Federal Reserve Sentiment and European Volatility

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June 30, 2026

Abstract

This paper uses Natural Language Processing (FinBERT) on FOMC Minutes, combined with daily market data, to examine the relationship between FOMC sentiment and European financial-market uncertainty over the period 2000-2025. Baseline regressions establish that Fed sentiment does not significantly predict directional daily changes in European volatility. However, ARX-GARCH estimates confirm a strong effect on conditional variance. In particular, a positive economic tone is associated with increases in the VSTOXX index, as investors anticipate tighter monetary policy, demonstrating that Fed sentiment acts as a major driver of uncertainty. Furthermore, out-of-sample forecasts indicate that incorporating sentiment improves variance predictions compared to standard models, especially during periods of economic instability such as 2020 and 2022. Overall, the findings show that Fed sentiment influences uncertainty in Europe, without changing the direction of equity indices.

I would like to offer my sincere thanks to my thesis supervisor, Professor Vasia Panousi, for her continuous support, expert mentorship, and invaluable feedback throughout this study. I hereby declare that this thesis represents my own original work. Any concepts or materials drawn from external sources have been appropriately cited. I acknowledge that if this statement is found to be false, it will lead to the invalidation of my thesis.

1 Introduction

United States monetary policy communication affect global financial conditions. Beyond changing interest rates, the release of Fed FOMC Minutes influences investor expectations and financial uncertainty. Because the US Federal Reserve has a major role in the global economy, these detailed publications directly affect international equities, including Europe.

During periods of economic uncertainty, such as the 2008 Financial Crisis, the COVID-19 pandemic, and the 2022 inflation period, investors closely monitored Federal Reserve communications for signals about future economic conditions and monetary policy. This highlights the importance of understanding how information released by the US central bank influences financial uncertainty abroad. Therefore, the main objective of this study is to examine whether Federal Reserve communication affects European market uncertainty.

The study combines Natural Language Processing (NLP) and econometric methods. It analyzes the relationship between the text of Federal Open Market Committee (FOMC) Minutes and the VSTOXX index over the period 2000–2025. Using the FinBERT model, a finance-specific transformer trained on financial text, FOMC communications are converted into sentiment scores. These scores are then combined with market data to investigate whether Federal Reserve communication contains information relevant for European market uncertainty.

First, OLS regressions examine whether FOMC sentiment is associated with changes in the VSTOXX on the announcement day and on the following trading day. The results show no statistically significant contemporaneous or lagged relationship.

Second, an ARX-GARCH model is used to account for volatility clustering in financial markets. The results indicate that FOMC sentiment is significantly related to changes in the VSTOXX and that volatility remains highly persistent over time.

Third, the forecasting analysis shows that adding sentiment data improves variance predictions. The model with the sentiment data produces smaller prediction errors than the standard models. This improvement is clear during the 2020 COVID-19 pandemic and the 2022 inflation period.

Finally, the analysis is extended to the DAX index to examine whether Federal Reserve communication affects German equity prices directly. While the results confirm strong volatility persistence, they provide little evidence that FOMC sentiment explains daily changes in the DAX.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the dataset, textual preprocessing methodology, and the construction of the sentiment measures. Section 4 presents the econometric framework and empirical analysis using OLS and ARX-GARCH models. Section 5 evaluates the predictive performance and robustness of the volatility forecasting framework and the Fed sentiment impact on German stock price changes. Finally, Section 6 concludes.

2 Related Literature

The relationship between central bank communication and financial market behavior has become an important topic in financial economics, particularly after periods of global uncertainty. Bomfim (2003) examines whether monetary policy announcements affect stock market volatility rather than simply asset returns. By using federal funds futures to isolate the surprise component of policy decisions and estimating a volatility model with announcement effects, the study finds that unexpected Federal Reserve decisions significantly increase short run market volatility, especially in the case of monetary tightenings. Ehrmann and Fratzscher (2007) extend this literature by examining the institutional structure of central bank communication. Using Reuters reports of speeches, interviews, and testimonies by central-bank officials, they compare communication strategies between the Federal Reserve and the European Central Bank (ECB). Their findings suggest that the Federal Reserve follows a more scattered and autonomous communication structure, while the ECB adopts a more coordinated approach.

More recent research incorporates Natural Language Processing (NLP) techniques into the analysis of monetary-policy communication. Hilscher, Nabors, and Raviv (2026) construct FinBERT sentiment indicators for Federal Reserve and ECB communications and analyze their predictive power using local projections. Their findings indicate that Federal Reserve sentiment predicts future policy rates and influences ECB expectations. Tetlock (2007) similarly demonstrates that textual sentiment extracted from financial news contains economically meaningful information. Using the General Inquirer (GI), a quantitative content analysis program on Wall Street Journal columns, Tetlock finds that pessimistic media tone predicts lower market returns and higher trading volume and that negative market performance also increases pessimistic language. Yang, Uy, and Huang (2020) improve upon dictionary-based methods through the development of FinBERT. Their evidence shows that FinBERT outperforms generic language models in financial sentiment classification tasks, making it particularly suitable for capturing nuanced language in FOMC minutes and central-bank statements.

A related strand of literature focuses on international volatility spillovers and the transmission of financial uncertainty across markets. Diebold and Yilmaz (2009) develop a spillover-index framework based on forecast-error variance decompositions in vector autoregressions to measure return and volatility transmission across global equity markets. Their results show that volatility spillovers intensify during crisis periods and differ from return spillovers, emphasizing the importance of analyzing volatility separately in transatlantic financial markets. While Bomfim (2003) shows that unexpected US monetary-policy decisions increase domestic market volatility, and Hilscher et al. (2026) find that Federal Reserve sentiment influences European policy expectations, few studies directly examine whether Federal Reserve rhetoric itself affects European equity volatility. Most spillover studies focus on interactions between financial markets rather than the effects of central bank communication.

The econometric literature on conditional variance provides the methodological approach for analyzing volatility persistence. Engle (1982) introduces the ARCH framework, showing that volatility is time varying and dependent on past shocks rather than constant over time. Bomfim (2003) later adds announcement effects into a conditional variance frame-

work, demonstrating that unexpected monetary policy news significantly alters market volatility dynamics. However, while ARCH and GARCH models effectively capture persistence and clustering in financial volatility, these studies do not include sentiment measures from central bank communication. Conversely, NLP based studies such as Hilscher et al. (2026) quantify central bank sentiment but focus primarily on policy rates and macroeconomic expectations rather than equity market volatility.

Taken together, the literature suggests that central bank communication influences financial markets primarily through expectations and uncertainty rather than through the direct prediction of returns. It also indicates that volatility spillovers are strong during crisis periods and that volatility should be modeled using conditional variance frameworks. At the same time, NLP advances and finance specific transformer models have made it possible to quantify central bank communication with greater precision than earlier dictionary based approaches. Nevertheless, few studies combine these models in a unified framework to examine whether FEDs communication directly affects European equity volatility. The present thesis addresses this gap by combining FinBERT-based sentiment analysis of FOMC minutes with an ARX-GARCH framework using VSTOXX, VIX, S&P 500, and DAX 40 data from 2000 to 2025. In contrast to studies focusing on returns or policy rate predictability, this thesis examines whether negative Federal Reserve rhetoric increases and extends uncertainty in European equity markets. Furthermore, by analyzing periods like the COVID-19 pandemic and the 2022 inflation surge, this study tests whether including sentiment analysis from Federal Reserve statements analysis from Federal Reserve statements makes our volatility and stock market predictions more accurate.

3 Data Description

This section outlines the data used in the analysis, providing summary statistics alongside a graphical examination of the variables.

3.1 Dataset Overview

The analysis utilizes textual data as well as high-frequency financial-market data for the period 2000-2025. The data on macroeconomic interest rates are from the Federal Reserve Economic Data (FRED) database. The European equity volatility data are from STOXX Ltd. (Qontigo). The data on global equity indices and implied volatility, i.e. S&P 500, DAX 40, and VIX, are from Yahoo Finance. The textual data for monetary policy analysis are retrieved from the website of the Board of Governors of the Federal Reserve System.

3.2 Textual Data

The linguistic component of this study relies on the official minutes of the Federal Open Market Committee (FOMC). A total of 205 documents were collected for each FOMC meeting over the 2000–2025 period. The documents were retrieved from the archives of the Board of Governors of the Federal Reserve System. Preprocessing of the documents included ASCII normalization, UTF-8 decoding, and the removal of special characters and structural noise.

3.3 Macroeconomic Data

To analyze the dynamics of international risk transmission, the dataset combines key volatility gauges, equity indices, and interest rate metrics. The primary dependent variable is the VSTOXX Index, which serves as the benchmark for European equity volatility. The data were obtained directly from STOXX Ltd. (Qontigo). The VSTOXX is based on EURO STOXX 50 options prices, and it measures the 30-day implied volatility of the European market, acting as a gauge of investor uncertainty in the Eurozone. The corresponding VSTOXX standardized Z-Score measures how many standard deviations the current European implied volatility is from its historical average. As such, it is used as a proxy of investors' uncertainty or "Market Fear".

Daily closing prices for the S&P 500 (GSPC), the German DAX 40 (GDAXI), and the CBOE Volatility Index (VIX) were retrieved via the Yahoo Finance API. In this context, the DAX serves as the primary representative of the European equity market, while the S&P 500 and VIX capture the average and volatility for the US market. Data on interest rates were sourced from the Federal Reserve Economic Data (FRED) database. The US three-month Treasury Bill rate (Ticker: DTB3) serves as the proxy for the US risk-free rate. The Eurozone benchmark is represented by the Long-Term Government Bond yield for Germany (Ticker: IRLTLT01DEM156N). While traditional interest rate differentials utilize matching maturities, this study deliberately constructs a cross-maturity spread. Instead of comparing interest rates with matching timeframes, this study compares different timeframes to track how financial risk moves from the US to Europe. Specifically, the 3-month US rate represents sudden US policy changes. The German 10-year yield acts as the benchmark for European long-term macroeconomic expectations and safe haven flows. By comparing these two rates, one can measure how sudden US monetary tightening affects Europe's long-term risk tolerance.

3.4 Variable Adjustments and Transformations

Several transformations were applied to the raw dataset. First, all continuous market variables (S&P 500, DAX 40, and VSTOXX) were converted into log-differences. This transformation induces stationarity and allows the GARCH models to estimate the conditional variance of daily market innovations. Second, a Cross Maturity Policy Spread was constructed as the differential between the US short-term and the European long-term benchmark interest rates ($US_Rate - EU_Rate$).

Additionally, a one-day time lag was applied to the sentiment scores. This means the model compares the Fed announcement on a given day with the European market reaction on the next day. This is used because US announcements happen after European markets have already closed for the day. Thus, the model only uses information that was available to investors before the European trading session began.

3.5 FOMC Sentiment Variables

The sentiment of the FOMC Minutes was quantified using the FinBERT model. FinBERT is a specialized Natural Language Processing (NLP) model, trained on financial datasets and designed to classify financial sentiment. The model produces one sentiment score for each FOMC document, indicating whether the tone of the meeting is relatively

positive or negative.

Additionally, a sentiment volatility index was created to measure how much the Fed's tone changes over time. This index calculates the rolling standard deviation of the sentiment scores across five consecutive FOMC meetings. A higher number means that the Fed's sentiment is changing frequently, while a lower number means sentiment stability.

3.6 Graphical Analysis

The objective of this section is to validate the core hypothesis of cross-border risk transmission. Figure 1 illustrates the trends in Market Uncertainty (VSTOXX Z-Score) and Fed Concern (Inverted Sentiment Z-Score) from 2000 to 2025. The red line represents Market uncertainty, while the blue line depicts Fed Concern. Overall, the two series exhibit a positive correlation (Pearson's $r = 0.255$, $p < 0.01$), and there is a strong synchronization between the two lines, particularly during periods of macroeconomic stress. Specifically, both variables show large increases during the 2008 Financial Crisis and the 2020 COVID-19 pandemic. During these events, high levels of Fed concern occur alongside high uncertainty (fear) in the European market.

Furthermore, the graph shows a clear pattern. During periods when the Fed shows low concern, such as the mid-2000s and from 2013 to 2017, European market volatility remains low. On the other hand, when the Fed shows high concern, European volatility consistently increases. However, the European market also reacts to local events. For example, during the European Sovereign Debt Crisis (2011–2012), European market volatility increased at the highest level in the sample, whereas the Fed concern index remained low. This shows that the European market can experience high volatility for reasons other than US developments.

Next, Figure 2 shows how European uncertainty behaves for different levels of Fed sentiment: Negative or pessimism, zero or normal, and positive or optimism. The vertical axis shows the VSTOXX level, and the horizontal axis shows the FinBERT score for Fed sentiment. During the 'Optimism' regime (green), VSTOXX volatility is low, and the data stays close to a low average. The 'Pessimism' category (red) shows a different pattern. The average VSTOXX level rises, and the data spreads out more, reaching high levels. This comparison shows that large market changes happen more often during pessimistic periods. When the Federal Reserve shows concern, market volatility in Europe increases.

Figure 3 compares European market volatility (top panel) with the changes in the Federal Reserve's tone (bottom panel). The red line shows the VSTOXX index. The blue line shows the variation in the text scores over time. Overall, periods of high variation in Fed sentiment often happen at the same time as, or just before, periods of high market volatility in Europe. When the Fed's tone changes frequently, European market volatility increases. Finally, because US announcements happen after European markets close, the European market reacts to these statements on the following trading day.

4 Econometric Analysis

This section presents the econometric models used to examine the relationship between Federal Reserve communication and the VSTOXX. The analysis starts with two Ordinary Least Squares (OLS) regressions. These models test whether the sentiment of FOMC communication is associated with changes in the VSTOXX on the announcement day and on the following trading day. In this way, both contemporaneous and lagged effects can be examined. The analysis then moves to an ARX-GARCH(1,1) model. Unlike OLS, this framework accounts for the volatility clustering that is often observed in financial markets. It also examines whether the effects of FOMC sentiment on the VSTOXX persist beyond the announcement day.

4.1 Contemporaneous Relationship

To investigate the immediate impact of US monetary policy sentiment on VSTOXX uncertainty, the first regression is specified as follows:

$$\Delta VSTOXX_t = \beta_0 + \beta_1 \cdot Sentiment_t + \varepsilon_t \tag{1}$$

where $\Delta VSTOXX_t$ is the daily change in the VSTOXX on the day of the FOMC announcement and $Sentiment_t$ is the FinBERT sentiment score. The equation (1) was estimated using Ordinary Least Squares (OLS) with robust standard errors (HC3). The results of equation (1) are presented in Table 1. The coefficient on the sentiment score is 0.4137, and it is statistically not significant ($p = 0.229$). This indicates that the FOMC tone does not systemically explain daily changes in the VSTOXX on the exact same day. This is likely due to asynchronous trading hours and time zone differences. Because FOMC announcements are released at 14:00 EST, after European markets have closed, the VSTOXX cannot absorb this new information until the next trading day. These findings match the visual evidence in Figure 4, which shows a flat regression line.

4.2 Lagged Spillover Effects

Next, the model tests the reaction of the VSTOXX on the day following an FOMC-minutes release. This accounts for the time difference between the US and Europe. The model is:

$$\Delta VSTOXX_{t+1} = \beta_0 + \beta_1 \cdot \text{Sentiment}_t + \varepsilon_{t+1} \tag{2}$$

where $\Delta VSTOXX_{t+1}$ is the change in the VSTOXX on the next trading day. The results of equation (2) are in the Table 2. The sentiment coefficient is 0.3595 and is statistically not significant ($p = 0.427$). This implies that Fed sentiment does not affect changes in European uncertainty in a lagged manner either. Overall, both OLS models show that the Federal Reserve's sentiment does not explain changes in the VSTOXX either in a contemporaneous or in a lagged fashion.

4.3 Addressing Heteroskedasticity: ARX-GARCH model

A GARCH or generalized autoregressive conditional heteroskedasticity model is a statistical model frequently used to forecast volatility in financial time-series data. It is designed to handle volatility clustering, i.e. the tendency for large market shocks to be followed by

more large shocks. This section uses an ARX-GARCH(1,1) model on the full sample of 6,939 observations.

The model consists of two main equations:

$$LogPct_VSTOXX_t = \text{const} + \phi \cdot LogPct_VSTOXX_{t-1} + \gamma \cdot Sentiment_t + \varepsilon_t \quad (3)$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (4)$$

where const is the intercept, $LogPct_VSTOXX_t$ is the log-percentage change in the VSTOXX at day t, $Sentiment_t$ is the Fed's sentiment on FOMC days, and ε_t is the error term. In the conditional variance equation (4), σ_t^2 is the conditional variance of the error term. To preserve the continuous daily timeline required by the GARCH model, the $Sentiment_t$ variable includes all trading days of the year. On the exact days of an FOMC release, it takes the FinBERT sentiment score. On all other days, it is set to zero to show that no announcement took place. In contrast, the previous OLS models completely removed the non-announcement days from the dataset, keeping strictly the event days without using any zeros. This allows the model to be estimated without missing dates, while keeping the information exactly the same as in the OLS model.The estimation results for equations (3) and (4) are in Table 3.

In the mean equation (3), the sentiment coefficient ($\gamma = 1.91$) is statistically significant at the 5% level. This positive value means that when the Fed's sentiment score increases (becomes more positive), the uncertainty (VSTOXX) also increases. This happens because when the Fed says the economy is strong, investors interpret this as a signal that the bank will raise interest rates to control inflation. This expectation of tighter monetary policy creates uncertainty, which drives the VSTOXX index upward. Alternatively, if the coefficient was negative ($\gamma < 0$), a higher sentiment score would correspond to a decrease in conditional variance. This would mean that a positive tone from the Fed calms investors and reduces uncertainty, signaling that the economy is stable and there is no need to raise interest rates. The lagged coefficient is negative ($\phi = -0.04$), showing that the VSTOXX tends to reverse partly its previous daily move.

In the conditional variance equation (4), the ARCH term ($\alpha = 0.09$) and the GARCH term ($\beta = 0.87$) are both statistically significant at the 0.1% level. The ARCH coefficient shows that recent shocks have an immediate effect on the current daily percent change of the VSTOXX. The sum of these coefficients ($\alpha + \beta = 0.9608$) represents the persistence of volatility shocks. This high persistence indicates that when a Fed sentiment creates uncertainty, the volatility does not disappear fully the next day. Specifically, 96.08% of the shock shifts into the next trading day, meaning only 3.92% of the initial turbulence decays immediately.

The gradual decay of this shock over time can be calculated using the persistence rate $(\alpha + \beta)^k$ for k days ahead. On the second day, 92.31% of the shock remains in the index, which slowly drops to 81.88% after five trading days (one week), and goes down to 44.84% after twenty trading days (one month). This mathematical structure confirms that Fed sentiment creates long-lasting shifts in European financial uncertainty that require multiple weeks to fully decay.

Overall, the ARX-GARCH model analyzes the Fed's sentiment impact better than the previous OLS regressions (1) and (2). By accounting for volatility clustering, the results show that FOMC communication affects the daily percent changes of the VSTOXX. This means that periods of high turbulence in the VSTOXX tend to cluster together. A highly volatile day is usually followed by another volatile day, while calm periods follow calm periods.

5 Robustness

This section presents robustness tests for the ARX-GARCH model. The sentiment variable is lagged, instead of contemporaneous, as in equation (3).

The new model consists of two equations:

$$LogPct_VSTOXX_t = \text{const} + \phi \cdot LogPct_VSTOXX_{t-1} + \gamma \cdot Sentiment_{t-1} + \varepsilon_t \quad (5)$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (6)$$

where const is the intercept, $LogPct_VSTOXX_{t-1}$ is the log-percentage change in the VSTOXX, $Sentiment_{t-1}$ is the lagged Fed sentiment score, ε_t is the error term, and σ_t^2 is the conditional variance. The estimation results for both equations (5) and (6) are reported in Table 4.

The mean equation (5) models the daily percent changes in the VSTOXX to test if yesterday's Fed sentiment can predict today's changes. The choice of the VSTOXX ($LogPct_VSTOXX_t$) as the dependent variable is supported by its relationship with the DAX. Specifically, the analysis calculates the correlation between the VSTOXX index and the 20-day rolling variance of the DAX daily percent changes. This calculation yielded a high correlation of 0.8217. This confirms that the VSTOXX captures German equity market turbulence well.

The conditional variance equation (6) models how the volatility of the VSTOXX changes over time. The conditional variance (σ_t^2) depends on the constant term (ω), the previous day's squared error (ε_{t-1}^2), and the previous day's variance (σ_{t-1}^2). The ARCH coefficient (α) measures the immediate impact of yesterday's unexpected shocks on today's volatility. The GARCH coefficient (β) captures the volatility clustering, showing how long these volatile periods persist in the VSTOXX daily percent changes.

The estimated coefficient for lagged Fed sentiment is positive ($\gamma = 1.74$), suggesting that a higher sentiment score increases the daily percent changes of the VSTOXX. However, this result is not statistically significant ($p = 0.106$). The coefficient for the lagged index change ($LogPct_VSTOXX_{t-1}$) is negative. This means that the VSTOXX tends to reverse partly of its previous daily move. In the variance equation, both the ARCH and GARCH coefficients are significant. This confirms volatility clustering. The sum of these two coefficients is close to one ($\alpha + \beta \approx 0.96$). This shows that the conditional variance is highly persistent and requires multiple days to decay.

Overall, the results show that while the Fed's sentiment does not strongly predict the exact next-day changes in the VSTOXX, the conditional variance remains highly persistent over time.

5.1 Forecasting Performance

This section evaluates how well the model predicts the future, a process known as out-of-sample forecasting. To do this, the model uses only data from before 2018. The model then forecasts the VSTOXX conditional variance for the period from 2018 to 2026. This separation of data is necessary to avoid overfitting. Overfitting happens when a model perfectly matches past data but fails to predict new events. Testing the model on unseen data provides an accurate measure of whether the Fed's sentiment helps forecast changes in the VSTOXX.

5.2 Visualizing the Volatility Forecast

Figure 5 presents the out-of-sample volatility forecasts for the period from 2018 to 2026. The gray line shows the absolute value of the percent changes in the VSTOXX. The light blue line displays the forecast of the baseline AR-GARCH model, which relies only on past market data and does not include the Fed sentiment variable. Finally, the red dashed line displays the forecast of the ARX-GARCH model with sentiment.

Over the entire period, both models successfully track the market's volatility. Visually, the two prediction lines overlap. They both capture major volatility spikes, such as the early 2020 COVID-19 shock and the 2022 inflation period. This visual overlap occurs because the market's own volatility persistence drives most of the forecast. When the market is highly volatile one day, it tends to stay volatile the next day. The baseline AR-GARCH model captures this effect. The ARX-GARCH model adds the lagged Fed sentiment. While this additional variable does not completely change the visual shape of the graph, it improves the model's forecasting accuracy, as the next section shows.

5.3 Forecast Accuracy Comparison

To measure if the Fed sentiment improves the predictions, the forecast errors of the two models shown in Figure 5 are compared using the Mean Absolute Deviation (MAD). The MAD measures the average size of a model's prediction errors. The difference in the MAD between the ARX-GARCH model (with Fed sentiment) and the baseline ARX-GARCH model (without Fed sentiment) is calculated as follows:

$$\Delta MAD = MAD_{\text{Sentiment}} - MAD_{\text{Baseline}} = -0.001757 \tag{7}$$

A lower MAD indicates that a model's predictions are closer to the realized market values. The negative result ($\Delta MAD = -0.001757$) shows that the ARX-GARCH model with Fed sentiment has a smaller average error than the baseline ARX-GARCH model. This means that adding the Fed sentiment variable reduces forecasting errors. In other words, Fed sentiment provides useful information that improves the predictions of European market volatility.

Therefore, the Fed sentiment serves a clear statistical purpose. It separates the impact of Fed's sentiment from the past volatility behavior of the VSTOXX. This shows that the conditional variance does not just repeat its own history. Instead, the Fed's sentiment directly affects European uncertainty.

5.4 Impact on German Stock Price Changes

To further evaluate the transmission of FOMC communication, the empirical focus shifts from market uncertainty to the benchmark German equity index. This analysis tests whether the Fed's sentiment directly affects German equity price movements, using the DAX index. While the previous sections examined the impact of Fed sentiment on European volatility and uncertainty, the baseline specification is now adjusted to estimate the conditional mean and variance of the DAX daily percent changes using a lagged approach:

$$LogPct_DAX_t = \text{const} + \phi \cdot LogPct_DAX_{t-1} + \gamma \cdot Sentiment_{t-1} + \varepsilon_t \tag{8}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{9}$$

where $LogPct_DAX_t$ represents the daily scaled log-percentage change of the DAX index, const is the intercept, $Sentiment_{t-1}$ is the lagged Fed sentiment score, ε_t is the error term, and σ_t^2 is the conditional variance. Equation (8) serves as the mean specification for both the Ordinary Least Squares (OLS) estimation and ARX-GARCH(1,1) framework, while equation (9) defines the time-varying variance structure in the ARX-GARCH model. This verifies if US monetary policy sentiment influences the actual direction of German equity price movements, rather than just shifting market uncertainty.

The estimation results for the OLS framework and the ARX-GARCH(1,1) specification are presented in Table 5 and Table 6. In the OLS model, the estimated coefficient for the lagged Fed sentiment is positive ($\gamma = 0.4610$) but statistically insignificant ($p = 0.141$). When controlling for time-varying variance through the ARX-GARCH(1,1) specification, the sentiment coefficient remains statistically insignificant ($\gamma = 0.1153, p = 0.650$). The R-squared value is close to zero in both models, which indicates that FOMC communication fails to predict daily changes in the DAX index.

In contrast, the variance component (9) of the GARCH model confirms the presence of volatility clustering. Both the ARCH coefficient ($\alpha = 0.0965, t = 8.468$) and the GARCH coefficient ($\beta = 0.8966, t = 76.303$) are highly significant at the 0.1% level. Their sum ($\alpha + \beta = 0.9931$) indicates extreme persistence in the conditional variance of the index daily percent changes.

Combined with the previous findings, these robustness tests show a clear difference. While Fed sentiment shocks significantly influence European uncertainty via the VSTOXX, they do not directly affect daily changes in the DAX index.

6 Conclusions

This study examined how US Federal Reserve communication affects European equities. By applying Natural Language Processing to FOMC Minutes and utilizing an ARX-GARCH framework, the analysis evaluated the impact of monetary policy sentiment on European financial uncertainty.

The empirical results establish a clear distinction between directional index movements and conditional variance. Baseline OLS regressions confirm that Fed sentiment has no significant contemporaneous or lagged relationship with daily changes in the VSTOXX. Furthermore, robustness tests indicate no direct effect on daily changes in the DAX. However, accounting for variance clustering through the ARX-GARCH framework demonstrates that FOMC sentiment significantly influences financial uncertainty in Europe, with these effects being highly persistent over time.

Furthermore, out-of-sample forecasting indicates that incorporating sentiment scores reduces prediction errors. Ultimately, while US central bank communication does not predict the exact daily direction of European equities, it serves as a significant and persistent driver of European uncertainty.

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Table 1: OLS Regression Results: Contemporaneous Market Reaction (Day T)

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**	**[0.025**	**0.975]**
Constant	-0.1647	0.127	-1.299	0.194	-0.413	0.084
FOMC Sentiment Score	0.4137	0.344	1.204	0.229	-0.260	1.087
Model Diagnostics:						
Dependent Variable: VSTOXX Change (T)			R-squared: 0.006			
Observations: 201			Adj. R-squared: 0.001			
Covariance Type: HC3 (Robust)			F-statistic (Prob): 1.449 (0.230)			

Table 1 aiming to capture the immediate market reaction of the VSTOXX index on the exact day of the FOMC Minutes release (Day T). See discussion in Section 4.1.

Table 2: OLS Regression Results: Lagged Market Reaction (Day $T + 1$)

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**	**[0.025**	**0.975]**
Constant	0.0058	0.172	0.034	0.973	-0.331	0.342
FOMC Sentiment Score	0.3595	0.452	0.795	0.427	-0.527	1.245
Model Diagnostics:						
Dependent Variable: VSTOXX Change ($T + 1$)			R-squared: 0.002			
Observations: 201			Adj. R-squared: -0.003			
Covariance Type: HC3 (Robust)			F-statistic (Prob): 0.632 (0.427)			

Table 2 estimates the lagged market response, specifically analyzing how European volatility incorporates the Fed's sentiment signals during the subsequent trading session (Day $T + 1$), accounting for time-zone differences and information digestion. See discussion in Section 4.2.

Table 3: ARX-GARCH(1,1) Model Results (Standardized Student's t Distribution)

Mean Model (AR-X)						
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**[0.025**	**0.975]**
Constant	-0.3166	0.0631	-5.018	$<$ **0.001*****	-0.440	-0.193
VSTOXX LogPct [t-1]	-0.0408	0.0123	-3.314	$<$ **0.001*****	-0.065	-0.017
FOMC Sentiment Score	1.9102	0.7550	2.529	**0.011***	0.430	3.391
Volatility Model (GARCH)						
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**[0.025**	**0.975]**
ω **(Constant)**	1.7322	0.5330	3.250	**0.001****	0.688	2.777
α_1 **(ARCH term)**	0.0908	0.0156	5.826	$<$ **0.001*****	0.060	0.121
β_1 **(GARCH term)**	0.8700	0.0263	33.063	$<$ **0.001*****	0.818	0.922
Distribution Parameters						
ν **(DoF)**	4.9429	0.2930	16.859	$<$ **0.001*****	4.368	5.518

Model Diagnostics:

Dependent Variable: VSTOXX_LogPct	Log-Likelihood: -21993.8
R-squared: 0.000 (Adj: -0.000)	AIC: 44001.6
Observations: 6939	BIC: 44049.5
Df Residuals / Model: 6936 / 3	Covariance Estimator: Robust

*Note: *, **, and *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.*

Table 3 presents the ARX-GARCH(1,1) model results for the VSTOXX daily percent changes. In the mean model, the coefficient for the Fed sentiment ($\gamma = 1.9102, p = 0.011$) is positive and statistically significant at the 5% level. In the volatility model, both the ARCH ($\alpha_1 = 0.0908$) and GARCH ($\beta_1 = 0.8700$) coefficients are highly significant ($p \leq 0.001$). Their sum ($\alpha_1 + \beta_1 = 0.9608$) shows that the conditional variance is highly persistent over time. Therefore, Fed sentiment directly increases European uncertainty. See discussion in Section 4.3.

Table 4: ARX-GARCH(1,1) Final Model: Impact of Sentiment with Student's t-Distribution

Mean Equation (ARX)						
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**[0.025**	**0.975]**
Constant	-0.3223	0.0624	-5.160	$<$ **0.001*****	-0.445	-0.200
VSTOXX LogPct [t-1]	-0.0417	0.0123	-3.390	$<$ **0.001*****	-0.066	-0.018
FOMC Sentiment Score [t-1]	1.7427	1.0780	1.617	0.106	-0.370	3.855
Volatility Equation (GARCH)						
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**[0.025**	**0.975]**
ω **(Constant)**	1.7545	0.5447	3.221	**0.001****	0.687	2.822
α_1 **(ARCH term)**	0.0918	0.0159	5.785	$<$ **0.001*****	0.061	0.123
β_1 **(GARCH term)**	0.8686	0.0268	32.360	$<$ **0.001*****	0.816	0.921
Distributional Parameter						
ν **(Degrees of Freedom)**	4.9418	0.2930	16.866	$<$ **0.001*****	4.368	5.516
Model Diagnostics:						
Dependent Variable: VSTOXX_LogPct			Log-Likelihood: -21994.6			
Observations: 6939			AIC: 44003.1			
Covariance Estimator: Robust			BIC: 44051.0			

*Note: *, **, and *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.*

Table 4 presents the ARX-GARCH(1,1) model results using lagged Fed sentiment to test its predictive power on the VSTOXX daily percent changes. In the mean equation, the coefficient for the lagged sentiment ($\gamma = 1.7427, p = 0.106$) is statistically insignificant, indicating that yesterday's Fed tone does not predict today's changes. In the volatility equation, both the ARCH ($\alpha_1 = 0.0918$) and GARCH ($\beta_1 = 0.8686$) coefficients are highly significant ($p \leq 0.001$). Their sum ($\alpha_1 + \beta_1 = 0.9604$) confirms that the conditional variance remains highly persistent over time. In conclusion, these findings demonstrate that while contemporary Fed sentiment drives the VSTOXX, it lacks direct predictive power over its next-day changes. See discussion in Section 5.

Table 5: OLS Regression Results for DAX Daily Percent Changes

OLS Estimation Summary						
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**[0.025**	**0.975]**
Constant	0.0246	0.0170	1.419	0.156	-0.009	0.058
FOMC Sentiment Score [t-1]	0.4610	0.3130	1.471	0.141	-0.153	1.075
Model Diagnostics & Residual Statistics:						
Dependent Variable: LogPct_DAX			R-squared: 0.001 (Adj: 0.000)			
Observations: 6615			F-statistic: 2.164 (p-val: 0.141)			
Log-Likelihood: -11680.0			AIC: 23360.0			
Df Residuals / Model: 6613 / 1			BIC: 23380.0			
Covariance Type: HAC (1 lag)			Condition No.: 14.1			
Omnibus: 881.837 (p-val: 0.000)			Jarque-Bera (JB): 10361.269 (p-val: 0.00)			
Skewness: -0.171			Kurtosis: 9.122			

Note: Standard Errors are heteroscedasticity and autocorrelation robust (HAC).

Table 5 presents the OLS regression results. The coefficient for the lagged Fed sentiment ($\gamma = 0.4610, p = 0.141$) is statistically insignificant. The low R-squared value (0.001) shows that the model lacks explanatory power. In conclusion, the OLS findings demonstrate that lagged Fed sentiment does not predict daily changes in the DAX index. See discussion in Section 5.4.

Table 6: ARX-GARCH(1,1) Model Results for DAX Daily Percent Changes

Mean Model (AR-X)						
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**[0.025**	**0.975]**
Constant	0.0847	0.0121	6.992	$<$ **0.001*****	0.061	0.108
DAX LogPct [t-1]	-0.0242	0.0121	-2.002	**0.045***	-0.048	-0.001
FOMC Sentiment Score [t-1]	0.1153	0.2540	0.454	0.650	-0.383	0.613
Volatility Model (GARCH)						
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**[0.025**	**0.975]**
ω **(Constant)**	0.0195	0.0048	4.055	$<$ **0.001*****	0.010	0.029
α_1 **(ARCH term)**	0.0965	0.0114	8.468	$<$ **0.001*****	0.074	0.119
β_1 **(GARCH term)**	0.8966	0.0118	76.303	$<$ **0.001*****	0.874	0.920
Distribution Parameter						
ν **(DoF)**	6.9348	0.6070	11.423	$<$ **0.001*****	5.745	8.125
Model Diagnostics:						
Dependent Variable: LogPct_DAX			Log-Likelihood: -10348.9			
R-squared: -0.001 (Adj: -0.002)			AIC: 20711.7			
Observations: 6614			BIC: 20759.3			
Df Residuals / Model: 6611 / 3			Covariance Estimator: Robust			

*Note: *, **, and *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.*

Table 6 presents the ARX-GARCH(1,1) model results. In the mean model, the coefficient for the lagged Fed sentiment ($\gamma = 0.1153, p = 0.650$) remains statistically insignificant. In contrast, the volatility model shows strong clustering, as both the ARCH ($\alpha_1 = 0.0965$) and GARCH ($\beta_1 = 0.8966$) coefficients are highly significant ($p < 0.001$). Their sum ($\alpha_1 + \beta_1 = 0.9931$) indicates that variance is highly persistent over time. In conclusion, these findings confirm that lagged Fed sentiment does not predict daily changes in the DAX index. See discussion in Section 5.4.

Figure 1

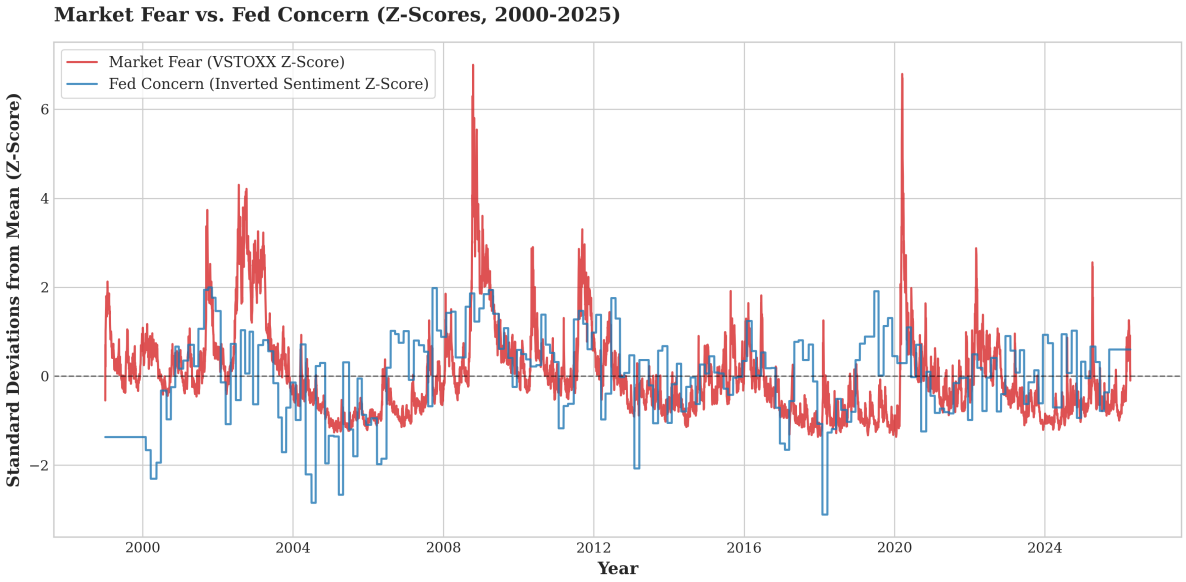


Figure 1 presents the normalized historical trajectory of Market Fear (VSTOXX Z-Score, red line) and Fed Concern (Inverted FinBERT Sentiment Z-Score, blue line) from 2000 to 2025, illustrated in standard deviations from the mean. See discussion in Section 3.6.

Figure 2

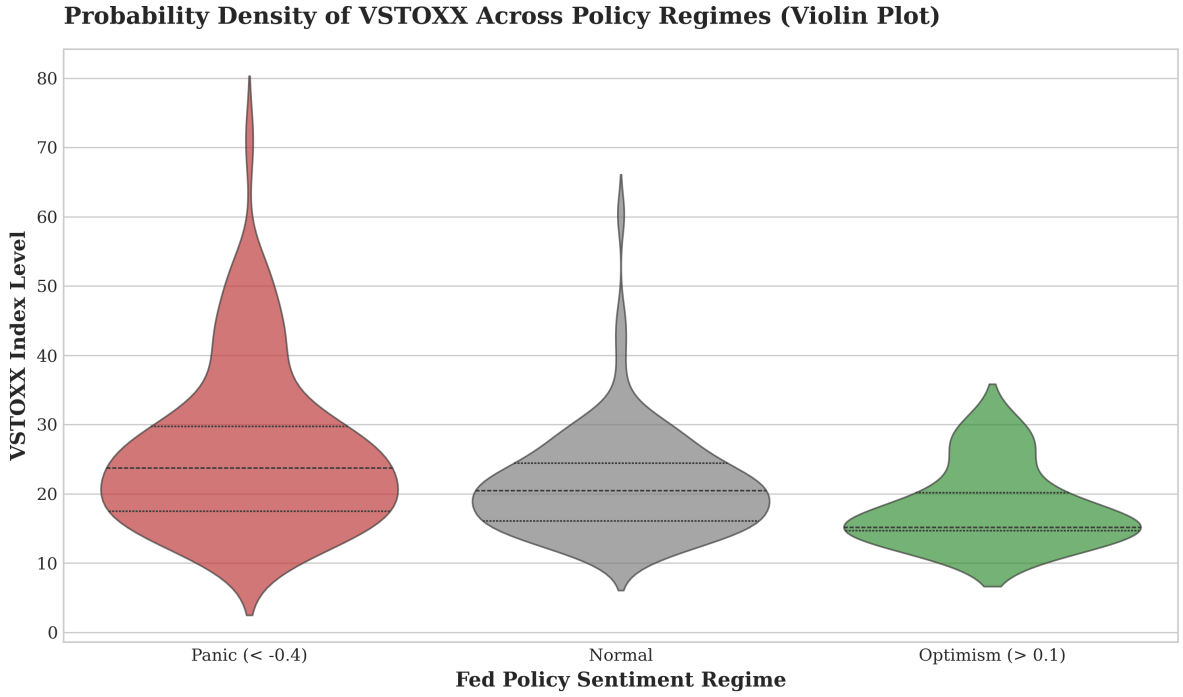


Figure 2 presents a Violin Plot of VSTOXX index levels categorized by Fed policy sentiment regimes (Panic, Normal, Optimism), illustrating the probability density, median, and interquartile ranges for each state. See discussion in Section 3.6.

Figure 3

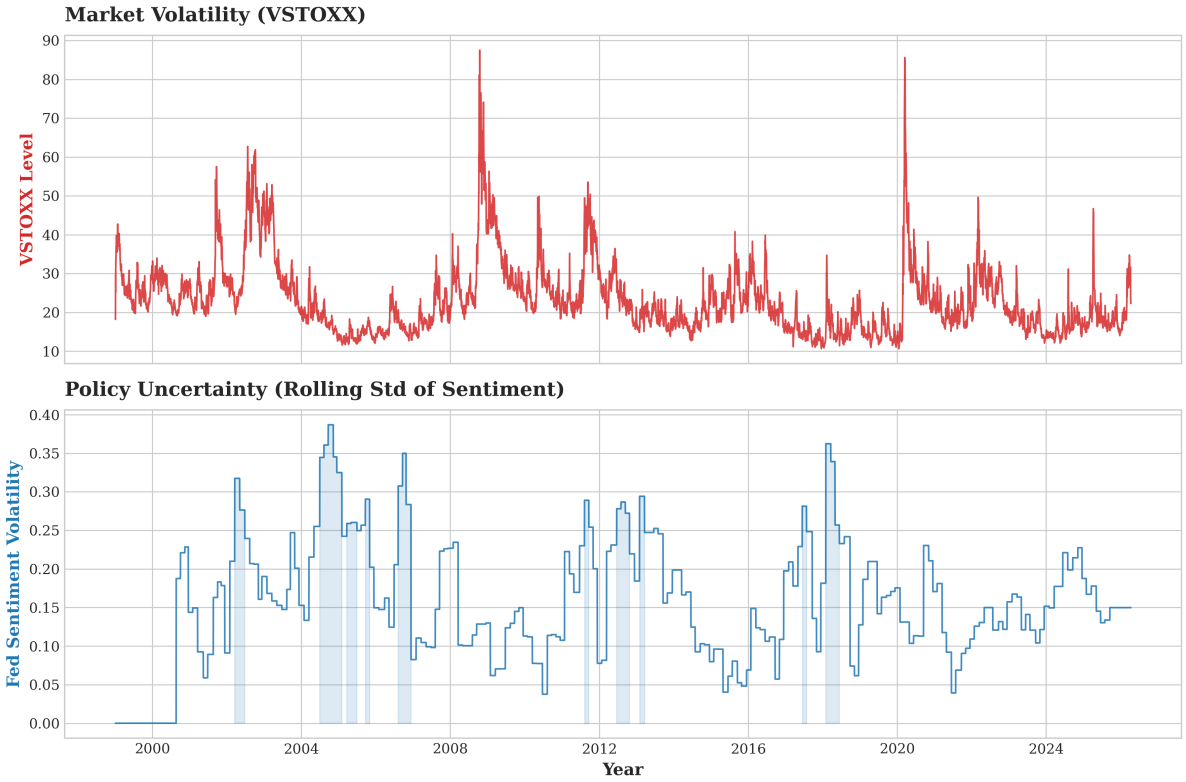


Figure 3 displays a comparative overlay of market instability (VSTOXX Level, top panel) and monetary policy uncertainty (Rolling Standard Deviation of Fed Sentiment, bottom panel) from 2000 to 2025. See discussion in Section 3.6.

Figure 4

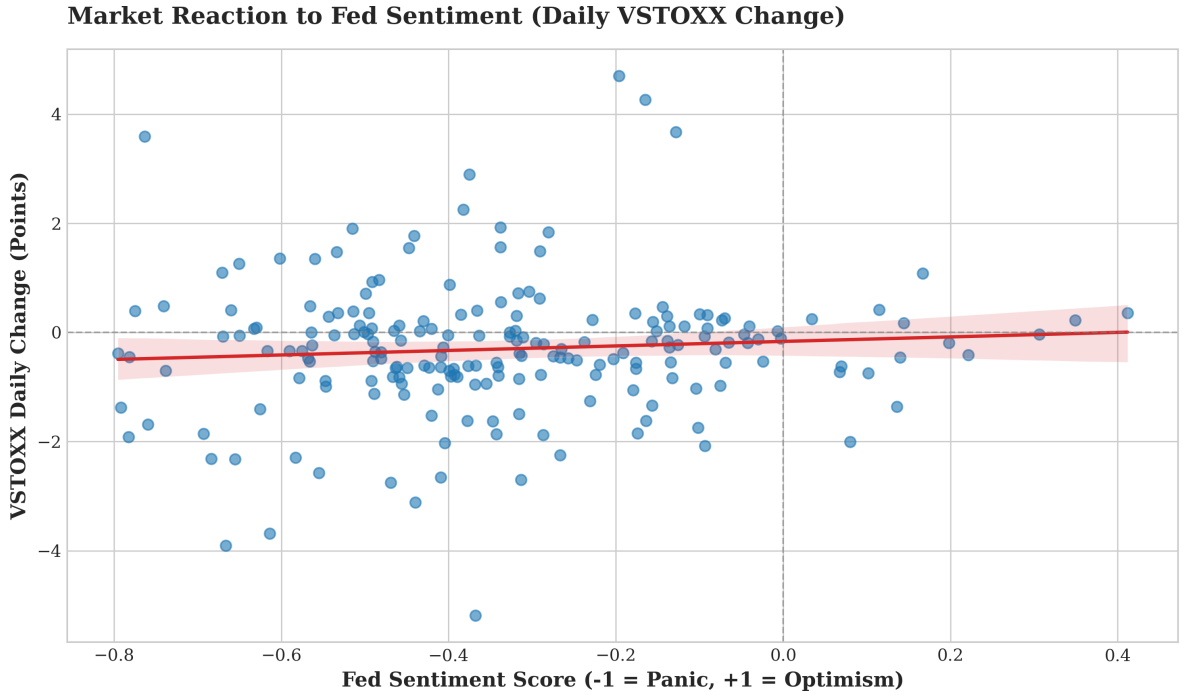


Figure 4 presents a scatter plot of the contemporaneous market reaction to Fed sentiment, mapping daily VSTOXX point changes against FinBERT sentiment scores, including an OLS regression line (solid red) and its 95% confidence interval. See discussion in Section 4.1.

Figure 5

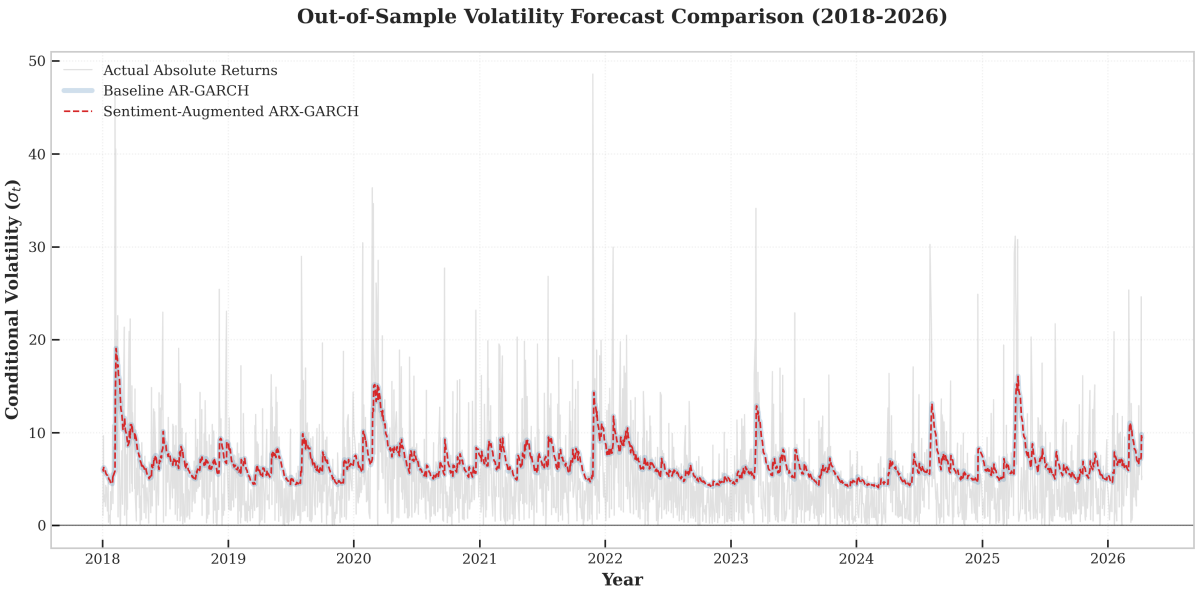


Figure 5 presents the out-of-sample volatility forecast comparison (2018–2026), displaying actual absolute returns (grey) alongside the predictions of the Baseline AR-GARCH (SteelBlue shadow) and the Sentiment-Augmented ARX-GARCH (dashed red line). See discussion in Section 5.2.