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Dovish Coos or Hawkish Screech? From Central Bank Talk to Economic Walk

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Dovish Coos or Hawkish Screech? From Central Bank Talk to Economic Walk

Kerstin Bernoth*

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Abstract

This paper investigates the effectiveness of the European Central Bank's (ECB) communication in shaping market expectations and real economic outcomes. Using a transformer-based large language model (LLM) fine-tuned to ECB communication, the tone of monetary policy statements from 2003 to 2025 is classified, constructing a novel ECB Communication Stance Indicator. This indicator contains forward-looking information beyond standard macro-financial variables. Identified communication shocks are distinct from monetary policy and central bank information shocks. A structural Bayesian VAR reveals that hawkish communication signals favorable economic prospects, raising output, equity prices, and inflation, but also increases bond market stress. These findings highlight communication as an independent and effective tool of monetary policy, while also underscoring the importance of carefully calibrating tone to balance market expectations, and financial stability.

Keywords: Monetary Policy, Central Bank Communication, Text Sentiment, Transformer-based Large Language Model, Bayesian Vector Autoregression, Local Projections.

JEL Classification: C32, E43, E47, E52, E58

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1 Introduction

Since the 1990s, central bank communication has become a cornerstone of modern monetary policy. In addition to conventional instruments, such as adjusting interest rates, central banks communicate with the aim of shaping the expectations of households, firms, and financial markets. Central banks seek to meaningfully impact inflation, output, and financial conditions by influencing expectations about the direction of monetary policy and revealing information about their economic assessment.

This paper analyzes the effectiveness of communication by the European Central Bank (ECB). Specifically, it investigates whether the ECB's official statements issued alongside monetary policy decisions between May 2003 and July 2025 improve the predictability of future interest rate decisions. Moreover, we estimate the unexpected component of the communication stance conditional on the prevailing economic and inflationary environments. We then examine how this communication shock is transmitted to real economic activity and financial markets.

Focusing on monetary policy statements is useful for several reasons. First, unlike central bank speeches, which often follow a broader narrative and allow for more thematic or contextual exploration, monetary policy statements are structured to deliver precise, intentional messages about the ECB's policy stance. This makes them well-suited for a systematic empirical study. Second, financial market participants closely monitor their content, with even minor changes in language potentially generating notable market reactions. Finally, these statements are issued at regular intervals, providing a consistent temporal framework for analysis.

There is a vast body of literature on central bank communication and its impact on the real economy, featuring many influential contributions. For example, early work by Gürkaynak et al. (2005) shows that Federal Open Market Committee (FOMC) statements influence asset prices beyond the effects of policy rate changes. This demonstrates that markets extract important signals from central bank communication alone. Subsequent research, including that of Ehrmann and Fratzscher (2007, 2009), finds that communication enhances transparency, improves policy predictability, and reduces market volatility. More recently, Czudaj and Nguyen (2025) used advanced text-based sentiment analysis of ECB communications to identify communication shocks that significantly impact interbank interest rates, inflation expectations, and real economic activity, independently of interest rate changes. For a comprehensive overview of the literature, see the excellent reviews by Blinder et al. (2008) and Czudaj and Nguyen (2025), which offer an extensive synthesis of empirical findings and the evolution of methodological approaches in the study of central bank communication.

We contribute to the large empirical macroeconomic literature on central bank communication by leveraging recent advances in large language models (LLMs), advancing prior methodologies along multiple dimensions. Manual coding methods (e.g., Musard-Gies, 2006; Rosa and Verga, 2007; Berger et al., 2011; Apel and Grimaldi, 2014) are labor-intensive, difficult to scale, and nearly impossible to replicate. Dictionary-based techniques (e.g., Picault and Renault, 2017; Czudaj and Nguyen, 2025) rely on static word lists that cannot accommodate contextual subtleties, irony, or evolving policy vocabularies. Even more advanced traditional natural language processing (NLP) methods, such as bag-of-words or topic models (e.g., Tobback et al., 2017; Hansen and McMahon, 2016; Shapiro and Wilson, 2022), disregard word order and syntactic structure, limiting their ability to detect nuanced shifts in tone. LLMs, by contrast, represent a breakthrough in text analysis, as they integrate contextual, syntactic, and semantic information at both the sentence and document levels. This enables them to detect subtle linguistic nuances and interpret implied meanings with a level of accuracy and applicability that was previously unreached. Reflecting these advantages, a growing body of work is adopting LLMs for sentiment classification and economic text analysis in the context of central bank communication (e.g., Gambacorta et al., 2024; Pfeifer and Marohl, 2023; Hansen and Kazinnik, 2024; Silva et al., 2025).

In this study, we adapt and extend a transformer-based architecture originally developed by Shah et al. (2023) to classify the tone of US Federal Reserve (US Fed) communications. To ensure relevance and precision for the European context, we retrain the model on the full corpus of speeches delivered by ECB Executive Board members between 1999 and July 2025, thereby capturing the ECB's distinct linguistic style. Our resulting model achieves highly accurate tone classification.

We then apply the newly developed sentiment model to classify each of the slightly more than 13,000 sentences contained in the ECB's official monetary policy statements as 'hawkish', 'dovish', or 'neutral'. Dovish sentences are associated with an easing of monetary policy, hawkish sentences with a tightening, and neutral sentences with an unchanged policy stance. A neutral sentence may also indicate that it does not convey any specific monetary policy signal. For each monetary policy statement, we then construct an aggregate measure, referred to as the *ECB Communication Stance Indicator*, which captures the overall hawkish–dovish tone conveyed in the statement.

Thereafter, we analyze whether the ECB's communication contains relevant information for current and future monetary policy decisions. We estimate a multinomial ordered logit model that incorporates the ECB's communication stance alongside macro-financial variables that may influence interest rate decisions. We find that ECB communication helps guide market expectations. The tone in monetary statements conveys meaningful forward-looking signals about future interest rate changes, up to three Governing Council meetings ahead, which go beyond the information embedded in macroeconomic indicators. However, while it improves the probabilistic assessment of rate decisions by shifting predicted probabilities in the correct direction, it only occasionally alters the final classification of the most likely policy outcome.

Next, the nature of the ECB communication shock and its relationship to both conventional monetary policy shocks and central bank information (CBI) shocks is explored. Monetary policy shocks are measured by high-frequency changes in interest rate expectations around policy announcements that reflect unexpected shifts in the policy stance, rather than revisions to the economic outlook. Central bank information (CBI) shocks, by contrast, capture the informational content of policy announcements: they arise when the central bank conveys its assessment of current or future economic conditions, such as growth or inflation prospects, leading markets to adjust their expectations accordingly (Nakamura and Steinsson, 2018; Stock and Watson, 2018; Jarocinski and Karadi, 2020; Bauer and Swanson, 2023). Our results show that the communication shock is distinct from both monetary policy and CBI shocks. This distinction highlights that communication functions as an independent instrument in the central bank's policy toolbox.

Finally, we estimate a structural Bayesian vector autoregression (BVAR) model to examine how communication shocks affect key macro-financial variables, including industrial production, inflation, bond market stress, and equity prices. To better understand the nature and transmission of these shocks, we compare their effects with those of monetary policy and CBI shocks. Our findings confirm that central bank communication serves as an effective and independent policy tool with significant real economic effects.

Its impacts share some similarities with those of CBI shocks but also display important differences. More specifically, following a hawkish communication shock, industrial production experiences a significant immediate increase, peaking around two months later before gradually returning to baseline levels. Equity prices rise immediately and significantly before the effect dissipates after roughly two months. Together, these dynamics suggest that hawkish communication shocks convey positive news about economic developments, consistent with the interpretation of CBI shocks as signaling improved economic outlooks. Inflation exhibits a significant increase, maintaining statistical significance for about two months. This sustained inflationary response contrasts with the muted inflation effects observed following CBI shocks.

Notably, a restrictive communication shock is associated with a lagged increase in bond market stress, suggesting potential tensions with financial stability. This contrasts with the response to CBI shocks, where bond market stress tends to decline, reflecting the market's perception of reduced financial risks. The rise in bond market stress after communication shocks highlights a possible trade-off policymakers face between conveying hawkish messages and maintaining market calm.

Overall, our findings underscore the importance of central bank communication as an independent policy instrument, capable of shaping expectations and influencing macro-financial conditions independently of interest rate changes. At the same time, they highlight the need for careful tone management, as even well-intentioned hawkish signals, while boosting confidence and signaling strength, can generate financial market stress, pointing to potential trade-offs between credibility, forward guidance, and financial stability.

The remainder of the paper is organized as follows. Section 2 presents the text-based sentiment model used to classify ECB monetary policy statements. Section 3 provides descriptive statistics for the newly constructed ECB Communication Stance Indicator. Section 4 examines the indicator's predictive power for future interest rate decisions. Section 5 introduces a novel measure of ECB communication shocks. Section 6 analyzes the macroeconomic effects of these shocks using a structural Bayesian VAR model. Section 7 concludes.

2 Measuring the Monetary Policy Stance in ECB Communications

We systematically analyze the tone of ECB's official statements accompanying monetary policy decisions between May 2003 and July 2025. While the Eurosystem started in January 1999, the starting point of our data collection is May 2003, when there was a major shift in the communication framework of the ECB. Notably, the monetary pillar was downgraded, while a broader, more qualitative monetary analysis was adopted. This shift in approach resulted in more systematic, forward-looking, and inflation-targeting-aligned communication (Issing, 2005). Thus, initiating the analysis in 2003 guarantees greater consistency in the rhetorical structure, terminology, and policy focus, enhancing comparability across statements and reducing structural noise in textual indicators of policy stance or sentiment.

Financial market participants and the financial press closely scrutinize the content of these official ECB statements. Unlike the more spontaneous and occasionally off-the-cuff remarks made in speeches by central bank officials, these statements are purpose-driven and carefully formulated. As such, they are more likely to contain intentional signals about the ECB's policy stance.

The structure of these statements has remained remarkably stable over time, making them particularly well-suited for empirical analysis. They typically begin by announcing the current monetary policy decisions, including any adjustments to key interest rates. This is followed by an assessment of the euro area's economic outlook, covering inflation dynamics and the balance of economic risks. The concluding section provides a detailed overview of the broader financial and monetary environment, along with forward-looking guidance on possible future developments and the spectrum of potential monetary policy responses. This consistent format offers an almost ideal setting for studying central bank communication. Even subtle changes in wording are likely to trigger measurable reactions in financial markets, underscoring the informational value embedded in these statements.

To classify the communication of the ECB, we build on the transformer-based large language model (LLM) of Shah et al. (2023), which is a fine-tuned RoBERTa-large model

(Liu et al., 2019) specialised for classifying central bank communication.[1] The model classifies sentences as 'hawkish', 'dovish' or 'neutral'. Dovish sentences are associated with an easing of monetary policy, hawkish sentences with a tightening, and neutral sentences with no change in interest rates. A neutral sentence may also indicate that it does not convey any specific monetary policy signal. The original model by Shah et al. (2023) is trained to classify communications from the US Fed. To account for potential differences in sentiment and communication style between the US Fed and the ECB, we extend the model by fine-tuning it on ECB communication. Appendix A provides a detailed description of the fine-tuning process.

The resulting sentiment model, specifically tailored to the ECB's communication style, classifies each of the slightly more than 13,000 sentences in the considered official monetary policy statements as signaling a more restrictive, expansionary, or neutral position. These sentence-level classifications are then aggregated into a single value for each Governing Council meeting at time t, the *ECB Communication Stance Indicator*, calculated as follows:

$$\text{ECB Communication Stance Indicator}_t = \frac{\#\text{ of Hawkish}_t - \#\text{ of Dovish}_t}{\text{Total } \#\text{ of Sentences}_t}$$

Positive indicator values indicate a hawkish stance at a given Governing Council meeting at time t, suggesting a restrictive orientation, while negative values reflect a dovish or accommodative tone.

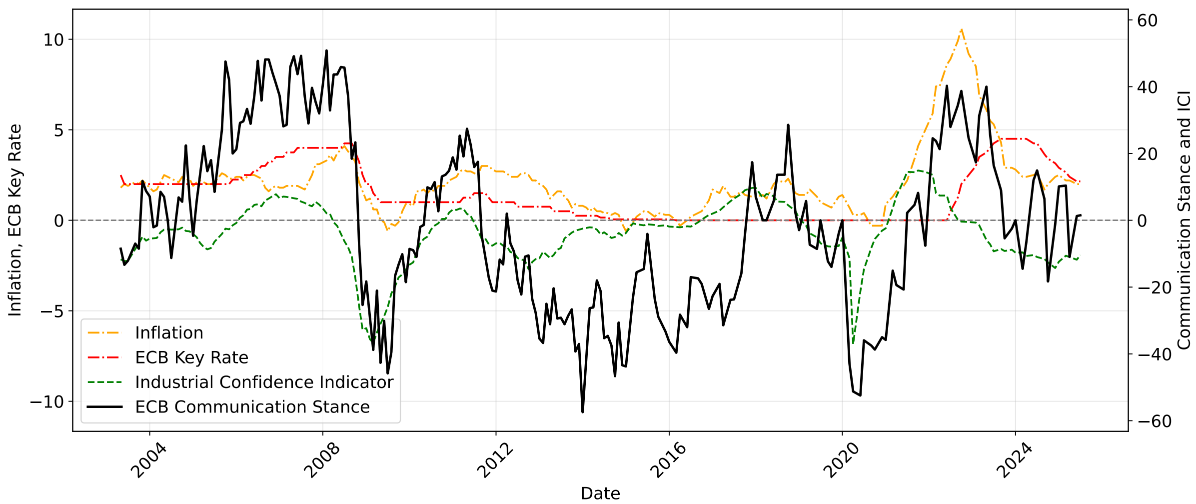
3 Descriptive Statistics of the ECB Communication Stance

Figure 1 shows the development of the ECB Communication Stance Indicator from mid-2003 through July 2025 together with key macroeconomic indicators. The communication stance varies considerably over time, closely aligning with key macroeconomic develop-

[1] RoBERTa-large is an extended version of BERT (Devlin et al., 2018), a transformer-based large language model (LLM). Transformer-based models use so-called self-attention mechanisms that relate each word in a sentence to all other words simultaneously, rather than processing them one at a time. This allows contextual relationships to be recognized efficiently. The simultaneous analysis of entire sentences and the dynamic weighting of word meanings enable RoBERTa-large to achieve a particularly deep and precise understanding of texts.

ments and policy phases. For instance, between 2004 and 2006, ECB communication was relatively neutral to slightly hawkish, which was consistent with the moderate growth and stable inflation that characterized that period. In the lead-up to the global financial crisis between 2006 and 2008, the ECB's official statements became increasingly hawkish, aligning with subsequent interest rate hikes. The outbreak of the global financial crisis in mid-2008 marked a sharp downward shift in the communication stance indicator, reflecting the ECB's increasingly accommodative tone. Between mid-2010 and late 2011, the indicator temporarily turned hawkish, coinciding with a brief period of economic stabilization, as captured by the Industrial Confidence Indicator (ICI), and the ECB's decision to raise interest rates due to inflation concerns in 2011. However, this tightening tone was short-lived. With the escalation of the sovereign debt crisis in late 2011, the communication turned dovish again as financial stress intensified. This dovish stance was sustained throughout the euro area's sovereign debt crisis until around 2018. This stance was consistent with interest rate cuts and the use of unconventional monetary policy tools.

Figure 1: ECB Communication Stance and Key Macroeconomic Indicators



The outbreak of the COVID-19 pandemic in early 2020 triggered another sharp decline in the Communication Stance Indicator, coinciding with falling inflation and deteriorating industrial confidence. During this period, the ECB's communication became markedly more expansionary. Despite a subsequent recovery in economic conditions and a steady rise in inflation from late 2020, the indicator remained negative throughout 2021. This suggests that monetary policy communication remained accommodative despite inflation being well above the ECB's target, which is consistent with the criticism heard at the time that the central bank was responding too slowly to inflationary pressures.

It was only at the end of 2021 that the ECB Communication Stance Indicator turned positive, signaling a shift to a more hawkish tone. This change coincided with a series of policy rate hikes that began in mid-2022. The indicator peaked in the second half of 2022, reflecting the ECB's determination to address persistently high inflation. Since then, however, the tone has gradually moderated. While the indicator remained positive, it trended downward throughout 2023 and into 2024. By mid-2024, ECB communication had approached a more neutral stance, in line with stabilizing inflation and a more uncertain economic outlook.

Overall, the indicator reflects a communication pattern that aligns with policy actions and economic conditions, while also capturing periods of potential lag or divergence between monetary policy rhetoric and implementation.

4 Predictive Power of ECB Communication for Interest Rate Decisions

To determine if the ECB's communication stance contains relevant information for current and future monetary policy decisions, a multinomial ordered logit model is estimated. To account for the zero lower bound on conventional interest rates in the euro area, which make a probability analysis of interest rate changes largely unreliable, for this exercise only, we exclude the period from October 2014, when the main refinancing rate was effectively zero, to July 2021. The latter date marks the point when inflation in the euro area started to exceed the 2% target, indicating that the probability of interest rate hikes was no longer negligible.

The dependent variable captures the direction of the policy rate decision in a given period t: a decrease ($\Delta i_t = -1$), no change ($\Delta i_t = 0$), or an increase ($\Delta i_t = +1$). Thus, the model accounts for the fact that the ECB adjusts policy rates in discrete steps and it focuses on the categorical nature of ECB decisions rather than the magnitude of rate changes. The observed interest rate decision Δi_t is assumed to reflect the discretization of an unobserved continuous latent variable Δi_t^*, representing the Governing Council's underlying inclination to adjust the policy rate. This latent propensity is modeled as a linear function of the communication stance indicator (CI_t) and a set of macro-financial and institutional variables X_t, motivated by economic theory and the policy framework of the ECB:

$$\Delta i^*_{t+h} = \beta\, \mathrm{CI}_t + X_t\gamma + \varepsilon_t, \quad \varepsilon_{t+h} \sim \mathrm{Logistic}(0,1), \tag{1}$$

The index $h \in \{0,1,2,3\}$ denotes the forecast horizon: when $h = 0$, the model estimates a contemporaneous relationship between the policy rate change and the explanatory variables at time t; for $h > 0$, it yields one-, two-, and three-step-ahead forecasts, respectively.

The observed outcome Δi_{t+h} is then determined by comparing the latent variable Δi^*_{t+h} to two threshold parameters, τ_1 and τ_2, such that:

$$\Delta i_{t+h} = \begin{cases} -1 & \text{if } \Delta i^*_{t+h} < \tau_1 \\ 0 & \text{if } \tau_1 \leq \Delta i^*_{t+h} \leq \tau_2 \\ 1 & \text{if } \Delta i^*_{t+h} > \tau_2 \end{cases} \tag{2}$$

Accordingly, the probabilities associated with each of the three possible outcomes are given by:

$$\begin{aligned} P(\Delta i_{t+h} = -1 \mid \mathrm{CI}_t, X_t) =& \Lambda(\tau_1 - \beta\, \mathrm{CI}_t - X_t\gamma) \\ P(\Delta i_{t+h} = 0 \mid \mathrm{CI}_t, X_t) =& \Lambda(\tau_2 - \beta\, \mathrm{CI}_t - X_t\gamma) - \Lambda(\tau_1 - \beta\, \mathrm{CI}_t - X_t\gamma) \\ P(\Delta i_{t+h} = 1 \mid \mathrm{CI}_t, X_t) =& 1 - \Lambda(\tau_2 - \beta\, \mathrm{CI}_t - X_t\gamma) \end{aligned} \tag{3}$$

where $\Lambda(\cdot)$ denotes the cumulative distribution function of the standard logistic distribution. The threshold parameters τ_1 and τ_2, along with the coefficients β and γ, are estimated by maximum likelihood.[2] Standard errors are computed using heteroscedasticity and autocorrelation consistent (HAC) covariance estimates with a lag length of three (Newey and West, 1987).

Consistent with the Taylor rule, the set of macro-financial variables X_t includes a measure for inflation and the real economic outlook. To capture inflation dynamics, we

[2]Empirical evidence for the ECB does not point to a clear, consistent trend in the response of the ECB to the real economy over time, once the effective zero lower bound is set aside. This is the reason why, in consideration of the relatively limited time span of our data, we refrain from estimating time-varying coefficients.

combine three related indicators: the year-on-year growth rate in the Harmonized Index of Consumer Prices (HICP), the HICP excluding energy and food prices (i.e., core inflation), and the one-year-ahead inflation projection derived from the quarterly macroeconomic projection exercises of the ECB. Since these three series are highly correlated, we use principal component analysis (PCA) on their standardized values to extract their common component. The resulting first principal component serves as a composite inflation indicator that captures both current and forward-looking assessments of inflation.

To capture the real economic outlook, we use the European Commission's Industrial Confidence Indicator (ICI) for the euro area. As an alternative, we consider the nowcast of real GDP growth from the quarterly Macroeconomic Projection Exercise of the ECB. Along with standard macroeconomic indicators, we incorporate the ECB's Composite Indicator of Systemic Stress (CISS) as a financial stability measure. This reflects the ECB's commitment to integrating financial stability considerations into its policy framework. We also incorporate the Geopolitical Risk Index (GeoRisk), recognizing that external shocks may indirectly affect financial markets and price dynamics, thereby influencing monetary policy decisions.[3]

Furthermore, we use the current interest level as a potential explanatory variable. Empirical studies of the decision-making process of the ECB confirm that a higher interest rate increases the likelihood of subsequent cuts, accompanied by mean reversion towards a perceived neutral rate (Gerlach-Kristen, 2003). Lastly, we take control for the interest rate decision made at the previous ECB Governing Council meeting to capture the ECB's tendency towards gradual, path-dependent policy adjustments (Sack and Wieland, 2000).

First, we analyze the extent to which interest rate decisions can be explained by the prevailing economic situation and the tone of the accompanying monetary policy statement. Thus, $h = 0$ in equations (1)-(3). The estimation results shown in Table 1 confirm a relationship that is in line with expectations: A higher inflation rate significantly increases the probability that the ECB Governing Council decides to raise interest rates. In two out of five regressions, we find that an interest rate hike at the previous meeting increases the likelihood of a subsequent rate hike. This reflects the well-known practice of central banks of adjusting key interest rates in small, sequential steps. Geopolitical risks also influences the interest rate decision. Rising geopolitical tensions are associated with

[3]This index was developed by Caldara and Iacoviello (2022) and is based on the frequency with which geopolitical events are referenced in newspapers.

a higher probability of interest rate cuts. In contrast, financial stability concerns and the prevailing level of interest rates appear to play no meaningful role in shaping current policy choices. Finally, the impact of the economic situation yields mixed results. The EU Industrial Confidence Indicator (ICI) is positive and significant in two of five regressions. Thus, the more optimistic industrial companies are about their current business situation and their expectations for the future, the higher the probability of an interest rate hike. The current assessment of real GDP growth does not exert a statistically significant influence on the Governing Council's interest rate decisions.

Table 1: Determinants of Interest Rate Changes ($h = 0$)

	(a)	(b)	(c)	(d)	(e)
Interest Change (lag)	1.03	0.99	0.99	1.11**	1.38**
	(0.65)	(0.64)	(0.64)	(0.56)	(0.61)
Communication Stance	0.03**	0.03**	0.02	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Inflation	0.62***	0.66***	0.63***	0.55***	0.36**
	(0.18)	(0.18)	(0.19)	(0.15)	(0.14)
Industrial Confidence	0.05	0.04	0.06	0.08***	0.07**
	(0.05)	(0.04)	(0.04)	(0.03)	(0.03)
Geo Risk	-0.03***	-0.03***	-0.03***	-0.02***	
	(0.01)	(0.01)	(0.01)	(0.01)	
Financial Stress Index	-2.50	-2.30	-1.84		
	(1.55)	(1.61)	(1.64)		
Interest Rate	-0.21	-0.22			
	(0.18)	(0.18)			
GDP Nowcast	-0.86				
	(1.02)				
-1/0	-6.81***	-6.58***	-6.11***	-5.38***	-2.81***
	(0.94)	(0.92)	(0.86)	(0.89)	(0.31)
0/1	1.77***	1.77***	1.76***	1.76***	1.70***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
AIC	191.1	189.5	188.5	189.0	195.5
N	166	166	166	166	166
Pseudo R^2	0.32	0.32	0.32	0.31	0.27

Notes: Estimated coefficients and thresholds from ordered logit models with Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors in brackets. Significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

The tone of the ECB's monetary policy statements is only significant in two out of five regressions. Thus, we find modest evidence that the verbal explanations offer additional information about the interest rate decision beyond what can be inferred from the macrofinancial environment in which the decisions are made. This supports the ECB's assertion that it primarily bases monetary policy decisions on fundamentals. Overall, the analyzed variables explain approximately 30% of fluctuations in interest rate changes.

Of major interest, however, is, whether the tone of ECB monetary policy statements contains forward-looking information relevant for *future* interest rate decisions. To analyze this, we first conduct a bivariate Granger causality test between the Communication Stance Indicator and interest rate changes. This test assesses whether past values of the tone indicator help predict future interest rate changes, beyond what can be predicted from past interest rates alone. The results show that the tone indicator contains statistically significant predictive information for future interest rate changes over a horizon of up to three Governing Council meetings.

Thus, to further investigate the predictive content of ECB communication, we estimate one-, two-, and three-step-ahead forecasts of interest rate decisions (i.e., $h \in \{1, 2, 3\}$ in equations (1)-(3)). The results are reported in Table 2.[4] Across all three forecast horizons, we find a robust positive relationship between the prevailing inflation rate and the likelihood of an interest rate hike at upcoming ECB Governing Council meetings. In addition, a key interest rate hike in the previous meeting significantly increases the probability of a further hike in the next two meetings. A higher prevailing interest rate level is associated with a lower likelihood of further tightening at Governing Council meetings one to three months ahead, consistent with mean-reverting dynamics around an estimated neutral rate. Moreover, we find that rising geopolitical tensions significantly reduce the probability of interest rate hikes at the next two meetings.

Most notably, the ECB Communication Stance Indicator exhibits strong and statistically significant predictive power for interest rate decisions across all forecast horizons. A more hawkish tone in the official monetary policy statement systematically increases the probability of a rate hike over the following three Governing Council meetings.

[4] Given the limited number of interest rate changes in the sample, we focus on in-sample forecast performance rather than recursive or rolling out-of-sample evaluations.

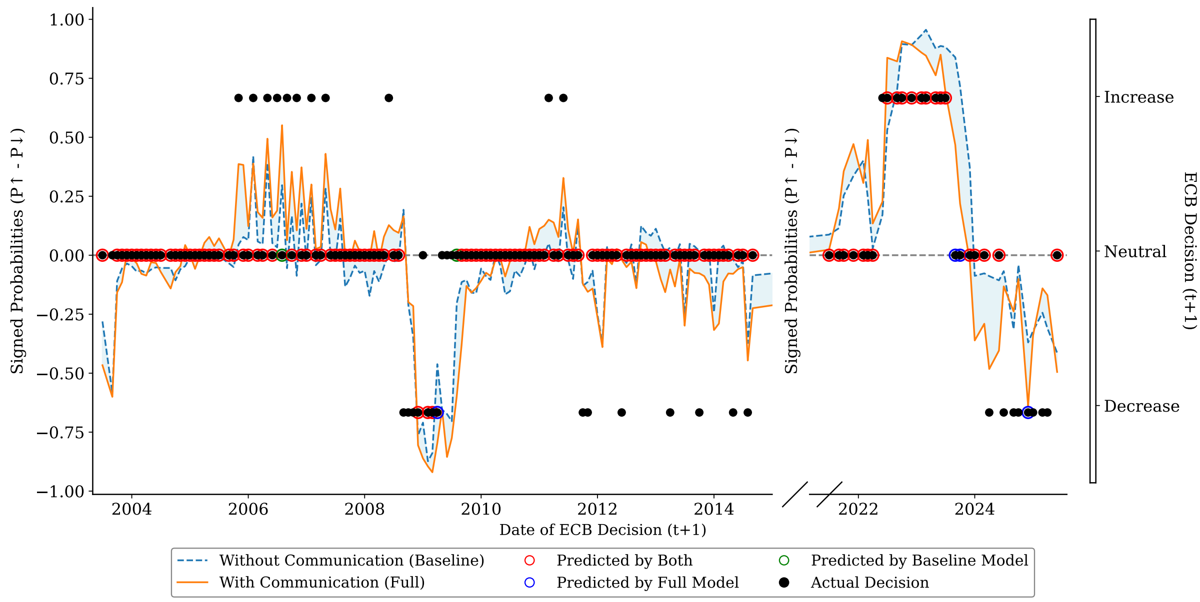
Table 2: Forecasts of ECB Interest Rate Changes

Variable	Δi_{t+1}				Δi_{t+2}				Δi_{t+3}			
	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
Interest Change (lag)	1.36*	1.35*	1.28*	1.56***	1.55**	1.55**	1.46**	1.67***	0.58	0.58	0.58	0.72
Communication Stance	0.07***	0.07***	0.05***	0.05***	0.06***	0.06***	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***
Inflation	0.65***	0.67***	0.63***	0.51***	0.57***	0.59***	0.54***	0.45***	0.49**	0.51***	0.50***	0.46***
Interest Rate	-0.97***	-0.98***	-0.83***	-0.80***	-1.15***	-1.15***	-0.95***	-0.92***	-1.04***	-1.05***	-1.03***	-1.04***
Industrial Confidence	-0.03	-0.04			-0.04	-0.05			0.00	-0.00		
Geo Risk	-0.02***	-0.02***	-0.02***	-0.01	-0.01*	-0.01*	-0.01*	-0.00	0.00	0.00	0.00	0.00
Stress	-3.59**	-3.48*	-2.70*		-3.12**	-3.04*	-2.07		-1.13	-1.04	-0.94	
GDP Nowcast	-0.49				-0.36				-0.37			
τ_1	-7.31***	-7.16***	-6.84***	-5.42***	-6.21***	-6.11***	-5.70***	-4.65***	-4.38***	-4.27***	-4.23***	-3.71***
τ_2	1.83***	1.83***	1.82***	1.80***	1.79***	1.79***	1.77***	1.75***	1.65***	1.65***	1.64***	1.64***
AIC	178.20	176.44	175.57	180.86	182.71	180.91	180.84	183.37	203.24	201.49	199.51	198.53
N	165	165	165	165	164	164	164	164	163	163	163	163
Pseudo R^2	0.364	0.363	0.359	0.330	0.345	0.344	0.336	0.318	0.260	0.259	0.259	0.255

Notes: Estimated coefficients and thresholds (cut points) from ordered logit models with Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Figures 2 illustrates the performance of the ordered logit models in forecasting ECB interest rate decisions one period ahead over time. The equivalent figures for the two- and three periods ahead are shown in Figures 5 and 6 in the Appendix. The graphs show the signed forecast probabilities, calculated as the difference between the predicted probability of an interest rate increase and the predicted probability of a decrease. Positive values indicate that the model assigns a higher likelihood to a rate hike, and negative values reflect expectations of a rate cut. The dashed blue line represents the baseline model's forecasts, which include only relevant macro-financial variables X_t.[5] The solid orange line adds the ECB's Communication Stance Indicator to the regressors (full model). The black dots denote the actual ECB interest rate decisions and the colored circles around the dots show which model correctly predicted the decision direction: red for both models, blue for the full model, green for the baseline model, and no color for incorrect predictions. Note that the model's point prediction is defined as the option with the highest predicted probability.

Figure 2: Forecast Performance - One Period Ahead



Notes: The vertical axis plots the signed forecast probability – the predicted probability of a hike minus that of a cut – with positive values indicating a tilt toward tightening. The dashed blue line is the baseline model using macro-financial variables only; the solid orange line adds the ECB Communication Stance Indicator (full model). Black dots mark actual interest rate decisions, with colored circles indicating correct predictions: red (both models), blue (full model only), green (baseline only), and no color (both incorrect).

[5] These are, in principle, all regressors used in column (c) of Table 2, i.e. the previous period's interest rate change, inflation, the current interest rate level, geopolitical risk and the financial stress indicator.

The figure shows that during periods of economic stress, such as the global financial crisis of 2008-2009 and the inflation-driven tightening cycle of 2022-2023, both the baseline model (without communication) and the full model (with communication) improve. During these periods, monetary policy actions become more predictable in advance as market expectations and central bank communication align with acute macro-financial pressures. Incorporating the communication stance from ECB policy statements generally increases forecast accuracy by shifting the signed probabilities closer to the observed policy decisions. Not only does the full model assign substantially higher probabilities to the actual policy direction, it also produces more frequent correct modal forecasts.

By contrast, during tranquil periods outside of acute crisis episodes, both models tend to correctly predict the direction of change whenever a policy adjustment occurs. However, the probabilities associated with interest rate changes are usually too low to change the baseline forecast of no change. This likely reflects the greater discretion and strategic timing involved in policy decisions under normal conditions, which makes meeting a policy adjustment more difficult to predict.

Overall, the graphical inspection suggests that, while forecast performance improves systematically during crises, even without communication, incorporating the ECB's communication stance tends to provide additional gains, especially in capturing directional pressures and, in some cases, improving modal accuracy. This visual evidence aligns with the statistical results from the Diebold-Mariano test presented in Table 3, which assesses the value of including ECB communication in terms of predictive accuracy. Across the two- and three-period forecast horizons, we find significant improvements in *probability forecast* accuracy, indicating that the inclusion of communication enhances the model's ability to assign higher probabilities to the actual policy decision. However, we find for no forecast horizon a significant improvement in *point forecast* accuracy, suggesting that these probability adjustments, although informative, are only in a few cases large enough to shift the most likely predicted outcome.

To summarize, we find that the tone of ECB communication conveys important forward-looking signals about the future policy decisions that go beyond the information contained in the considered macroeconomic indicators. However, its influence changes the ultimate forecast classification of the interest rate decision only in a few cases.

Table 3: Diebold-Mariano Test Results for Forecast Performance

	Forecast Horizon		
	1	2	3
Point Forecast	0.41	0.16	0.48
Probability Forecast	0.12	0.03	0.09

Notes: Point forecasts are based on squared forecast errors and probability forecasts are evaluated using Brier scores. This table reports p-values from the Diebold-Mariano test comparing forecast accuracy of models with and without communication variables. Lower p-values indicate stronger evidence of difference in predictive performance.

5 A Measure of ECB Communication Shocks

This section derives a communication shock, defined as the part of the communication stance that is not explained by current macro-financial conditions. Following Cieslak and McMahon (2024), we identify this shock as the residual from a regression of the ECB Communication Stance Indicator on the same set of contemporaneous macro-financial variables, as described above, i.e. inflation, economic sentiment, and financial and geopolitical risk indicators. In addition, we also add the indicator's own lag to control for persistence.

The estimated determinants of the ECB communication stance indicator are reported in Table 4. We find that the tone of ECB official statements becomes more hawkish in response to higher inflation and a more optimistic economic outlook, as captured by the ICI - findings that are consistent with theoretical expectations. Financial stability concerns and geopolitical tensions do not influence the communication stance significantly. Overall, the model explains approximately 85 percent of the variation in the ECB Communication Stance Indicator.

We use regression (d) in Table 4 as our benchmark model, since it shows the best model fit with respect to the AIC criterion. Its model residual captures the non-systematic component of the ECB's communication that is not explained by observed fundamentals or past communication; it is interpreted as the exogenous communication shock. Formally, the shock is defined as:

$$\varepsilon_t = \mathrm{CI}_t - (\hat{\alpha} + X_t\hat{\beta} + \hat{\rho}\,\mathrm{CI}_{t-1}), \tag{4}$$

where CI_t denotes the Communication Stance Indicator at time t, X_t is the vector of

Table 4: Determinants of the ECB Communication Stance Indicator

	(a)	(b)	(c)	(d)
const	1.53	0.09	0.11	1.39*
	(3.35)	(2.99)	(2.96)	(0.75)
Communication Stance	0.82***	0.82***	0.82***	0.82***
	(0.04)	(0.04)	(0.04)	(0.04)
Inflation	1.22*	1.10*	1.10*	1.19**
	(0.65)	(0.59)	(0.59)	(0.55)
Industrial Confidence	0.31***	0.35***	0.35***	0.36***
	(0.10)	(0.09)	(0.09)	(0.09)
Geo Risk	0.00	0.01	0.01	
	(0.03)	(0.03)	(0.03)	
GDP Nowcast	-0.08	0.03		
	(0.42)	(0.43)		
Financial Stress Index	-3.94			
	(4.75)			
R-squared	0.85	0.85	0.85	0.85
AIC	1665.8	1664.8	1662.8	1660.9
N	221	221	221	221

Notes: Estimated coefficients from OLS regressions with Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors in brackets. Significance: * p<0.10, ** p<0.05, *** p<0.01.

macro-financial variables, and CI_{t-1} is the lagged stance indicator.[6]

Figure 3 displays the actual ECB Communication Stance Indicator alongside its fitted values from the regression model, as well as the residual component– the unexplained part of communication – that is interpreted as the communication shock.

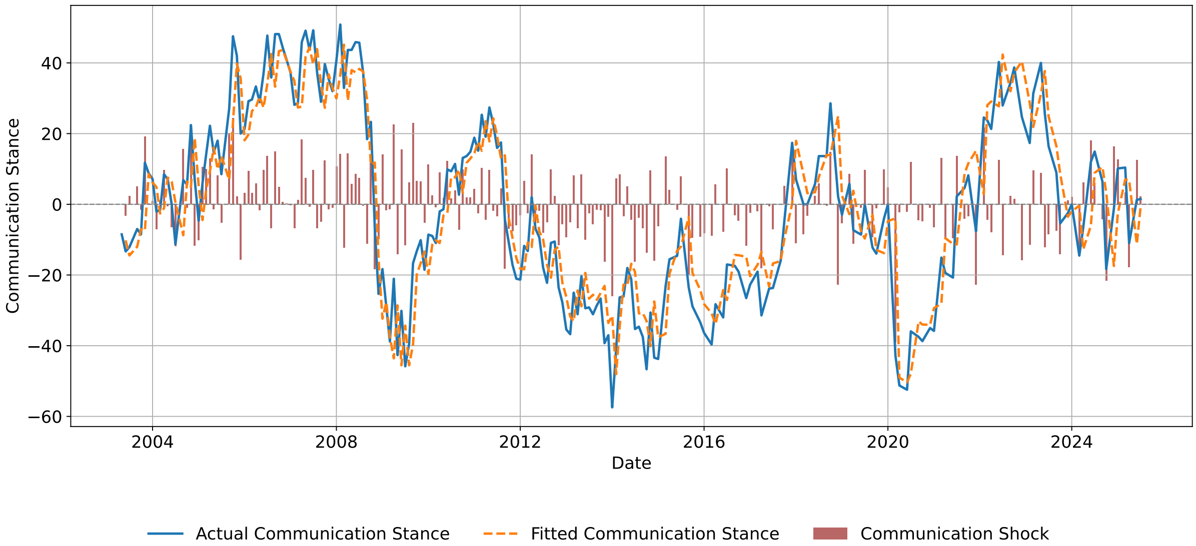
6 The Transmission of ECB Communication Shocks

6.1 Methodology and Data

In the following analysis, the nature of ECB communication shocks and their implications for the real economy are investigated. First, we explore how they are related to conventional monetary policy shocks and central bank information shocks (CBI), as outlined by Stock and Watson (2018); Jarocinski and Karadi (2020), and Bauer and Swanson

[6]We assess the adequacy of this specification using the Durbin-Watson and Ljung-Box tests, both of which confirm that including the lagged dependent variable effectively eliminates autocorrelation in the residuals.

Figure 3: ECB Communication Shock



Notes: This figure depicts the actual ECB Communication Stance Indicator (solid line) alongside the fitted component predicted by regression (d) shown in Table 4. The discrepancies between the two series (shown as bars) represent the communication shock.

(2023).[7] Next, we estimate the transmission dynamics of communication shocks to the real economy, benchmarking these effects against those of traditional monetary policy and CBI shocks to differentiate these distinct channels.

If communication shocks convey information about the ECB's current or future intentions regarding monetary policy, we would expect them to be correlated with conventional monetary policy shocks observed in the current or following months. However, it seems also plausible that communication shocks are related to the CBI shocks; that is, they reveal the ECB's private assessment of economic conditions. To investigate, whether such a relationship between these three shocks exists, each shock is regressed on the others. Appendix Table 6 shows the results. We fail to reject the null hypothesis of no correlation among these shocks, which confirms their orthogonality.[8] Hence, the communication shock can be regarded as a distinct shock.

For each of the three externally identified structural shock series – the communi-

[7]We follow the approach of Jarocinski and Karadi (2020) and distinguish monetary policy shocks from contemporaneous information shocks by analyzing the high-frequency co-movement of interest rates and stock prices in a narrow window around ECB policy announcements. Data are provided by the Euro Area Monetary Policy Event Study Database. Monetary policy shocks correspond to negative co-movements of interest rates and stock prices, while positive co-movements indicate information shocks. Orthogonal measures are obtained via the median rotation, which uniquely decomposes the two.

[8]Moreover, we also test, whether the communication shock is significantly related to the monetary policy shock in the *subsequent* period. We also reject this.

cation shock, the monetary policy shock, and the central bank information shock – we estimate a separate model to assess their transmission to the real economy. To facilitate comparison across shock types, all shock variables are standardized to have zero mean and unit variance.

Our primary empirical tool is a structural Bayesian vector autoregression (BVAR) model, specified in reduced form as:

$$Y_t = C_0 + \sum_{l=1}^{p} C_l Y_{t-l} + u_t, \tag{5}$$

where Y_t is a $(k \times 1)$ vector of endogenous variables at time t, the coefficient matrices C_l $(k \times k)$ capture the dynamic effects at lag l, C_0 is a $(k \times 1)$ vector of intercepts, and the reduced-form innovations $u_t \sim N(0, \Sigma)$ are assumed to be jointly normally distributed with mean zero and positive-definite covariance matrix Σ. By assumption, the system is stable and causal, i.e., all roots z of the characteristic polynomial $\det\left(I_k - C_1 z - C_2 z^2 - \cdots - C_p z^p\right) = 0$ lie outside the unit circle, ensuring the existence of a convergent vector moving average MA representation.

In our application, $k = 6$ for each model. Similar to Jarocinski and Karadi (2020), Y_t includes the respective shock variable alongside a set of macroeconomic and financial indicators: interest rates, equity prices, real activity measures, inflation, and financial stress indicators. For interest rates, we employ the monthly average of two-year German government bond yields. Because their yields are relatively unaffected by sovereign credit risk premia, German bonds provide a more accurate reflection of monetary policy conditions than generic euro area benchmarks. We prefer the two-year maturity over shorter maturities because it remains less constrained by the zero lower bound during our sample period.[9] Real activity is measured by monthly industrial production in log levels, while inflation is captured by the annual growth rate of the HICP.[10] Equity market conditions are represented by the monthly average of the Euro Stoxx 50 index. As our financial stress indicator, we include the Bond Market Sub-Index of the ECB's Composite Indica-

[9]As a robustness check, we also run the estimations with the ten-year German bond yield, with the idea that it captures forward guidance effects and serves as a reliable indicator of the monetary policy stance, particularly relevant for unconventional policy instruments. However, the results did not differ from that of the 2-year bond yield.

[10]As robustness checks, we also estimated models using real GDP (interpolated to monthly frequency) and the GDP deflator, both in log levels. Results were qualitatively similar and are available upon request.

tor of Systemic Stress (CISS), which captures strains in euro area bond markets through measures such as realized volatility of German 10-year yields and corporate-government bond spreads.[11] Due to stationarity requirements, both bond yields and equity prices enter as first differences, with their impulse responses reported in cumulative form for economically meaningful level interpretations:[12]

Structural identification follows a recursive Cholesky decomposition with the externally identified shock ordered first, consistent with Plagborg-Moller and Wolf (2021) and Caldara and Herbst (2019). This ordering ensures the exogeneity of our structural shocks, allowing impulse responses to capture their dynamic propagation without contamination from contemporaneous feedback effects. The remaining variables are ordered by their relative speed of adjustment: industrial production, HICP inflation, two-year government bond yield, bond market stress, and equity prices.[13]

The structural decomposition is:

$$u_t = P\varepsilon_t \tag{6}$$

where P is the lower triangular Cholesky factor of Σ and $\varepsilon_t \sim N(0, I_6)$ stacks mutually orthogonal structural shocks. Estimation employs the widely used Minnesota prior (Doan et al., 1984), with prior means set to random walks for each variable and variance hyperparameters calibrated automatically as in Banbura et al. (2010). This methodology is widely recognized for its robust forecasting performance and reliable inference in moderate sample settings, where traditional unrestricted VARs are often prone to overfitting and parameter instability (Doan et al., 1984; Banbura et al., 2010). However, as we discuss in the robustness section, we find comparable results when using a frequentist SVAR approach, as described by Gertler and Karadi (2015) and local projections, as described in Jordà (2005).

[11]Unlike the excess bond premium used by Jarocinski and Karadi (2020), this measure encompasses both primary and secondary corporate bond markets, providing broader coverage of bond market conditions.

[12]Stationarity of all variables was verified using Augmented Dickey-Fuller and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests.

[13]It is important to note that when the main interest lies in measuring the effects of the externally identified structural shock ordered first in the recursive (Cholesky) decomposition, as is the case in this paper, the ordering of the remaining variables is less critical. Changes in the order of these other variables primarily affect the identification and interpretation of shocks related to them, but have minimal impact on the effects associated with the first identified shock (see, e.g., Plagborg-Moller and Wolf (2021), Caldara and Herbst (2019)).

The optimal lag length is selected by comparing marginal likelihoods over $p = 1, \ldots, 6$. All three specifications select $p = 2$. Posterior inference uses 10,000 MCMC draws after discarding 1,000 burn-in iterations.

Impulse responses derive from the structural moving average (MA) representation of our SVAR model:

$$Y_t = \sum_{h=0}^{\infty} \Phi_h P \varepsilon_{t-h}. \tag{7}$$

The impulse response function (IRF) for variable i to a one-standard deviation in the shock j at horizon h is defined as

$$\text{IRF}_{i,j,h} = \frac{\partial Y_{i,t+h}}{\partial \varepsilon_{j,t}} = (\Phi_h P)_{i,j}, \tag{8}$$

where $(\Phi_h P)_{i,j}$ denotes the (i,j)-th element of the matrix product $\Phi_h P$. For variables entering in first differences, i.e. two-year German bond yields and the (log) Eurostoxx 50 index, we report cumulative impulse responses.

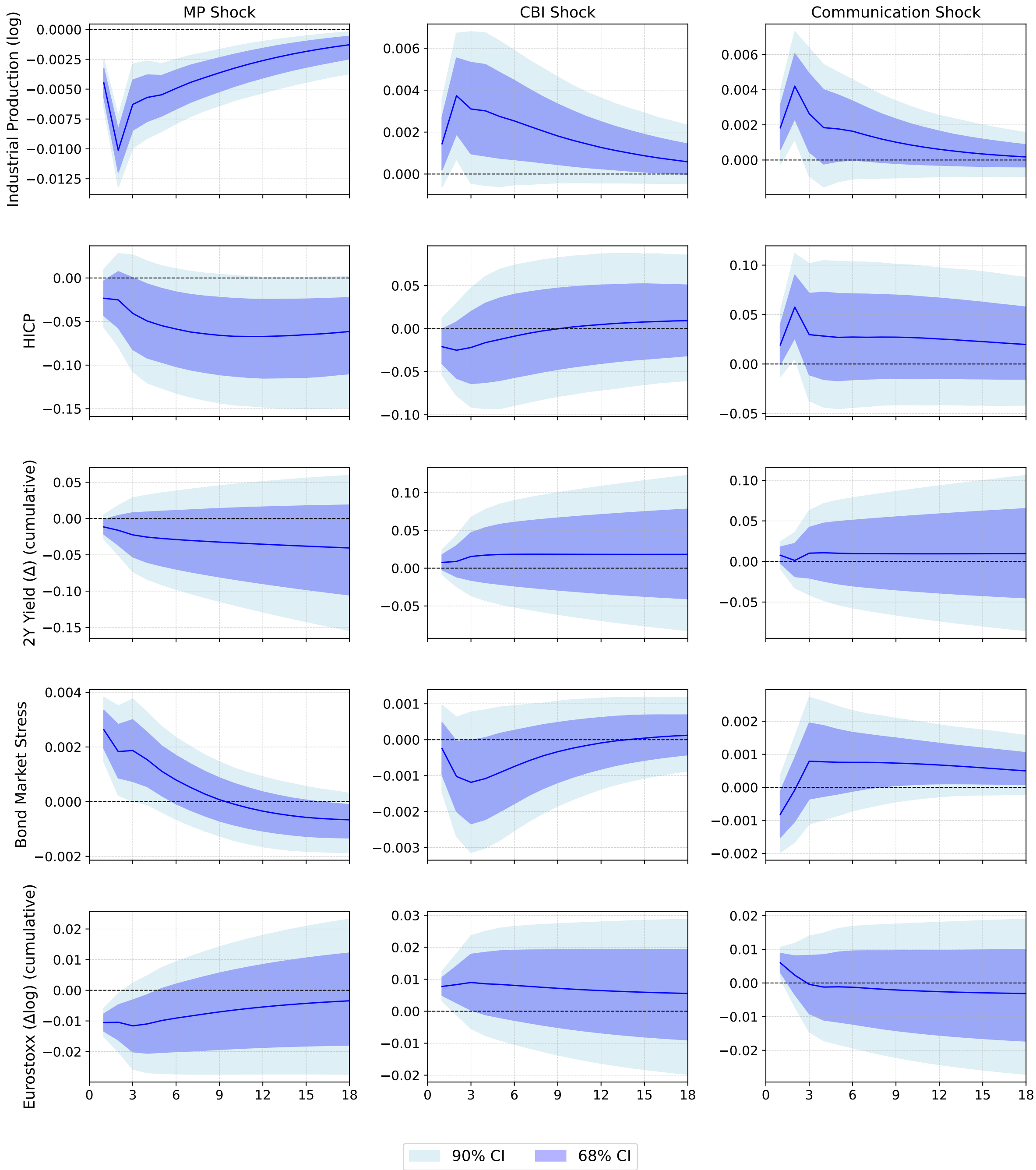
6.2 Impulse Responses

The first column of Figure 4 presents the impulse responses to a one standard-deviation monetary policy shock. The estimated responses align qualitatively with established findings in the monetary transmission literature and demonstrate statistically significant effects across most variables.

Following a one standard-deviation contractionary monetary policy shock, industrial production exhibits a sharp initial decline followed by a gradual recovery, with the response remaining significantly negative for more than 18 months. Inflation (HICP) shows a persistent and significant decline throughout the 18-month horizon, demonstrating the effectiveness of monetary policy in controlling price dynamics.

Rather than the expected increase predicted by standard monetary transmission theory following a contractionary shock, the two-year German government bond yield shows a modest decline. However, this response remains statistically insignificant. This likely reflects the inclusion of the ZLB period in our sample, during which conventional monetary policy transmission through interest rate adjustments was limited even at the

Figure 4: Impulse Responses from Bayesian SVAR Model



Notes: Impulse response functions show the effects of a one-unit structural shock on selected macro-financial variables over time. Shaded areas indicate 68% and 90% credible intervals, reflecting estimation uncertainty.

two-year maturity. Bond market stress initially increases before gradually declining, with the response being statistically significant for about six months, reflecting the immediate increase in risk premia following policy tightening. Equity prices exhibit a significant but temporary decline of approximately one percentage point in the immediate aftermath of the monetary policy shock. However, this effect is short-lived and becomes statistically insignificant after two months.

The second column illustrates the responses to a one standard-deviation CBI shock. Overall, these responses are consistent with the scenario in which central bank information shocks signal good news about the economy through monetary policy tightening. This shock is associated with a significant immediate and persistent increase in industrial production. Bond market stress declines significantly after three months, slowly reverting toward zero, indicating reduced financial market tensions after the release of information. The stock index increases immediately and significantly, with the effect slowly reverting toward zero over time. Unlike Jarocinski and Karadi (2020), we do not confirm a significant response in inflation or the two-year German bond yield.

Most notably, the third column of Figure 4 presents the impulse responses to a one standard-deviation hawkish ECB communication shock representing a novel contribution to the literature. We find that ECB communication has a statistically significant impact on real and financial variables, with a transmission pattern that is distinct from conventional monetary policy shocks and partially overlaps with CBI shocks (e.g., Newey and West (1987); Jarocinski and Karadi (2020)).

Following a hawkish communication shock, industrial production rises significantly and immediately, peaking around two months later before gradually returning to baseline levels. Equity prices respond immediately and significantly, but this effect dissipates after approximately three months. The concurrent increase in production and equity prices suggests that hawkish communication shocks convey positive information about the economic situation, which aligns with the interpretation of CBI shocks. Inflation also rises significantly and persistently, maintaining elevated levels for around two months – a phenomenon not observed after CBI shocks. The two-year German government bond yield exhibits no significant response over the entire horizon, consistent with ZLB-related constraints that apply throughout much of the sample period. Notably, restrictive communication shocks are accompanied by a delayed rise in bond market stress, which indicates potential challenges to financial stability. This contrasts with the decline in bond market stress observed following CBI shocks.

Overall, our findings suggest that central bank communication is an effective, independent policy tool with significant implications for the real economy. While its effects share similarities with those of central bank information shocks, notable differences emerge in the transmission mechanisms, particularly in how inflation and bond market stress respond. The observed rise in bond market tensions following hawkish communication shocks highlights a potential policy trade-off between delivering tightening signals and preserving market stability.

6.3 Variance Decomposition and Cumulative Effects of Communication Shocks

To evaluate the impact of communication shocks on macro-financial variables, Table 5 presents the forecast error variance decomposition (FEVD) across various time horizons.[14]

Table 5: Forecast Error Variance Decomposition by Shock and Horizon (percent)

	Communication				MP				CBI			
Variable	3M	6M	12M	18M	3M	6M	12M	18M	3M	6M	12M	18M
Industrial Production	3.4%	2.9%	2.1%	1.7%	11.3%	12.1%	10.7%	8.3%	4.0%	5.0%	4.3%	3.2%
HICP	1.8%	1.9%	1.9%	1.8%	2.1%	3.3%	4.7%	5.2%	1.6%	1.9%	1.9%	1.9%
2Y Yield	2.5%	3.0%	3.0%	2.9%	3.0%	3.8%	4.4%	4.6%	2.7%	3.5%	3.5%	3.4%
Bond Market Stress	2.3%	2.4%	2.8%	2.7%	4.8%	2.6%	2.5%	4.2%	3.0%	3.0%	2.0%	2.0%
Eurostoxx	2.8%	4.1%	4.8%	5.0%	6.4%	6.2%	5.9%	6.0%	5.0%	5.7%	5.8%	5.7%

Communication shocks account for between 1.7% and 5.0% of the forecast error variance across the analyzed variables, with the greatest impact observed in financial markets. For instance, the share explained in the Eurostoxx 50 index rises from about 3% after three months to 5% after eighteen months. Contributions to bond market stress and two-year yields also reach around 3% at longer horizons. By contrast, real economy variables such as industrial production and inflation account for smaller shares, ranging from 1.7% and 3.4%, and these contributions tend to decline over time. Overall, communication shocks are similar in magnitude to central bank information shocks across both real and financial variables. Conventional monetary policy shocks, by comparison, exert

[14]The FEVD indicates the proportion of forecast uncertainty attributable to communication shocks for each variable at different time horizons.

effects on financial markets of a similar order of magnitude, but they explain a substantially larger share of real activity than either communication or information shocks.

Figure 7 in the Appendix shows the cumulative impact of ECB communication on the selected macro-financial variables over time. The results reveal significant temporal clustering, with the most substantial cumulative effects occurring from 2007 to 2012, which coincided with the global financial crisis and the European sovereign debt crisis. With the exception of bond market stress, all variables exhibit positive cumulative impacts during this period, suggesting that communication shocks primarily conveyed accommodative policy signals. The decline in bond market stress observed during this period illustrates that ECB communication effectively reduced financial market tensions and eased bond risk premia amid the crisis.

Between 2007 and the end of 2012, industrial production levels were approximately 2.5 percentage points higher and Eurostoxx 50 equity levels were about 8 percentage points higher due to communication shocks. Inflation increased by around 0.3 percentage points annually, and two-year bond yields increased by about 11 basis points cumulatively. These results demonstrate that ECB communication successfully supported real growth and inflation during the crisis by mitigating deflationary and recessionary pressures. The tapering of cumulative effects after 2012 corresponds with the normalization of policy communication intensity.

In summary, although the real economic impact of the ECB's communication is not large in absolute terms, our findings underscore the importance of communication as a tool for managing expectations and financial conditions, complementing conventional monetary policy measures.

6.4 Robustness

We further assess robustness with a frequentist SVAR, as outlined in Gertler and Karadi (2015)), using a wild bootstrap for inference to accommodate non-Gaussian and heteroskedastic errors (Gonçalves and Kilian 2004; see also Bruns and Lütkepohl 2023). We fix the lag length to the BVAR choice above and identify shocks as in the baseline. For each bootstrap replication ($B = 10.000$), we re-estimate the VAR and compute orthogonalized IRFs.

To complement this, we also apply local projections, as described in Jordà (2005), which are often used in monetary policy research (e.g., Jordà et al. (2020); Jordà and Taylor (2025)). Local projections (LPs) are robust in small samples, require fewer restrictive assumptions, and allow horizon-by-horizon identification rather than imposing a single global model.[15] At each horizon we estimate OLS with heteroskedasticity-robust (Eicker-Huber-White) standard errors, which are well-behaved in short samples. We choose the optimal lag length by minimizing AIC among specifications that pass a Breusch-Godfrey residual autocorrelation test ($p \geq 0.10$). If no model up to the initial cap (12 lags) passes, we expand the search in steps of three (up to 18) and pick the best admissible model.

Figures 8 and 9 display the impulse responses from both estimations with 68% and 90% bands (for comparability with the Bayesian presentation) and additionally 95% bands in line with frequentist practice. For variables modeled in first differences, we plot cumulative responses by summing horizon-specific coefficients and cumulate the corresponding bands accordingly.[16] Overall, the results are consistent with the baseline BVAR, with financial market responses particularly robust across methods and somewhat greater model sensitivity for real activity and prices.

7 Conclusions

This paper provides new evidence on the effectiveness and transmission of European Central Bank (ECB) communication, focusing on the tone of official monetary policy statements from May 2003 to July 2025. Using a transformer-based large language model (LLM) fine-tuned to ECB speeches, we construct a high-precision sentiment classifier and derive a Communication Stance Indicator that captures the overall hawkish or dovish tone. This enables a systematic analysis of communication as an independent policy instrument.

To assess the informational content of the indicator, we estimate a multinomial ordered logit model that incorporates both the communication stance and relevant macro-financial controls. The results show that ECB statements provide meaningful forward-

[15] Recent comparative studies highlight a bias-variance trade-off. LPs often deliver lower bias-especially at longer horizons, while SVARs tend to have lower variance. Both approaches yield reliable inference under standard conditions (Caldara and Herbst, 2019; Plagborg-Moller and Wolf, 2021; Stock and Watson, 2018).

[16] For the frequentist SVAR, we report bias-corrected and accelerated (BCa) intervals (Efron, 1987) for raw IRFs and, for cumulative responses, we cumulate each bootstrap IRF path and take percentile intervals from the resulting distribution.

looking signals about interest rate decisions, up to three Governing Council meetings ahead.

We then isolate the unexpected component of the communication stance, i.e., a communication shock, by conditioning on the prevailing macroeconomic environment. This shock is shown to be empirically distinct from both conventional monetary policy and central bank information (CBI) shocks, highlighting the role of communication as an independent tool in the ECB's policy toolbox. Using a structural Bayesian vector autoregression (BVAR), we estimate the macroeconomic effects of communication shocks and benchmark them against monetary and CBI shocks.

Hawkish communication shocks, despite signaling a tighter policy stance, are found to raise industrial production, equity prices, and inflation in the short run. These dynamics resemble those of CBI shocks and suggest that financial markets interpret an unexpected hawkish tone not merely as a signal of future tightening, but as a reflection of improved economic prospects. At the same time, bond market stress increases with a delay, indicating potential tensions between signaling strength and maintaining financial stability.

These findings have important implications for both central bank communication and the general understanding of monetary policy transmission. They underscore the importance of tone in monetary policy statements: while hawkish language can strengthen central bank credibility and confidence in the outlook, it can also increase market volatility if not carefully calibrated. From a methodological perspective, the study shows that LLM-based sentiment classification is a powerful tool for future research on central bank communication and expectation formation.

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A Fine-Tuning the Transformer-Based Large Language Model to ECB Communication

The original model by Shah et al. (2023) is trained to classify communications from the US Federal Reserve. To account for potential differences in sentiment expression between the US Fed and the ECB, we adapt the model by fine-tuning it on ECB communication. For this purpose, we collect a training sample containing all speeches delivered by members of the ECB's Executive Board from January 1999 to June 2025. In order to reduce noise in the training data and to ensure that only policy-relevant content is analyzed, the text corpus was first filtered for content. Speeches were only included in the analysis if the title contained one of the following keywords: Inflation expectations, policy rate, deposit rate, refinancing rate, quantitative easing/tightening, prices, economic activity, inflation/deflation, employment, GDP, financial stability, unemployment, growth, exchange rate, productivity, deficit, demand, or monetary policy.

After applying these filter criteria, the training dataset contains 417 speeches, totaling around 27,000 sentences. In the next step, only those sentences were retained that could be assigned by the language model originally trained on the US Federal Reserve of Shah et al. (2023) with at least 95 per cent classification certainty to one of the three categories 'hawkish', 'dovish' or 'neutral'. It is worth noting that less than 10 per cent of ECB communications had to be excluded from the dataset according to this criterion. This indicates a high degree of similarity in the communication style between the US Federal Reserve and the ECB - at least with regard to the core monetary policy statements.

The remaining 24,480 sentences are used to further train and refine the model and thus learn the linguistic nuances characteristic of the ECB. For this, the tokenized ECB dataset was split 90:10 into training (90%) and validation (10%) sets. The model was fine-tuned for three epochs using Hugging Face's Trainer with standard hyperparameters (learning rate $= 2 \times 10^{-5}$, batch size=8, weight decay=0.01) chosen based on published best-practice recommendations for transformer fine-tuning and our available compute budget (Devlin et al., 2018; Liu et al., 2019). Evaluation (accuracy) and mode checkpointing occur at the end of each epoch. We did not perform an exhaustive grid search because tuning dozens of transformer hyperparameters via brute-force search is extremely costly in time and GPU resources, yet yields only marginal performance gains beyond well-established defaults (Liu et al., 2019). Instead, we rely on the empirically validated defaults for RoBERTa-large - an approach that balances efficiency with strong out-of-the-box accuracy. As is the standard in machine learning, the metric for evaluating the performance of the trained network is based on how well it can accurately predict the tone in sentences in the monetary policy statement that were not used to train the network parameters. We find that our trained model achieves an accuracy of 98%.

B Tables

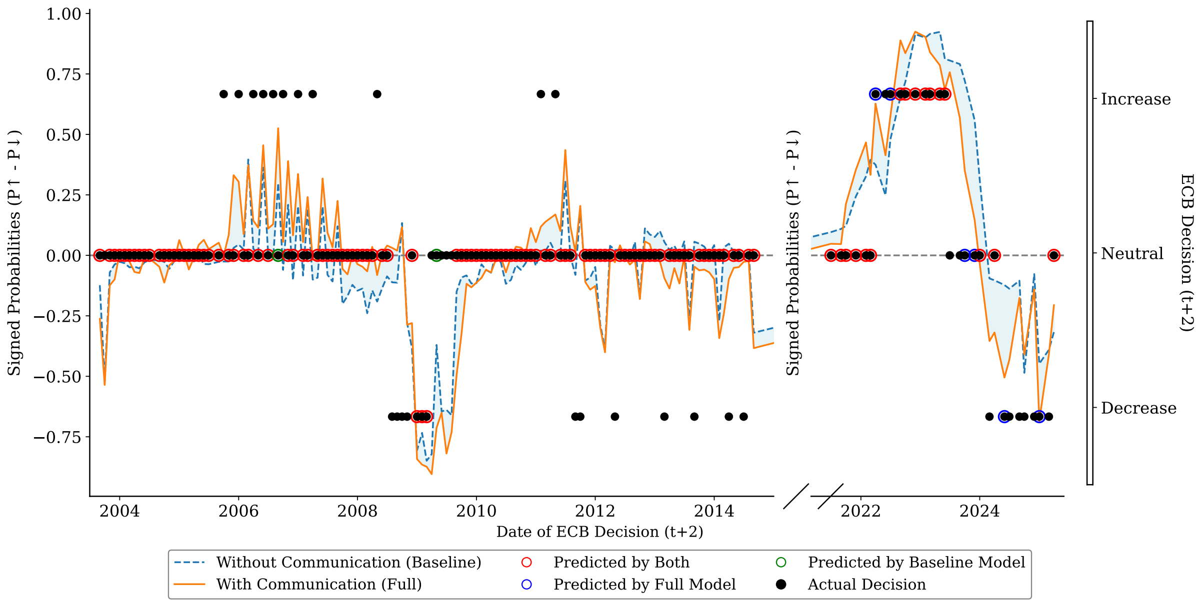
Table 6: Orthogonality Tests Among Standardized Shocks

	Communication Shock	MP Shock	CBI Shock
	(1)	(2)	(3)
Monetary Policy Shock	–	-0.13	-0.11
		(0.15)	(0.12)
CBI Shock	-0.13	–	-0.03
	(0.15)		(0.08)
Communication Shock	-0.11	-0.04	–
	(0.11)	(0.07)	
Observations	267	267	267
R^2	0.03	0.02	0.01

Note: Each column reports results from a separate OLS regression with robust standard errors. The dependent variable is indicated at the top of each column. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

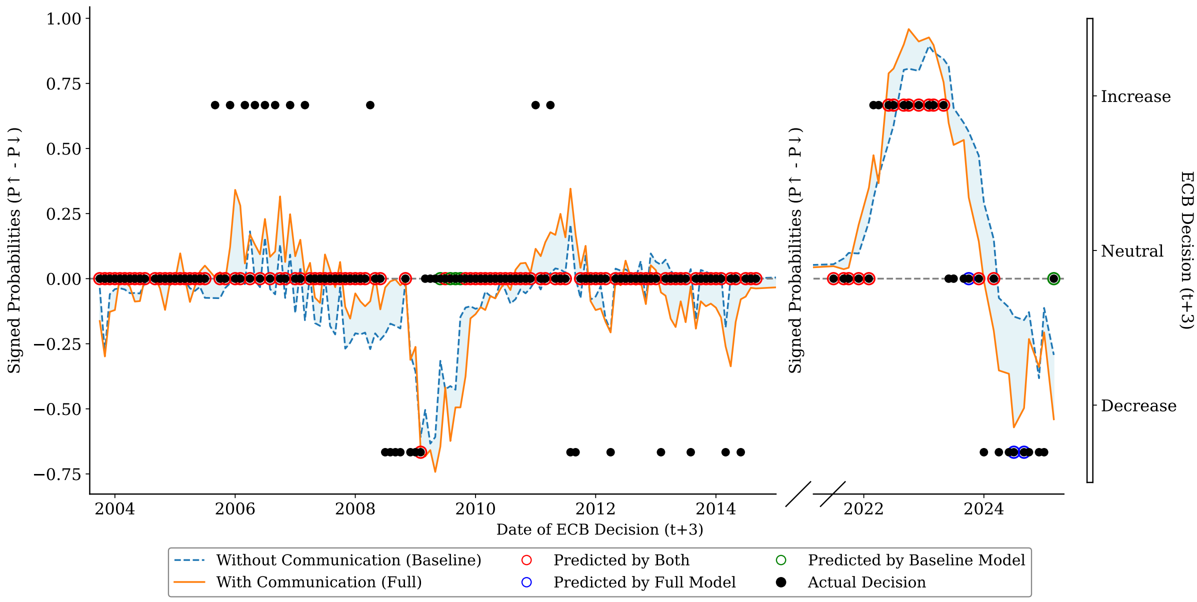
C Figures

Figure 5: Forecast Performance - Two Periods Ahead



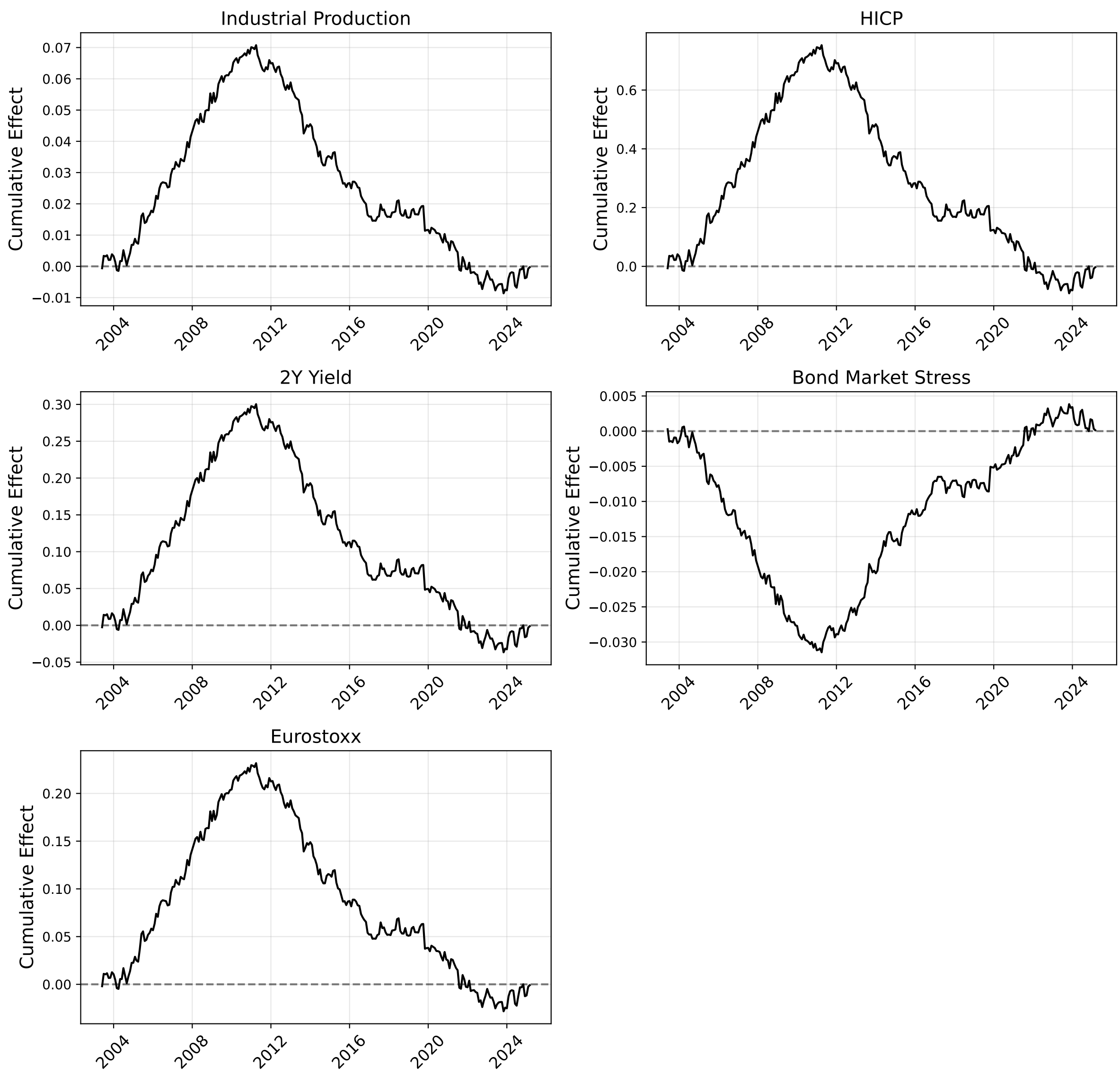
Notes: The vertical axis plots the signed forecast probability – the predicted probability of a hike minus that of a cut – with positive values indicating a tilt toward tightening. The dashed blue line is the baseline model using macro-financial variables only; the solid orange line adds the ECB Communication Stance Indicator (full model). Black dots mark actual interest rate decisions, with colored circles indicating correct predictions: red (both models), blue (full model only), green (baseline only), and no color (both incorrect).

Figure 6: Forecast Performance - Three Periods Ahead



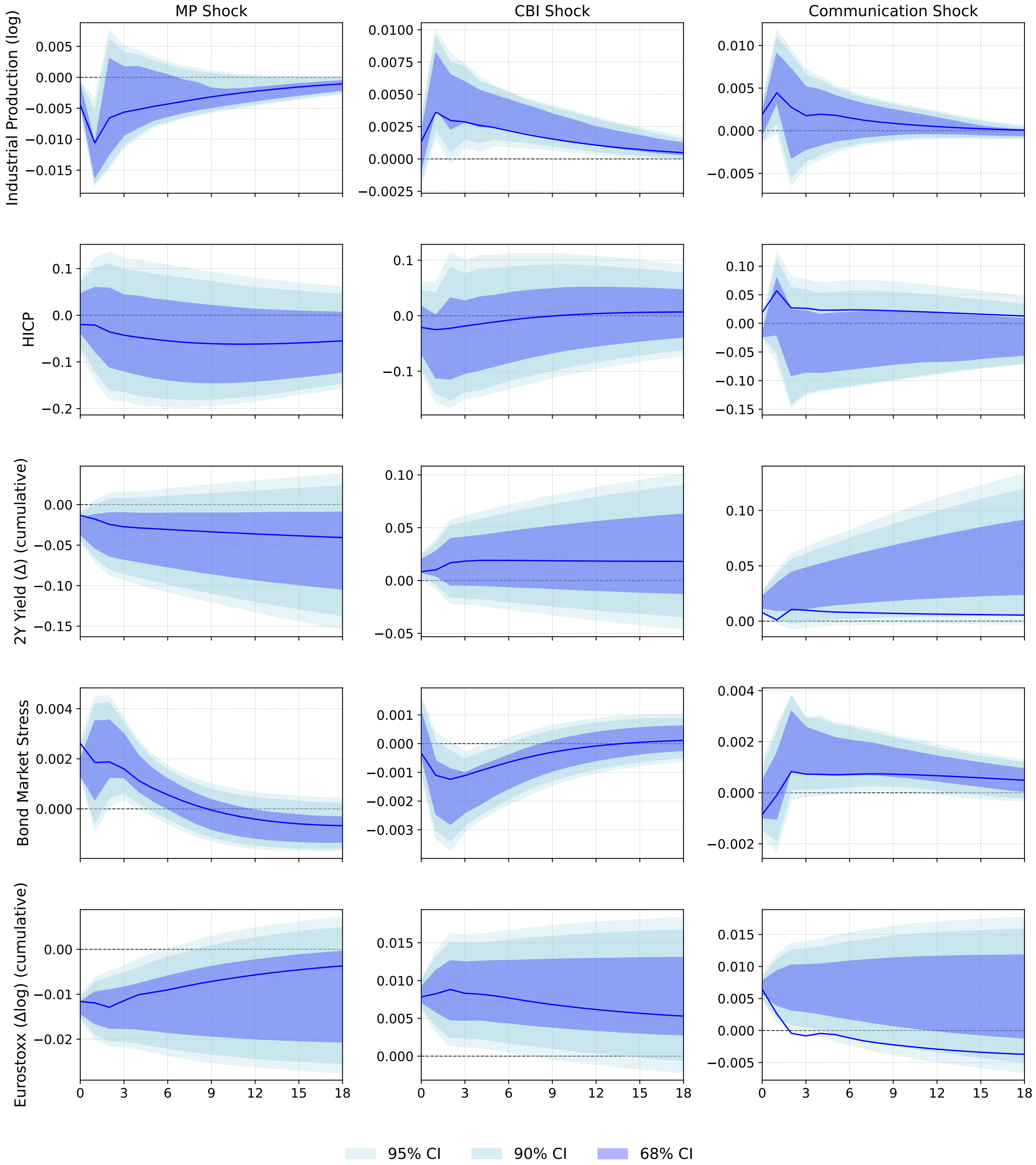
Notes: The vertical axis plots the signed forecast probability – the predicted probability of a hike minus that of a cut – with positive values indicating a tilt toward tightening. The dashed blue line is the baseline model using macro-financial variables only; the solid orange line adds the ECB Communication Stance Indicator (full model). Black dots mark actual interest rate decisions, with colored circles indicating correct predictions: red (both models), blue (full model only), green (baseline only), and no color (both incorrect).

Figure 7: Cumulative Impact of Communication Shock



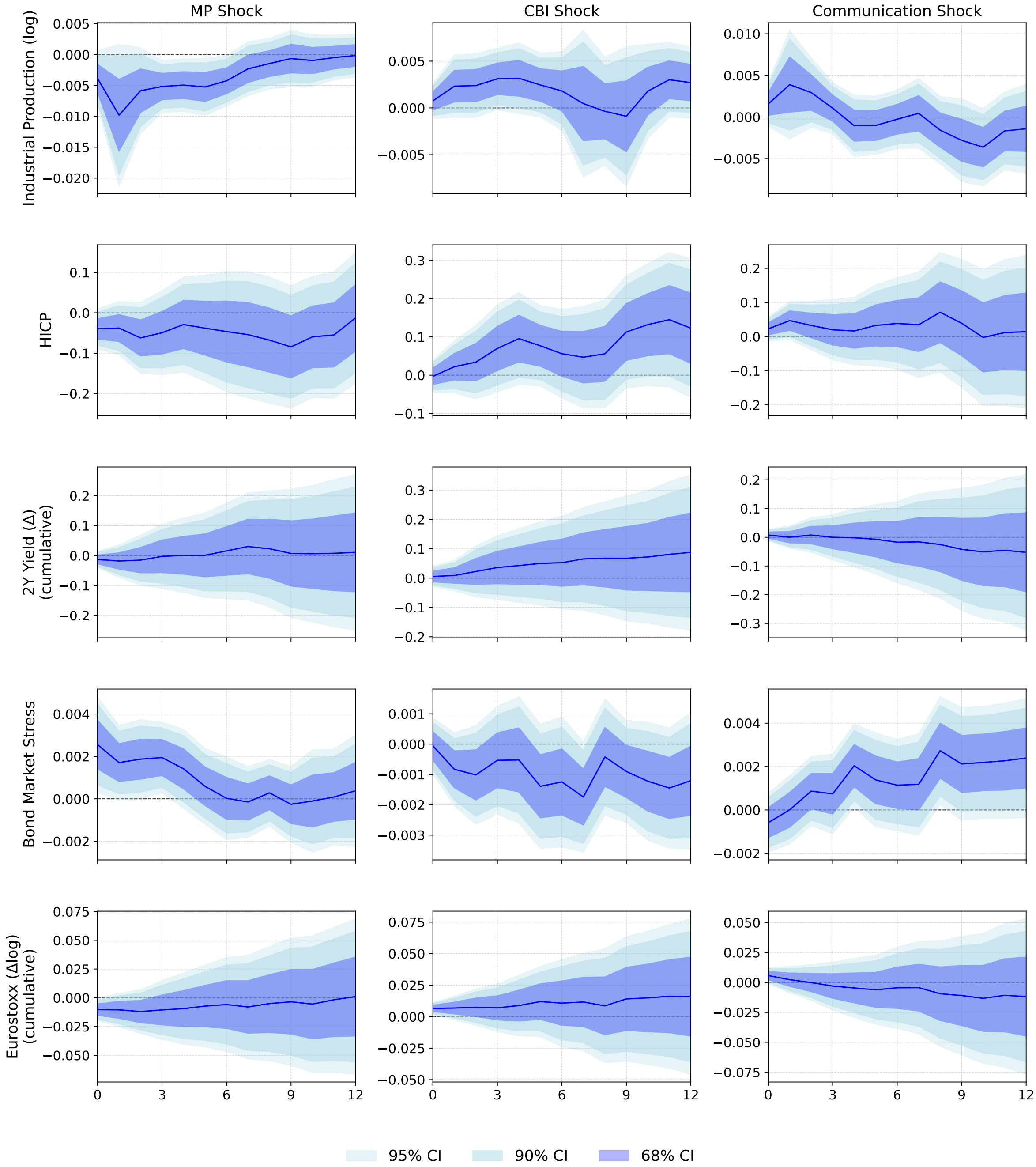
Notes: Cumulative impacts of the ECB communication shock on key macro-financial variables derived from counterfactual BVAR simulations. Positive (negative) values indicate increases (decreases) due to the shock. The shock is identified structurally and isolates policy communication effects beyond macro fundamentals.

Figure 8: Impulse Responses from SVAR Model



Notes: Impulse response functions show the effects of a one-unit structural shock on selected macro-financial variables over time. Shaded areas indicate 68%, 90%, and 95% confidence intervals, reflecting estimation uncertainty.

Figure 9: Impulse Responses from Local Projections



Notes: Impulse response functions show the effects of a one-unit structural shock on selected macro-financial variables over time. Shaded areas indicate 68%, 90%, and 95% confidence intervals, reflecting estimation uncertainty.