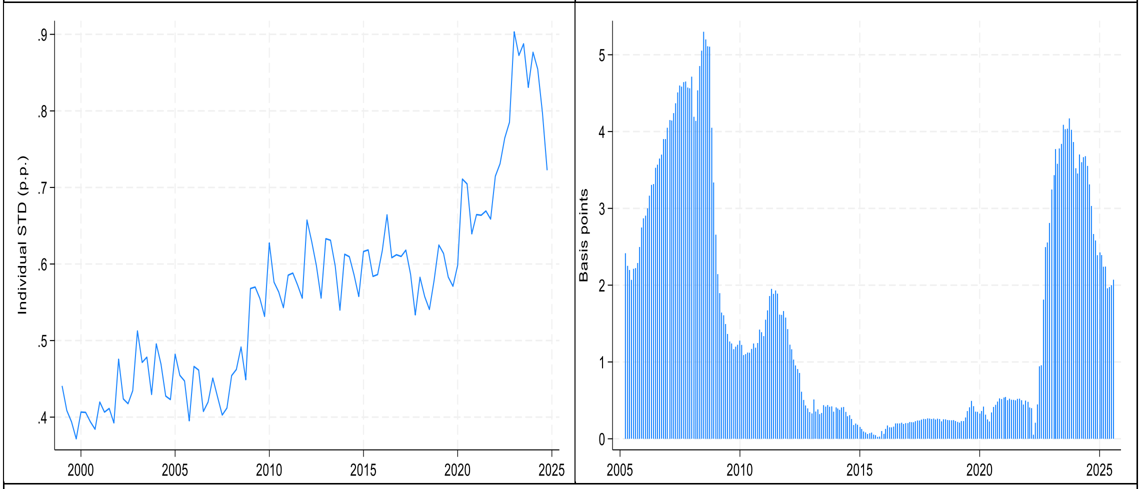
[10] In the SPF, each respondent provides a probability distribution over predefined inflation intervals. The mean of individual standard deviations isolates respondents' own predictive uncertainty, whereas the cross-sectional dispersion of point forecasts captures disagreement, a concept theoretically and empirically distinct from uncertainty (see Rich and Tracy 2010). Relying on the mean individual standard deviation follows standard practice in empirical analysis based on surveys (e.g. Boero, Smith, and Wallis 2008), as it avoids conflating heterogeneous beliefs with the uncertainty perceived by each forecaster.

[11] In the euro area, the staggered publication of national consumer price index releases reduces the informational content of the aggregate euro-area HICP figure, because much of the news is incorporated into asset prices before the aggregate release becomes available. Appendix 2 shows that national inflation surprises affect inflation linked swap (ILS) rates in proportion to the respective country weight in the HICP index, while the aggregate euro-area surprise becomes insignificant once national surprises are included as controls.

abstracting from lower-frequency macroeconomic dynamics. Periods with elevated perceived inflation uncertainty – such as the post-2008 environment and the post-pandemic recovery, both characterized by unusually large shifts in euro-area inflation forecasts (see ECB 2012 Monthly Bulletin; ECB 2021 Economic Bulletin) – coincide with sharper market reactions to incoming inflation data.

Figure 2 – Perceived inflation uncertainty and interest rate volatility

(a) perceived inflation uncertainty | **(b) interest rate volatility and inflation news**



Notes: Left panel: mean of the individual std of 1-year ahead inflation expectations reported by ECB SPF respondents. Quarterly data. Right panel: absolute daily changes in 1-year OIS rates on German inflation release days.

Communication on "learning" environment. In June 2022, the expression "data dependence" was introduced in the ECB Monetary Policy Statement (ECB, 2022b). As we have reported in Section 1, in explaining the rationale for such introduction, Lane (2024) explicitly referred to a high-learning environment and to the need to use new data within a Bayesian learning framework.

References to a learning approach in the use of incoming data under conditions of heightened uncertainty had already appeared in earlier speeches by ECB's Executive Board members and national central bank governors, albeit without being explicitly framed in terms of data dependence.[12]

To trace the evolution of communication signalling the use of incoming data to update forecasting models, we construct a monthly measure of the learning environment, (*LE*), using speeches delivered by ECB Executive Board members between 1999 and 2024. This measure is built from a predefined vocabulary associated with high-learning contexts in monetary policy communication, including the terms "forecast errors", "learning", "data-dependent", "underlying inflation", "data driven" and "meeting-by-meeting." Figure 3a documents the monthly average number of these

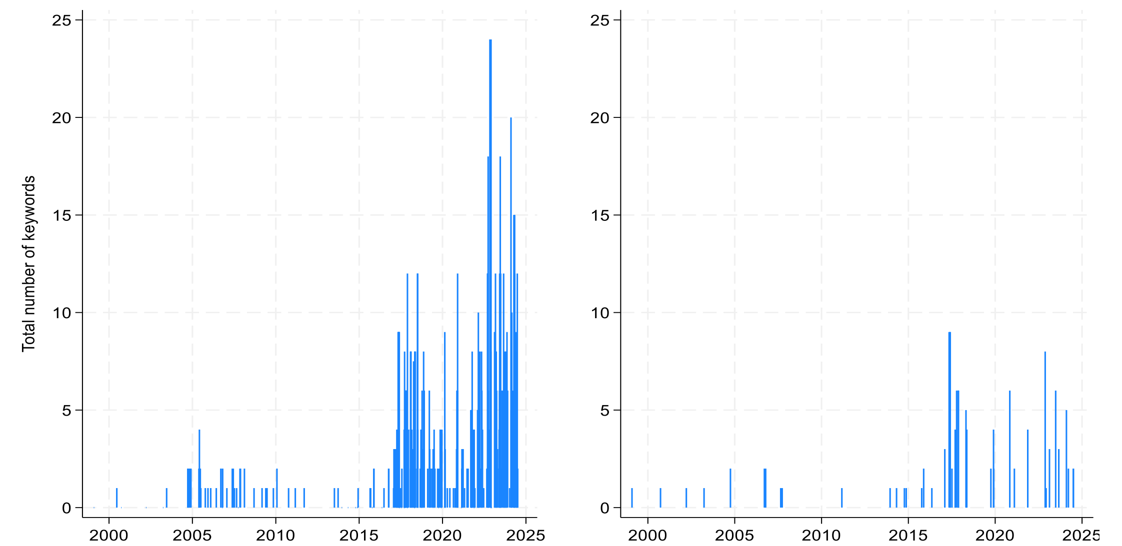
[12] For instance, in 2010 President Trichet affirmed that "*We may need to consider a richer characterisation of expectation formation. Rational expectations theory has brought macroeconomic analysis a long way over the past four decades. But there is a clear need to re-examine this assumption. Very encouraging work is under way on new concepts, such as learning and rational inattention*.", Trichet (2010).

keywords appearing in each speech. Additional details on the construction of the text-based measures are provided in Appendix 3.

In some instances, members of the ECB's Executive Board or national central bank governors stressed that the central bank does not react to individual data releases, with the intention of underlining the broad-based nature of the inflation assessment and possibly a greater confidence in the central bank's forecasting framework (and, arguably, a less intense learning activity). In July 2024, for instance, president Lagarde clarified that "*… while the flow of new information constantly adds to and improves our picture of medium-term inflation, we are not pushed around by any specific data point. Data dependence does not mean data point dependence*" (Lagarde, 2024). Figure 3b reports the monthly frequency of the term "No/Not data point" co-occurring with "monetary policy".[13]

Figure 3 – Central bank signal of a high (or low) learning environment

(a) Learning indicator (LE) | **(b) No-data-point indicator (NDP)**



Notes: The left panel displays the monthly average number of words signalling a "learning environment," while the right panel shows the monthly average number of words indicating "no data-point dependency" in monetary policy speeches delivered by ECB Executive Board members between 1999 and 2024.

2. Empirical Results

In Figure 2 we considered an encompassing measure of perceived inflation uncertainty; in what follows we will focus on a specific facet of uncertainty, namely the one that surrounds ECB assessment of the macroeconomic outlook, as the precisions of its forecasts can be very different in different periods (see Figure 1).

[13] For instance, in 2017, ECB President Draghi stated in a Hearing of the Committee on Economic and Monetary Affairs of the European Parliament: "*our monetary policy strategy prescribes that we should not react to individual data points and short-lived increases in inflation*."

Specifically, this section examines whether the reaction of market interest rates to inflation news and to releases of the central bank assessment of macroeconomic developments changes when market participants perceive the central bank to be operating in a high-learning regime characterised by elevated uncertainty about its assessment of the economic outlook.

Sensitivity of market interest rates to inflation news and central bank assessment of macroeconomic developments in a high-learning environment can be assessed by estimating the following equation by OLS:

$$\Delta i_t = \beta_0 + \beta_1 \varepsilon_t^{CB} + \beta_2 LE_{t-1} + \beta_3 LE_{t-1}\varepsilon_t^{CB} + \beta_4 \varepsilon_t^{\pi} + \beta_5 LE_{t-1}\varepsilon_t^{\pi} + \beta_6 D_{t-1}^{NDP} + \beta_7 D_{t-1}^{NDP}\varepsilon_t^{CB} LE_{t-1} + \beta_8 D_{t-1}^{NDP}\varepsilon_t^{\pi} LE_{t-1} + u_t$$

where Δi_t denotes the daily change in the 1-year OIS rate; ε_t^{π} captures inflation surprises in German HICP inflation flash releases, computed as the realised minus expected inflation rate (Bloomberg survey), normalised by the sample standard deviation of this difference, and used as a proxy for euro-area inflation surprises;[14] ε_t^{CB} denotes the ECB information shock constructed following Jarocinski and Karadi (2020), normalized by its sample standard deviation.[15] Although these shocks do not exactly coincide with the market surprises associated with the publication of ECB projections – because they also reflect information conveyed in the press release and are available even for meetings without new projections – they remain the most reliable proxy for the type of informational surprise we want to capture, as they are purged of the confounding effect of the simultaneous policy-rate decision.[16]

LE_{t-1} denotes the learning-environment indicator in month t-1, divided by its sample standard deviation and is interacted with inflation news or central bank information shocks to allow the sensitivity of rates to these shocks to vary systematically with the perceived learning environment. D_{t-1}^{NDP} is a dummy equal to 1 when the 'no-data-point' indicator in month t−1 is non-zero, and 0 otherwise The specification also includes triple interactions of D_{t-1}^{NDP} and LE_{t-1} with inflation surprises and ECB information shocks. These coefficients capture how the effect of inflation and information surprises changes when both conditions hold simultaneously – that is, when

[14] Similar results are obtained when using inflation surprises from other large euro-area countries.

[15] Information shocks are identified by observing an opposite-sign response of interest rates and stock market prices within a very short time window around ECB Governing Council announcements. Specifically: the joint 30-minute co-movement of the 3-month OIS rate, and the EURO STOXX 50 index is analyzed in a window from 5 minutes before to 25 minutes after the press release. Results are robust to including 1-year OIS rates, as well as to enlarging the window to incorporate the press conference interval when the ECB's macroeconomic projections are released only during the press conference rather than in the press statement. See also Appendix 4 for a plot of these shocks.

[16] The ECB Governing Council meets to adopt monetary policy decisions 8 times a year, but only in half of these meetings new macroeconomic projections are published.

the ECB signals that it is operating in a learning environment, but it is not reacting to individual data releases. Intuitively, the triple interaction identifies whether the marginal effect of inflation news (or information shocks) becomes stronger or weaker when these two sources of uncertainty coexist, compared with what would be implied by each factor in isolation; u_t is a residual.

Table 1 reports the estimated sensitivity of daily changes in the one-year OIS rate to inflation surprises and ECB information surprises as a function of LE_{t-1}. The baseline specification in column 1 shows that interest rate changes are positively correlated with both types of surprises. The correlation with inflation surprises increases when the ECB signals that it is operating in a high-learning environment, while the correlation with ECB information surprises falls. This pattern indicates that investors treat inflation surprises as more informative about future policy when the ECB faces greater uncertainty about its own macroeconomic assessment, and that they discount information shocks under the same conditions.

Table 1 – ECB communication and sensitivity of expected interest rates to inflation and central bank information surprises

	(1)	(2)
ϵ^{CB}	0.477**	0.440**
	(0.205)	(0.191)
$\epsilon^{CB} \times LE(t-1)$	-0.277***	-0.268***
	(0.0467)	(0.0423)
ϵ^{π}	0.366**	0.396**
	(0.162)	(0.170)
$\epsilon^{\pi} \times LE(t-1)$	0.321***	0.374***
	(0.101)	(0.0707)
$D^{NDP}(t-1) \times \epsilon^{CB} \times LE(t-1)$		0.314*
		(0.158)
$D^{NDP}(t-1) \times \epsilon^{\pi} \times LE(t-1)$		-0.308***
		(0.114)
N	484	484

Notes: Standard errors are robust to heterogeneity and autocorrelation.

Column (2) introduces the interactions with D_{t-1}^{NDP}, which capture how ECB communication stating that policy is *not dependent on single data points* affects the propagation channels. The triple interaction $D_{t-1}^{NDP}\varepsilon_t^{CB}LE_{t-1}$is positive and statistically different from zero. This indicates that in months following such communication, markets react more strongly to central bank information shocks also when the broader data-dependence indicator LE_{t-1} is high. Conversely, the coefficient of $D_{t-1}^{NDP}\varepsilon_t^{\pi}LE_{t-1}$ is negative and statistically different from zero. This suggests that no-data-point communication dampens the amplification effect of inflation news on expected interest rates. In other words, conditional on the central bank operating in a "learning environment", stating that its decisions are not driven by individual data releases leads markets to place greater weight on central bank communication relative to high-frequency macro data.

As a robustness check, we re-estimate the model with the LE_{t-1} measure by (i) augmenting the specification with interactions of inflation surprises and the ECB information shock with several measures of aggregate uncertainty[17] and (ii) replacing the baseline LE_{t-1}indicator with an alternative measure capturing the frequency of the terms "uncertainty", "uncertain", and "risk" in Executive Board speeches.

Under specification (i), the coefficients on these additional interaction terms are generally small and statistically insignificant, indicating that the amplification of the response to inflation news in high-learning periods is not driven by broader uncertainty conditions such as financial volatility, energy-price volatility, or supply-chain pressures. Under specification (ii), the interaction term based on the alternative LE_{t-1} measure is not statistically significant, suggesting that financial markets form perceptions of macroeconomic uncertainty independently of generic references to "uncertainty" in central-bank communication. This result may appear surprising, given that since 2022 the ECB has frequently used references to "uncertainty" and "data dependence" in close proximity. However, the evidence shows that markets distinguish between the two: while references to "uncertainty" reflect broad macroeconomic conditions, explicit mentions of "no data-point dependence" provide more operational guidance about the policy reaction function.

3. Imperfect Information and central bank communication

The empirical results documented in the previous section can be interpreted through the lens of a simple model of imperfect information, built around two key relationships. First, the central bank follows a policy rule whereby the nominal interest rate responds to current inflation,

$$i_t = \gamma_\pi \pi_t, \tag{1}$$

where i_t is the interest rate, π_t is the inflation rate and γ_π is the monetary policy response coefficient.

[17] Specifically, we use the euro-area equity volatility index (VSTOXX), the three-month volatility of the log price of oil and gas, the annual change in food prices, the New York Fed's Global Supply Chain Pressure Index (GSCPI; see Benigno et al. 2022), and the European policy-related economic uncertainty (EPU) index constructed from newspaper articles discussing policy uncertainty.

Inflation dynamics follow a forward-looking Phillips curve,[18]

$$\pi_t = \alpha \mathbb{E}^P(\pi_{t+1}|\mathcal{I}_{t-1}^P) - \beta i_t + e_t \tag{2}$$

where $\mathbb{E}^P(\pi_{t+1}|\mathcal{I}_{t-1}^P)$ denotes the *t+1* inflation expectations formed by private agents using their *t-1* information set, $\mathcal{I}_{t-1}^P$ (which will be formally defined below), and e_t is a cost-push shock with both transitory and persistent (i.e. AR(1)) components,

$$\begin{cases} e_t = \omega_t + u_t, & u_t \sim N(0, \tau_u^{-1}) \\ \omega_t = \rho_\omega \omega_{t-1} + \varepsilon_t^\omega, & \varepsilon_t^\omega \sim N(0, \tau_\omega^{-1}) \end{cases} \tag{3}$$

where u_t and ε_t^ω are *i.i.d.* and serially uncorrelated.

Assuming rational expectations and full information, the minimum state variable (MSV) solution implies:

$$\begin{cases} \pi_t = A\omega_{t-1} + B\varepsilon_t^u & \varepsilon_t^u \sim N(0, \tau_u^{-1} + \tau_\omega^{-1}) \\ A = (1 + \beta\gamma_\pi - \alpha\rho_\omega)^{-1}\rho_\omega & B = (1 + \beta\gamma_\pi)^{-1} \end{cases} \tag{4}$$

We now relax the assumption of full information. The central bank observes inflation and the expectations that feed into the Phillips curve, but it cannot observe separately the persistent and transitory components of the cost-push shock. The private sector, in turn, observes inflation and a noisy central bank signal about future inflation, but lacks knowledge of the structural Phillips curve.[19]

Private agents assume that inflation is composed of a latent, slow-moving component (i.e., underlying inflation), θ_t, and white noise, ξ_t:[20]

$$\begin{cases} \pi_t = \theta_t + \xi_t & \xi_t \sim N\left(0, \tau_\xi^{-1}\right) \\ \theta_t = \rho_\theta \theta_{t-1} + \varepsilon_t^\theta & \varepsilon_t^\theta \sim N\left(0, \tau_\theta^{-1}\right) \end{cases} \tag{5}$$

The central bank publishes its own projection for inflation at time *t+1* based on time-*t* information set, $\mathbb{E}^{CB}(\pi_{t+1}|\mathcal{I}_t^{CB})$, and it communicates the degree of confidence it assigns to this forecast.[21] The private sector assumes that the central bank shares the same model of inflation (5), and hence considers the projections to be derived as:

[18] This formulation is equivalent to the New Keynesian Phillips curve under a simplified formulation of the demand side of the economy, i.e. under the assumption that in the IS curve the output gap x_t depends only on the contemporaneous real interest rate: $x_t = -\sigma(i_t - \pi_t)$.

[19] We assume that private agents and financial markets have the same knowledge.

[20] This slow-moving underlying inflation is akin to a reduced-form drift, as in Eusepi et al. (2025).

[21] In practice, the central bank may publish a fan chart – that is, a bell-shaped distribution around the expected value, or it may provide qualitative information about its data-dependence approach (i.e., backward-looking or forward-looking type). A backward-looking approach is typically associated with greater uncertainty and lower confidence in its projections.

$$\mathbb{E}^{CB}(\pi_{t+1}|\mathcal{I}_t^{CB}) = \mathbb{E}^{CB}(\theta_{t+1}|\mathcal{I}_t^{CB}) = \rho_\theta \mathbb{E}^{CB}(\theta_t|\mathcal{I}_t^{CB}) = \rho_\theta(\theta_t + \eta_t)$$

where η_t is a reduced form noise capturing the central bank's estimation error of θ_t. In other words, the projection is interpreted by the private sector as a noisy signal of underlying inflation at time t, θ_t.

In what follows, to have an unbiased (in the perception of the private sector) signal of θ_t, we will adopt as the central bank's signal the linear transformation of the projections $\pi_t^{CB} \equiv \mathbb{E}^{CB}(\pi_{t+1}|\mathcal{I}_t^{CB})/\rho_\theta$, which the private sector perceives to have the following form:

$$\pi_t^{CB} = \theta_t + \eta_t \qquad \eta_t \sim N(0, \tau_\eta^{-1}) \tag{6}$$

We assume for simplicity that ξ_t and η_t are considered by the private sector as uncorrelated.[22] The parameter τ_η captures the (perceived) precision of the signal and in this simple model it reflects the announced central bank's confidence in its own projections. It is the theoretical counterpart of the textual indices used in the empirical part (Section 3) and is assumed to be constant in this simple model.

The timing of the model unfolds as follows (Figure 4). At the beginning of time t, private agents make their decisions based on the information available at $t-1$. After these decisions are implemented, agents observe the relevant signals – namely, actual inflation and the central bank's projection – and update their prior on underlying inflation, θ_t, using Bayes' rule applied to the corresponding state space model. This yields the posterior distribution of θ_t, and updated estimates of θ_{t+k}, for any horizon k. Formally, the information set of the private sector at time t, is given by:

$$\mathcal{I}_t^P \equiv \{\pi_r, \pi_r^{CB} | r \leq t\}.$$

In contrast, as discussed above, we assume the central bank has full knowledge of equations (1) and (2) and observes both realized inflation and the private-sector expectations that feed into the Phillips curve. However, it faces an informational friction too: it cannot distinguish between the persistent and transitory components of the cost-push shock – that is, it observes e_t, but cannot disentangle ω_t from u_t.

As a result, in forecasting inflation, the central bank solves a standard signal-extraction problem, based on the state-space system defined by equations (2) and (3). Its information set is defined as:

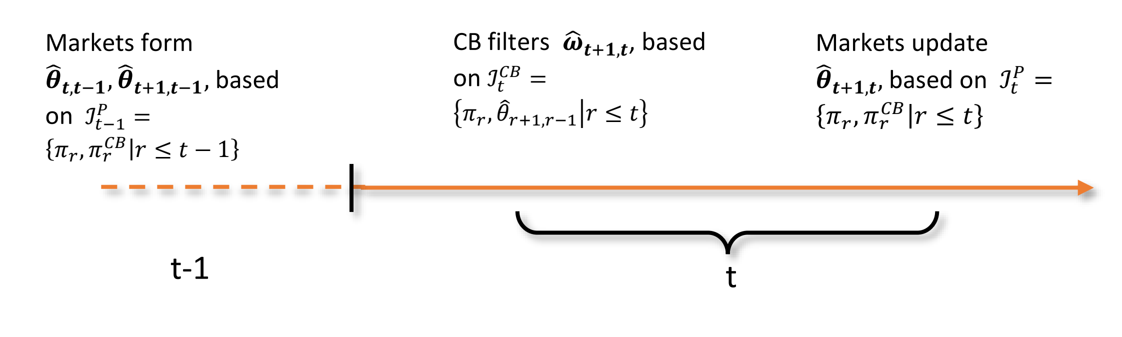
$$\mathcal{I}_t^{CB} \equiv \{\pi_r, \hat{\theta}_{r+1,r-1} | r \leq t\}$$

[22] In a more realistic framework, we could assume that they are treated by the private sector as positively correlated, but that would not affect our main result: as long as the relative variance of ξ_t and η_t is allowed to change, that would yield qualitatively the same results that we show below in Proposition 1.

where $\hat{\theta}_{r+1,r-1}$ denotes the private sector's forecast of θ_{r+1}, based on information available in time *r-1*, that is:

$$\hat{\theta}_{r+1,r-1} \equiv \mathbb{E}^P(\theta_{r+1}|\mathcal{I}^P_{r-1})$$

Figure 4 – The timing of the model



We now focus on the private sector's filtering problem. Upon observing π_t and π_t^{CB}, agents update their estimate of the latent state using a Kalman filter applied to the state-space model (5). The updating equations are given by:

$$\begin{cases} \hat{\theta}_{t+1,t} = \rho_\theta \hat{\theta}_{t,t-1} + \rho_\theta \omega_{\tau_\xi,t} \varepsilon_t^\pi + \rho_\theta \omega_{\tau_\eta,t} \varepsilon_t^{CB} \\ P^\theta_{t+1,t} = \rho_\theta^2 \left(\left(P^\theta_{t,t-1} \right)^{-1} + \tau_\xi + \tau_\eta \right)^{-1} + \tau_\theta^{-1} \end{cases} \tag{7}$$

where ε_t^π and ε_t^{CB} denote the innovation (surprises) in realized inflation and in central bank's signal

$$\begin{cases} \varepsilon_t^\pi = \pi_t - \hat{\theta}_{t,t-1} \\ \varepsilon_t^{CB} = \pi_t^{CB} - \hat{\theta}_{t,t-1} \end{cases} \tag{8}$$

and

$$\begin{cases} \omega_{\tau_\xi,t} = \frac{\tau_\xi}{\left(P^\theta_{t,t-1}\right)^{-1} + \tau_\xi + \tau_\eta} \\ \omega_{\tau_\eta,t} = \frac{\tau_\eta}{\left(P^\theta_{t,t-1}\right)^{-1} + \tau_\xi + \tau_\eta} \end{cases} \tag{9}$$

4.1. Sensitivity of market interest rates to inflation news and central bank communication

The following proposition formalizes the notion that the more "confident" the central bank is perceived to be in its projections – i.e., the more precise its signal (the higher τ_η) – the more weight the private sector places in central bank projections, and the less on realized inflation.

PROPOSITION 1. Assume that market participants observe the central bank's interest rate rule (1), form expectations about underlying inflation, θ_t, using the Kalman filter (7), and that the expectation hypothesis of the term structure holds. Then, their responsiveness to the central bank signal is increasing τ_η, while the responsiveness to inflation news is decreasing in τ_η.

Proof.

Under the expectations-hypothesis (EH) the continuously compounded yield on an *n*-period zero-coupon bond equals the average of expected short rates:

$$r_t^{(n)} = \frac{1}{n}\sum_{k=0}^{n-1} \mathbb{E}^P\left(i_{t+k}|\mathcal{I}_t^P\right), \qquad n \geq 1$$

Since market participants know the monetary policy rule $i_t = \gamma_\pi \pi_t$ and form inflation expectations using the Kalman filter (7), we can write:

$$i_{t+k}|\mathcal{I}_t^P \sim N\left(\gamma_\pi \rho_\theta^{k-1}\hat{\theta}_{t+1,t}, {\gamma_\pi}^2\left(\rho_\theta^{2(k-1)}P_{t+1,t}^\theta + \tau_\theta^{-1}\sum_{j=0}^{k-2}\rho^{2j} + \tau_\xi^{-1}\right)\right)$$

To establish the result, it suffices to examine the expectations of policy rates *k*-periods ahead (with $k \leq 1$), and their sensitivity to signals.

The revision in the expectation of i_{t+k} between time $t-1$ and t is:

$$i_{t+k,t} - i_{t+k,t-1} = \gamma_\pi \rho_\theta^k \left(\frac{\tau_\xi}{\left(P_{t,t-1}^\theta\right)^{-1} + \tau_\xi + \tau_\eta}\varepsilon_t^\pi + \frac{\tau_\eta}{\left(P_{t,t-1}^\theta\right)^{-1} + \tau_\xi + \tau_\eta}\varepsilon_t^{CB}\right).$$

Differentiating the expression with respect to ε_t^{CB} yields:

$$\begin{aligned}\frac{\partial}{\partial \varepsilon_t^{CB}}\left(i_{t+k,t} - i_{t+k,t-1}\right) &= \gamma_\pi \rho_\theta^k \frac{\tau_\eta}{\left(P_{t,t-1}^\theta\right)^{-1} + \tau_\xi + \tau_\eta} \\ &= \gamma_\pi \rho_\theta^k \frac{1}{\left(\left(P_{t,t-1}^\theta\right)^{-1} + \tau_\xi\right)/\tau_\eta + 1},\end{aligned}$$

which is increasing in τ_η (as a more precise central bank signal increases the weight on ε_t^{CB}).

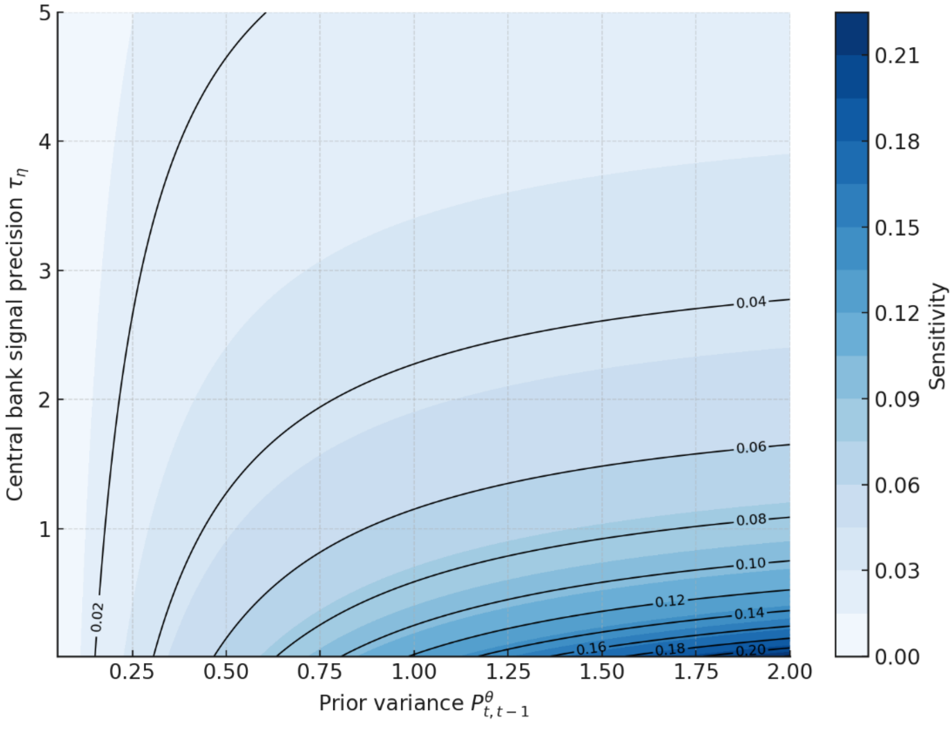
Instead, differentiating the expression with respect to ε_t^π yields:

$$\frac{\partial}{\partial \varepsilon_t^{\pi}}\left(i_{t+k,t} - i_{t+k,t-1}\right) = \gamma_\pi \rho_\theta^k \frac{\tau_\xi}{\left(P_{t,t-1}^\theta\right)^{-1} + \tau_\xi + \tau_\eta},$$

which is decreasing in τ_η (as a more precise central bank signal reduces the weight on ε_t^π). ■

Figure 5 displays how the sensitivity of market interest rate to an inflation surprise varies with both the prior precision $\left(P_{t,t-1}^\theta\right)^{-1}$ and the perceived precision of the central bank's projections, τ_η. The darker areas indicate higher sensitivity. Two mechanisms emerge. First, for a given prior precision, higher τ_η reduces sensitivity: when projections are perceived as more reliable, markets place less weight on realized inflation in updating expectations, thereby dampening the response of yields. Second, for a given τ_η, higher $\left(P_{t,t-1}^\theta\right)^{-1}$ also lowers sensitivity, as a more informative prior reduces the marginal role of new information. The joint effect implies that market interest rates are most responsive when priors are imprecise and central bank projections are seen as noisy, while it reacts least when agents have precise priors and perceive the projections as reliable. This illustrates how the interaction between private information and central bank signals shapes the volatility of longer-term interest rates.

Figure 5 – Isocurves of interest rate sensitivity to inflation news in ($\boldsymbol{P_{t,t-1}^\theta}$, $\boldsymbol{\tau_\eta}$) space



Note: The figure shows the sensitivity of the two-year yield to an inflation surprise as a function of the prior precision τ_θ (x-axis) and the perceived precision of the central bank's projections $\boldsymbol{\tau_\eta}$ (y-axis). Sensitivity is highest when both priors are imprecise and projections are perceived as noisy, and it decreases as either prior information or the central bank's projections are regarded as more reliable. The parameter values used in the simulations are: n=2, γ_π = 1.5, α = 0.5, β = 0.5, $\rho_\theta = \rho_\omega$ = 0.9, τ_ω^{-1} = 1.5, $\tau_\xi = \tau_u$ = 0.1. The variances P_0^θ and P_0^ω are initialized to τ_θ^{-1} and τ_ω^{-1}.

These theoretical predictions align closely with our empirical findings in Section 3. There, we show that revisions in market interest rates – measured via changes in OIS rates – respond less strongly to surprises in the assessment of the macroeconomic outlook provided by the central bank, when the central bank itself communicates to be less confident on this assessment, and more strongly to inflation surprises. Specifically, the empirical coefficient on the "Learning Environment" (LE_t) communication is positive, consistent with the interpretation that a high value of LE_t corresponds to a low signal's precision, "learning mode" regime — i.e., a low τ_η. By contrast, a high value for the "No-Data-Point" indicator, NDP_t, implies higher precision. This is precisely the mechanism described in the first equation of (7), where lower τ_η increases the sensitivity of beliefs to incoming data.

4.2. Discussion of Future Extensions and Policy Trade-Offs

Even in its simple formulation, the model captures the fact that market interest rates volatility and responsiveness to news shift endogenously depending on how heavily agents weight central bank communication relative to other sources of information. While it provides a useful benchmark to study the interaction between communication and market expectations, several extensions could enrich the analysis. We leave them for future research.

First, the precision of the central bank's signal could be modelled as time-varying, reflecting shifts in forecasting quality or in the degree of macroeconomic uncertainty. Allowing for such dynamics would capture the idea that in tranquil periods, when models perform well, projections are perceived as more reliable, while during turbulent phases (for example, due to a sequence of large shocks), if the quality of central bank projections degrades, they may be regarded as noisier. Introducing time variation in signal precision would therefore generate richer state-dependent dynamics, with market sensitivity to news and the volatility of interest rates varying endogenously with the evolving credibility of the central bank's assessments. This extension could also help interpret observed changes in market reactions across different regimes, for example the stronger responsiveness documented during episodes of repeated forecast errors and heightened uncertainty.

Second, we could model how the private sector *perception* of the central bank's signal precision is formed. In this paper, we have implicitly assumed that any central bank announcement on τ_η is taken at face value by the private sector (or, equivalently, that τ_η is observable).[23] Instead, we could assume that it is an unobserved variable, and that the private sector has to form beliefs not just about future inflation, but also about the reliability of the central bank forecasts themselves, creating a two-layer learning

[23] For a model where there is a mismatch between the public and central bank's interpretation of how confident the bank is of its own announcements, see Gáti and Handlan (2025).

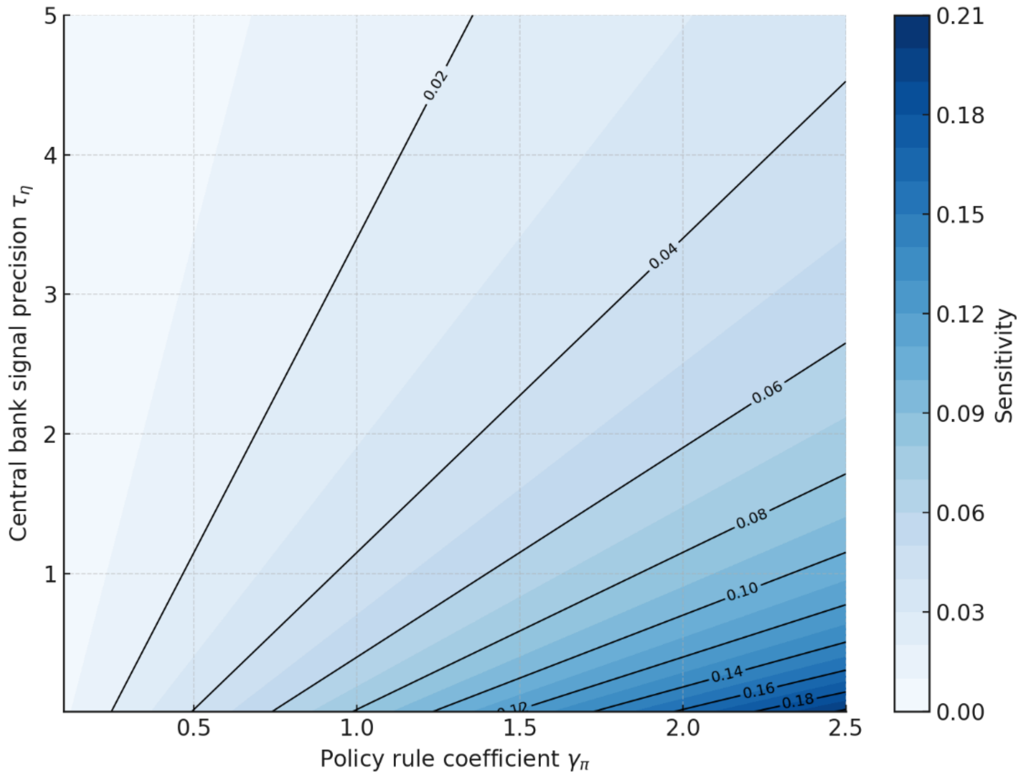
problem. In forming this belief on τ_η, the private sector might use as inputs not only central bank communication, but also observable variables like the variance of past prediction errors of central bank's projections. In such a setting, central bank statements could be interpreted as signals on both dimensions: the outlook for inflation and the credibility of the tools used to assess it. This extension would provide a more realistic representation of how communication shapes expectations, since in practice market participants often have to infer both the central bank's view of the economy and the degree of confidence it places in that view. It would also open the door to analyzing how misperceptions about forecast reliability may amplify volatility or distort the transmission of policy signals.

Third, the framework could be extended to examine the joint use of the policy coefficient on inflation in the interest rate rule, γ_π, and the perceived precision of the central bank's projections, τ_η, as complementary instruments of monetary policy. For instance, one could analyze for a given value of γ_π the level of τ_η that delivers a specific degree of market sensitivity to inflation news, or equivalently the trade-offs between aggressiveness in the policy rule and the reliability attributed to the central bank's projections.

Figure 6 illustrates this idea by plotting isocurves of sensitivity in the (γ_π, τ_η) space. Each curve corresponds to a constant sensitivity of market interest rate revisions to inflation surprises. The figure shows that higher values of γ_π tend to increase sensitivity, while higher values of τ_η tend to reduce it. Hence, combinations of a more aggressive policy rule (larger γ_π) and projections perceived as more precise (larger τ_η) may yield the same market responsiveness. This highlights a policy trade-off: if projections are perceived as less precise, a more moderate policy rule may help limit volatility; conversely, a stronger policy response would require that projections be regarded as sufficiently reliable in order to avoid excessive market reactions. However, a thorough analysis of this trade-off requires a general equilibrium approach: even if γ_π increases sensitivity, it might ensure more stable prices, hence reducing the average size of inflation news; the overall effect on inflation volatility is therefore ambiguous.

Finally, the framework could be employed to address normative questions, such as the optimal calibration of communication precision across different states of the economy, or the welfare costs arising when agents simultaneously learn about fundamentals and about the reliability of central bank projections. A prerequisite for such an analysis is to specify explicitly the information set of the central bank, since alternative assumptions regarding informational advantages or frictions can substantially alter the trade-off between stabilizing interest rate volatility and preserving credibility across different regimes.

Figure 6 – Isocurves of interest rate sensitivity to inflation news in (γ_π, τ_η) space



Note: The figure plots combinations of the policy rule coefficient $\boldsymbol{\gamma_\pi}$ and the perceived precision of central bank projections $\boldsymbol{\tau_\eta}$ that yield the same sensitivity of market interest rates revisions to inflation surprises. Higher $\boldsymbol{\gamma_\pi}$ raises sensitivity, while higher $\boldsymbol{\tau_\eta}$ reduces it, implying that more aggressive policy rules require more precise projections to maintain a given level of market responsiveness. The parameter values used in the simulations are: τ_θ = 1.0, α = 0.5, β = 0.5, $\rho_\theta = \rho_\omega$ = 0.9, τ_ω^{-1} = 1.5, $\tau_\xi = \tau_u$ = 0.1. The variances P_0^θ and P_0^ω are initialized to τ_θ^{-1} and τ_ω^{-1}.

5. Conclusions

This paper has examined how central bank communication on the confidence attached to projections influences the sensitivity of financial markets to macroeconomic news. The empirical evidence for the euro area shows that when markets perceive the central bank to operate in a high-learning environment, they react less strongly to the release of central bank information on the macroeconomic outlook, and more strongly to inflation surprises. A simple model of Bayesian learning with imperfect information rationalizes this finding by showing how the perceived precision of central bank projections governs the weight private agents place on central bank's signals relative to incoming data.

The results indicate that communication about the confidence in projections should not be viewed solely as a matter of transparency. Rather, it may shape the responsiveness of market expectations and the volatility of interest rates, thereby becoming an additional policy instrument. A key policy trade-off emerges: while a signal perceived as highly precise can stabilize expectations in tranquil times, it may also encourage markets to underreact to fundamentals when uncertainty is elevated. Conversely, signalling low confidence can improve market discipline in turbulent periods but risks adding unnecessary volatility when the outlook is stable.

While the normative question of how central banks should optimally communicate the confidence on their macroeconomic projections (i.e., the precision of their signals) remains outside the scope of this paper, it represents a promising direction for future research.

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Appendix 1 - Data dependence in the communication strategies of the ECB and the Federal Reserve.

The expression "data dependence" was first employed in September 2013, by the Federal Open Market Committee (FOMC), in reference to the future pace of asset purchases under the QE program. In their statement, the FOMC noted that "*participants generally were satisfied that investors had come to understand the data-dependent nature of the Committee's thinking about asset purchases*" (FOMC, 2013a). In October 2013, the term was employed to differentiate between a state-contingent approach to QE and a calendar-based possibility. The latter was deemed to be "*counter to the data-dependent, state-contingent nature of the current asset purchase program*" (FOMC, 2013b).

In September 2014, the term was employed in discussing about future policy rate decisions. The FOMC participants agreed that the timing of the first increase in the federal funds rate and the appropriate path of the policy rate thereafter would depend on incoming economic data and their implications for the outlook. It was observed that "*the reference to 'considerable time' in the current forward guidance could be misinterpreted as a commitment rather than as data-dependent*" (FOMC, 2014a). In December 2014, the Committee reiterated that future policy rate decisions would be data dependent. Furthermore, it clarified the meaning of its "forward looking" approach in terms of the expected evolution of macro variables and ex-post realised values. The Committee's members agreed that "*policy decisions would remain data dependent*" and they included wording in the statement noting that "*if incoming information indicated faster progress towards the Committee's employment and inflation objectives than the Committee expected, then increases in the target range for the federal funds rate would have occurred sooner than anticipated*" (FOMC, 2014b). In January 2015, the Committee further clarified that the concept of data dependence had to be used in order to inform the market that its forward guidance on policy rates was not calendar-dependent but state-dependent ("*policy decisions will be data dependent, and that unanticipated economic developments could therefore warrant a path of the federal funds rate different from that currently expected by investors";* FOMC, 2015).

In January 2016, the President of the St. Louis Fed, J. Bullard, talked about the forward-looking nature of data dependence, noting that "*not all data points imply a change in the stance, but only those that are (ex-post) unexpected and they affect future path of variables that are in the objective function of the central bank since monetary policy operates with long and variable lags*" (Bullard, 2016). He also connected for the first time the data-dependence to the concept of uncertainty and signal extraction asserting that "*every observation on the economy contains a certain amount of signal and a certain amount of noise. The art of policymaking includes separating the signal from the noise*".

Similarly, in October 2018, Vice Chairman R.H. Clarida provided a dual motivation for the use of data dependence in setting the path of the federal funds rate.[24] According to the first motivation, the monetary policy reaction is data dependent in the sense that incoming data reveal at the time of each FOMC meeting where *the economy is* at the time of each meeting relative to the goals of monetary policy. A second sense in which monetary policy should be data dependent comes into play when key parameters that describe the structure of the economy are unknown. In this case incoming data can reveal signals that will enable the central bank to update its estimates of the key parameters in order to obtain its best projections of where the economy is heading ("*As I have already stressed, r* and u* are uncertain, and I believe we should continue to update our estimates of them as new data arrive*."; Clarida, 2018).

In October 2019 Chairman Powell discussed the dual function of data dependence, emphasising that in an uncertain environment data dependence implies a learning process in order to *"sort out in real time, as best we can, what the profound changes underway in the economy mean for issues such as the functioning of labor markets, the pace of productivity growth, and the forces driving inflation"* (Powell, 2019).

The ECB also referred to data dependence in its official communication in the most recent years. In April 2022, in the context of considerable economic uncertainty, the ECB stated that future policy decisions "*will depend on the incoming data*" (ECB, 2022a). In June 2022, the expression "data dependence" was explicitly introduced in the Monetary Policy Statement (ECB, 2022b). In explaining the reasons for introducing data dependence in the Monetary Policy Statement, Phillip Lane in 2024 affirmed that *"the June monetary policy statement added "data dependence" to this list [optionality, gradualism, and flexibility]. […] In particular, the conjunctural environment could be interpreted as a "high learning" setting in which an unusually-wide set of future inflation and growth paths could be envisaged, such that Bayesian updating on the basis of incoming data would be an essential element in a disciplined approach to policy calibration*" (Lane, 2024).

In March 2023, the ECB once again explicitly referenced uncertainty, stating that the elevated level of uncertainty reinforced the importance of a data-dependent approach to the Governing Council's policy rate decisions. It is noteworthy that the ECB explicitly stated in the same GC that data dependence should be interpreted in terms of its reaction function in three dimensions: "*its assessment of the inflation outlook in light of the incoming economic and financial data, the dynamics of underlying inflation, and the strength of monetary policy transmission*" (ECB, 2023).

[24] Clarida (2018): "*If, for example, incoming data in the months ahead were to reveal that inflation and inflation expectations are running higher than projected at present and in ways that are inconsistent with our 2 percent objective, then I would be receptive to increasing the policy rate by more than I currently expect will be necessary. Data dependence in this sense is easy to understand, as it is of the type implied by a large family of policy rules in which the parameters of the economy are known.*"

Finally in July 2024, president Lagarde clarified the distinction between data dependence and data-point dependence, stressing that "… *while the flow of new information constantly adds to and improves our picture of medium-term inflation, we are not pushed around by any specific data point. Data dependence does not mean data point dependence*" (Lagarde, 2024).[25]

[25] In the same speech, President Lagarde, also clarified the role of models and new data in predicting inflation in the medium term. "*Faced with multiple large shocks, there was significant uncertainty about how to interpret and rank the information we were receiving from the economy. On the one hand, it would have been risky to rely too much on models trained on historical data, as those data may no longer have been valid. We could not know, for instance, whether shifts in preferences, higher energy prices and geopolitics had changed the structure of the economy. On the other hand, relying too much on current data might have been equally misleading if they had turned out to have little predictive power for the medium term. […] Our forecasts provided a comprehensive assessment of future inflation, assuming the underlying parameters of the economy remained stable. At the same time, looking at current data allowed us to identify the persistent components of inflation and account for structural changes that might have been missing from our forecast models.*"

Appendix 2 – ILS rate sensitivity to inflation news in the euro area

In the euro area, HICP inflation prints are typically released first in larger member states, followed by other countries, and only subsequently consolidated into the euro area headline release. This staggered sequencing generates a gradual flow of information, allowing markets to update expectations step by step as new country-level data becomes available.

We run horse-race regressions to assess whether the contribution of country-specific inflation news to euro-area inflation expectations varies along the yield curve. Specifically, we estimate

$$\Delta ILS_t^{(k)} = a_{EZ}^{(k)} s_t^{EZ} + a_{DE}^{(k)} s_t^{DE} + a_{FR}^{(k)} s_t^{FR} + a_{IT}^{(k)} s_t^{IT} + a_{ES}^{(k)} s_t^{ES} + e_t^{(k)}$$

where $\Delta ILS_t^{(k)}$ denotes the daily change in inflation linked swap (ILS) rate maturing k-year ahead, s_t^x is the inflation surprise for country x, normalized to have mean zero and standard deviation equal to one, and $e_t^{(k)}$ is a residual. We focus on the coefficients $a_x^{(k)}$, where k indicates the maturity of ILS rates, and examine how they change when the euro-area surprise s_t^{EZ} is included alone, as opposed to jointly with the inflation surprises of the four largest member states (DE, FR, IT, and ES).

Table A.1 reports the results for 1-year, 2-year, 5-year, 10-year, and 30-year ILS rates, with heteroskedasticity-robust standard errors. Yields at all maturities move in the same direction following inflation announcements, but the magnitude of the response decreases with maturity, indicating that short-term rates are most sensitive to inflation news. This pattern is intuitive, as inflation surprises primarily affect expectations of near-term inflation.

Columns 1–5 present the estimated coefficients for the euro area inflation news, which are statistically different from zero at the 1-year maturity. However, once I regress ILS rate changes on the full set of inflation surprises, the effect of euro-area inflation surprises is no longer statistically significant, even at the short end of the curve (Columns 6–10). Among the large member states, German inflation surprises exert the strongest influence on inflation expectations across maturities, particularly at the long end of the yield curve. For instance, a one-standard-deviation German inflation surprise increases long-term ILS rates by two to three times more than comparable surprises in France. This likely reflects Germany's large weight in the HICP index, the timeliness of its release, and the close market attention paid to German inflation data.

Table A.1 – ILS rate sensitivity to inflation news in the euro area

	(1) 1Y	(2) 2Y	(3) 5Y	(4) 10Y	(5) 30Y	(6) 1Y	(7) 2Y	(8) 5Y	(9) 10Y	(10) 30Y
s^{EZ}	1.26**	0.46	0.31	0.30	0.25	0.69	-0.05	0.08	0.23	0.18
	(0.58)	(0.33)	(0.26)	(0.21)	(0.16)	(0.59)	(0.33)	(0.27)	(0.21)	(0.16)
s^{DE}						2.11***	1.57***	1.13***	0.91***	0.70***
						(0.63)	(0.37)	(0.24)	(0.16)	(0.13)
s^{FR}						1.93***	1.18***	0.53***	0.36**	0.34***
						(0.44)	(0.29)	(0.16)	(0.16)	(0.11)
s^{IT}						1.65***	1.57***	0.59***	0.15	0.17
						(0.50)	(0.36)	(0.22)	(0.18)	(0.15)
s^{ES}						0.98*	0.62*	0.40*	0.38**	0.18
						(0.51)	(0.35)	(0.22)	(0.16)	(0.13)
N	242	247	244	244	248	933	955	934	935	934
F	4.76	1.94	1.40	2.00	2.47	13.13	14.51	11.32	11.54	9.04

Notes: standard errors are robust to heteroskedasticity.

Appendix 3: Construction of the Learning-Environment Measure

The text corpus consists of all the speeches delivered by members of the ECB Executive Board between 1 January 1999 and 31 December 2024. Full texts and metadata (date, title, speaker) were downloaded from the ECB's official "Speeches" archive, which provides a complete and consistent repository of Executive Board communication.

The measure is based on a predefined dictionary of terms commonly associated with a communication environment in which policymakers emphasise forecast updating, model learning, or the use of new information. The baseline vocabulary contains the following expressions: "meeting-by-meeting", "forecast errors", "data-dependent", "learning", "underlying inflation", and "data-driven". For all speeches delivered in month t by members of the ECB Executive Board, we count the number of occurrences of each term. We then compute the monthly average number of keyword hits by dividing the total number of keywords by the number of speeches in month t. To control for differences in speech length, we also construct a relative-frequency version in which keyword counts are normalised by the total word count of each speech. Both absolute and normalised measures yield similar dynamics.

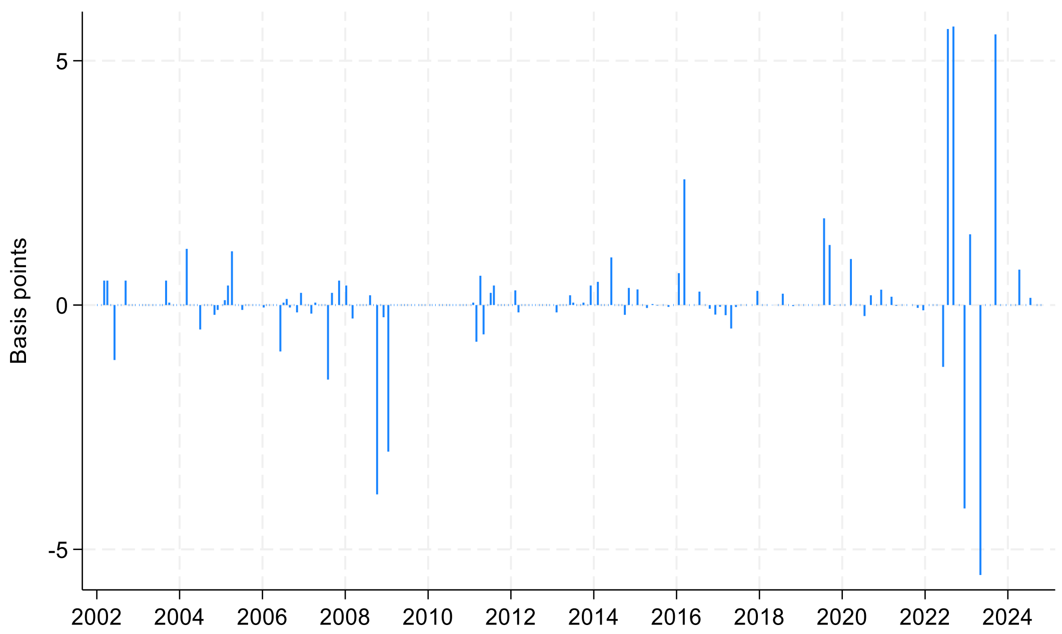
Table A.2 reports summary statistics for the selected keywords, conditional on the word appearing at least once in a speech. The average number of occurrences ranges from 2.8 for "learning" to 4.6 for "meeting-by-meeting", with standard deviations between 1.7 and 2.1. Minimum values are mechanically equal to 1 by construction, while maximum counts vary between 6 and 9 across terms. These figures show that, when used, learning-related expressions tend to appear multiple times within a speech, supporting their relevance as markers of a communication environment that emphasises forecast updating, model learning, and the use of incoming data.

Table A.2 – Summary statistics of LE keywords

	Mean	Median	Min	Max	Std Dev.
Meeting-by-meeting	4.6	4	1	8	2.1
Forecast errors	3.0	3	1	6	1.8
Data-dependent	3.9	4	1	8	1.7
Learning	2.8	2	1	6	1.7
Underlying inflation	3.6	3	1	9	1.9

Appendix 4: ECB information shocks

Figure A.1 – ECB information shocks



Note: Information shocks are identified by observing an opposite-sign response of interest rates and stock market prices within a very short time window around ECB Governing Council announcements. Specifically: the joint 30-minute co-movement of the 3-month Overnight Index Swap (OIS) rate, and the EURO STOXX 50 index is analyzed in a window from 5 minutes before to 25 minutes after the press release.