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Crypto Listens: Asymmetric Reactions to Text-based Signals in Central Bank Communications

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Abstract

The growing influence of cryptocurrencies in global financial markets has raised questions about the impact of central bank communications on their price dynamics. This paper investigates how central bank communication affects the behaviour of cryptocurrency markets. Using a dataset of over 6,000 central bank speeches and a broad panel of crypto assets, we quantify sentiment, uncertainty, and fear tone through natural language processing and assess their impact using local projection methods. Our results show that positive tone initially depresses returns while raising volatility, whereas uncertainty and fear produce mixed return responses and amplify price fluctuations in the short run. Heterogeneity across asset types reveals stronger responses among emerging, high-performing, and non-stablecoin cryptocurrencies. The findings highlight the informational role of central bank narratives in shaping outcomes in speculative and decentralised markets, with important implications for communication policy and financial stability monitoring.

Keywords: Cryptocurrency, Central Bank Communication, Text Analysis, Sentiment Analysis, Monetary Policy
JEL Classification: D53, E52, E58, G15, O33

1 Introduction

The recent milestone of Bitcoin surpassing \$100,000[1] marks a defining moment in the evolution of cryptocurrencies, solidifying their role as a transformative force in the global financial system. The evolution of cryptocurrencies has not gone unnoticed by central banks, which have begun to engage with the phenomenon more actively, offering their perspectives through public speeches (Waller, 2022; Panetta, 2023), reports (Sardar et al., 2024; Watsky et al., 2024), and policy actions (Barr, 2023; Beau, 2023; Enria, 2023). These communications often reveal the evolving perceptions of central banks and play a critical role in shaping market perceptions, influencing regulatory discourse, and potentially affecting the behaviour of participants in cryptocurrency markets. The sentiment expressed in central bank speeches, ranging from outright scepticism over their volatility and potential for financial instability (Panetta, 2022) to cautious acknowledgment of their innovative potential (Menon, 2022), holds the potential to influence market participants' behaviour and, subsequently, the price dynamics of cryptocurrencies. Given the speculative nature of crypto markets and their sensitivity to external signals, understanding the interplay between central bank sentiment and crypto asset prices becomes critical.

While the link between macroeconomic factors and news and cryptocurrency prices has been studied extensively (Corbet et al., 2020; Pyo and Lee, 2020; Jiang et al., 2023), less attention has been paid to the role of qualitative signals, such as central bank speeches, in shaping crypto market outcomes. Our research aims to address this gap by exploring the potential relationship between the sentiment conveyed in central bank speeches regarding cryptocurrencies and the price movements of these digital assets.

Analysing how the sentiment conveyed in central bank speeches impacts cryptocurrency price dynamics is crucial for several reasons. First, it provides insights into how institutional narratives influence emerging and speculative markets, filling a critical gap in the literature. Cryptocurrencies operate within a framework distinct from traditional financial systems, where sentiment and perception may play a disproportionately large role in driving price fluctuations. Second, it equips policymakers with tools to craft effective communication strategies that mitigate market volatility without stifling innovation. Strategic messaging can help manage market expectations, reduce the risk of speculative bubbles, and foster a healthier environment for sustainable innovation within the crypto ecosystem. Besides, as the crypto ecosystem increasingly integrates with mainstream finance, identifying the interplay between central bank sentiment and cryptocurrency prices is essential for designing informed regulatory frameworks and promoting financial stability in this rapidly evolving domain. With cryptocurrencies now influencing broader economic systems, from payment infrastructures to investment portfolios, a lack of understanding could lead to unintended consequences such as contagion effects or misaligned regulatory responses.

Our analysis utilises distinct datasets to explore the relationship between central bank

[1] Bitcoin surpassed the \$100,000 mark for the first time on December 4, 2024, reaching an all-time high (see https://www.nbcnews.com/business/markets/bitcoin-100000-rcna181008).

sentiment and cryptocurrency markets. First, cryptocurrency market data was sourced from CoinMarketCap, comprising daily market prices for both currently and previously listed tokens. Sentiment and emotion variables were derived from English transcripts of central bank speeches delivered by governors and senior officials, sourced from the Bank for International Settlements (BIS).

Using a variety of econometric specifications, we first find that central bank sentiment, uncertainty, and fear exert statistically significant effects on both irregular returns and short-term volatility in cryptocurrency markets. Positive sentiment shocks initially lead to a decline in irregular returns, followed by a delayed recovery. In contrast, uncertainty and fear shocks produce a modest increase in irregular returns before triggering a strong decline at the end of the time horizon.

Our second set of results focuses on short-term volatility responses to central bank sentiment, uncertainty, and fear. Positive sentiment increases volatility during the first weeks, possibly reflecting speculative behaviour encouraged by optimistic tone. This contrasts with traditional markets, where similar communication tends to stabilise prices (Hansen and McMahon, 2016). Uncertainty shocks lead to moderate and temporary increases in volatility. Fear initially reduces volatility before a delayed rise occurs, possibly indicating investor caution followed by re-evaluation of broader conditions.

Our last set of results explores how the effects of central bank communications differ across various segments of the crypto market. The response to sentiment shocks is more volatile for emerging cryptocurrencies, while established coins exhibit more coherent and stable patterns, possibly due to deeper liquidity and more experienced investor bases. Stablecoins show muted responses to all types of shocks, in line with their design and limited exposure to speculative flows. High-performing cryptocurrencies react more negatively to fear and uncertainty, while low performers often show delayed or positive adjustments. These asymmetries highlight how coin maturity, stability, and recent performance condition market sensitivity to policy tone. Overall, our results support the idea that structural features of digital assets shape the transmission of central bank signals.

Our study offers insights across multidisciplinary domains in economics and finance. First, it expands the literature related to the study of this new asset class. Unlike most traditional assets, cryptocurrencies are particularly volatile[2] and sentiment-driven. Sentiment analysis has become an essential tool for understanding how qualitative factors, such as public statements and social media activity, shape the dynamics of the crypto market. Sentiment data from platforms such as Twitter and Google Trends has been shown to effectively forecast short-term cryptocurrency prices and returns (Wolk, 2020; Kraaijeveld and De Smedt, 2020). Huynh (2021) demonstrates that the negative sentiment

[2]For instance, from 2020 to 2024, Bitcoin has been more three times as volatile as various equity indices (see https://www.fidelitydigitalassets.com/research-and-insights/closer-look-bitcoins-volatility). Also, Baur and Dimpfl (2018) find that asymmetric volatility effects in cryptocurrency markets differ significantly from those in equity markets. Specifically, they observe that positive shocks increase volatility more than negative shocks.

in the tweets of US President Donald Trump serves as a predictor of Bitcoin returns, trading volumes, and volatility, with these effects remaining significant during the COVID-19 pandemic. Similarly, Lennart (2023) examines the "Musk Effect," revealing that Elon Musk's cryptocurrency-related tweets substantially affect Bitcoin trading volume and short-term returns, although the price effects are more pronounced for Dogecoin. Anamika et al. (2023) find that investor optimism about Bitcoin leads to price appreciation and that sentiment surrounding Bitcoin impacts the prices of other cryptocurrencies. In addition, Lachana and Schröder (2025) show that investor sentiment extracted from Seeking Alpha, a social media platform, outperforms sentiment from traditional media like the Wall Street Journal in predicting short-term market returns, while Pyun (2024) finds that stock popularity derived from real-time group chats on Discord better predicts future returns and trading activity than forum-style posts on Reddit, highlighting the importance of synchronous social interaction settings.

Second, our study contributes to the extensive literature examining the role of central bank communications in influencing financial markets. Central banks leverage public communications to guide expectations and reduce uncertainty. Research highlights that such communications can significantly impact asset prices, interest rates, and market volatility. For instance, Neuhierl and Weber (2019) show that changes in federal funds futures predict stock returns and that the tone of speeches by FOMC members correlates with these changes, especially during periods of high uncertainty. Furthermore, Leombroni et al. (2021) demonstrate that European Central Bank (ECB) communications can affect long-term interest rates by influencing credit risk premia, particularly during the European sovereign debt crisis. Rosa (2011) finds that the surprise component of Federal Reserve statements drives significant and rapid reactions in U.S. equity indices, with statements explaining up to 90% of the variation in stock price responses to monetary policy surprises. In addition, Mullings (2022) examines the impact of ECB communications on financial market liquidity, finding that sentiments on economic outlook primarily affect money market liquidity, while hawkish monetary policy tones reduce liquidity in other markets, while Ahrens et al. (2024) use supervised multimodal NLP on U.S. Federal Reserve speeches to analyse how monetary policy news impacts market volatility and tail risk via forecast revisions of GDP, inflation, and unemployment.

Third, our study builds upon recent literature exploring the impact of monetary policy on cryptocurrencies. Recent research highlights that cryptocurrencies are increasingly influenced by central bank policies. Karau (2023) shows that Bitcoin prices did not respond immediately to U.S. monetary policy announcements in the past but began reacting similarly to other risky assets starting in late 2020. The study also reveals that monetary tightening has led to increased Bitcoin prices due to demand for Bitcoin as a tool for capital flight. Buthelezi (2024) shows that U.S. monetary tightening decreases cryptocurrency prices and stabilises markets at lower price levels. Focusing on emerging economies, Marmora (2022) finds that monetary policy announcements drive local Bitcoin demand, particularly when public attention to inflation is heightened. Elsayed and Sousa (2022) find limited but notable spillovers between international monetary policies and cryptocurrencies, especially during unconventional monetary policy periods. Their study highlights strong links between monetary policy in the US and Eurozone and between Bitcoin and Litecoin. Aldasoro et al. (2025) document that crypto shocks have little impact on money market funds (MMFs) but significantly affect stablecoin market capitalization, while U.S. monetary policy shocks influence both markets differently, with MMF assets rising and stablecoin capitalization falling after monetary tightening.

Our findings underscore several policy considerations. Firstly, we stress the critical role of central bank communications in shaping the dynamics of cryptocurrency markets. The sensitivity of crypto prices to central bank sentiments highlights the need for transparent and carefully crafted communication strategies. Central banks must balance their messaging to avoid unnecessary alarm or excessive market euphoria, ensuring that their statements accurately reflect risks and opportunities without provoking unintended market reactions. Second, understanding this relationship can help regulators and policymakers in monitoring and stabilising markets. Knowing that central bank speeches influence not only cryptocurrency markets but also related sectors, monetary authorities can align their communications with broader regulatory efforts to promote financial stability. Coordinated actions between central banks and regulatory bodies can further mitigate the potential spillover effects of crypto market volatility on the wider financial system. Regulators may also consider establishing frameworks that monitor and analyse sentiment-related indicators to anticipate and mitigate potential market disruptions. They could even create early-warning systems to address risks stemming from sudden market shifts triggered by sentiment-driven behaviours. Finally, the sentiment-driven nature of cryptocurrencies may highlight the need for investor education. Many retail investors are drawn to cryptocurrencies based on hype or emotional reactions rather than informed decision-making. Regulators should focus on creating educational campaigns that emphasise the speculative nature of these assets and the risks involved. Transparent risk disclosures and guidelines on how sentiment impacts cryptocurrency prices can empower investors to make better decisions, fostering a more stable and resilient market.

The remainder of the paper is structured as follows. Section 2 presents the main data employed in this study and outlines the empirical strategy used to identify the effects of interest. Section 3 provides an overview of the main results and presents robustness checks. Section 4 concludes.

2 Data and Methodology

2.1 Data

2.1.1 Endogenous (Dependent) Variables

Our cryptocurrency data set was sourced from CoinMarketCap. We download daily market price data for cryptocurrencies on CoinMarketCap, both currently and previously listed. For all coins, we compute daily log-returns (which we summarise by taking the mean over each week) and weekly irregular returns, using the "abnormal" component from the STL (Seasonal and Trend decomposition using Loess) approach of Cleveland and Devlin (1988). We use irregular (as opposed to e.g. abnormal) returns to overcome potential issues with beta instability and significance. We also compute 7- and 30-day volatility by considering rolling standard deviations for each week. We selected weekly frequency as an appropriate middle ground that ensures data granularity (for crypto prices) and data aggregation (for the central bank speech data described below). Descriptive statistics of our selected endogenous variables are supplied in Table 1, while the descriptives of all endogenous variables considered can be found in Appendix A.

Table 1: Descriptive Statistics of Variables

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Median	Pctl. 75	Max
Endogenous (Dependent)								
Irregular Returns	935,471	0.0005	0.2100	-0.7000	-0.0910	-0.0001	0.0880	0.7600
Volatility (7 d)	1,137,432	0.0880	0.1100	0.0003	0.0310	0.0550	0.0990	0.7200
Shock (Independent)								
Loughran Sentiment	606	-0.0033	0.0051	-0.0320	-0.0059	-0.0029	0.0000	0.0110
Uncertainty	606	0.0099	0.0040	0.0000	0.0092	0.0110	0.0120	0.0220
Fear	606	0.0150	0.0060	0.0000	0.0140	0.0160	0.0180	0.0330
Control								
EPUCGGDP Index	606	24,526.0000	9,161.0000	11,889.0000	17,905.0000	22,826.0000	29,236.0000	55,685.0000
PY Crypto Market Index	606	0.0019	0.0330	-0.1700	-0.0085	0.0006	0.0160	0.2800
Total Crypto Volume	606	23.0000	6.5000	0.0000	20.0000	26.0000	27.0000	29.0000
UCRY Policy Index	571	102.0000	3.8000	99.0000	100.0000	100.0000	104.0000	115.0000
VIX Index	606	17.0000	6.8000	9.1000	13.0000	16.0000	21.0000	66.0000

2.1.2 Shock (Independent) Variables

Our shock variables come from the sentiment and emotions associated with the speeches of central bankers and central bank officials. We download raw data from the BIS database.[3] The data set consists of English transcripts of speeches that were delivered by central bank governors and other senior central bank officials. The data is selected to be policy-relevant. As this data set dates back to 1997, we filter the sample to select speeches from each country

[3]See https://www.bis.org/cbspeeches/index.htm.

that were made after the first time cryptocurrencies were discussed. In this way, we ensure that cryptocurrencies were at least a topic of public discourse in each of the countries in our sample when each speech was delivered. Out of the 19,172 speeches in the entire data set, our data includes 6,637 speeches from central bankers of 62 countries, starting from 11 May 2013 and ending on 11 October 2024.

We proceed to run sentiment and emotion analysis on these speeches, using an arsenal of analysis tools. We compute sentiment using an AI library (Wiseman, nd) as well as the popular VADER (Hutto and Gilbert, 2014) approach, but also compute dictionary-based sentiment using the Loughran (Loughran and McDonald, 2011), the AFINN (Nielsen, 2011), the Bing (Hu and Liu, 2004) and the NRC (Mohammad and Turney, 2013) dictionaries. The Loughran and NRC dictionaries also have a set of keywords associated with emotions. We use these to compute the emotions associated with each speech.

Similarly to our endogenous data set, we use weekly data by summarising the mean sentiment and emotions of speeches that were delivered on each week. Descriptive statistics of the shock variables used are supplied in Table 1, while the descriptives of all shock variables computed can be found in Appendix B.

2.1.3 Control Variables

We use an extended list of control variables in the sample. First, we use the VIX index as a measure of volatility in traditional financial markets (Whaley, 2009). We also consider the price of gold (in USD), given its potential to hedge against financial market instability (Shahzad et al., 2020). As proxies of world economic activity, we use the MSCI All Country World Index (ACWI), which captures large and mid-cap companies from both developed and emerging markets, as well as the Global OECD Leading Economic Indicator (MEPRGLEI), which considers the average of Leading Economic Indicators of OECD countries. The data aforementioned were sourced from Bloomberg LP (2024). We additionally employ the global policy uncertainty from Davis (2016) and crypto market (policy and price) uncertainty from Lucey et al. (2022). We also account for the performance of the crypto market as a whole, by considering a market-cap weighted market index comprising of the cryptocurrencies that make up at least 80% of the market on any given day (Polyzos and Youssef, 2025). Finally, we consider market liquidity by controlling for the total value of crypto trading.

We compute pairwise correlations and exclude control variables that have high correlations with others. The correlations of control variables selected are demonstrated in Figure 1 and the correlations of all control variables considered are shown in Appendix D. Descriptive statistics of the selected control variables are shown in Table 1, while the descriptives of all the control variables considered can be found in Appendix C.

2.2 Methods

Our method of choice for computing the impact of the shock variables on our endogenous variables are the local projections of Jordà (2005). Local projections (LPs) provide a flexible

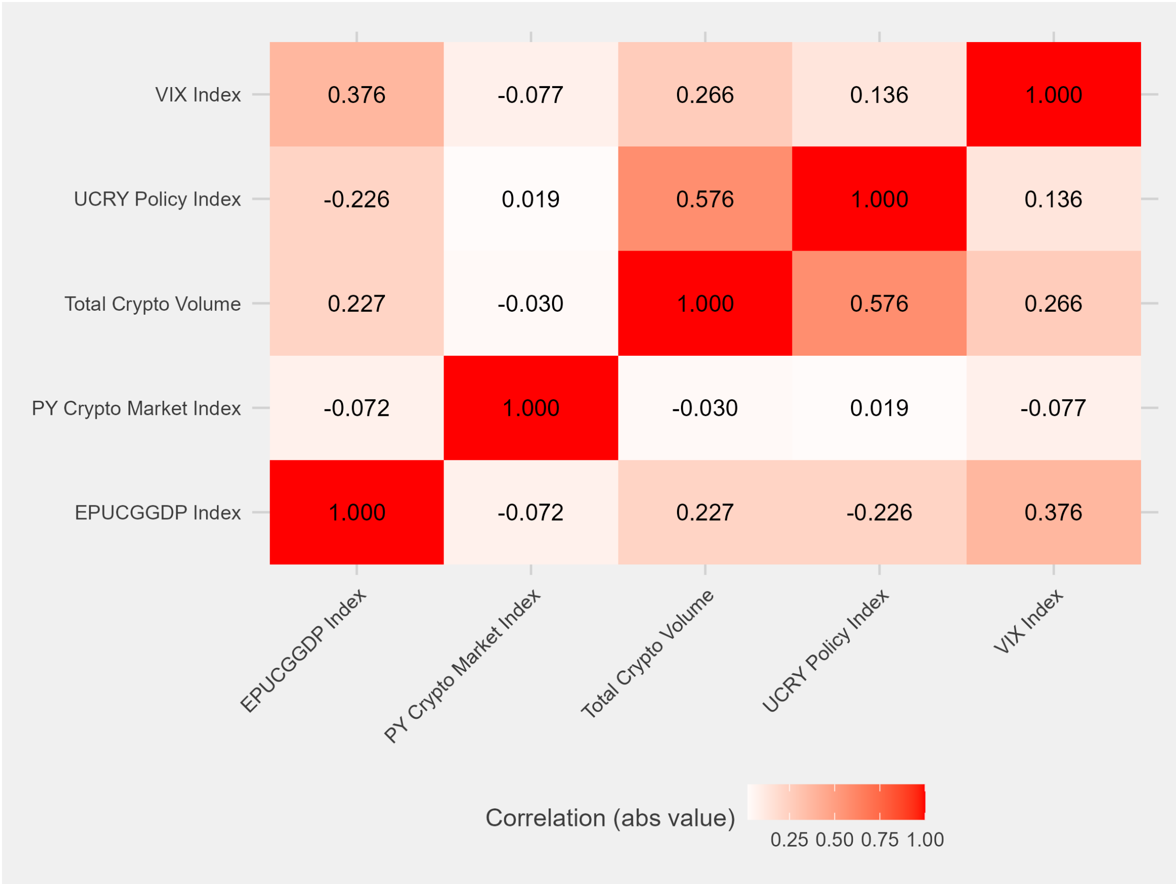


Figure 1: Pairwise Correlations of Selected Control Variables

Note: *This figure displays the pairwise correlations among the control variables used in the empirical analysis, focusing on the subset of selected controls retained for estimation.*

and robust method for analysing the dynamic effects of shocks on endogenous variables. This approach has recently gained prominence due to its ability to estimate impulse response functions (IRFs) without the need to invert a system of equations, as is typically required in vector autoregressions (VARs). The LP methodology involves estimating the impact of shock variables on endogenous variables over different time horizons through a series of regressions and is very popular in finance and economics research (Plagborg-Møller and Wolf, 2021; Ginn, 2024; De Haan and Wiese, 2022; Auerbach and Gorodnichenko, 2012; Jordà et al., 2015; Ramey, 2011).

The baseline LP model estimates the response of an endogenous variable y_{t+h} to a shock z_t using the regression equation:

$$y_{t+h} = \beta_h z_t + \gamma_h \mathbf{X}_t' + u_{t+h}, \tag{1}$$

where y_{t+h} is the value of the endogenous variable at horizon h, z_t is the exogenous shock at time t, $\mathbf{X}_t$ is a vector of control variables or lagged endogenous variables, β_h is the impulse response coefficient at horizon h, and u_{t+h} is the error term. The sequence of β_h coefficients across horizons provides the impulse response function, capturing the dynamic effects of the shock. In this manner, the estimation of Equation 1 allows us to trace the temporal response of these variables to the identified shock.

We extend the baseline model by incorporating first-differences transformation for the for the dependent and shock variables, to address potential non-stationarity and structural breaks and to isolate changes rather than levels of the dependent variables. Additionally, to account for unobserved heterogeneity across individual cryptocurrencies and across time, we include individual random effects. We apply Beck and Katz (1995) robust covariance estimation to address heteroskedasticity and autocorrelation, clustered by time.

The equation for the extended model is:

$$\Delta y_{i,t+h} = \beta_h \Delta z_t + \gamma_h \mathbf{X}_t' + \mu_i + u_{i,t+h} \tag{2}$$

where $\Delta y_{i,t+h}$ is the first difference of the endogenous variable for cryptocurrency i at time $t + h$; Δz_t is the first difference of the shock variable; β_h represents the impulse response of the endogenous variable to the shock at horizon h; $\mathbf{X}_t$ is a vector of first-differenced lagged control variables with associated coefficients γ_h; μ_i represents the individual random effects, assumed to be uncorrelated with the regressors; and $u_{i,t+h}$ is the error term. We use an 8-week time horizon ($1 \leq h \leq 8$) and compute 95% confidence intervals for the impulse responses.

Impulse response functions derived from LPs are equally powerful as VAR models and are robust to model misspecifications because they do not rely on a specific system structure (Plagborg-Møller and Wolf, 2021). Instead, they focus on estimating the direct relationships between shocks and responses for each horizon separately. This approach simplifies interpretation and computation, especially in cases with large datasets, as is ours.

3 Empirical Results

3.1 Baseline scenario

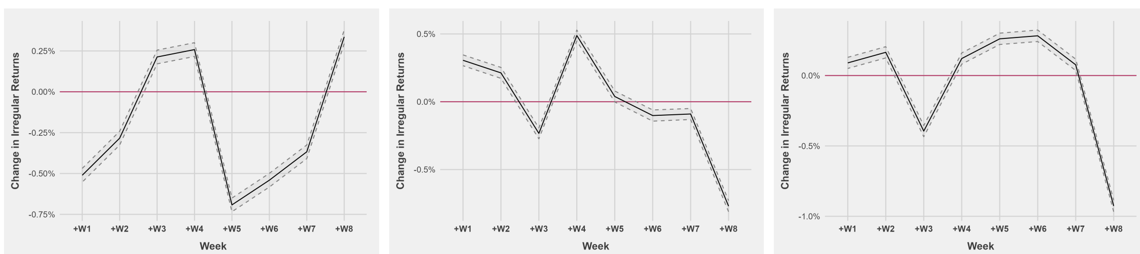
Panel (i) presents the estimated impulse response[4] of irregular cryptocurrency returns following a sentiment shock, defined as a positive shift in the tone of central bank speeches. In the immediate aftermath of sentiment shock (first week), irregular returns exhibit a statistically significant decline of approximately 0.5 percentage points. Although it may be counterintuitive - in traditional financial markets a positive central bank tone typically leads to immediate asset price increases (Schmeling and Wagner, 2025) -, this response may reflect market participants interpreting improved sentiment from central banks as a signal of potential regulatory tightening or reduced monetary accommodation—factors often viewed unfavorably in the context of speculative assets such as cryptocurrencies. Subsequently, returns begin to recover, turning positive around the third week, suggesting a delayed adjustment possibly driven by speculative buying or re-evaluation of the initial communication.

Panel (ii) shows that a central bank uncertainty shock initially leads to a modest increase in irregular cryptocurrency returns, followed by a sharp decline in the third week and a temporary rebound in the fourth week. Early volatility may reflect speculative trading and short-term mispricing as market participants attempt to interpret ambiguous policy signals. From the fifth week onward, returns decline steadily, culminating in a significant negative effect by the eighth week. Heightened policy uncertainty might erode investor confidence, increase perceived risk, and trigger reallocation away from speculative assets. While most empirical studies focus on traditional financial markets - for instance, Qi et al. (2022) show that increases in economic policy uncertainty weaken investor sentiment and destabilise financial conditions -, these mechanisms may likely be relevant for crypto markets as well. In fact, our delayed negative return response to uncertainty complements Mahmoudi (2023), who finds a persistent adverse effect using monthly data.

Panel (iii) shows that a rise in fear expressed in central bank speeches leads to a short-term increase in irregular cryptocurrency returns, followed by a sharp decline in the third week. The initial boost may reflect a flight from traditional assets, as investors seek perceived alternatives during periods of policy-related anxiety (Lehnert, 2022). Cryptocurrencies might also benefit from speculative positioning, with some market participants interpreting fear as a signal of future financial instability or monetary easing. Returns then recover briefly but drop sharply by the eighth week, suggesting that persistent fear ultimately undermines confidence and fuels market volatility.

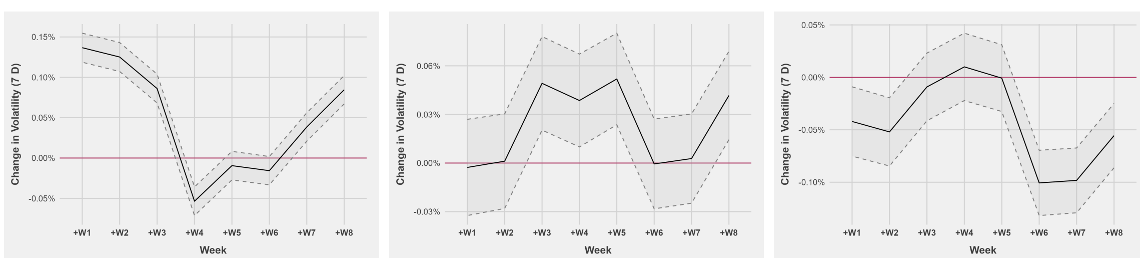
[4] Countries are classified ad hoc into three categories for weighting based on their impact on global cryptocurrency markets. Category 1 (low impact) includes nations with minimal crypto adoption and weak economic presence, assigned a weight of 1. Category 2 (moderate impact) includes countries with moderate influence either economically or in crypto activity, weighted at 3. Category 3 (high impact) consists of major global and crypto market players with significant economic power and adoption, assigned the highest weight of 5. Importantly, the core empirical results are not sensitive to the application of this weighting structure: all findings remain qualitatively robust when equal weights are used instead, as the reader can see in the robustness check section.

Panels (iv), (v), and (vi) of Figure 2 present the dynamic effects of central bank speech sentiment, uncertainty, and fear on 7-day crypto price volatility, respectively. Panel (iv) explores how central bank sentiment affects the seven-day volatility of cryptocurrency prices. The impulse response reveals a consistent and significant increase in volatility following positive sentiment shocks. Such a pattern may suggest that optimistic tone in central bank communication may paradoxically elevate short-term instability in cryptocurrency markets. One possible explanation is that positive sentiment reduces perceived macroeconomic risk, encouraging speculative behaviour and increasing trading activity in high-volatility assets such as cryptocurrencies. In contrast, evidence from traditional financial markets often shows that upbeat central bank communication helps stabilise asset prices and reduce volatility (Hansen and McMahon, 2016). The divergence underscores the distinct dynamics of crypto markets, where investor reactions to macro signals can amplify rather than dampen market fluctuations.



(i) Sentiment (ii) Uncertainty (iii) Fear

Irregular Returns



(iv) Sentiment (v) Uncertainty (vi) Fear

Volatility

Figure 2: Impact of Central Bank Speeches on Cryptocurrencies

***Note**: This figure presents the impulse responses of cryptocurrencies to central bank tone shocks. The top row shows the responses of cumulative irregular returns to sentiment, uncertainty and fear shocks. The middle row shows the corresponding responses of 7-day realised volatility to the same set of shocks. Each column corresponds to a different type of tone shock.*

Panel (v) presents the response of market volatility to central bank uncertainty. The effect is relatively neutral during the initial weeks, followed by a moderate increase in volatility that peaks between weeks four and five. When central banks convey uncertainty, it tends to unsettle investors and elevate informational noise in the market (Mumtaz et al., 2023). However, this effect appears to be transitory. Our results suggest that uncertainty-induced volatility is not persistent, possibly due to information resolution or adaptive investor expectations over time. Panel (vi) examines how volatility in the cryptocurrency market responds to fear-related language in central bank speeches. The initial response is a slight decline in volatility, potentially reflecting a short-term dampening effect as markets absorb the message without immediate reaction. Fear-laden signals from central banks may not trigger immediate concern, either because of the asset class's decoupling from conventional macroeconomic fundamentals or because investors interpret the message as indicative of stress in fiat-based financial systems rather than in crypto itself. Such interpretations may temporarily suppress volatility, with a delayed adjustment emerging only as narratives evolve or uncertainty intensifies.

Our findings align with recent evidence that cryptocurrencies respond atypically to central bank signals, often amplifying reactions to monetary policy shocks rather than dampening them (Karau, 2023).

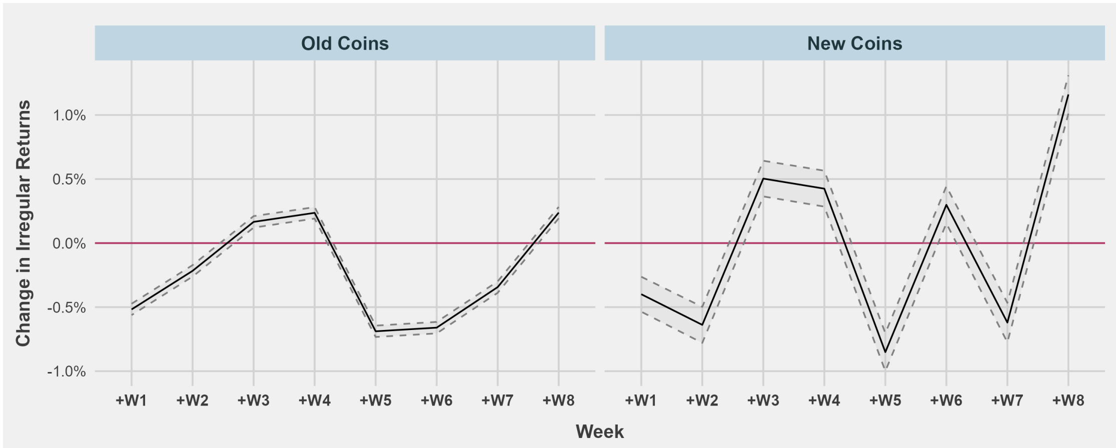
3.2 Further Analyses

To gain deeper insight into how central bank communications affect cryptocurrency markets, we conduct a series of heterogeneity analyses to examine whether these effects vary across distinct categories of digital assets. In particular, we analyse differences in market responses between emerging and established cryptocurrencies, stablecoins and non-stablecoins, as well as among top-performing cryptocurrencies. These distinctions enable us to evaluate whether factors such as market maturity, asset stability, and recent performance influence the sensitivity of various cryptocurrencies to signals conveyed in central bank speeches.

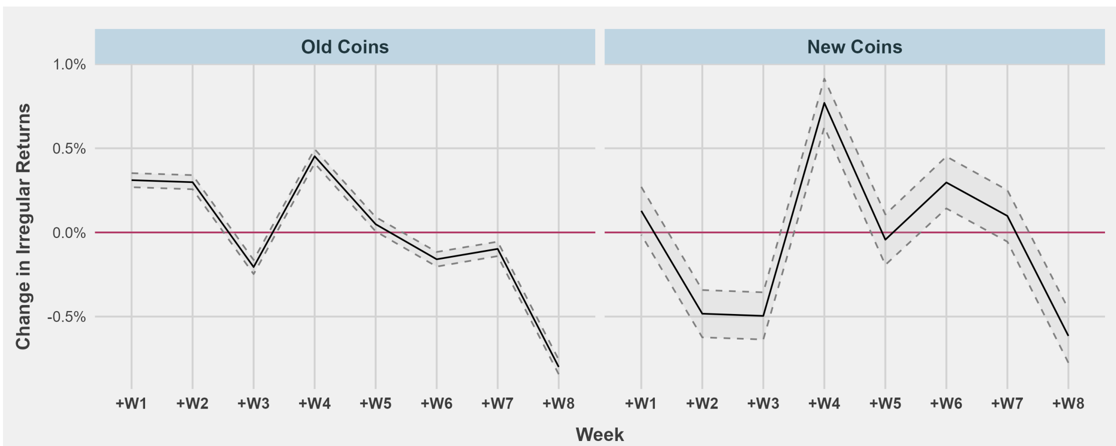
3.2.1 Emerging vs Established Coins

In this subsection, we investigate whether the impact of central bank communications varies between emerging and established cryptocurrencies. We define emerging cryptocurrencies as those within the first six months following after their Initial Coin Offering (ICO), following Polyzos et al. (2024), who show that market efficiency is significantly higher during this early post-ICO phase. Their analysis—based on a large-scale dataset combining price data and social media signals—demonstrates that cryptocurrencies tend to respond more closely to public information in the first 180 days of trading. In our dataset, an average of approximately 21% of coins are considered emerging on any given week, as per this categorisation approach. Figure 3 presents the estimated impulse response functions for irregular returns of emerging and established cryptocurrencies following a central bank sentiment shock. The figure reveals notable differences in how the two groups react to shifts in central bank tone.

Panels (i), (ii) and (iii) shows that mature cryptocurrencies absorb optimistic policy signals with greater coherence, possibly due to more stable investor bases and deeper market liquidity. Emerging cryptocurrencies exhibit a more erratic and volatile response. The



(i) Sentiment



(ii) Uncertainty

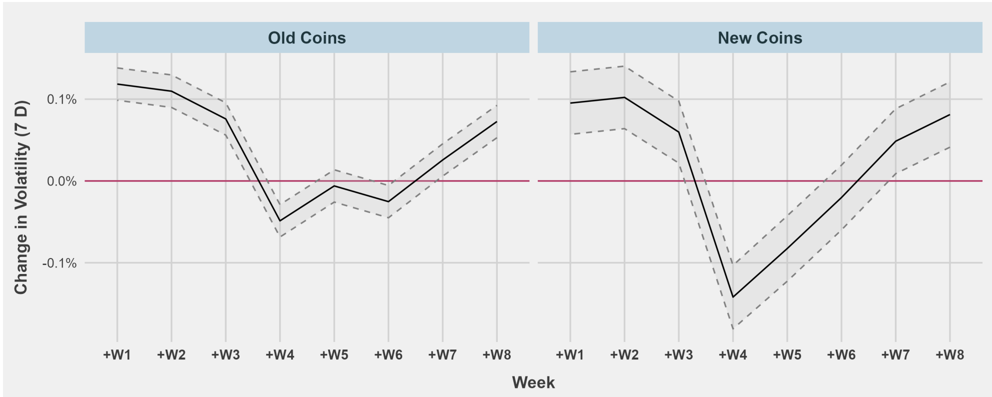
(iii) Fear

Figure 3: Impact of Central Bank Speech Sentiment on Emerging vs Established Cryptocurrency Irregular Returns

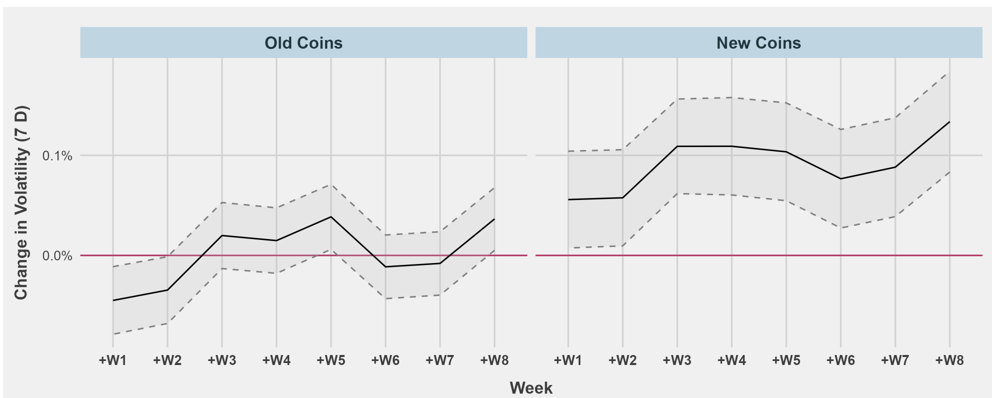
Note: *This figure presents the impulse responses of cumulative irregular returns to central bank tone shocks, estimated separately for emerging and established cryptocurrencies. Each panel corresponds to a different type of tone shock: sentiment (Panel i), uncertainty (Panel ii) and fear (Panel iii).*

volatility observed in the IRF among emerging cryptocurrencies may be partially attributed to their lower liquidity and greater exposure to manipulative practices. Illiquid markets are generally more susceptible to insider trading and price manipulation (Aggarwal and Wu, 2006). In the cryptocurrency context, Ng (2024) shows that wash trading activity intensifies precisely when legitimate trading volumes are low, underscoring the strategic exploitation of illiquidity.

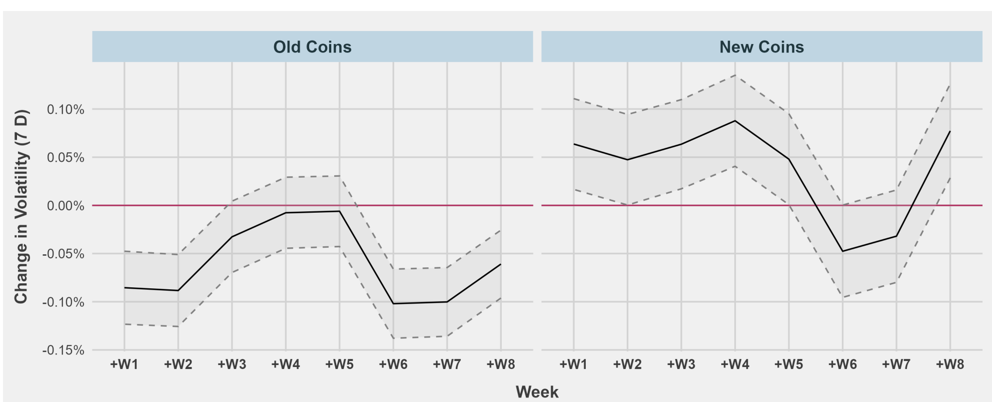
Figure 4 shows the effects of sentiment, uncertainty, and fear in central bank speeches on 7-day cryptocurrency volatility for both emerging and established cryptocurrencies. Sentiment shocks lead to an initial increase in volatility of similar magnitude across both groups. After the fourth week, both series show a negative response, more pronounced in emerging coins. Uncertainty does not generate a significant response for established cryptocurrencies but results in a persistent increase in volatility for emerging ones. The differences are most pronounced in response to fear. Volatility among established coins remains stable, consistent with our baseline results in the previous section. Nevertheless, emerging coins show a strong and sustained increase in volatility during the first weeks.



(i) Sentiment



(ii) Uncertainty



(iii) Fear

Figure 4: Impact of Central Bank Speech Sentiment on Emerging vs Established Cryptocurrency Volatility

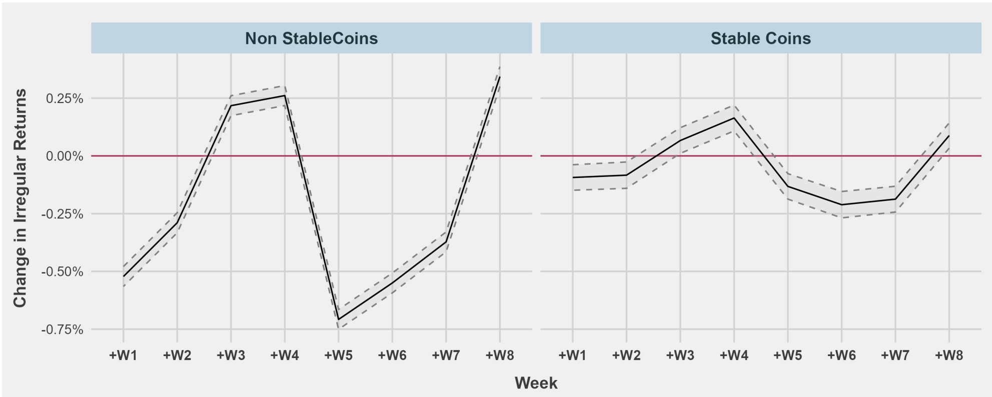
Note: *This figure presents the impulse responses of 7-day volatility to central bank tone shocks, estimated separately for emerging and established cryptocurrencies. Each panel corresponds to a different type of tone shock: sentiment (Panel i), uncertainty (Panel ii) and fear (Panel iii).*

3.2.2 Stablecoins vs Non Stablecoins

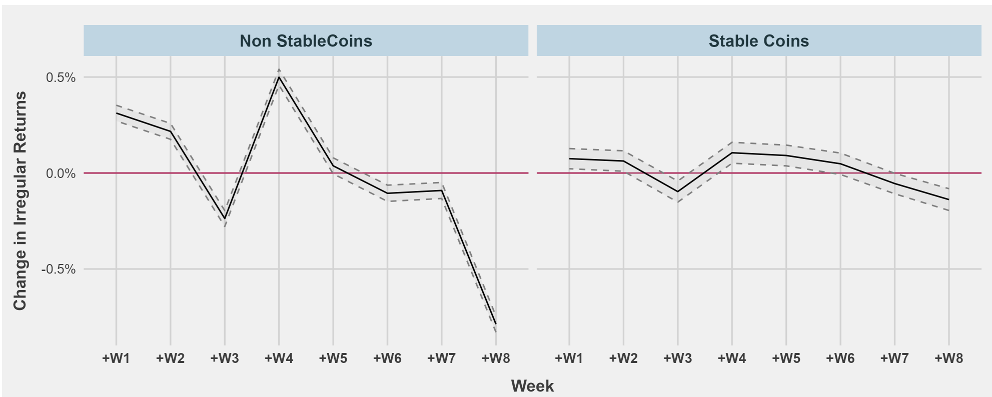
We investigate whether the impact of central bank communications varies between crypto that are relatively "stable" and those ones characterised by greater price volatility. In particular, we define stablecoins as the cryptocurrencies that fall within the lowest 5% of the volatility distribution in our sample, measured using the standard deviation of daily returns over a 7-day rolling window.[5]

Figures 5 and 6 present the impulse response functions of cumulative irregular returns and 7-day volatility respectively, for non-stablecoins and stablecoins following central bank communication shocks. The responses reveal clear differences in sensitivity and behaviour. Non-stablecoins essentially replicate what we saw in our baseline results. In contrast, stablecoins show muted and, in most of the cases, statistically insignificant responses throughout. The divergence with the non-stablecoins scenario underscores the differing functions and market dynamics of the two asset types. It seems our definition of "non-stable" cryptocurrencies captures coin that are more sensitive to external informational shocks, including policy communication.

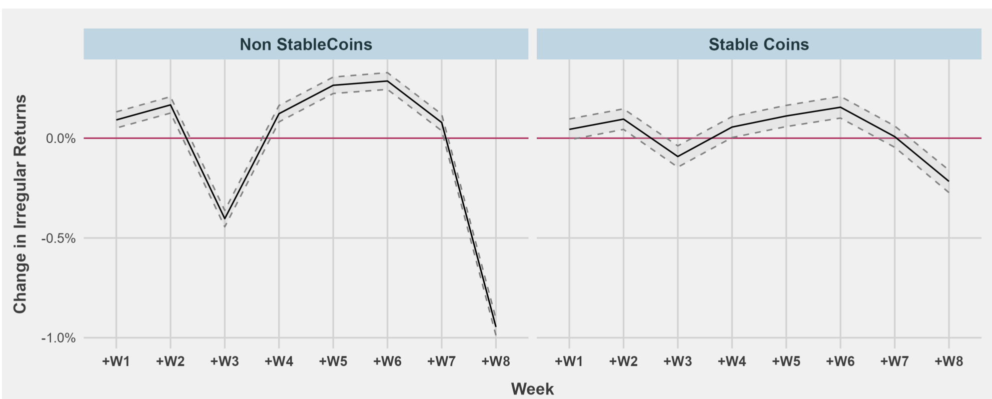
[5]Note that our definition of stablecoins does not match the conventional classification. Term "stablecoin" is commonly used to refer to cryptocurrencies explicitly designed to maintain a fixed value relative to a reference asset.



(i) Sentiment



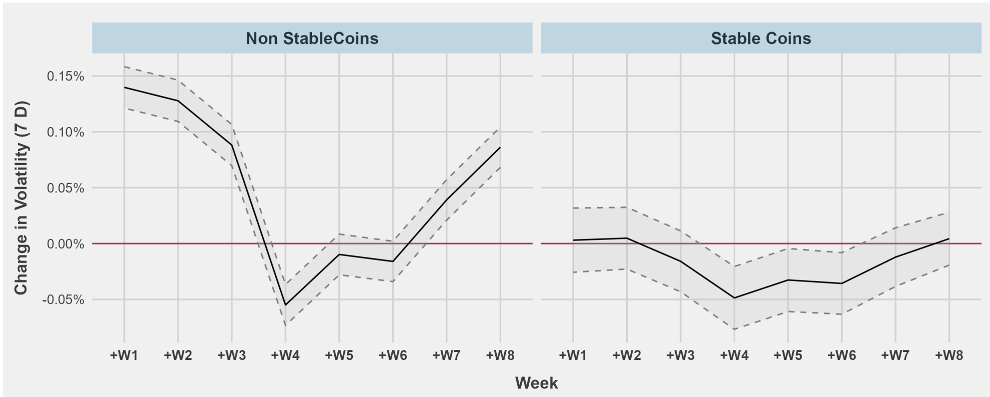
(ii) Uncertainty



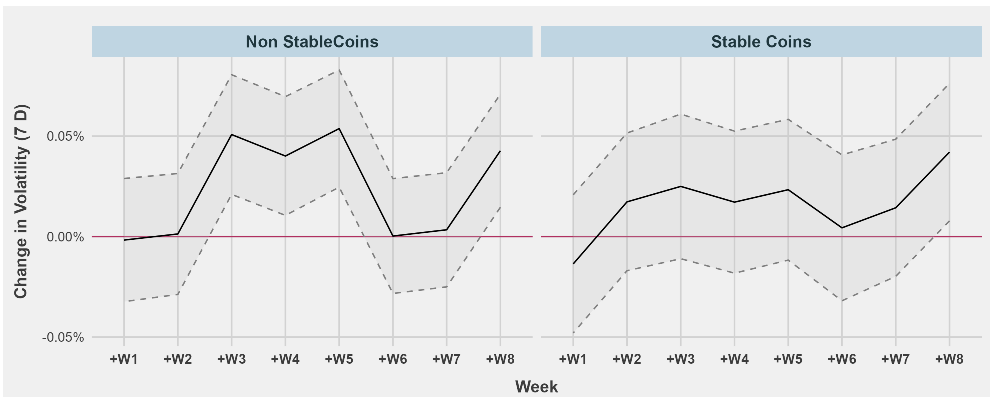
(iii) Fear

Figure 5: Impact of Central Bank Speech Sentiment on Stablecoin Irregular Returns

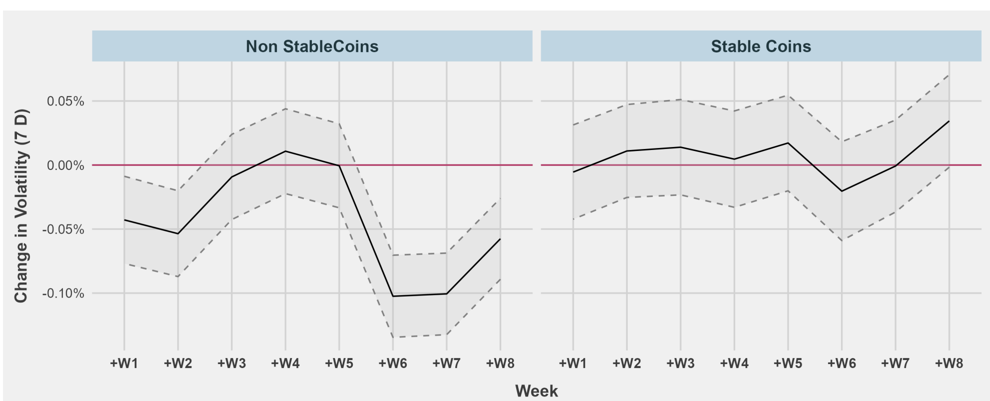
Note: *This figure presents the impulse responses of cumulative irregular returns to central bank tone shocks, estimated separately for stablecoins and non-stablecoin cryptocurrencies. Each panel corresponds to a different type of tone shock: sentiment (Panel i), uncertainty (Panel ii) and fear (Panel iii).*



(i) Sentiment



(ii) Uncertainty



(iii) Fear

Figure 6: Impact of Central Bank Speech Sentiment on Stablecoin Volatility

***Note**: This figure presents the impulse responses of 7-day volatility to central bank tone shocks, estimated separately for emerging and established cryptocurrencies. Each panel corresponds to a different type of tone shock: sentiment (Panel i), uncertainty (Panel ii) and fear (Panel iii).*

3.2.3 High vs low performing cryptocurrencies

In this subsection, we explore whether the sensitivity of cryptocurrencies to central bank communications is moderated by recent market performance. Specifically, we split the sample based on cumulative irregular returns, identifying high-performing cryptocurrencies as those whose normal returns lie above the median within a defined pre-shock period. The stratification allows us to assess whether assets that have recently outperformed the broader market exhibit systematically different responses to shocks in central bank sentiment, uncertainty and fear. High-performing crypto may attract greater speculative attention, exhibit momentum-driven dynamics or be more susceptible to investor overreaction and thus performance-based asymmetries would be an interesting topic to analyse.

Figures 7 and 8 present the estimated impulse response functions for irregular returns and 7-day volatility of high and low performing crypto following a sentiment, uncertainty and fear shock.

In terms of the impact on cumulative irregular returns, sentiment (positive) shocks bring about a negative response across both subsamples, but high-performing coins recover and reverse this decline approximately five weeks after the shock. In response to uncertainty shocks, there is an immediate positive effect in both subsamples, yet this effect is sustained only among low-performing cryptocurrencies. Finally, the responses to fear-related shocks in central bank communications diverge across groups: high-performing coins show negative and persistent reactions, while low-performing ones exhibit smaller but positive and sustained responses. Investor positioning and expectations may be key in shaping market responses. High-performing assets may be more vulnerable to corrections following shifts in sentiment or perceived risk, whereas low-performing cryptocurrencies may attract contrarian attention or be less exposed to adverse sentiment swings. These patterns point to meaningful performance-based asymmetries in how central bank communication influences crypto market behaviour.

Regarding the impact on volatility, we note similar patterns across both subsamples in the responses to all shocks.

(i) Sentiment

(ii) Uncertainty

(iii) Fear

Figure 7: Impact of Central Bank Speech Sentiment on High Performing Cryptocurrency Irregular Returns

Note: *This figure presents the impulse responses of cumulative irregular returns to central bank tone shocks, estimated separately for high- and low-performing cryptocurrencies. Each panel corresponds to a different type of tone shock: sentiment (Panel i), uncertainty (Panel ii) and fear (Panel iii).*

(i) Sentiment

(ii) Uncertainty

(iii) Fear

Figure 8: Impact of Central Bank Speech Sentiment on High Performing Cryptocurrency Volatility

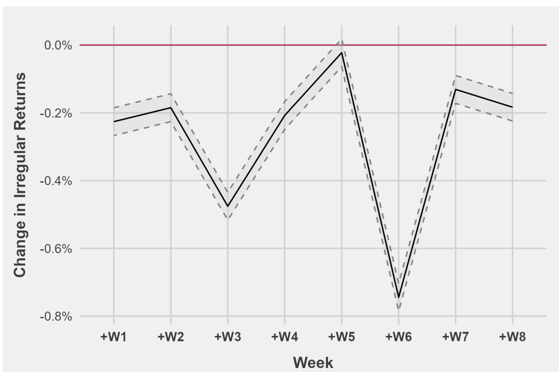
Note: *This figure presents the impulse responses of 7-day volatility to central bank tone shocks, estimated separately for high- and low-performing cryptocurrencies. Each panel corresponds to a different type of tone shock: sentiment (Panel i), uncertainty (Panel ii) and fear (Panel iii).*

3.3 Robustness Checks

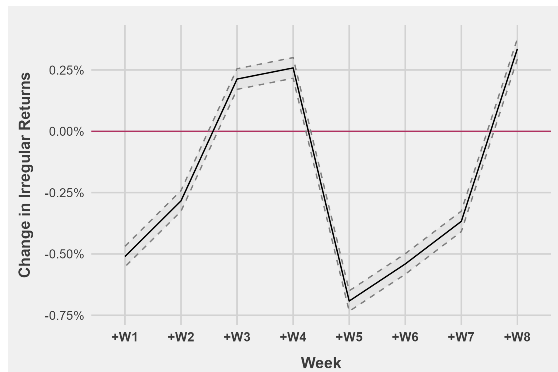
To ensure the reliability of our findings, we conduct a series of robustness checks that test the sensitivity of our results to alternative specifications and methodological choices.

3.3.1 Computing sentiment using AI models

First, we re-estimate the core models using an alternative method for computing sentiment—namely, sentiment scores derived from AI-based natural language processing models. While our baseline analysis relies on a combination of dictionary-driven sentiment measures (Loughran), this robustness check leverages a transformer-based language model trained on financial and policy text.

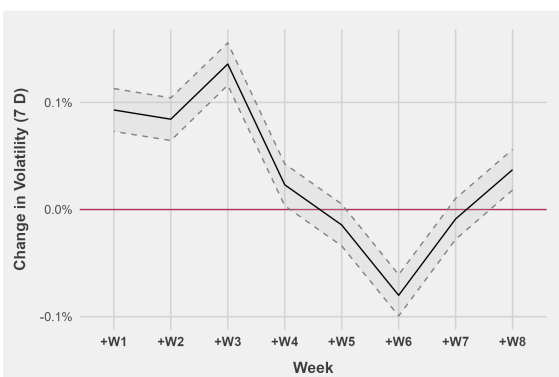


(i) AI Sentiment

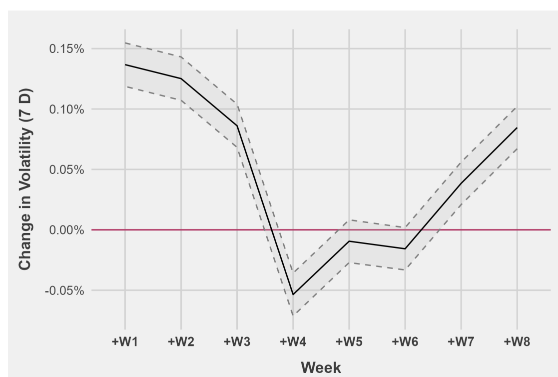


(ii) Loughran Sentiment (baseline)

Irregular Returns



(iii) AI Sentiment



(iv) Loughran Sentiment (baseline)

Volatility

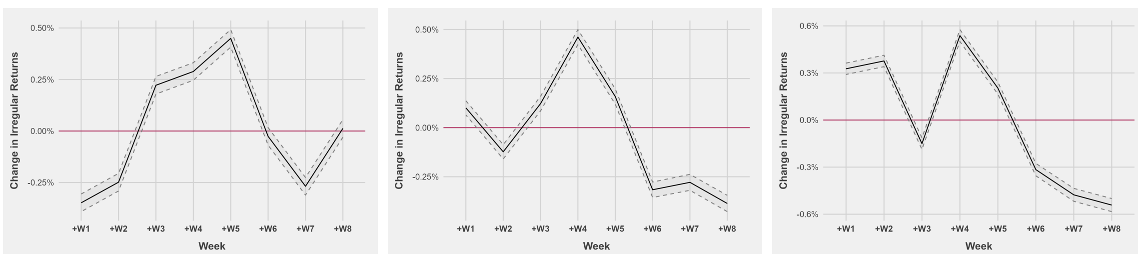
Figure 9: Robustness check using AI-computed Sentiment

Note*: This figure presents a robustness check comparing the impulse responses to sentiment shocks based on AI-computed sentiment and Loughran sentiment (baseline). The top row shows the responses of cumulative irregular returns and the bottom row shows the responses of 7-day volatility. Each panel contrasts results using the two sentiment measures.*

Figure 9 compares the impulse response functions of irregular returns and 7-day volatility using both sentiment specifications. Panels (i) and (ii) show that the general pattern of the response in irregular returns is preserved across both measures. Both specifications feature an early decline, and an even larger drop in weeks 5 and 6. The IRFs related to the 7-day volatility results in panels (iii) and (iv) also reflect consistent dynamics across both sentiment measures, although the AI-based measure generates a smaller and less stable response, with statistical significance limited to the early weeks.

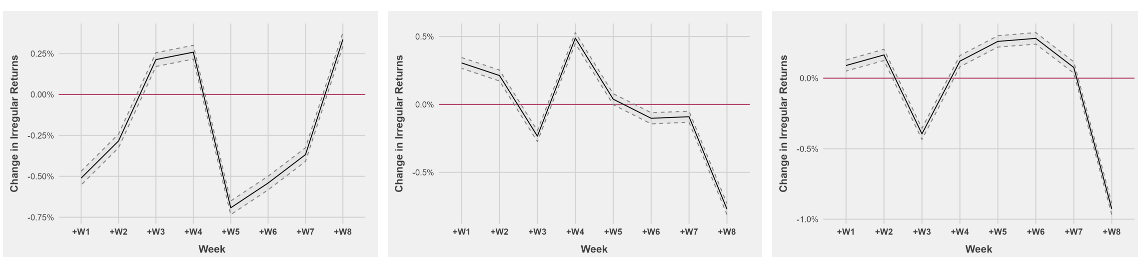
3.3.2 Using sentiment only from selected countries

We use sentiment only from selected countries with wide crypto adoption. We conduct a robustness test by restricting the sample to countries with the highest assigned weight in the baseline model. These are countries with both strong economic influence and wide crypto adoption (corresponding to a weight factor of 5). The purpose is to address the concern that smaller or less relevant countries may be driving the results.



(i) Sentiment (ii) Uncertainty (iii) Fear

Selected Countries



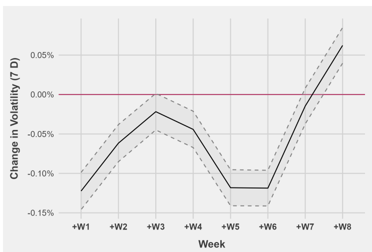
(iv) Sentiment (v) Uncertainty (vi) Fear

Baseline Sample

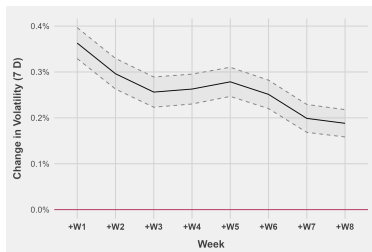
Figure 10: Robustness check on Irregular Returns using sentiment from selected countries

Note: *This figure presents a robustness check on the impulse responses of cumulative irregular returns to sentiment, uncertainty and fear shocks. The top row shows results using central bank communications from a selected group of countries and the bottom row displays the baseline estimates based on the full sample. Each column corresponds to a different type of tone shock.*

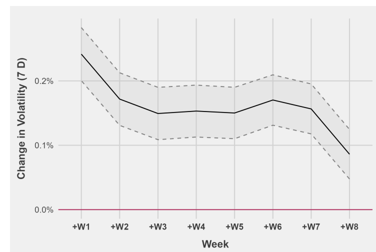
In Figure 10, our IRFs of irregular returns closely mirror those of the baseline sample. Nevertheless, the the impulse responses on 7-day volatility differ (see Figure 11). In the selected countries sample, volatility decreases following a sentiment shock, while in the baseline, it increases during the same period. In both cases, volatility rises again after the eighth week. Uncertainty shocks have a consistently positive effect on volatility in the selected countries sample. In contrast, the baseline sample also shows a positive response, though it is less stable and becomes statistically insignificant at several points. Uncertainty from major central banks may raise doubts about future policy directions or economic conditions, prompting higher perceived risk and increased volatility. Market participants may interpret this ambiguity as a lack of control or clarity, especially in speculative markets like crypto. In contrast, uncertainty from smaller central banks may carry less informational weight and provoke weaker reactions.



(i) Sentiment

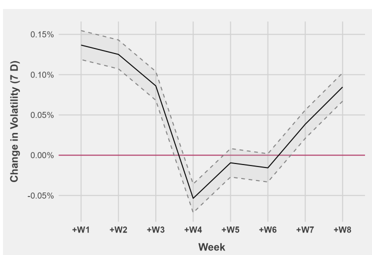


(ii) Uncertainty

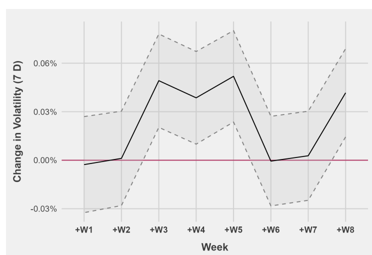


(iii) Fear

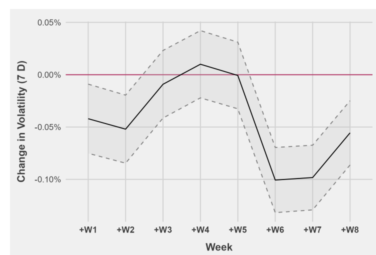
Selected Countries



(iv) Sentiment



(v) Uncertainty



(vi) Fear

Baseline Sample

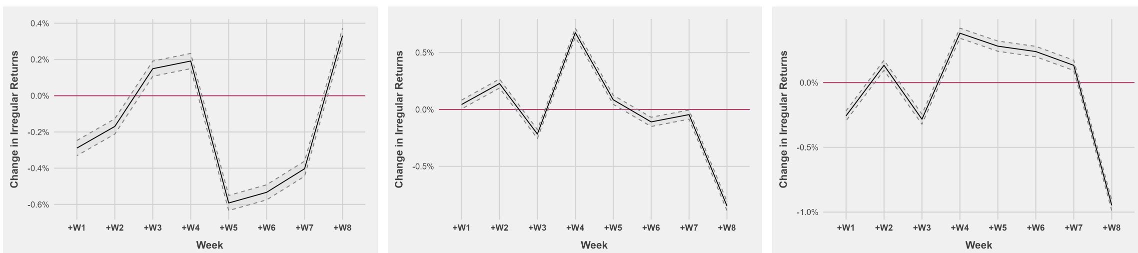
Figure 11: Robustness check on Volatility using sentiment from selected countries

Note: *This figure presents a robustness check on the impulse responses of 7-day volatility to sentiment, uncertainty and fear shocks. The top row shows results using central bank communications from a selected group of countries and the bottom row displays the baseline estimates based on the full sample. Each column corresponds to a different type of tone shock.*

The divergence is more pronounced in the case of fear. In the selected countries sample, fear shocks increase volatility throughout the horizon. The baseline sample, however, shows a negative response, with volatility falling below zero after the shock - and especially after week 5. It is clear than fear expressed by major central banks can raise perceptions of systemic risk and prompt defensive trading. In crypto markets, such signals often lead to abrupt portfolio shifts and greater price fluctuations. Investors may interpret fearful language as an indication of deteriorating conditions. Messages from credible and globally influential institutions tend to provoke stronger market responses. Nguyen et al. (2022) find that the federal funds rate has a greater impact on both cryptocurrencies and stablecoins than the Chinese interbank rate, underscoring the stronger influence of the Federal Reserve compared to emerging market central banks on these markets.

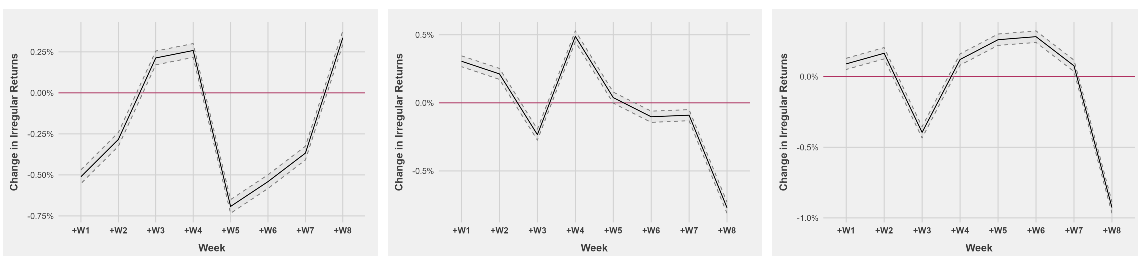
3.3.3 Using unweighted sentiment and emotions

We perform a robustness check using unweighted sentiment and emotion scores, giving all countries equal importance. The analysis removes the influence of the weighting scheme used in the baseline. As the reader can appreciate, the impulse response functions remain consistent in both direction and timing across shock types. Our result confirm that the main findings do not depend on our weighting strategy.



(i) Sentiment (ii) Uncertainty (iii) Fear

Using unweighted sentiment/emotions

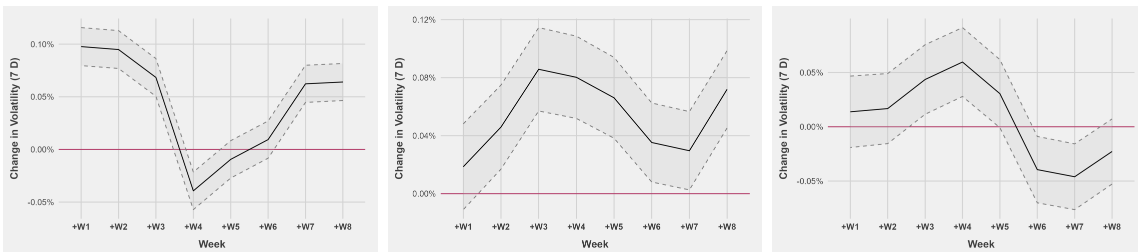


(iv) Sentiment (v) Uncertainty (vi) Fear

Baseline Approach (Weighted)

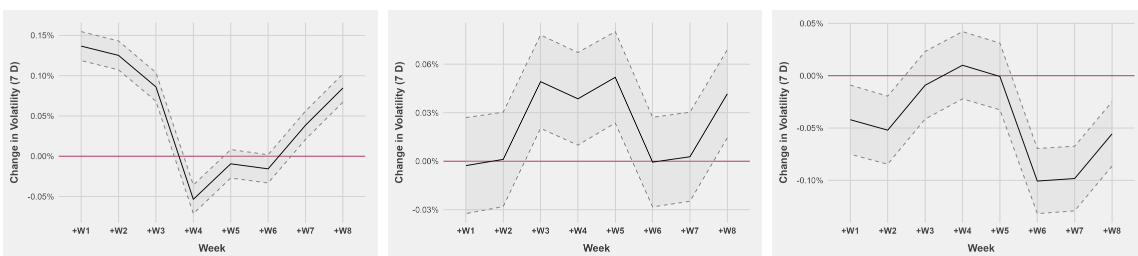
Figure 12: Robustness check on Irregular Returns using unweighted sentiment and emotions

Note: *This figure presents a robustness check on the impulse responses of cumulative irregular returns to sentiment, uncertainty and fear shocks. The top row shows results using unweighted sentiment and emotion measures and the bottom row shows the baseline results using weighted tone indicators. Each column corresponds to a different type of tone shock.*



(i) Sentiment (ii) Uncertainty (iii) Fear

Using unweighted sentiment/emotions



(iv) Sentiment (v) Uncertainty (vi) Fear

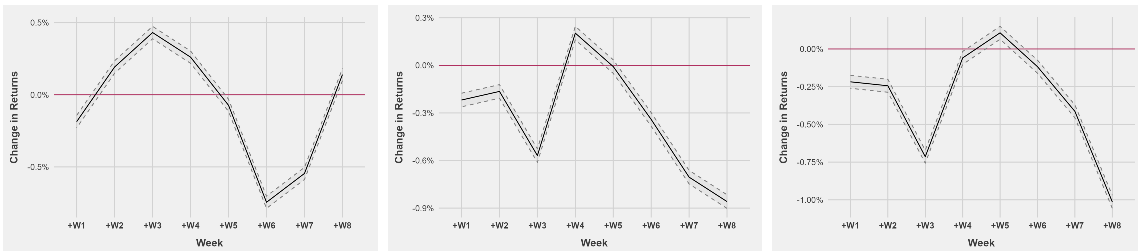
Baseline Approach (Weighted)

Figure 13: Robustness check on Volatility using unweighted sentiment and emotions

Note: *This figure presents a robustness check on the impulse responses of 7-day volatility to sentiment, uncertainty and fear shocks. The top row shows results using unweighted sentiment and emotion measures and the bottom row shows the baseline results using weighted tone indicators. Each column corresponds to a different type of tone shock.*

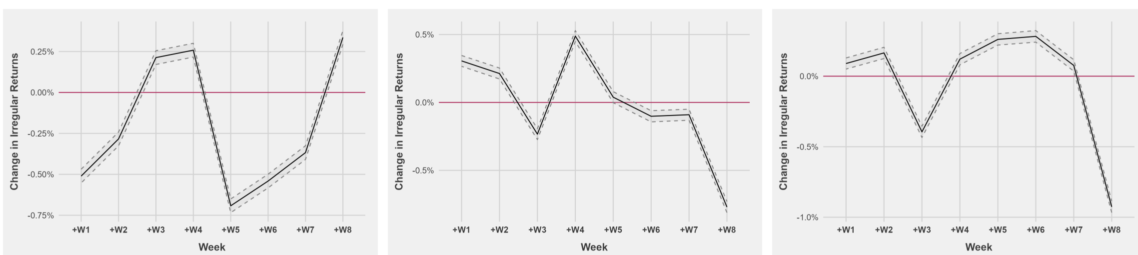
3.3.4 Mean cryptocurrency returns

We re-estimate the models using mean weekly returns instead of cumulative irregular returns. The goal is to test whether the results depend on the definition of the dependent variable. The impulse responses show similar patterns in sign, timing and statistical significance. The direction and structure of the effects remain stable. The findings do not appear to be driven by the return transformation.



(i) Sentiment (ii) Uncertainty (iii) Fear

Selected Countries



(iv) Sentiment (v) Uncertainty (vi) Fear

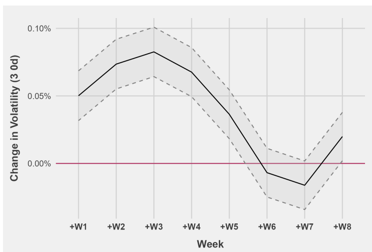
Baseline Model

Figure 14: Robustness check using mean returns instead of irregular returns

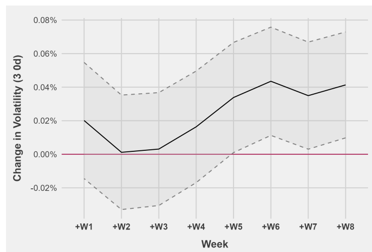
Note: *This figure presents a robustness check on the impulse responses to central bank tone shocks using mean returns instead of irregular returns. The top row shows responses of average weekly returns to sentiment, uncertainty and fear shocks and the bottom row shows the baseline results using irregular returns. Each column corresponds to a different type of tone shock.*

3.3.5 Computing volatility over a longer period

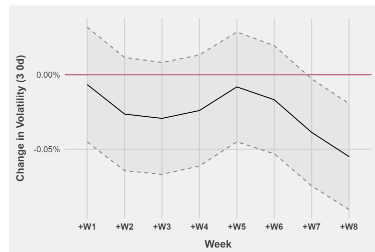
Figure 15 compares IRFs estimated using our baseline approach with 7-day volatility to those derived from a longer 30-day volatility horizon. Results reveal that the dynamics of positive sentiment shocks remain qualitatively consistent across both specifications. Nonetheless, uncertainty and fear shocks are not significant during the first six weeks. Given the high frequency and rapid pace of crypto market developments, a one-month horizon may smooth over short-term dynamics and obscure immediate reactions to central bank communication. Crypto assets often exhibit abrupt price movements in response to news, making shorter volatility windows more appropriate for capturing the effects of shocks.



(i) Sentiment

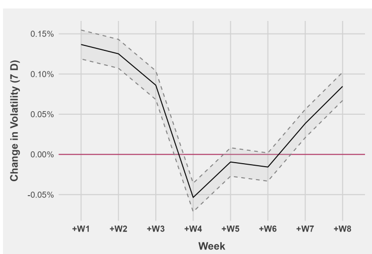


(ii) Uncertainty

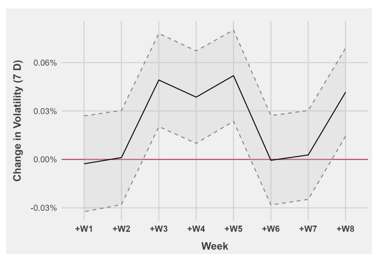


(iii) Fear

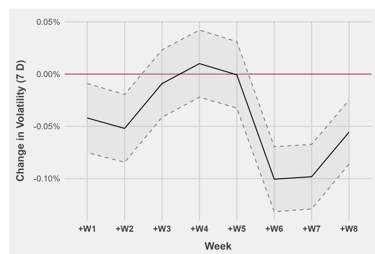
Using 30-day Volatility



(iv) Sentiment



(v) Uncertainty



(vi) Fear

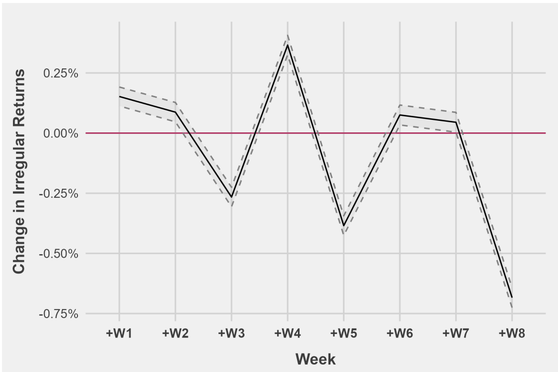
Baseline approach with 7-day Volatility

Figure 15: Robustness check using volatility computed over a longer time period

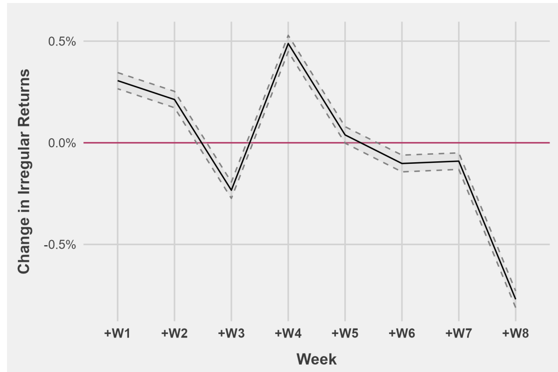
***Note**: This figure presents a robustness check on the impulse responses of cryptocurrency volatility to sentiment, uncertainty and fear shocks. The top row uses 30-day realised volatility and the bottom row shows the baseline results using 7-day realised volatility. Each column corresponds to a different type of tone shock.*

3.3.6 Examining uncertainty emotion vs trust emotion

As a final robustness check, we assess whether the effects attributed to uncertainty in central bank communications are also observed when using a conceptually opposite emotion, namely trust as per the NRC dictionary (Mohammad and Turney, 2013). To facilitate a direct comparison, we invert the trust variable so that higher values represent lower trust, aligning its interpretation with that of uncertainty. This allows us to test whether the crypto market reacts similarly to the absence of trust as it does to the presence of uncertainty. The results show that both measures elicit broadly similar response patterns.

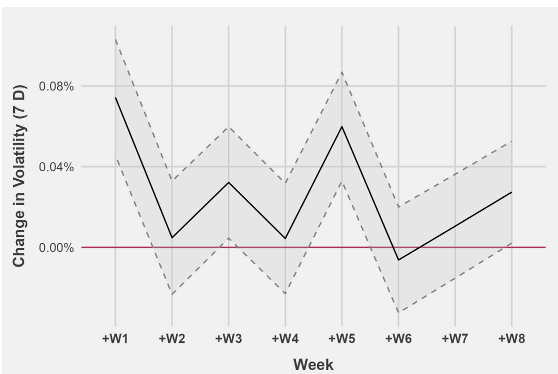


(i) Trust

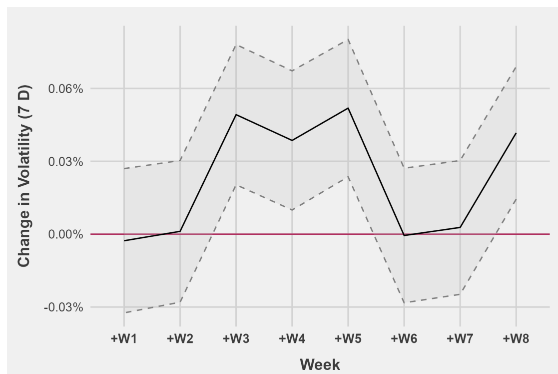


(ii) Uncertainty (baseline)

Irregular Returns



(iii) Trust



(iv) Uncertainty (baseline)

Volatility

Figure 16: Robustness check using trust emotion

Note: *This figure presents a robustness check comparing the impulse responses to inverted trust shocks and uncertainty shocks (baseline). The top row shows responses of cumulative irregular returns and the bottom row shows responses of 7-day realised volatility. Each panel contrasts results using the two emotion indicators.*

4 Conclusion

Central bank communication plays an increasingly important role in shaping expectations and influencing financial market behaviour. Although its effects on traditional assets are well documented, much less is known about how cryptocurrencies respond to monetary signals. The rapid growth of digital assets and their integration into financial systems raise important questions about the transmission of institutional messages in these decentralised and highly speculative markets.

Our paper shows that the sentiment, uncertainty, and emotional tone expressed in central bank speeches have measurable effects on both cryptocurrency returns and short-term volatility. Optimistic sentiment tends to reduce returns in the short term but later leads to a recovery, while also increasing volatility. Uncertainty shocks produce mixed reactions that ultimately reduce returns and temporarily raise volatility. Fear shocks result in an initial increase in returns, followed by a significant decline and a delayed increase in volatility. These effects suggest that crypto markets react strongly to emotional and ambiguous signals, often amplifying rather than smoothing the impact of central bank communication. The results also reveal substantial heterogeneity. New and high-performing cryptocurrencies respond more forcefully to central bank messages, while "stable" cryptocurrencies show little reaction. Our baseline results remain robust across different sentiment measures, weighting schemes, and specifications for returns and volatility.

The findings carry several implications for policymakers. Central banks influence crypto market dynamics even in the absence of direct regulation. Clear, consistent communication may reduce excessive volatility and speculative responses in this space. At the same time, vague or overly optimistic language may contribute to destabilising behaviour. Policymakers should consider the informational role of central bank tone when assessing the broader financial implications of digital assets. Future research could explore real-time reactions using high-frequency data or examine investor heterogeneity by distinguishing between retail and institutional responses. Additional work could also assess how decentralised financial platforms transmit or absorb central bank signals. As the crypto sphere continues to mature, understanding how these platforms interact with traditional institutions will remain a critical area for both academic inquiry and policy design.

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A Descriptive Statistics of Endogenous Variables

Table A1: Descriptive Statistics of Endogenous Variables

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Median	Pctl. 75	Max
Mean Daily Returns	1,137,632	-0.0029	0.0350	-0.1300	-0.0160	-0.0019	0.0088	0.1300
Irregular Returns	935,471	0.0005	0.2100	-0.7000	-0.0910	-0.0001	0.0880	0.7600
Volatility (7 d)	1,137,432	0.0880	0.1100	0.0003	0.0310	0.0550	0.0990	0.7200
Volatility (10 d)	1,132,092	0.0910	0.1100	0.0004	0.0330	0.0570	0.1000	0.7400
Volatility (30 d)	1,104,328	0.1000	0.1200	0.0006	0.0400	0.0660	0.1100	0.7600
Cumulative Irregular Returns	932,160	0.0005	0.2100	-0.7100	-0.0910	-0.0003	0.0890	0.7600

B Descriptive Statistics of Shock Variables

Table A2: Descriptive Statistics of Shock Variables

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Median	Pctl. 75	Max
Loughran Sentiment	606	-0.0033	0.0051	-0.0320	-0.0059	-0.0029	0.0000	0.0110
AI Sentiment	606	-0.0067	0.0840	-0.3500	-0.0500	0.0000	0.0360	0.4800
Vader Compound	606	0.7900	0.3400	-1.0000	0.7900	0.9800	1.0000	1.0000
Anger	606	0.0063	0.0027	0.0000	0.0058	0.0068	0.0077	0.0190
Anticipation	606	0.0230	0.0085	0.0000	0.0240	0.0260	0.0270	0.0360
Constraining	606	0.0033	0.0015	0.0000	0.0029	0.0035	0.0042	0.0084
Disgust	606	0.0031	0.0014	0.0000	0.0027	0.0033	0.0038	0.0130
Fear	606	0.0150	0.0060	0.0000	0.0140	0.0160	0.0180	0.0330
Joy	606	0.0110	0.0043	0.0000	0.0100	0.0120	0.0130	0.0240
Litigious	606	0.0037	0.0021	0.0000	0.0026	0.0039	0.0050	0.0140
Sadness	606	0.0079	0.0035	0.0000	0.0071	0.0082	0.0097	0.0290
Superfluous	606	0.0005	0.0003	0.0000	0.0004	0.0006	0.0007	0.0021
Surprise	606	0.0059	0.0024	0.0000	0.0055	0.0064	0.0072	0.0170
Trust	606	0.0430	0.0150	0.0000	0.0450	0.0470	0.0500	0.0710
Uncertainty	606	0.0099	0.0040	0.0000	0.0092	0.0110	0.0120	0.0220

C Descriptive Statistics of Control Variables

Table A3: Descriptive Statistics of Control Variables

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Median	Pctl. 75	Max
EPUCGGDP Index	606	24,526.00	9,161.00	11,889.00	17,905.00	22,826.00	29,236.00	55,685.00
MEPRGLEI Index	606	107.00	6.90	96.00	101.00	107.00	114.00	119.00
MXWD Index	606	539.00	128.00	351.00	422.00	512.00	649.00	853.00
PY Crypto Market Index	606	0.00	0.03	-0.17	-0.01	0.00	0.02	0.28
Total Crypto Quantity Volume	606	31.00	11.00	0.00	25.00	29.00	42.00	49.00
Total Crypto Volume	606	23.00	6.50	0.00	20.00	26.00	27.00	29.00
UCRY Policy Index	571	102.00	3.80	99.00	100.00	100.00	104.00	115.00
UCRY Price Index	571	102.00	4.00	99.00	100.00	100.00	104.00	113.00
VIX Index	606	17.00	6.80	9.10	13.00	16.00	21.00	66.00
XAU Curncy	606	1,538.00	354.00	1,057.00	1,254.00	1,341.00	1,826.00	2,658.00

D Pairwise Correlations of All Control Variables

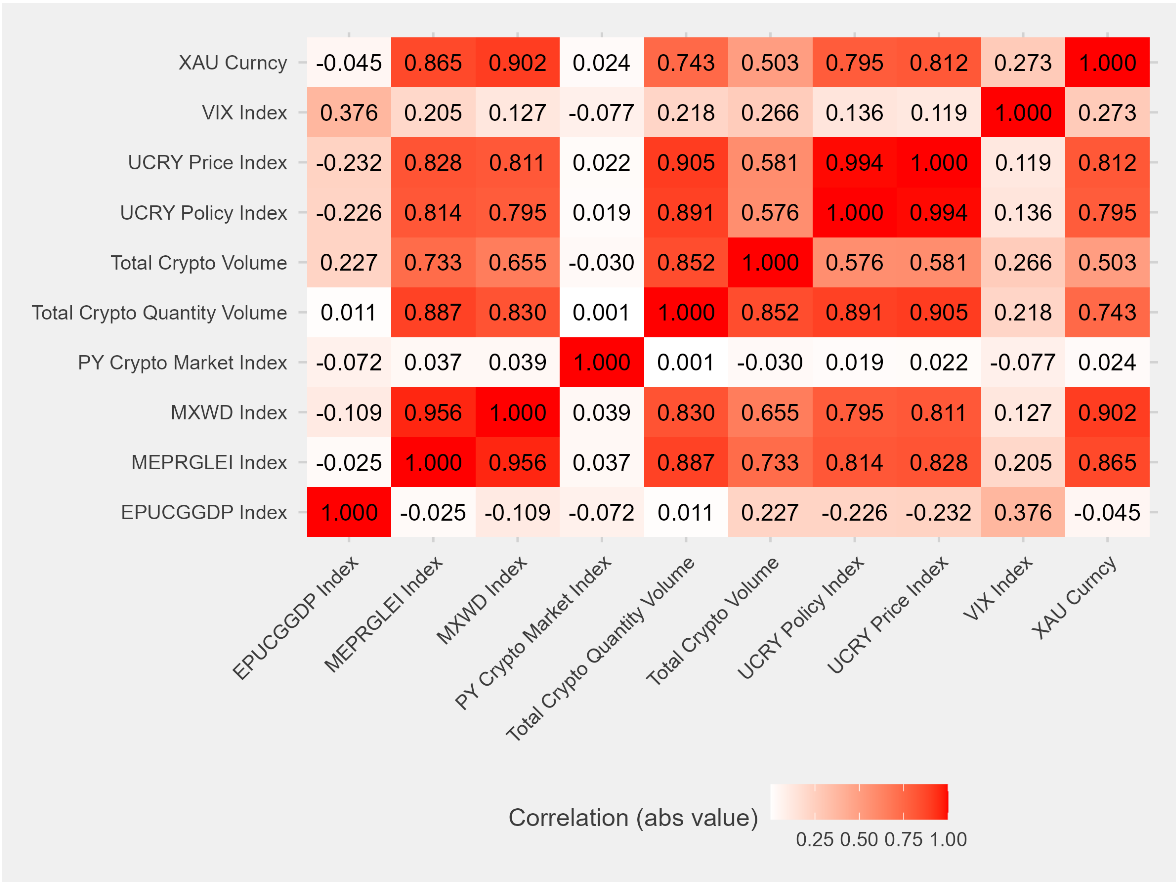

Figure A1: Pairwise Correlations of All Control Variables

Note: *This figure displays the pairwise correlations among the full set of control variables used in the empirical analysis.*