The Effects of Information Ambiguity on Financial Market Responses to ECB Monetary Policy Shocks

Based on Machine Learning

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Abstract

This thesis investigates how information ambiguity—arising from conflicting interpretations of the same ECB monetary policy event—affects financial market responses. Using Bloomberg and Reuters articles as inputs, I extract sentiment and uncertainty scores with OpenAI's large language model and construct an information ambiguity index based on the variance of these mixed signals. I then estimate impulse response functions through local projections to test whether markets respond differently under high information ambiguity. Results show that information ambiguity initially dampens the response of stock market volatility (VSTOXX) but amplifies it over time, consistent with delayed belief updating. For trading volume (FEZ ETF), the interaction effect alternates in sign—positive in the short run, negative at the medium horizon, positive again, and eventually negative—indicating a non-monotonic pattern driven by an initial burst of speculative activity, mid-horizon repositioning fatigue, renewed engagement, and eventual dissipation. These findings highlight information ambiguity as a time-varying amplifier that reshapes the timing, intensity, and direction of market reactions to monetary policy shocks.

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1 Introduction

Understanding how financial markets respond to monetary policy decisions has long been a core focus in macroeconomics and finance. Traditional research has mostly examined how markets react to the magnitude and direction of policy actions—such as changes in interest rates, forward guidance, or asset purchase programs—under the assumption that the information transmitted by central banks is clearly understood by all agents (e.g., Bernanke et al., 2005).

However, more recent literature has shifted attention toward the information environment in which monetary policy decisions are received and interpreted by investors. This body of work emphasizes that market responses depend not only on the substance of the central bank's actions, but also on how clearly and consistently those actions are conveyed through publicly available channels (Nakamura et al., 2018). In other words, financial markets are sensitive not just to what the central bank does, but to how those actions are framed and understood by the broader public. Even when the policy stance itself is unambiguous, investors' reactions can vary depending on how they interpret—or misinterpret—the meaning and future implications of the announcement.

As part of this growing focus on the interpretation of monetary policy information, a substantial strand of research has explored the effects of uncertainty—typically understood as a lack of information or heightened unpredictability—on financial markets. These studies find that uncertainty can amplify market volatility (Jurado et al., 2015), raise risk premia (Pastor et al., 2012), and depress firm-level outcomes such as investment (Bloom, 2009).

Yet comparatively less attention has been devoted to a specific but related channel: the effects of information ambiguity, which arises not from the absence of information, but from the presence of multiple, potentially conflicting interpretations of the same monetary policy event.

To address this gap, this thesis investigates how information ambiguity influences financial market responses to the European Central Bank (ECB) monetary policy shocks. Specifically, it focuses on the period immediately following ECB announcements, when investors turn to financial news outlets to interpret the implications of the decision. In a fragmented information environment, however, these interpretations may diverge. For instance, following the same ECB announcement, Bloomberg might emphasize the hawkish stance and inflation-fighting commitment of the Governing Council, while Reuters might highlight concerns over financial fragmentation and the introduction of backstop tools like the Transmission Protection Instrument (TPI). The divergence in tone, emphasis, and overall message from these two reputable sources can leave investors uncertain about the true intent and expected impact of the policy decision, giving rise to what is defined as information ambiguity.

In this research, it is operationalized as the statistical disagreement between sentiment scores extracted from Bloomberg and Reuters articles surrounding ECB monetary policy announcements. This approach draws inspiration from the conceptual framework developed by Angeletos et al., 2013, who model investors as agents receiving noisy signals about an underlying state of the world. In line with this literature, I treat each article's sentiment score as a noisy signal about the "true" implications of the monetary policy decision. The greater the divergence between these signals, the higher the information ambiguity investors face. Unlike Knightian uncertainty, which refers to ambiguity about the probabilities of future states, the information ambiguity studied here is narrowly focused on signal disagreement and interpretation frictions in the short-term market context.

Specifically, I study the effects of information ambiguity on two key financial indicators: stock market volatility and trading volume. These variables are particularly relevant because they capture both the perceived risk in financial markets and investor engagement or hesitation in the face of uncertain conditions.

The analysis focuses on a set of monetary policy shocks from 2012 to 2023, identified using changes in overnight index swap (OIS) rates within a narrow window around ECB monetary policy meetings. These high-frequency shocks capture market surprises, isolating the unexpected component of ECB decisions (Altavilla et al., 2019).

For each shock event, articles from Bloomberg and Reuters are collected and processed to extract sentiment and uncertainty scores. The sentiment scores (S_1, S_2) are obtained using GPT-4, which classifies each article's tone with respect to the future economic outlook. The uncertainty scores (σ_1^2, σ_2^2) reflect the clarity or confidence of the sentiment expressed.

These scores are used to construct the information ambiguity index, which is defined as the variance of the investors' combined belief, conditional on the two observed signals. The index is standardized (expressed in standard deviation units from the mean) to allow for meaningful comparisons across time.

Market responses are then estimated using local projections, where the dependent variables are daily stock market volatility (measured via the VSTOXX index) and trading volume (proxied by the FEZ ETF). These indicators reflect both risk perceptions and investor activity, and are particularly sensitive to short-run uncertainty.

Therefore, the contribution of this work aims to be threefold:

1. It introduces a model-based measure of information ambiguity that captures the statistical disagreement between sentiment signals extracted from financial news sources.

2. It applies modern large language models (LLMs), specifically OpenAI's GPT-4, to systematically classify the sentiment and tone of monetary policy-related articles, allowing for fine-grained textual analysis of financial reporting.

3. It empirically tests the effects of information ambiguity on financial market variables using the local projections (LP) methodology (Jordà, 2005), offering a dynamic view of market reactions over time.

The empirical results suggest that information ambiguity acts as a dynamic filter in the monetary policy transmission process, altering both the speed and coherence of market adjustments. When information ambiguity is high, markets exhibit a cautious stance—stock market volatility responses are initially muted, but intensify over time as beliefs are gradually updated. This delayed amplification in stock market volatility points to a friction in belief adjustment, rather than to an outright dampening of policy effects. Trading volume, by contrast, displays an irregular pattern: initial surges in trading activity likely reflect speculative repositioning and signal uncertainty, followed by pullbacks as market participants reassess their strategies. The reappearance of positive effects at intermediate horizons suggests renewed interpretation efforts, while the eventual decline in trading volume reflects exhaustion or resolution of the information ambiguity.

Together, these patterns emphasize that information ambiguity does not merely suppress reactions, but redistributes them across time—disrupting the synchronization of responses and increasing dispersion in investor behavior following monetary policy news.

Understanding how information ambiguity affects financial market behavior is crucial for central banks and policymakers. If market reactions to policy moves are distorted by conflicting narratives, the transmission of monetary policy may become less effective or more volatile. Moreover, in periods of rapid tightening or easing, timely and efficient transmission is essential to achieving macroeconomic stabilization goals. By highlighting the role of financial media in shaping the perceived clarity of policy decisions, this research also speaks to broader questions about information processing, investor behavior, and the transparency of communication in the age of algorithmic trading and news analytics.

The remainder of the thesis is structured as follows. Section 2 introduces the data sources and describes how sentiment and uncertainty scores are extracted from Bloomberg and Reuters articles related to ECB monetary policy announcements. Section 3 presents the construction of the information ambiguity index, which combines the sentiment signals to quantify disagreement and signal noise across media sources. Section 4 outlines the empirical methodology, detailing the local projection approach used to estimate the effects of monetary policy shocks under varying levels of information ambiguity. It then presents and interprets the main results, focusing on impulse response functions of financial market indicators such as stock market volatility and trading volume. Finally, Section 5 concludes.

2 Data and Construction of Sentiment and Uncertainty Scores

2.1 Overview

Understanding how financial markets respond to monetary policy shocks hinges not only on the shock itself but on how that information is interpreted and absorbed.

In this section, I describe the data sources used for the thesis, the methodology adopted to compute sentiment and uncertainty scores using OpenAI's GPT-4 model, and the rationale for each decision in the empirical pipeline. Unlike traditional dictionary-based methods, I leverage large language models (LLMs) to provide a more nuanced understanding of how news content—surrounding European Central Bank (ECB) monetary policy events—is received and processed by market participants. I then present and discuss the time-series evolution of these scores in relation to the ECB deposit facility rate and market-based measures of monetary policy surprises.

2.2 Monetary Policy Shocks

The analysis focuses on the euro area monetary policy shocks over the period from January 2012 to October 2023, using exogenous shock measures derived from the high-frequency event-study methodology developed by Altavilla et al., 2019 and updated in the EA-MPD (Euro Area Monetary Policy Event-Study Database). These shocks are based on changes in overnight index swap (OIS) rates in a tight window around ECB policy announcements and are considered a standard in the literature for identifying unexpected monetary policy innovations. I specifically focus on the component of the policy surprise that affects the short end of the yield curve, captured by the change in the 1-month OIS rate, and treat it as the "target rate shock". These shocks are scaled by 0.25 following Bernanke et al., 2005, such that the impulse responses can be interpreted as responses to a 25-basis-point surprise.

2.3 News-Based Textual Data: Bloomberg and Reuters

To capture how monetary policy shocks are interpreted by financial markets, I collected textual data from Bloomberg and Reuters, two of the most influential financial news agencies.

For each monetary policy event date (see Appendix C for the full list of dates), I selected one Bloomberg article and one Reuters article published on the same day or within a 24-hour window. This pairing allows us to observe variation in tone and interpretation between two sources with different editorial and institutional characteristics.

Articles were selected manually based on two criteria: (i) their relevance to the ECB monetary policy event in question, and (ii) their explicit discussion of the monetary policy decision, its rationale, and/or expected consequences. I excluded purely technical summaries, market tickers, or articles that only tangentially referenced the ECB's decision. All articles were preprocessed to remove headers, tickers, and metadata. I retained only the body text to ensure consistency across sources. This corpus of paired articles forms the input for sentiment and uncertainty scoring using GPT-4.

2.4 Sentiment and Uncertainty Scoring Using OpenAI

2.4.1 Signal Representation and Score Definition

To formalize how information is extracted from textual financial news and interpreted by market participants, I model each news article as emitting a signal $S_{i,t}$, where i indexes the source (Bloomberg or Reuters), and t indexes the monetary policy event date. Each signal reflects the perceived sentiment about the monetary policy decision as interpreted by that source.

Mathematically, each signal is defined as:

$$S_{i,t} = \mu_t + \varepsilon_{i,t} \tag{1}$$

where:

- μ_t is the latent or "true" sentiment component reflecting the actual economic implications of the ECB policy decision at time t,

- $\varepsilon_{i,t}$ is an idiosyncratic noise term capturing source-specific ambiguity, editorial framing, or information loss.

I assume $\epsilon_{i,t} \sim \mathcal{N}(0, \sigma^2_{i,t})$, that is, the noise is normally distributed with mean zero and variance $\sigma^2_{i,t}$.

In this framework, the sentiment score $S_{i,t}$ is a scalar representing the polarity of the message: a score closer to +1 indicates a strongly positive interpretation (e.g., optimism about the economy), while a score closer to –1 reflects a strongly negative interpretation. A value near 0 represents a neutral stance.

In parallel, each article is also assigned an uncertainty score $\sigma^2_{i,t}$, which reflects the model's assessment of how confidently the sentiment was expressed. Higher values of $\sigma^2_{i,t}$ indicate greater ambiguity or inconsistency in the tone or message of the article. Formally, I interpret the uncertainty score as proportional to the variance of the signal noise, i.e.:

$$\text{Uncertainty}_{i,t} \propto \mathbb{V}[\varepsilon_{i,t}] \tag{2}$$

These two components— $S_{i,t}$ and $\sigma^2_{i,t}$—jointly define each article's informational signal. While the sentiment score captures the directional tone of the economic message, the uncertainty score captures the noisiness or reliability of that signal, providing a richer characterization of how policy announcements are interpreted.

This formulation is consistent with the information-processing models used in macro-finance, where agents update their beliefs based on noisy public signals. Here, the sentiment scores from Bloomberg and Reuters act as competing signals that may either reinforce or contradict each other in tone and clarity, ultimately shaping investor expectations and market responses.

2.4.2 Motivation for Using Large Language Models

Traditional approaches to textual sentiment and uncertainty measurement in finance—such as dictionary-based techniques (e.g., Loughran and McDonald, 2011)—rely on word frequencies and fixed lexicons. While widely used, these methods are limited in their ability to capture the nuanced and context-dependent nature of financial language, especially in high-stakes macroeconomic settings. Words such as "unexpected," "hawkish," or "resilient" may have highly variable implications depending on surrounding context and syntactic structure.

Recent advances in natural language processing, particularly the development of large language models (LLMs) such as GPT-4 by OpenAI, offer a powerful alternative. These models can interpret sentiment and uncertainty in full-text documents by considering grammar, context, and semantic nuance, overcoming many limitations of keyword-based methods. GPT-4 was selected for this analysis because of its robust performance on financial reasoning tasks (Bürgler et al., 2024) and its demonstrated alignment with human assessments in financial sentiment evaluation (Yang et al., 2024).

2.4.3 Methodology

For each article, I applied two standardized prompts to GPT-4 via the OpenAI API: one for extracting a sentiment score and another for assessing uncertainty. The sentiment prompt asked the model to evaluate whether the article conveyed a positive, negative, or neutral outlook on the economic implications of the ECB decision, using a score from -1 (very negative) to +1 (very positive). The uncertainty prompt instead evaluated the degree of ambiguity, disagreement, or doubt expressed in the article regarding future economic developments, producing a score from 0 (no uncertainty) to 1 (very high uncertainty).

The same prompt templates were used for all articles to ensure consistency. Each article was submitted in full (with appropriate length truncation below the token limit), and the GPT-4 response was parsed and stored as a numeric score. To ensure robustness, scores were clipped to remain within the valid range and rounded to two decimal places. In cases of unclear responses or parsing errors, the article was reprocessed. No manual tuning, score calibration, or label assignment was performed after model output, ensuring full automation and reproducibility of the scoring procedure.

2.5 Market Outcome Variables: VSTOXX and FEZ ETF

To assess how financial markets respond to monetary policy announcements under varying levels of information ambiguity, I focus on two high-frequency market indicators that capture volatility and trading behavior:

- VSTOXX: the implied volatility index for the Euro Stoxx 50, widely used to proxy market uncertainty.
- FEZ ETF: the SPDR Euro Stoxx 50 ETF, representing real-time equity market behavior and trading volume in response to macroeconomic news.

Both variables are observed at the daily frequency and aligned temporally with each ECB monetary policy announcement. VSTOXX reflects changes in risk sentiment and expected volatility, while FEZ ETF volumes proxy trading activity and investor engagement. Together, they provide complementary insights into the effect of policy communication and sentiment disagreement on euro area asset markets.

2.6 Visualization of Sentiment and Uncertainty Scores

To explore the time-series behavior of the sentiment and uncertainty scores extracted from news articles, I construct two sets of visualizations.

Figure 1 plots the demeaned sentiment scores across Bloomberg and Reuters articles (per monetary policy event) against the ECB deposit facility rate (a key policy instrument) and the 1-month OIS-based monetary policy shock series obtained from the EA-MPD database.

This visualization allows us to observe whether changes in policy stance (as proxied by the deposit rate) and the surprise component of policy decisions (as captured by OIS shocks) co-move with shifts in the tone of financial media coverage.

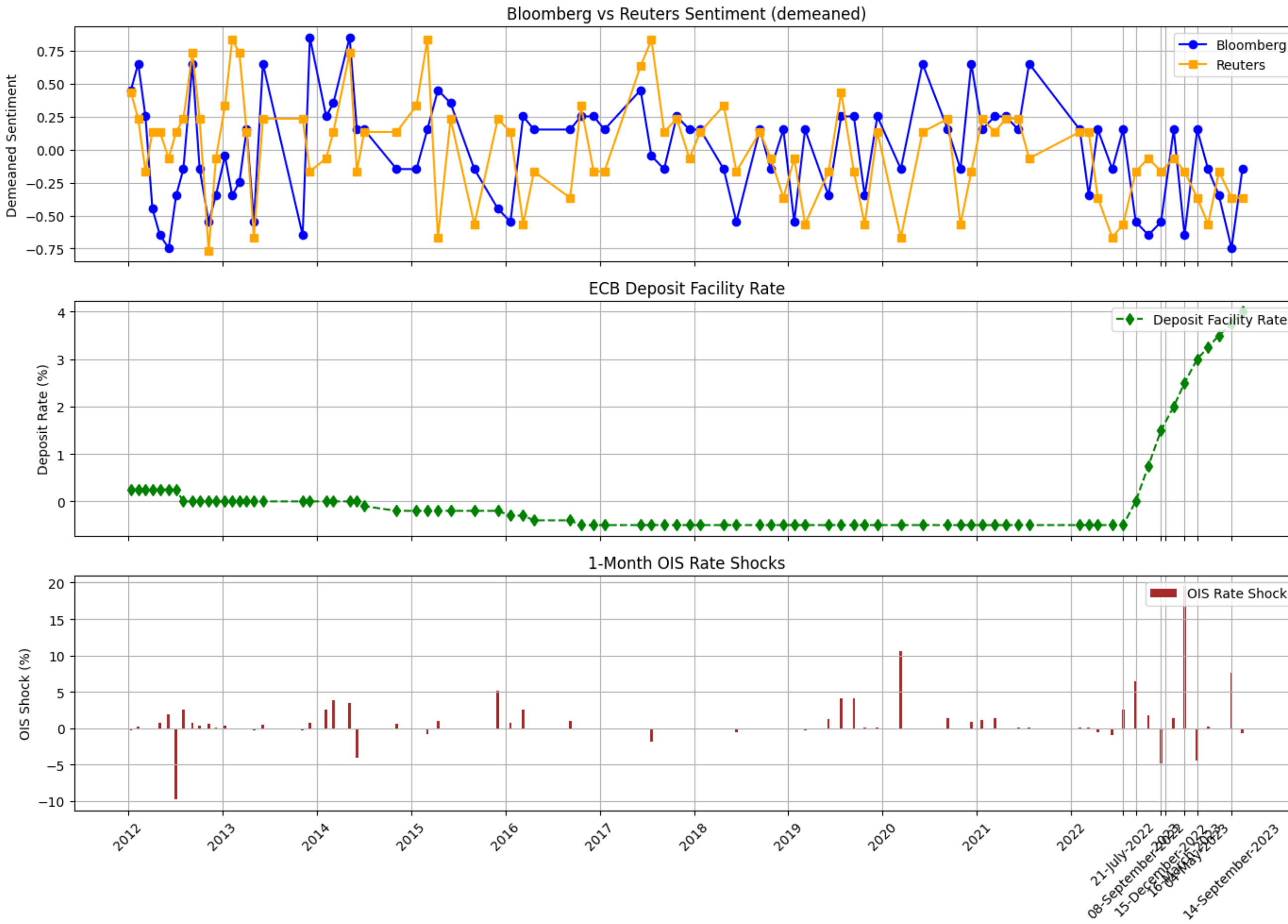

Figure 1: Sentiment scores (demeaned) from Bloomberg and Reuters with ECB deposit rate and OIS shocks

Figure 2 presents the time-series of the average uncertainty scores (again across Bloomberg and Reuters) for each monetary policy event, without overlaying other variables. This figure isolates the evolution of the perceived confidence, clarity, or coherence in the media narrative across time and monetary policy cycles.

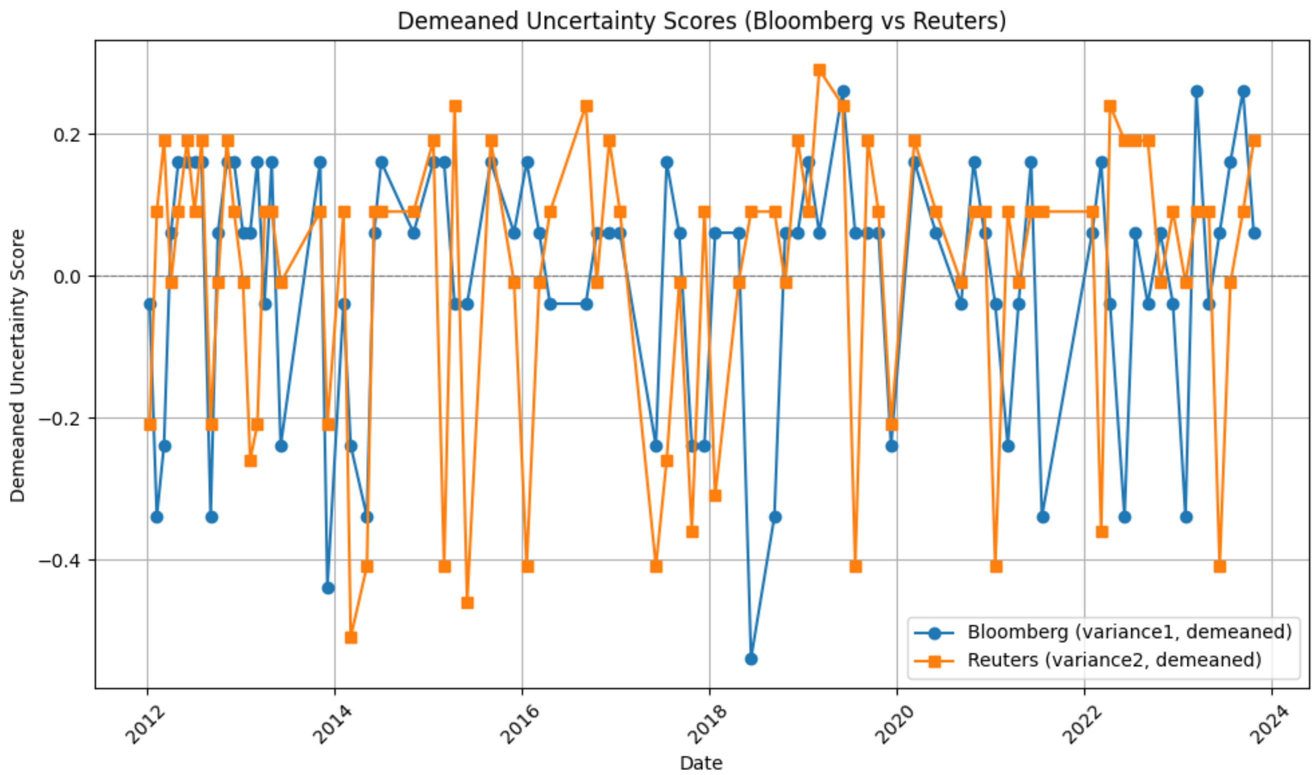

Figure 2: Uncertainty scores (demeaned) from Bloomberg and Reuters around ECB monetary policy events

To maintain comparability across events and sources, all sentiment and uncertainty scores were standardized on a consistent scale. Sentiment scores range from -1 (very negative) to +1 (very positive), while uncertainty scores range from 0 (no uncertainty) to 1 (very high uncertainty). For visualization purposes, both sets of scores were demeaned across time to highlight relative deviations from the series mean.

These visualizations lay the groundwork for the empirical analysis by enabling a first inspection of media disagreement, sentiment shifts, and structural breaks in the tone and uncertainty surrounding ECB announcements.

2.7 Descriptive Patterns and Preliminary Insights

This section explores the descriptive patterns emerging from the time-series evolution of the sentiment and uncertainty scores derived from Bloomberg and Reuters articles surrounding ECB monetary policy announcements. While the main empirical analysis will be developed in later sections, the preliminary visualization and interpretation of these textual signals offer valuable insights into how financial media narrative evolves in response to monetary policy decisions and how these signals relate to policy indicators such as the ECB deposit facility rate and short-term OIS-based monetary policy shocks. The first plot, which shows the time series of sentiment scores—extracted separately from Bloomberg and Reuters articles—with the ECB's deposit facility rate and one-month OIS rate surprises, reveals visible and recurrent divergence between Bloomberg and Reuters sentiment around key monetary policy events, indicating variation in narrative tone or interpretation between the two sources.

Several episodes stand out. For example, during the ECB's policy tightening in July 2022, Bloomberg sentiment appears more positive than Reuters, reflecting stronger emphasis on inflation control. However, in September 2022, Reuters sentiment registers higher scores, suggesting a more optimistic tone and reduced perceived risk relative to Bloomberg. This alternating pattern highlights that the divergence between the two sources is not unidirectional, but event-specific — shaped by editorial tone, narrative framing, and the particular aspects of policy each outlet chooses to emphasize.

Overlaying both the one-month OIS shocks and the ECB deposit facility rate with the sentiment series uncovers how financial market narratives respond to policy tightening. Large positive OIS shocks—signaling a more hawkish-than-expected ECB stance—tend to coincide with negative shifts in sentiment scores. This pattern becomes particularly pronounced during the tightening cycle starting in mid-2022, when sentiment scores from both sources not only turned more negative but also began to diverge more markedly, reflecting increasing disagreement in how the two news outlets interpreted the ECB's commitment to price stability, policy rationale, and economic outlook.

The second plot focuses on uncertainty scores over time, again separated by source. These scores capture the degree of noise in the articles' interpretation of each policy decision, as measured by GPT-4. Notably, uncertainty from both Bloomberg and Reuters displays strong time variation, with noticeable peaks around major ECB turning points. For instance, uncertainty increases around early 2020 (coinciding with the onset of the COVID-19 pandemic). These peaks likely reflect the inherent difficulty in forecasting monetary policy in periods of economic regime shifts or when forward guidance is unclear.

Moreover, there is meaningful divergence between Bloomberg and Reuters uncertainty at several points. For example, in mid-to-late 2022, Bloomberg articles show a relatively lower level of uncertainty compared to Reuters, suggesting that Bloomberg narratives may have been more decisive or unidirectional in interpreting ECB policy goals. In contrast, Reuters uncertainty remains elevated over a longer stretch, possibly capturing greater hesitancy or internal variation in how the policy stance was framed.

Taken together, these plots provide preliminary validation for the empirical strategy developed in the thesis. The variation in sentiment and uncertainty across time and sources illustrates the plausibility of using these scores as distinct inputs into an information ambiguity framework. Furthermore, the presence of divergence during key policy moments, alongside meaningful time-series structure, affirms the relevance of sentiment disagreement and signal noisiness in shaping financial market responses to monetary policy announcements.

3 Information Ambiguity Index

3.1 Overview

This section introduces the construction of the information ambiguity index, which quantifies the level of interpretative disagreement across Bloomberg and Reuters sentiment assessments of the same ECB monetary policy shock.

The index is rooted in the idea that financial markets do not interpret central bank announcements in a vacuum, but rather in a fragmented informational environment where different sources may highlight diverging aspects of the same policy event.

Building on the sentiment and uncertainty measures developed in Section 2, this section formalizes how these signals are combined to capture disagreement (signal divergence) and noise (signal imprecision), which together constitute the measure of information ambiguity.

3.2 Construction

Each monetary policy announcement is associated with two primary textual signals:

- S_1: sentiment score from Bloomberg articles (ranging from –1 to +1),
- S_2: sentiment score from Reuters articles (same scale).

These sentiment scores are treated as noisy signals about the true latent economic content of the ECB's monetary policy stance. Formally, I assume each sentiment signal $S_{i,t}$ at time t takes the form:

$$S_{1,t} = \mu_t + \epsilon_{1,t} \quad \text{and} \quad S_{2,t} = \mu_t + \epsilon_{2,t}$$

where:

- μ_t is the unobservable true signal of the policy stance (e.g., the central tendency of market-relevant information),
- $\epsilon_{i,t} \sim \mathcal{N}(0, \sigma_i^2)$ represents signal noise,
- σ_1^2 and σ_2^2 are time-varying uncertainty scores (also extracted via GPT-4).

The investor does not directly observe the true economic content μ_t, but instead updates their beliefs by forming a Bayesian posterior from the two noisy and potentially conflicting signals $S_{1,t}$ and $S_{2,t}$. Under this framework, the aggregated belief signal $S_{mixed,t}$ represents a weighted average of the two signals:

$$S_{\text{mixed},t} = wS_{1,t} + (1 - w)S_{2,t} \tag{3}$$

where $w \in [0, 1]$ reflects the relative precision or informativeness of the two signals. From a Bayesian perspective, this aggregation mirrors the classical posterior belief update: when signals are conditionally independent and drawn from distributions centered around the same latent state, the optimal posterior is a weighted average where weights are inversely proportional to the variance (or noise) of each signal.

In this context, when $w = 0.5$, the investor treats both sources as equally reliable, due to lack of additional prior about one source being systematically more accurate. The mixed signal thus captures a Bayesian belief that incorporates both signals proportionally, reflecting the investor's attempt to combine information from multiple sources to infer the implications of the policy shock.

The core idea is to define the information ambiguity index as the variance of this aggregated belief signal:

$$\text{Var}(S_{\text{mixed},t}) = E(S_{mixed,t}^2) - (E(S_{mixed,t}))^2 \tag{4}$$

Expanding the terms using the expressions for $E(S_{1,t})$ and $E(S_{2,t})$, and substituting the definitions of $S_{1,t}$ and $S_{2,t}$, we obtain:

$$\text{Var}(S_{\text{mixed},t}) = w(S_{1,t}^2 + \sigma_{1,t}^2) + (1 - w)(S_{2,t}^2 + \sigma_{2,t}^2) - S_{mixed,t}^2 \tag{5}$$

The full derivation is reported in Appendix A.

This formulation allows us to capture both components of information ambiguity:

- Signal disagreement (how far apart are Bloomberg and Reuters in their interpretation),
- Signal noise (how confident is each source in its own interpretation).

3.3 Interpretation and Conceptual Rationale

The construction of the information ambiguity measure draws directly from the theoretical underpinnings of signal extraction problems in macro-finance. Specifically, it captures situations in which agents receive conflicting or noisy signals about the meaning and implications of a central bank's policy action. In this thesis, such ambiguity is extracted from textual sentiment signals provided by two major financial news sources—Bloomberg and Reuters—based on their coverage of European Central Bank (ECB) monetary policy announcements.

At its core, the measure operationalizes information ambiguity along two critical dimensions: (i) disagreement between sources and (ii) signal noise, i.e., the confidence with which each source expresses its sentiment. Disagreement is proxied by the absolute difference in sentiment scores between the two sources $|S_{1,t} - S_{2,t}|$, where $S_{1,t}$ and $S_{2,t}$ are the GPT-4-derived sentiment scores for each article. High values of $|S_{1,t} - S_{2,t}|$ indicate that the two news outlets offer divergent interpretations of the same policy event, suggesting the presence of interpretive conflict in the information environment.

The second component—signal noise—relates to the uncertainty or dispersion associated with each sentiment signal, captured by GPT-4-based uncertainty scores $\sigma_{1,t}^2$ and $\sigma_{2,t}$. These reflect how confidently the model assessed each article's sentiment. Lower scores indicate that the model found a clear and unambiguous stance in the article's language, while higher scores indicate more equivocal or ambiguous language that lacks a clear directional tone. In economic terms, higher signal noise implies that the perceived signal about the ECB's intentions is less reliable or more difficult to interpret.

Low information ambiguity arises in cases where (i) both signals are similar in magnitude and direction ($|S_{1,t} - S_{2,t}| \approx 0$), and (ii) both signals are reported with high confidence (low $\sigma_{1,t}^2$ and $\sigma_{2,t}^2$). This configuration suggests a coherent and well-understood policy message, consistently interpreted by financial intermediaries. Market participants in such contexts are likely to face minimal friction when incorporating central bank signals into their expectations.

Conversely, high information ambiguity occurs when the sentiment signals diverge substantially (large $|S_{1,t} - S_{2,t}|$) or when either or both are expressed with high noise (high σ_i^2). In such instances, the information environment is characterized by confusion, com-

peting narratives, or editorial uncertainty—precisely the conditions in which market participants may find it difficult to anchor expectations or assess the true stance of policy.
This framework aligns with the conceptual model of "interpretation frictions" developed by Angeletos et al., 2013, who describe how investors extract noisy signals about fundamental variables and update beliefs. While Angeletos et al., 2013 focus on agent-level information processing, this thesis applies their logic in a novel, media-based context. Here, the "signals" are constructed from real-world narratives in news media, and the ambiguity stems from differences in how those narratives are constructed and perceived.
This interpretation is especially relevant in modern macro-financial settings where communication is increasingly intermediated by real-time information flows. Unlike formal central bank press releases, media commentary introduces an additional interpretive layer—one that can either clarify or distort the intended message. As such, the information ambiguity score derived here captures both direct disagreement and second-order uncertainty, making it a robust proxy for the market-facing opacity of policy signals.
The resulting measure is not intended to replace traditional macroeconomic uncertainty indicators, but rather to complement them by focusing on interpretive uncertainty in the very short term, i.e., the hours and days following policy announcements. It is precisely in this window that markets react most sharply, and where ambiguity in policy communication can exert a disproportionate influence on investor behavior.

3.4 Information Ambiguity Index Time Series and Visual Patterns

The time-series behavior of the constructed information ambiguity index is analyzed and related to key monetary policy instruments: the ECB deposit facility rate and 1-month Overnight Index Swap (OIS) shocks. This visual inspection complements the quantitative analysis by offering descriptive evidence of comovement with policy indicators.
The upper panel of Figure 3 displays the information ambiguity index over time, where each observation corresponds to a monetary policy event date. The index, bounded between 0 and 1, is constructed as the variance of the weighted sentiment signal derived from paired Bloomberg and Reuters articles using GPT-4. The values of the index show marked fluctuation, ranging roughly between 0.3 and 1, with considerable variation both across and within years. Importantly, the information ambiguity index does not follow

a deterministic trend, but rather exhibits localized spikes, suggesting episodic surges in interpretive disagreement or signal noise across sources.

The lower panel in Figure 3 plots the ECB deposit facility rate over the same time period. While the deposit rate remained flat or slightly negative for a prolonged period post-2014, a steep increase is visible beginning in mid-2022, consistent with the ECB's tightening cycle in response to inflationary pressures. Interestingly, some of the highest information ambiguity values occur precisely in this regime-switching environment (e.g., July and September 2022), reflecting heightened market disagreement about the pace and implications of normalization. This suggests a link between regime shifts in policy rates and elevated media disagreement, aligning with theories of heightened information ambiguity under novel or unexpected policy moves.

The third panel (bottom) further reinforces this intuition by introducing OIS-based monetary policy shocks, as computed from the EA-MPD database. These high-frequency shocks isolate the unanticipated component of each policy decision, i.e., the surprise. Several peaks in OIS shocks (e.g., 21 July 2022 and 8 September 2022) coincide with elevated information ambiguity readings, providing empirical support for the hypothesis that larger surprises—where markets fail to fully anticipate the ECB's action—are also associated with greater interpretational divergence across media outlets.

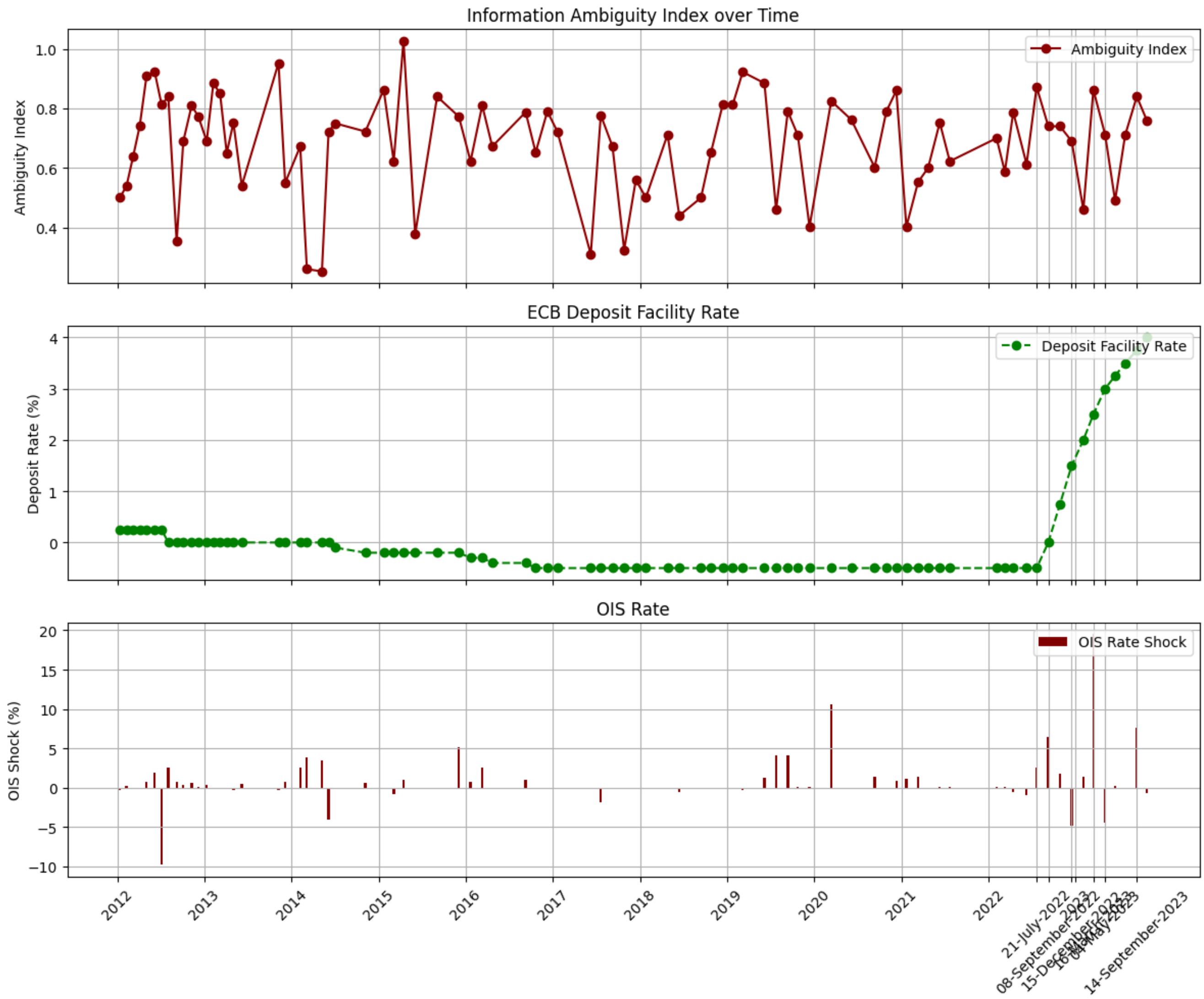

Figure 3: Information ambiguity indices with ECB deposit rate and OIS shocks

In sum, the visual patterns suggest three key takeaways. First, information ambiguity is inherently time-varying and not mechanically linked to the level of policy rates. Second, information ambiguity tends to rise during monetary regime changes and following large, unanticipated policy moves—highlighting moments of interpretive friction. Third, the index also displays episodic spikes, often unrelated to structural shifts, pointing to signal noise across sources. Together, these insights motivate the core empirical investigation that follows, where I examine whether such ambiguity systematically influences market volatility and trading volume.

4 Empirical Analysis: The Effects of Information Ambiguity on Financial Market Responses

4.1 Overview

This section presents the empirical strategy and results aimed at evaluating how financial markets respond to monetary policy shocks under varying levels of information ambiguity. In particular, I estimate the dynamic effects of European Central Bank (ECB) monetary policy surprises on financial market indicators—namely stock market volatility and trading volume—while conditioning these responses on the level of information ambiguity surrounding the shock. The core hypothesis tested is whether information ambiguity amplifies, dampens, or alters the timing of market responses to ECB monetary policy surprises.

I implement the estimation using the Local Projections (LP) framework introduced by Jordà, 2005, which is well-suited for tracing the time profile of impulse response functions (IRFs) without imposing dynamic restrictions associated with vector autoregressions (VARs). The LP setup allows us to run regressions for multiple forecast horizons and directly estimate the impact of a monetary policy shock, as well as its interaction with the level of information ambiguity, on each outcome variable.

4.2 Empirical Specification

The model estimated is the following local projection regression, run separately for each forecast horizon h:

$$\log y_{t+h} - \log y_{t-1} = \alpha_h + \beta_h \varepsilon_t + \delta_h A_t + \gamma_h (\varepsilon_t \cdot A_t) + u_{t+h} \tag{6}$$

where:

- y_{t+h} is the outcome variable at horizon h, either the VSTOXX index (stock market volatility) or FEZ ETF trading volume.
- ε_t is the ECB monetary policy shock on day t, identified through a high-frequency identification (HFI) approach based on changes in Overnight Index Swap (OIS)

rates from the EA-MPD database,

- A_t is the standardized information ambiguity index for the same policy event, constructed from sentiment and uncertainty scores,
- γ_h captures the interaction effect: the marginal impact of the policy shock at horizon h when information ambiguity increases by one standard deviation,
- β_h and δ_h represent the baseline effects of the shock and the information ambiguity index, respectively,
- α_h is the intercept, and u_{t+h} is the error term.

This regression allows us to examine how the response of financial markets to monetary policy shocks is shaped by the level of information ambiguity in the information environment. The estimation is conducted at multiple horizons: $h = 7, 30, 60, 90$ days after the shock, which correspond to short-, medium-, and long-term windows.

4.3 Shock Identification and Scaling

To isolate the unanticipated component of monetary policy announcements, I use the high-frequency identification (HFI) strategy developed in the monetary policy event-study literature. Specifically, I use changes in the 1-month Overnight Index Swap (OIS) rate measured in a narrow window around the ECB press conference. This captures monetary policy surprises that are orthogonal to previously available information and are therefore exogenous.

I standardize the raw monetary policy surprises $\varepsilon_t^{\text{raw}}$ over the sample period (2012–2023) by first subtracting the sample mean and then dividing by the sample standard deviation. This transformation expresses the shocks in standard deviation units, ensuring comparability across time and events.

To improve interpretability, I then rescale the standardized shocks so that each unit corresponds to the effect of a 25 basis point monetary policy surprise. Formally:

$$\varepsilon_t^{\text{scaled}} = 0.25 \times \frac{\varepsilon_t^{\text{raw}} - \bar{\varepsilon}}{\sigma_\varepsilon} \tag{7}$$

This means that the impulse responses reported throughout the analysis correspond to the cumulative effect of a one-standard-deviation shock, scaled to reflect an average 25 basis point increase in the policy rate.

This approach aligns with best practices in high-frequency monetary policy research (Bachmann et al., 2022) and allows for meaningful economic interpretation of the estimated responses.

4.4 Standardization of the Information Ambiguity Index

The ambiguity index A_t is constructed by combining sentiment scores ($S_{1,t}$, $S_{2,t}$) and uncertainty scores ($\sigma^2_{1,t}$, $\sigma^2_{2,t}$) from Bloomberg and Reuters articles, using the following weighted variance formula:

$$A_t = w\left(S^2_{1,t} + \sigma^2_{1,t}\right) + (1-w)\left(S^2_{2,t} + \sigma^2_{2,t}\right) - S^2_{\text{mixed},t} \tag{8}$$

To ensure that the interaction term is interpretable and statistically well-behaved, I standardize the information ambiguity index across all monetary policy dates as follows:

$$A_t^{\text{standardized}} = \frac{A_t - \bar{A}}{\sigma_A} \tag{9}$$

This z-score transformation expresses each value of the index in terms of standard deviations from its sample mean. As a result, a value of $A_t^{\text{standardized}} = 1$ indicates that information ambiguity on date t is one standard deviation above the average level in the sample. This transformation also allows the interaction coefficient γ_h to be interpreted as the marginal effect of a monetary policy shock when information ambiguity is one standard deviation higher than average.

4.5 Regression Results: Estimated Interaction Effects

For each forecast horizon $h \in \{7, 30, 60, 90\}$, I estimate the regression specified in 6 using Ordinary Least Squares (OLS). To assess the statistical significance of the estimated coefficients, I construct confidence intervals using a non-parametric bootstrap procedure with 1000 replications, clustered by event date. This resampling technique accounts for potential heteroskedasticity and small-sample bias, while preserving the time-series structure of monetary policy announcements.

I compute both 95% and 68.5% bootstrap confidence intervals. The 95% intervals capture a wide range of possible coefficient values and reflect the overall uncertainty in the estimates. While many intervals include zero—implying that the effects may not be statistically distinguishable from zero—the 68.5% intervals help highlight directional tendencies and the evolution of the effects across horizons. In contexts with limited statistical power, 68.5% intervals are useful for visualizing emerging patterns that may be substantively relevant even if not statistically conclusive.

The regression is estimated separately for each outcome variable. All outcome variables are expressed in logarithmic form so that the coefficients can be interpreted as approximate percentage changes. For example, a coefficient $\gamma_h = 0.01$ implies that, at horizon h, the interaction between a 25 basis point restrictive monetary policy shock and a one-standard-deviation increase in information ambiguity leads to a 1% increase in the outcome variable y_{t+h} relative to y_{t-1}.

In the main body of the thesis, I report below the estimated coefficients for the interaction term γ_h only. Table 1 presents these estimates along with 68.5% bootstrap confidence intervals, which are useful for visualizing directional tendencies and the time profile of the interaction effect, even in the absence of strong statistical significance.

For completeness, Appendix B includes full regression tables reporting all estimated coefficients—β_h (shock), δ_h (information ambiguity), and γ_h (interaction)—for each forecast horizon. Those tables also display both 68.5% and 95% confidence intervals, based on 1000 non-parametric bootstrap replications clustered by event date. In addition, Appendix B contains all impulse response function (IRF) plots corresponding to these estimates.

Horizon (days)	**Stock Market Volatility (VSTOXX)**		**Trading Volume (FEZ ETF)**	
7	-0.2080	[-0.3622, -0.0230]	0.3961	[-0.0643, 1.0110]
30	-0.0367	[-0.2035, 0.1629]	-0.0905	[-0.4004, 0.3069]
60	0.0288	[-0.1282, 0.2620]	0.2330	[-0.2221, 0.7860]
90	0.1056	[-0.0187, 0.2556]	-0.1707	[-0.4745, 0.5402]

Table 1: Estimated Interaction Effects of MP Shocks and Information Ambiguity (68.5% CI)

Although most 68.5% confidence intervals include zero, the point estimates of γ_h suggest meaningful directional patterns. For stock market volatility (VSTOXX), the interaction effect is negative at shorter horizons (7 and 30 days) but turns positive at 60 and 90 days.

This shift suggests that, under high information ambiguity, the initial volatility response is dampened, but uncertainty may accumulate over time, ultimately amplifying volatility at longer horizons.

For trading volume (FEZ ETF), the pattern is more mixed: the interaction effect is positive at 7 days, negative at 30 days, positive again at 60 days, and negative at 90 days. This alternating sign may reflect the evolving role of information ambiguity—initial trading surges as investors react to conflicting signals, followed by a temporary pullback amid unresolved uncertainty. As more clarity emerges, trading re-engages at 60 days, but eventually stabilizes or weakens as ambiguity fades or is priced in at 90 days.

These patterns support the hypothesis that information ambiguity affects not only the magnitude but also the timing and direction of financial market adjustments to monetary policy shocks. In the next section, I turn to impulse response plots to visualize these dynamics more clearly over time.

4.6 Impulse Response Plots and Interpretation of Results

Figure 4 displays the estimated impulse response function (IRF) for the VSTOXX index, which serves as a proxy for Eurozone stock market volatility. The green line shows the response to a 25 basis point monetary policy tightening shock when the level of information ambiguity is one standard deviation above its mean (i.e., the γ_h coefficient). The shaded area corresponds to the 68.5% bootstrap confidence interval. For comparison, the blue line shows the baseline response to the same monetary policy shock when information ambiguity is at its average level (i.e., the β_h coefficient). Since the regression specification includes both the shock, information ambiguity, and their interaction, and the monetary policy shock is identified via high-frequency surprises around ECB press conferences, both response paths can be interpreted causally.

The impulse response functions (IRFs) for stock market volatility reveal distinct dynamics across short, medium, and longer horizons.

In the short run (0-30 days), the interaction effect is negative, suggesting that when information ambiguity is high, financial markets initially react with reduced stock market volatility. This outcome, despite a concurrent increase in trading volume, discussed in more detail below, can be understood through the lens of investor behavior under information ambiguity. When information ambiguity is high, market participants face

uncertainty about the precise stance and implications of the monetary policy signal. In such an environment, rather than aggressively reallocating capital based on a strong directional belief, investors may engage in more cautious forms of trading—such as hedging, defensive repositioning, or marginal portfolio rebalancing. These actions contribute to higher trading volume but are not associated with large, one-sided bets that would generate significant price swings. Instead, the absence of a dominant narrative leads to a dispersion of expectations and a lack of coordinated movements in asset prices. As a result, market dynamics exhibit subdued price reactions and limited cross-sectional dispersion, ultimately reducing realized stock market volatility. This mechanism is consistent with the idea that informational frictions can decouple volume from volatility in the short run when investors act on diverse or conflicting interpretations of policy news.
As we transition into the medium run (30-60 days), the interaction effect becomes positive, indicating that the stock market volatility suppressed in the short term resurfaces with a delay. Once investors begin to process the ambiguous signals, either by aligning on a dominant interpretation or by updating their expectations incrementally, we observe a reacceleration of asset repricing. This results in heightened volatility. This phase reflects a delayed transmission of the monetary policy signal. Information ambiguity initially slowed market reactions, but as investors gradually resolve the noise, they begin to reposition their portfolios more decisively. The market response becomes more coordinated and aggressive, particularly as more informed investors take directional positions. Therefore, stock market volatility increases not because new information has arrived, but because the market is catching up with the initial policy shock.

In the long run (60-90 days), the amplification continues or even strengthens. The interaction effect remains significantly positive, suggesting that information ambiguity may not only delay market adjustment but also prolong and disperse it. Persistent disagreement or slow convergence of beliefs may lead to fragmented trading behavior. Investors interpret the same signal differently even weeks after the event, causing staggered repositioning across market participants. This results in noisy price dynamics, consistent with models of information frictions and heterogeneous updating. Thus, rather than exhibiting a quick and unified market correction, high information ambiguity leads to a protracted and uneven response, with stock market volatility rising not all at once but in waves, as the signal is slowly assimilated.

Although the 68.5% confidence intervals do include zero at almost all horizons—limiting formal statistical significance—the consistent directional shift across time adds robustness to the economic interpretation. These results align with the hypothesis that information ambiguity affects both the timing and the magnitude of financial market adjustments to monetary policy shocks. They also suggest that policy effectiveness may be conditioned not only by the content of announcements, but also by the clarity and consistency of the information environment in which they are released.

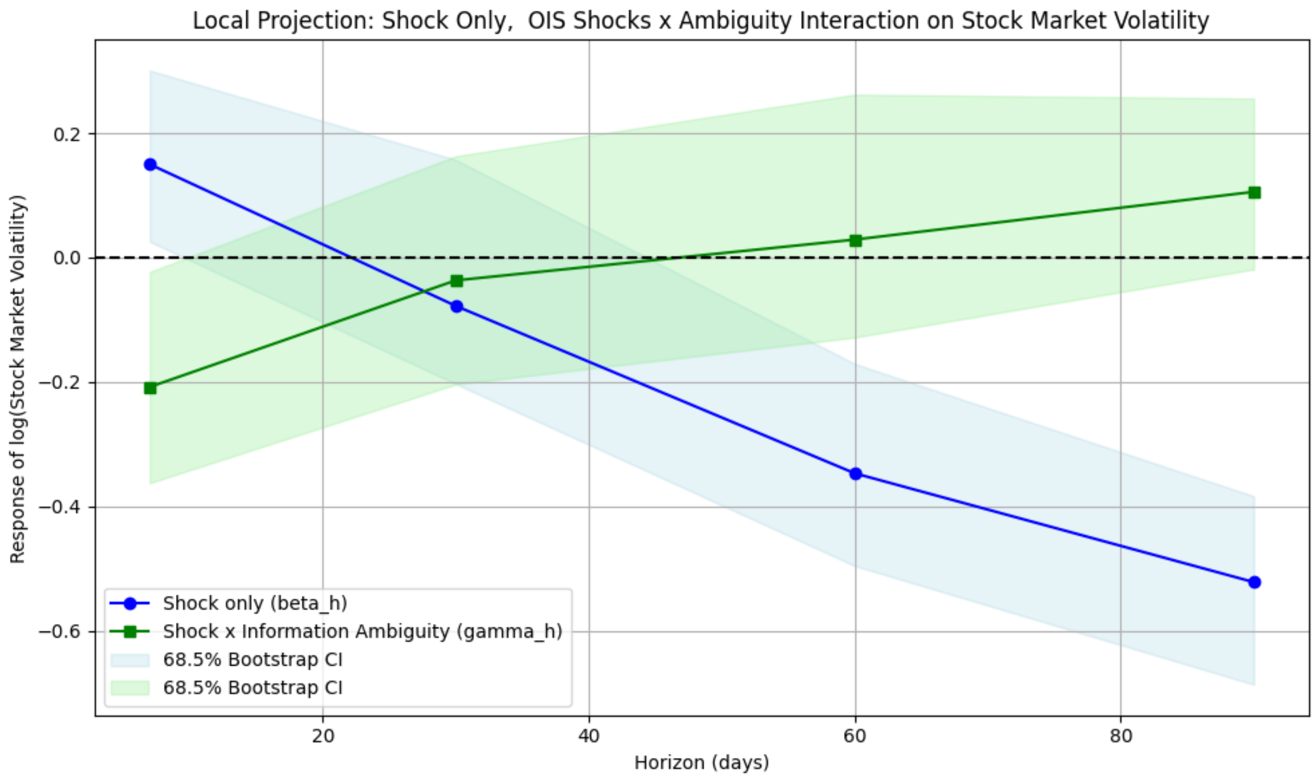

Figure 4: Effect of Monetary Policy Shocks and Information Ambiguity on Stock Market Volatility

I now turn to Figure 5, which presents the IRFs for daily trading volume of the FEZ ETF, used as a proxy for investor activity and liquidity in euro area equity markets. Similar to the stock market volatility plot, the green line captures the interaction term (γ_h), while the blue line shows the baseline shock-only effect.

At the short-term horizon (7 days), the interaction coefficient is positive, suggesting that high information ambiguity tends to stimulate a burst of trading activity in the immediate aftermath of a monetary policy shock. This can be interpreted as the result of heterogeneous interpretations of the policy signal, which fuel short-lived waves of speculative repositioning and portfolio hedging, as investors try to front-run or infer macroeconomic implications. These trades, however, are not based on a common understanding, and thus do not result in coordinated asset price movements—explaining why volatility initially falls despite the increase in volume. Trading under information ambiguity, in this phase, is reactive but cautious, with capital being reallocated defensively and without conviction.

By the medium-term horizon (30 days), the interaction effect turns negative. As initial uncertainty lingers and new clarifying information fails to emerge, market participants grow more cautious. The burst of activity in the short run gives way to trading fatigue or decision paralysis, with investors increasingly reluctant to adjust their exposure further in an unclear informational environment. In this phase, information ambiguity no longer fuels activity but acts as a suppressor, reducing trading volume as agents adopt a wait-and-see approach. This dynamic mirrors the initial dampening effect observed on volatility, confirming the temporary nature of ambiguity-induced reactions.

At the 60-day horizon, the effect becomes positive again, indicating a renewed surge in trading activity. This rebound reflects a phase where investors begin to gradually resolve the information ambiguity, either by assimilating new macroeconomic signals or aligning on a more coherent interpretation of the initial policy move. As beliefs adjust and confidence returns, agents resume repositioning—this time in a more directional and deliberate manner, which contributes to both volume and volatility increases. Information ambiguity here acts less as a paralyzing force and more as a delayed catalyst of market activity.

Finally, by the 90-day horizon, the interaction effect turns negative once more, suggesting that the influence of information ambiguity dissipates. This may reflect either a resolution of disagreement—resulting in stabilization—or the irrelevance of the initial shock. As expectations converge and a consensus forms around the central bank's stance, trading activity subsides. Information ambiguity no longer drives behavior, and the market reverts to a more informed and stable equilibrium.

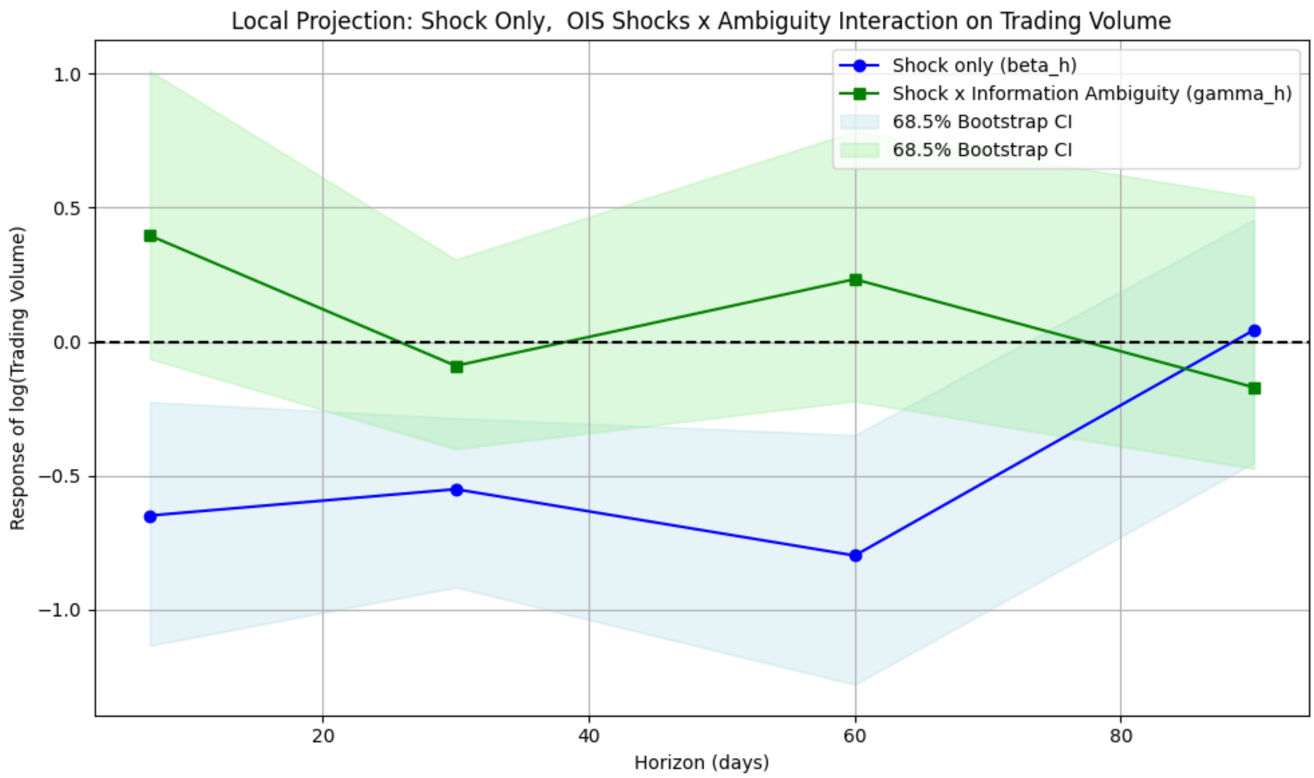

Figure 5: Effect of Monetary Policy Shocks and Information Ambiguity on Trading Volume

In summary, the impulse responses presented in this section demonstrate that the effects of monetary policy shocks on both stock market volatility and trading volume are meaningfully shaped by the prevailing level of information ambiguity. While the estimated effects vary in sign and magnitude across horizons, the results consistently point to a nuanced role for information ambiguity—amplifying or dampening market reactions depending on the timing and context.

5 Conclusion

This thesis examined how information ambiguity alters the transmission mechanism of European Central Bank (ECB) monetary policy shocks to financial markets. Using sentiment and uncertainty scores derived from Bloomberg and Reuters articles using OpenAI's large language model, I constructed an information ambiguity measure and explored its interaction with monetary policy surprises, applying local projections to estimate impulse responses in stock market volatility (VSTOXX) and trading volume (FEZ ETF).

The findings reveal that information ambiguity significantly conditions financial market reactions by reshaping the timing and pattern of these responses.

For stock market volatility, high information ambiguity dampens reactions in the short term (0–30 days), as investors adopt a cautious stance in response to unclear signals. This initial suppression is not due to indifference, but rather to dispersed expectations and defensive portfolio reallocation. In the medium term (30–60 days), stock market volatility rises as market participants gradually resolve the information ambiguity and realign their interpretations, triggering a repricing phase. In the long run (60–90 days), stock market volatility amplification persists—suggesting that information ambiguity exerts a lasting influence by delaying belief updating and causing staggered reactions. Ultimately, information ambiguity shifts the temporal structure of stock market volatility, fragmenting the adjustment path rather than suppressing it.

For trading volume, the response is more nuanced and alternating in sign. In the short term (7 days), information ambiguity fuels a spike in trading activity, reflecting speculative repositioning amid diverging interpretations of the policy signal. However, by 30 days, this burst gives way to caution, as the absence of clear narratives suppresses reallocation. At 60 days, trading activity rises again, consistent with a phase of partial resolution and more directional repositioning. By 90 days, trading volume declines, suggesting stabilization or the irrelevance of information ambiguity. These fluctuations indicate that information ambiguity stimulates trading under initial surprise, suppresses it when uncertainty persists, and resurfaces when resolution begins—before eventually fading once market consensus forms.

Overall, the evidence points to information ambiguity as a dynamic friction—it does not uniformly magnify or suppress asset price and volume responses, but instead reshapes them across horizons. It introduces temporal dispersion and staggered belief updating, especially when narratives conflict or lack clarity. These findings underscore that the monetary policy transmission mechanism depends not only on the shock magnitude, but also on the informational environment in which the shock is interpreted. Information ambiguity affects both the intensity and the sequencing of market adjustments, revealing the need for monetary policymakers and market participants to account for media-driven uncertainty in understanding financial reactions to central bank actions.

References

Altavilla, C., Brugnolini L., Gürkaynak R.S., Motto, R. & Ragusa, G. (2019). Measuring euro area monetary policy. *Journal of Monetary Economics*, 108, 162-179.

Angeletos, G.-M. & La'O, J. (2013). Sentiments. *Econometrica*, 81(2), 739–779.

Bachmann, R., Gödl-Hanisch, I. & Sims, E. R. (2022). Identifying monetary policy shocks using the central bank's information set. *Journal of Economic Dynamics and Control*, 145, 104555.

Bernanke, B. S., Boivin, J. & Piotr E. (2005). Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach. *The Quarterly Journal of Economics*, 120(1), 387–422.

Bernanke, B. S. & Kuttner, K. N. (2005) What Explains the Stock Market's Reaction to Federal Reserve Policy? *The Journal of Finance*, 60(3), 1057-1592, i-iv, 1593-1512.

Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrica*, 77(3), 623-1001.

Breitung, C., Kruthof, G. & Müller, S. (2023). Contextualized Sentiment Analysis using Large Language Models. *Available at SSRN 4615038*.

Bürgler, V., Davidson, B. & Bürgler, M. (2024). Democratizing Financial Information using GPT-4o. *Available at SSRN 5130935*.

Jordà, O. (2005). Estimation and Inference of Impulse Responses by Local Projections. *American Economic Review*, 95(1), 161–182.

Jurado, K., Ludvigson, S. C. & Ng, S. (2015). Measuring Uncertainty. *American Economic Review*, 105(3), 1177–1216.

Kirtac, K. & Germano, G. (2024). Sentiment trading with large language models. *Finance Research Letters*, 62(B).

Nakamura, E. & Steinsson, J. (2018). High-Frequency Identification of Monetary Non-Neutrality: The Information Effect Get. *The Quarterly Journal of Economics*, 133(3), 1283–1330.

Noguer I Alonso, M. & Dupouy, H. (2024). Large Language Models as Financial Analysts. *Available at SSRN 4945481*.

Pastor, L. & Veronesi, P. (2012). Uncertainty about Government Policy and Stock Prices. *Journal of Finance*, 67(4), 1219-1264.

Rahimikia, E. & Drinkall, F. (2024). Re(Visiting) Large Language Models in Finance. *Available at SSRN 4963618*.

Yang, H., Zhang, B., Wang, N., Guo, C., Zhang, X., Lin, L., Wang, J., Zhou, T., Guan, M., Zhang, R. & Dan Wang, C. (2024). FinRobot: An Open-Source AI Agent Platform for Financial Applications using Large Language Models. *Available at* https://doi.org/10.48550/arXiv.2405.14767.

Appendix

A Information Ambiguity Index

The derivation of the information ambiguity index is the following:

$$Var(S_{mixed,t}) = E(S^2_{mixed,t}) - (E(S_{mixed,t}))^2,$$

where the first term is:

$$E(S^2_{mixed,t}) = wE(S^2_{1,t}) + (1-w)E(S^2_{2,t}),$$

$$E(S^2_{1,t}) = E(S_{1,t})^2 + Var(S_{1,t})$$

Thus,

$$E(S^2_{1,t}) = (E(\mu_t + \epsilon_{1,t}))^2 + Var(\mu_t + \epsilon_{1,t}),$$

which becomes

$$E(S^2_{1,t}) = \mu^2_t + \sigma^2_{1,t},$$

since regarding the first term, μ_t is a constant and $E(\epsilon_t) = 0$, and since regarding the second term, $Var(\mu_t) = 0$, $Var(\epsilon_t) = \sigma^2_t$. Therefore, we have:

$$E(S^2_{1,t}) = S^2_{1,t} + \sigma^2_{1,t},$$

since we do not know μ_t as we observe $S_{1,t}$
and the second term is:

$$(E(S_{mixed,t}))^2 = (E(wS_{1,t} + (1-w)S_{2,t}))^2 = S^2_{mixed,t},$$

since $E(S_{1,t}) =\mu_t + E(\epsilon_{1,t}) = \mu_t$ as $E(S_t) = \mu_t$.
The same applies to $S_{2,t}$.
Therefore $(E(wS_{1,t} + (1-w)S_{2,t}))^2 = (wS_{1,t} + (1-w)S_{2,t})^2 = S^2_{mixed,t}$.
The variance (information ambiguity index) is then:

$$w(S^2_{1,t} + \sigma^2_{1,t}) + (1-w)(S^2_{2,t} + \sigma^2_{2,t}) - S^2_{mixed,t}$$

B

Table 2: Regression Results with 68.5% Bootstrap Confidence Intervals

Panel A: Dependent Variable – Stock Market Volatility (VSTOXX)

Horizon (days)	β_h (Shock)	δ_h (Ambiguity)	γ_h (Interaction)
7	0.1498 [0.0256, 0.3006]	0.0124 [-0.0140, 0.0365]	-0.2080 [-0.3622, -0.0230]
30	−0.0776 [−0.2030, 0.1572]	-0.0139 [−0.0431, 0.0086]	-0.0367 [−0.2035, 0.1629]
60	−0.3467 [−0.4955, −0.1707]	-0.0596 [−0.1133, -0.0071]	0.0288 [-0.1282, 0.2620]
90	-0.5217 [−0.6862, −0.3835]	-0.0567 [-0.0976, -0.0187]	0.1056 [-0.0187, 0.2556]

Panel B: Dependent Variable – Trading Volume (FEZ ETF)

Horizon (days)	β_h (Shock)	δ_h (Ambiguity)	γ_h (Interaction)
7	−0.6498 [−1.1356, -0.2253]	0.1271 [0.0157, 0.2373]	0.3961 [−0.0643, 1.0110]
30	−0.5513 [−0.9176, -0.2852]	0.1692 [0.0731, 0.2684]	-0.0905 [−0.4004, 0.3069]
60	-0.7993 [−1.2810, -0.3486]	0.1719 [0.0713, 0.2897]	0.2330 [−0.2221, 0.7860]
90	0.0428 [−0.4521, 0.4571]	0.1230 [0.0286, 0.2080]	-0.1707 [−0.4745, 0.5402]

Notes: All coefficients estimated from LP regressions. 68.5% bootstrap confidence intervals from 1000 replications clustered by event date

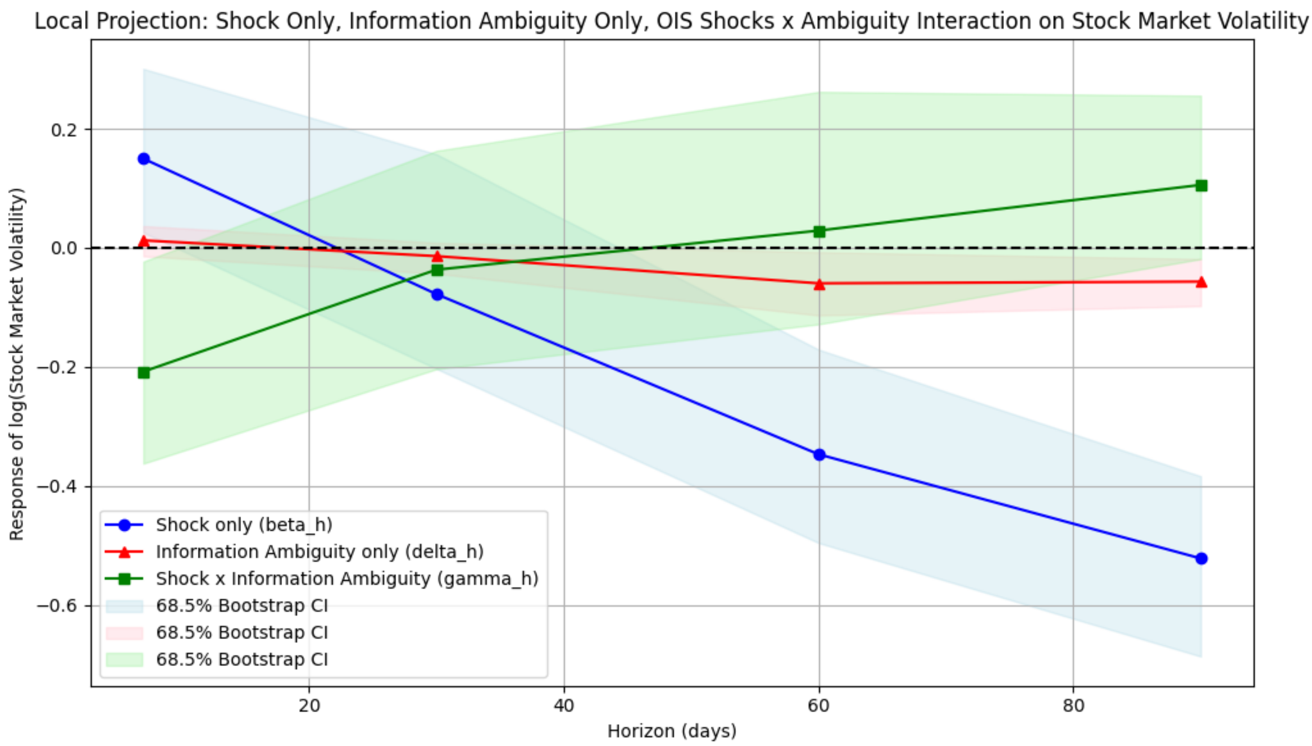

Figure 6: Effect of Monetary Policy Shocks and Information Ambiguity on Stock Market Volatility

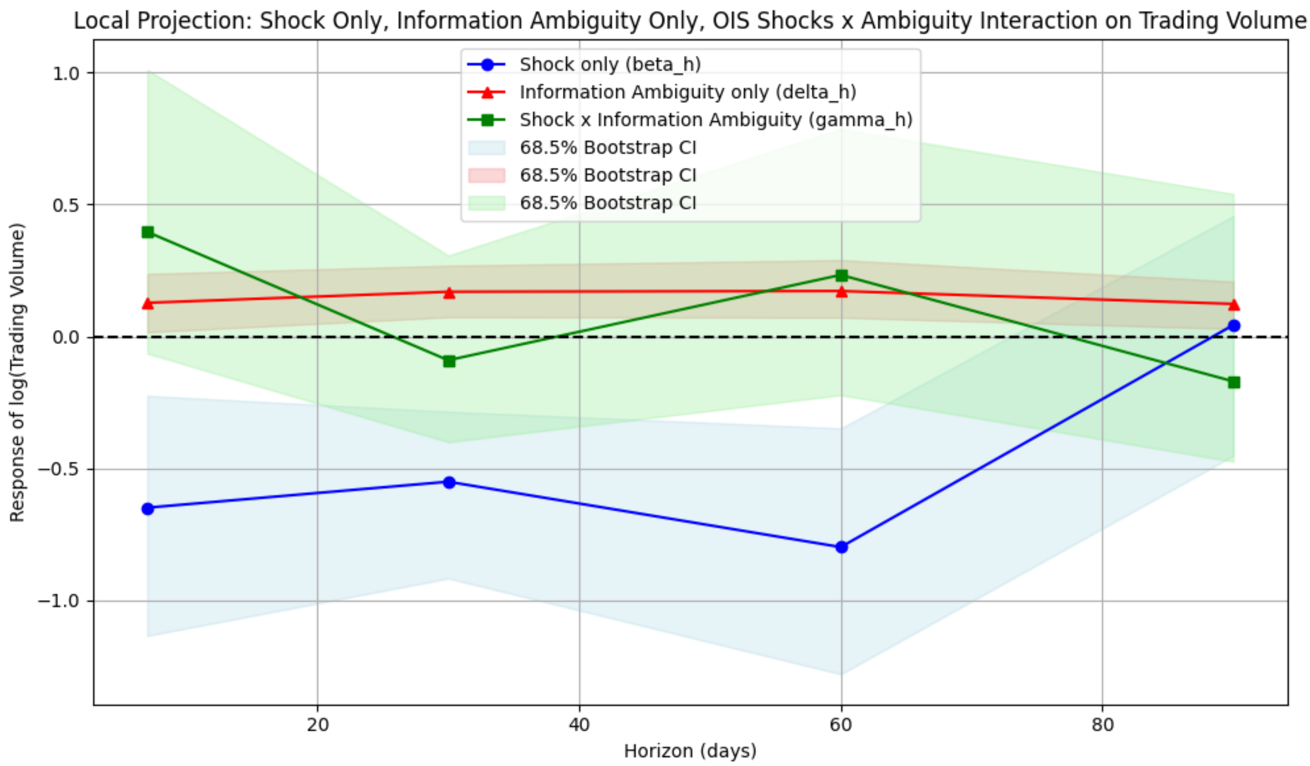

Figure 7: Effect of Monetary Policy Shocks and Information Ambiguity on Trading Volume

Table 3: Regression Results with 95% Bootstrap Confidence Intervals

Panel A: Dependent Variable – Stock Market Volatility (VSTOXX)

Horizon (days)	β_h (Shock)	δ_h (Ambiguity)	γ_h (Interaction)
7	0.1498 [-0.1026, 0.4593]	0.0124 [-0.0411, 0.0599]	-0.2080 [-0.5461, 0.1823]
30	–0.0776 [-0.3463, 0.3453]	-0.0139 [-0.0701, 0.0307]	-0.0367 [-0.4450, 0.3538]
60	–0.3467 [-0.6761, -0.0152]	-0.0596 [-0.1761, 0.0348]	0.0288 [-0.2731, 0.5394]
90	-0.5217 [-0.8826, -0.2516]	-0.0567 [-0.1378, 0.0171]	0.1056 [-0.1736, 0.4259]

Panel B: Dependent Variable – Trading Volume (FEZ ETF)

Horizon (days)	β_h (Shock)	δ_h (Ambiguity)	γ_h (Interaction)
7	–0.6498 [–1.7024, 0.1599]	0.1271 [-0.0799, 0.3489]	0.3961 [-0.5698, 1.7864]
30	–0.5513 [-1.3744, 0.0157]	0.1692 [0.0041, 0.3639]	-0.0905 [-0.7658, 0.7716]
60	-0.7993 [-1.8528, 0.1132]	0.1719 [-0.0464, 0.3927]	0.2330 [-0.7155, 1.5024]
90	0.0428 [–1.0098, 0.8525]	0.1230 [-0.0482, 0.2898]	-0.1707 [-0.8554, 1.3590]

Notes: All coefficients estimated from LP regressions. 95% bootstrap confidence intervals from 1000 replications clustered by event date.

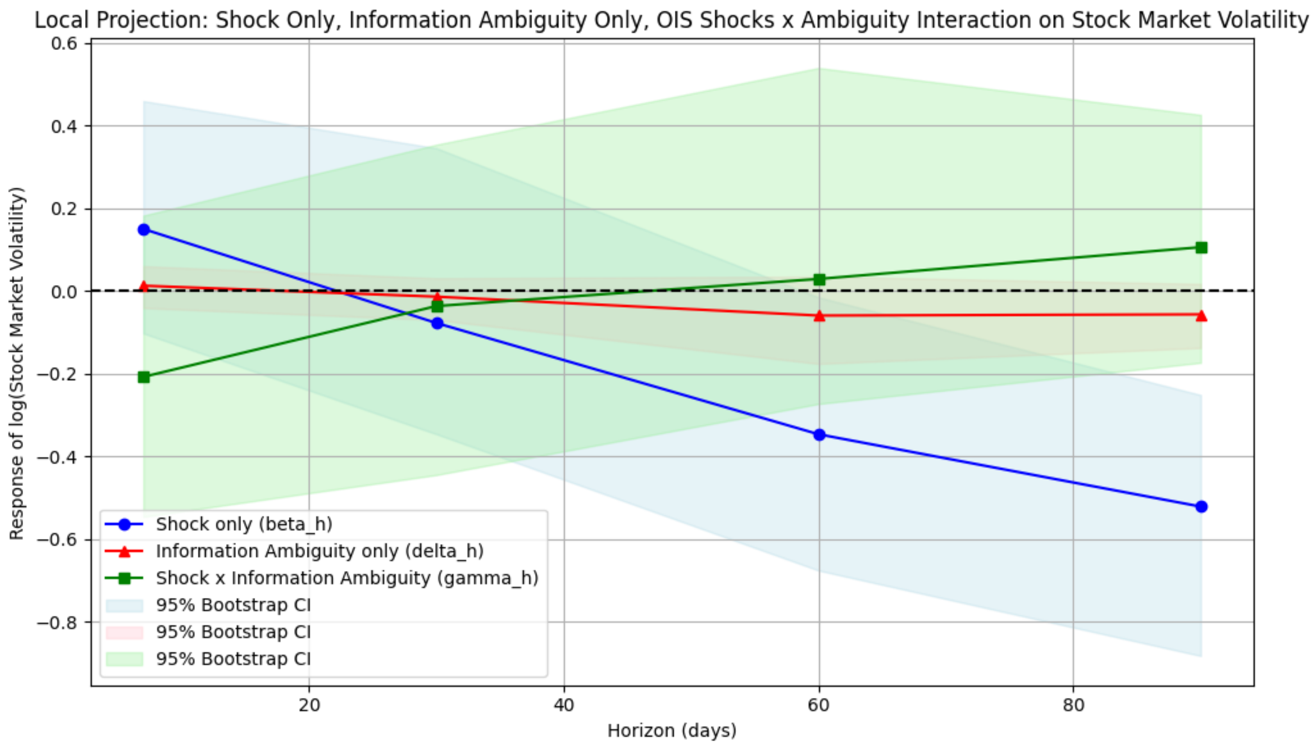

Figure 8: Effect of Monetary Policy Shocks and Information Ambiguity on Stock Market Volatility

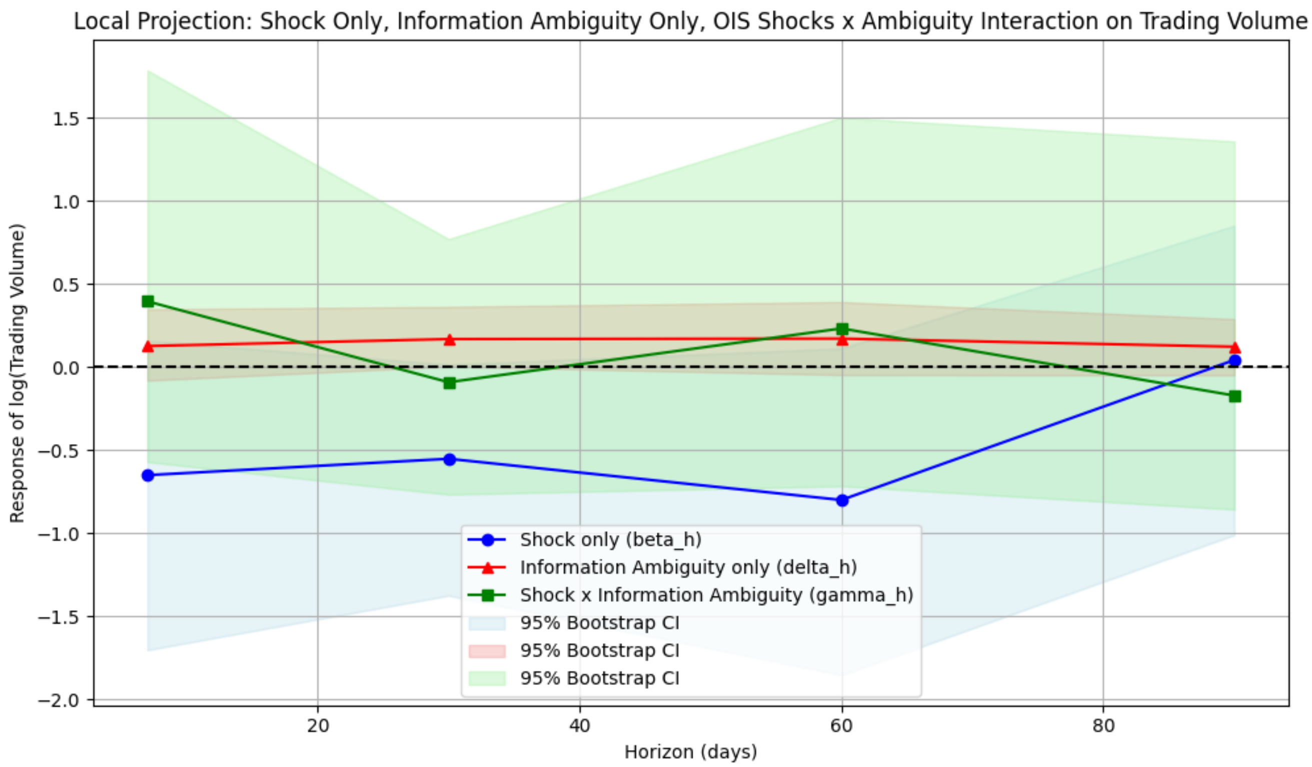

Figure 9: Effect of Monetary Policy Shocks and Information Ambiguity on Trading Volume

C

The following list reports the full set of ECB monetary policy shock dates included in the analysis. These dates are derived from the EA-MPD database and correspond to high-frequency surprises around ECB monetary policy announcements.

12 January 2012, 9 February 2012, 8 March 2012, 4 April 2012, 3 May 2012, 6 June 2012, 5 July 2012, 2 August 2012, 6 September 2012, 4 October 2012, 8 November 2012, 6 December 2012, 10 January 2013, 7 February 2013, 7 March 2013, 4 April 2013, 2 May 2013, 6 June 2013, 7 November 2013, 5 December 2013, 6 February 2014, 6 March 2014, 8 May 2014, 5 June 2014, 3 July 2014, 6 November 2014, 22 January 2015, 5 March 2015, 15 April 2015, 3 June 2015, 3 September 2015, 3 December 2015, 21 January 2016, 10 March 2016, 21 April 2016, 8 September 2016, 20 October 2016, 8 December 2016, 19 January 2017, 8 June 2017, 20 July 2017, 7 September 2017, 26 October 2017, 14 December 2017, 25 January 2018, 26 April 2018, 14 June 2018, 13 September 2018, 25 October 2018, 13 December 2018, 24 January 2019, 7 March 2019, 6 June 2019, 25 July 2019, 12 September 2019, 24 October 2019, 12 December 2019, 12 March 2020, 4 June 2020, 10 September 2020, 29 October 2020, 10 December 2020, 21 January 2021, 11 March 2021, 22 April 2021, 10 June 2021, 22 July 2021, 3 February 2022, 10 March 2022, 14 April 2022, 9 June 2022, 21 July 2022, 8 September 2022, 27 October 2022, 15 December 2022, 2 February 2023, 16 March 2023, 4 May 2023, 15 June 2023, 27 July 2023, 14 September 2023, 26 October 2023.