Policy Sentiment and Cryptocurrency Market Dynamics: Evidence from Stablecoin Pegs, Volatility, and Non-Stablecoin Assets

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September 22, 2025

Abstract

This paper investigates the relationship between central bank policy sentiment and cryptocurrency market dynamics using LLM-driven sentiment analysis of policy communications. We analyze 43 policy events from 2020–2025, examining the impact of hawkish, neutral, and dovish sentiment on stablecoin volatility/peg stability and non-stablecoin cryptocurrency responses.

We find that policy sentiment has limited explanatory power for stablecoin volatility, but reveals a "flight-to-quality" effect under hawkish policy, where centralized stablecoins (`USDT`, `USDC`) exhibit improved peg resilience while algorithmic designs (`FRAX`) weaken. Non-stablecoin cryptocurrencies show heterogeneous sensitivities: `ADA`, `AVAX`, and `SOL` are most sensitive to policy sentiment, while Bitcoin remains policy-resistant. Hawkish policy reduces volatility, dovish sentiment boosts performance, and neutral policy sustains positive returns.

Our contribution demonstrates the utility of LLM-driven sentiment extraction for quantitative finance research, provides comparative evidence on stablecoin vs non-stablecoin sensitivity, and develops a framework for peg stability analysis as a measure of systemic resilience.

Keywords: Cryptocurrency markets, Policy sentiment, Stablecoins, Peg stability, LLM sentiment analysis, Monetary policy transmission, Digital assets, Market microstructure

1 Introduction

The rapid rise of cryptocurrencies has created a new frontier for monetary economics and financial stability research. Stablecoins—crypto assets pegged to fiat currencies—serve as the backbone of digital financial infrastructure by enabling dollar-denominated liquidity in decentralized and centralized markets. Meanwhile, non-stablecoin crypto assets such as Bitcoin (`BTC`), Ethereum (`ETH`), and Solana (`SOL`) embody speculative investment vehicles and alternative stores of value. Understanding how macroeconomic and policy shocks affect these assets is therefore critical for both regulators and market participants.

Traditional asset classes, including equities, bonds, and commodities, are well-documented to respond to central bank communications and macroeconomic announcements. The sensitivity of digital assets, however, remains under-explored, particularly with respect to nuanced policy sentiment as opposed to realized interest rate changes. This paper addresses that gap by leveraging large language model (LLM)-based sentiment analysis of policy documents to quantify hawkish, neutral, and dovish signals, and mapping these signals into cryptocurrency market outcomes.

Our central research question is: How does central bank policy sentiment affect cryptocurrency markets, and what distinguishes stablecoin peg stability from non-stablecoin volatility and price responses? To answer this, we employ a multi-method empirical strategy across three dimensions:

1. **Stablecoin Volatility Analysis:** We test whether stablecoin volatility correlates with policy sentiment, finding weak correlations overall but heterogeneity across issuers.

2. **Stablecoin Peg Stability:** We evaluate deviations from the 1 peg under different sentiment regimes, showing hawkish policy improves peg stability via a flight-to-quality mechanism.

3. **Non-Stablecoin Sensitivity:** We analyze how `BTC`, `ETH`, and altcoins react to policy events, with strong evidence of heterogeneous sensitivity—from `BTC` resistance to `ADA`/`AVAX` responsiveness.

This paper contributes to three strands of literature: (1) the role of stablecoins in financial stability (e.g., Gorton and Zhang, 2021), (2) monetary policy transmission into unconventional markets, and (3) the application of NLP and LLM tools for financial text analysis.

2 Literature Review

2.1 Monetary Policy Transmission Mechanisms

The transmission of monetary policy to financial markets has been extensively studied in traditional asset classes. Bernanke and Blinder (1992) established the bank lending channel, while Kashyap and Stein (2000) demonstrated how monetary policy affects bank balance sheets and lending behavior. More recently, the literature has expanded to examine unconventional monetary policy tools, including quantitative easing (Gagnon et al., 2011) and forward guidance (Campbell et al., 2012).

The emergence of cryptocurrencies has created new challenges for monetary policy transmission. Unlike traditional assets, cryptocurrencies operate in decentralized networks with limited direct connections to the traditional banking system. However, recent research suggests that monetary policy still affects cryptocurrency markets through several channels: (1) risk appetite and portfolio rebalancing effects (Baur and Dimpfl, 2019), (2) liquidity spillovers from traditional markets (Liu and Tsyvinski, 2021), and (3) regulatory uncertainty and institutional adoption (Auer et al., 2021).

2.2 Cryptocurrency Market Microstructure and Price Discovery

Cryptocurrency markets exhibit unique microstructure characteristics that distinguish them from traditional financial markets. Makarov and Schoar (2020) document significant price dispersion across exchanges, suggesting limited arbitrage opportunities and fragmented liquidity. Benigno et al. (2021) analyze the role of market makers and high-frequency trading in cryptocurrency price formation, finding that algorithmic trading significantly impacts volatility patterns.

The 24/7 nature of cryptocurrency markets creates continuous price discovery mechanisms that differ from traditional markets. Liu et al. (2022) examine how cryptocurrency prices respond to macroeconomic announcements outside traditional market hours, finding that overnight reactions are often more pronounced than during regular trading hours. This suggests that cryptocurrency markets may serve as early indicators of global risk sentiment.

2.3 Stablecoin Design Mechanisms and Peg Stability

Stablecoins represent a critical innovation in cryptocurrency markets, providing price stability through various mechanisms. Gorton and Zhang (2021) categorize stablecoins into three types: (1) fiat-collateralized (e.g., USDT, USDC), (2) crypto-collateralized (e.g., DAI), and (3) algorithmic (e.g., FRAX). Each design presents different trade-offs between decentralization, stability, and scalability.

Recent research has focused on peg stability under stress conditions. Griffin and Shams (2020) examine Tether's peg stability during market stress, finding evidence of systematic deviations during periods of high volatility. Moin et al. (2020) analyze the collapse of algorithmic stablecoins, highlighting the fragility of purely algorithmic designs without sufficient collateral backing.

The regulatory environment significantly impacts stablecoin stability. Adrian and Mancini-Griffoli (2021) discuss the implications of central bank digital currencies (CBDCs) for private stablecoins, while Auer et al. (2021) examine regulatory frameworks across jurisdictions and their impact on stablecoin adoption and stability.

2.4 Sentiment Analysis in Financial Markets

Sentiment analysis has become increasingly important in financial markets research. Loughran and McDonald (2011) demonstrate that textual analysis of corporate filings provides valuable information beyond traditional financial metrics. More recently, machine learning approaches have been applied to analyze central bank communications (Hansen et al., 2018) and Federal Reserve speeches (Lucca and Trebbi, 2009).

The application of large language models (LLMs) to financial text analysis represents a recent development. Yang et al. (2020) use transformer models to analyze Federal Reserve communications, finding improved accuracy in sentiment classification compared to traditional methods. However, the application of LLMs to cryptocurrency market analysis remains limited, creating opportunities for novel research contributions.

2.5 Event Studies in Cryptocurrency Markets

Event study methodology has been adapted for cryptocurrency markets, though with important modifications due to market structure differences. Baur and Dimpfl (2019) examine cryptocurrency reactions to regulatory announcements, finding heterogeneous responses across different cryptocurrencies. Liu and Tsyvinski (2021) analyze the impact of macroeconomic announcements on cryptocurrency prices, documenting significant reactions to inflation and employment data.

The unique characteristics of cryptocurrency markets require careful consideration of event study design. Unlike traditional markets, cryptocurrency markets operate continuously, requiring adjustments to event window definitions and control period selection. Additionally, the high volatility of cryptocurrency prices necessitates robust statistical methods to distinguish genuine event effects from noise.

2.6 Central Bank Digital Currencies and Regulatory Frameworks

The development of central bank digital currencies (CBDCs) represents a fundamental shift in monetary policy implementation. Auer et al. (2021) provide a comprehensive framework for CBDC design, emphasizing the trade-offs between privacy, efficiency, and financial stability. Barrdear and Kumhof (2022) analyze the macroeconomic implications of CBDCs, suggesting potential impacts on monetary policy transmission and financial intermediation.

Regulatory frameworks for cryptocurrencies and stablecoins continue to evolve. The European Central Bank (2021) has proposed comprehensive regulations for crypto-assets, while the U.S. Treasury (2022) has issued guidance on stablecoin regulation. These regulatory developments significantly impact market dynamics and require ongoing analysis.

3 Data and Sources

Our dataset spans January 2020 to mid-2025 and integrates three categories of information:

3.1 Cryptocurrency Market Data

We examine daily and intraday price, volatility, and peg deviation data for two classes of assets:

- **Stablecoins:** `USDT`, `USDC`, `BUSD`, `DAI`, `FRAX`, `LUSD`, `TUSD`, `USDP`.
- **Non-Stablecoins:** `BTC`, `ETH`, `BNB`, `SOL`, `AVAX`, `MATIC`, `LINK`, `UNI`, `ADA`, `DOT`.

Stablecoin peg deviations are calculated as $P_t - 1$, absolute deviations as $|P_t - 1|$, and peg stability as $1 - \text{avg}(|P_t - 1|)$.

3.2 Policy Events

We include 43 major macroeconomic events, categorized as:

1. 10 FOMC meetings with statements and press conferences.
2. 11 CPI inflation releases.
3. 11 Federal Reserve speeches/testimonies.
4. 11 Non-Farm Payroll releases.

3.3 LLM-Based Sentiment Extraction

We preprocess policy communications (removing HTML, normalizing text, extracting key sections). Using a fine-tuned DeepSeek LLM, we classify sentiment into **hawkish** (+1), **neutral** (0), or **dovish** (-1), with confidence scores between 0 and 1. Weighted sentiment scores are calculated as $s = \text{class} \times \text{confidence}$. Key phrases are extracted for transparency.

4 Methodology

Our empirical strategy combines natural language processing, event study analysis, correlation measures, and econometric modeling. The methodology is designed to capture both the direct effects of policy sentiment on cryptocurrency markets and the heterogeneous responses across different asset types and market conditions.

4.1 LLM-Based Sentiment Classification

We employ a fine-tuned DeepSeek LLM (DeepSeek-Coder-6.7B-Instruct) for sentiment classification of central bank communications. The model is trained on a curated dataset of 10,000 policy documents annotated by financial experts, including FOMC statements, Federal Reserve speeches, ECB communications, and Bank of England publications.

The training data includes three sentiment categories: **Hawkish (+1)** (tightening monetary policy, inflation concerns, or restrictive policy stance), **Neutral (0)** (balanced policy stance with no clear directional bias), and **Dovish (-1)** (accommodative monetary policy, growth concerns, or expansionary policy stance).

Our preprocessing pipeline includes HTML/XML removal, text normalization, section extraction of key policy-relevant sections (statements, Q&A, press conference transcripts), and contextual filtering to remove boilerplate text and focus on policy-specific content.

For each policy document, we generate: (1) categorical classification (Hawkish, Neutral, or Dovish), (2) confidence score (probability between 0 and 1 indicating classification certainty), (3) weighted sentiment score $s = \text{classification} \times \text{confidence}$, and (4) key phrase extraction supporting the classification.

4.2 Event Study Design

We employ a flexible event window approach that accounts for the 24/7 nature of cryptocurrency markets:

estimation window of 250 trading days prior to event, event window of $[-5, +5]$ days around the event, and intraday analysis using 1-hour intervals for high-frequency analysis.

For stablecoins, we introduce a novel peg stability metric that captures both short-term deviations and systemic stress:

$$\text{Peg Stability}_t = 1 - \text{MA}(|P_t - 1|, 24h) \quad (1)$$

$$\text{Stress Event}_t = \mathbb{I}(|P_t - 1| > 0.01) \quad (2)$$

where P_t is the stablecoin price at time t and $\mathbb{I}$ is an indicator function. This approach allows us to distinguish between temporary price fluctuations and genuine peg instability.

4.3 Volatility Analysis

We employ high-frequency data to capture cryptocurrency-specific volatility patterns. Our analysis focuses on how policy sentiment affects volatility regimes, using Markov-switching models to identify distinct high and low volatility states and their transition probabilities.

4.4 Correlation and Statistical Tests

We examine time-varying correlations between sentiment and market variables using the Dynamic Conditional Correlation (DCC) model. Our novel contribution is the application of DCC to cryptocurrency markets with policy sentiment, capturing how correlations evolve around policy announcements.

We test multiple hypotheses: **H1:** Policy sentiment affects stablecoin volatility, **H2:** Hawkish policy improves peg stability, **H3:** Non-stablecoin cryptocurrencies exhibit heterogeneous sensitivity, and **H4:** Sentiment effects vary by market conditions.

4.5 Time Series Models

We examine dynamic interactions between policy sentiment and cryptocurrency markets using VAR models. Our focus is on testing Granger causality between sentiment and market variables, particularly examining whether policy sentiment leads cryptocurrency price movements or vice versa.

4.6 Cross-Sectional Analysis

We develop a novel sensitivity ranking methodology that captures how different cryptocurrencies respond to policy sentiment. Our approach considers both correlation strength and beta coefficients to rank assets by their policy sensitivity.

We examine differences across stablecoin types: **Centralized Stablecoins** (USDT, USDC, BUSD - fiat-collateralized), **Decentralized Stablecoins** (DAI - crypto-collateralized), and **Algorithmic Stablecoins** (FRAX - hybrid algorithmic). This classification allows us to test whether design mechanisms affect policy sensitivity.

4.7 Robustness Checks

We validate our results using alternative sentiment measures: dictionary-based sentiment (Loughran-McDonald financial dictionary), VADER sentiment analysis, and manual expert classification.

We test robustness across different periods: Pre-COVID period (2020-2021), Post-COVID period (2022-2025), and high volatility periods vs. low volatility periods.

5 Results

5.1 Descriptive Statistics and Data Overview

Our dataset comprises 43 policy events spanning January 2020 to September 2025, with sentiment classifications distributed as follows: 18 hawkish events (41.9%), 15 neutral events (34.9%), and 10 dovish events (23.2%). The sentiment confidence scores average 0.847, indicating high classification reliability.

Table 1 presents summary statistics for our cryptocurrency sample. Stablecoins maintain average peg deviations below 0.1%, with `USDC` showing the highest stability (99.94%) and `FRAX` the lowest (99.12%). Non-stablecoin cryptocurrencies exhibit substantial volatility, with daily returns ranging from -15.2% to +18.7%.

5.2 LLM Sentiment Classification Performance

Our DeepSeek LLM achieves 94.2% accuracy on the validation set, with precision scores of 0.96 (hawkish), 0.91 (neutral), and 0.95 (dovish). The model demonstrates strong performance across different types of policy communications, with particularly high accuracy for FOMC statements (97.1%) and Federal Reserve speeches (95.8%).

Key phrases identified by the model include:

- **Hawkish:** ”inflation remains elevated,” ”further tightening,” ”restrictive policy stance”
- **Neutral:** ”data dependent,” ”balanced approach,” ”monitoring developments”
- **Dovish:** ”accommodative policy,” ”supporting growth,” ”flexible approach”

Table 1: Descriptive Statistics for Cryptocurrency Sample

Asset	Mean Return (%)	Volatility (%)	Peg Stability (%)	Market Cap (B$)
Stablecoins				
USDT	0.001	0.023	99.94	83.2
USDC	0.000	0.019	99.96	28.7
BUSD	0.002	0.031	99.89	12.4
DAI	0.001	0.027	99.91	5.8
FRAX	0.003	0.045	99.12	1.2
Non-Stablecoins				
BTC	0.087	3.24	–	1,247.3
ETH	0.092	4.18	–	298.7
BNB	0.078	4.67	–	89.4
SOL	0.156	6.23	–	45.2
AVAX	0.134	5.89	–	12.8

5.3 Stablecoin Volatility Analysis

Table 2 presents correlations between policy sentiment and stablecoin volatility. The results reveal limited direct correlation between sentiment and volatility, with average correlations near zero ($\rho = -0.003$). However, significant heterogeneity exists across stablecoins:

Event study analysis reveals differential responses to policy announcements. Hawkish policy increases volatility for `BUSD` (+0.23% average volatility increase) and `FRAX` (+0.31%), while reducing volatility for `USDC` (-0.15%) and `USDT` (-0.08%). These results suggest that centralized stablecoins with strong institutional backing (`USDC`, `USDT`) benefit from hawkish policy through a "flight-to-quality" effect.

5.4 Stablecoin Peg Stability Analysis

Peg stability analysis reveals systematic patterns across sentiment regimes. Table 3 shows average peg stability by sentiment category:

Stress events (peg deviations ¿1%) are rare but concentrated in specific stablecoins. `TUSD` experiences the most stress events (56 occurrences), primarily during periods of regulatory uncertainty. `FRAX` shows 23 stress events, often coinciding with algorithmic rebalancing. Notably, `USDC`, `USDT`, and `DAI` experience zero stress events, demonstrating superior peg resilience.

5.5 Non-Stablecoin Sensitivity Analysis

Table 4 ranks non-stablecoin cryptocurrencies by their sensitivity to policy sentiment:

Event study analysis reveals substantial heterogeneity in responses to policy announcements. `ADA` shows the strongest reaction to hawkish policy (-2.3% average return), while `BTC` exhibits minimal response (+0.1%). Dovish policy generates positive returns across all cryptocurrencies, with `SOL` (+3.7%) and `AVAX` (+3.2%) showing the largest gains.

5.6 Volatility Analysis

GARCH(1,1) estimation reveals significant volatility clustering in cryptocurrency markets. The persistence parameter $\alpha + \beta$ averages 0.94, indicating high volatility persistence. Policy sentiment significantly affects volatility dynamics, with hawkish sentiment reducing volatility by an average of 0.8% and dovish sentiment increasing volatility by 1.2%.

Markov-switching models identify two distinct volatility regimes: high-volatility (regime 1) and low-volatility (regime 2). Policy sentiment affects regime transition probabilities, with hawkish sentiment increasing the probability of transitioning to the low-volatility regime by 15%.

5.7 Cross-Sectional Analysis

Larger cryptocurrencies exhibit lower sensitivity to policy sentiment. The correlation between market capitalization and sentiment sensitivity is $\rho = -0.67$, suggesting that size provides resilience to policy shocks. This finding supports the "digital gold" hypothesis for `BTC` and the "utility token" hypothesis for smaller cryptocurrencies.

Layer-1 blockchains (`ETH`, `SOL`, `AVAX`) show higher sensitivity than utility tokens (`LINK`, `UNI`). This suggests that infrastructure tokens are more exposed to policy-driven risk appetite changes, while utility tokens maintain more stable valuations.

Table 2: Correlations Between Policy Sentiment and Stablecoin Volatility

Stablecoin	Correlation	t-statistic	p-value
USDT	-0.012	-0.89	0.374
USDC	-0.065	-4.23	0.000
BUSD	+0.057	3.67	0.000
DAI	-0.023	-1.45	0.148
FRAX	+0.089	5.12	0.000
LUSD	-0.034	-2.18	0.030
TUSD	+0.041	2.67	0.008
USDP	-0.018	-1.12	0.264

Table 3: Peg Stability by Policy Sentiment

Stablecoin	Hawkish	Neutral	Dovish
USDT	99.97	99.94	99.91
USDC	99.98	99.95	99.93
BUSD	99.95	99.89	99.84
DAI	99.94	99.91	99.88
FRAX	98.89	99.15	99.34
LUSD	99.96	99.93	99.90
TUSD	99.87	99.82	99.79
USDP	99.92	99.89	99.86

Table 4: Cryptocurrency Sensitivity to Policy Sentiment

Cryptocurrency	Correlation	Beta	Rank
ADA	+0.156	1.23	1
AVAX	+0.142	1.18	2
SOL	+0.138	1.15	3
LINK	+0.134	1.12	4
MATIC	+0.127	1.08	5
UNI	+0.119	1.05	6
DOT	+0.112	1.02	7
ETH	+0.089	0.95	8
BNB	+0.076	0.88	9
BTC	-0.023	0.67	10

5.8 Robustness Checks

Results remain robust across alternative sentiment measures. Dictionary-based sentiment analysis yields correlations within 0.02 of our LLM-based results. Manual expert classification confirms our automated classifications in 91.3% of cases.

Results are consistent across different time periods. Pre-COVID correlations average 0.134, while post-COVID correlations average 0.141, indicating stable relationships over time. High-volatility periods show stronger sentiment effects, suggesting that policy sentiment matters more during market stress.

5.9 Comparative Insights

Our analysis reveals fundamental differences between stablecoin and non-stablecoin responses to policy sentiment. Stablecoins demonstrate systemic resilience through their peg mechanisms, with policy sentiment having limited direct effects on peg stability. Non-stablecoins, in contrast, exhibit clear sensitivity to policy cycles, reflecting their role as speculative assets and alternative stores of value.

The heterogeneous responses across cryptocurrencies suggest that market structure, liquidity, and design mechanisms are key determinants of policy sensitivity. Centralized stablecoins benefit from institutional backing during hawkish policy, while algorithmic designs face increased stress. Among non-stablecoins, infrastructure tokens show higher sensitivity than utility tokens, reflecting different risk-return profiles.

6 Discussion

6.1 Theoretical Implications

Our findings provide important insights into the transmission mechanisms of monetary policy to cryptocurrency markets. The differential responses between stablecoins and non-stablecoins highlight the role of market structure in determining policy sensitivity.

The limited sensitivity of stablecoins to policy sentiment reflects their unique design mechanisms. Centralized stablecoins (`USDT`, `USDC`) benefit from institutional backing and regulatory compliance, creating a "flight-to-quality" effect during hawkish policy periods. This finding supports the hypothesis that regulatory clarity and institutional support enhance market stability.

Algorithmic stablecoins (`FRAX`) exhibit greater sensitivity due to their reliance on algorithmic mechanisms rather than direct collateral backing. The increased volatility during policy announcements suggests that algorithmic designs may be vulnerable to sudden changes in market conditions, highlighting the importance of robust collateral mechanisms.

The heterogeneous responses of non-stablecoin cryptocurrencies reveal important insights into their role in the financial system. `BTC`'s resistance to policy sentiment supports its characterization as "digital gold," serving as a store of value rather than a speculative asset. This finding aligns with recent research suggesting that Bitcoin's correlation with traditional assets has decreased over time.

High-beta cryptocurrencies (`ADA`, `AVAX`, `SOL`) act as amplifiers of policy shocks, reflecting their role as growth assets sensitive to risk appetite. This pattern suggests that these cryptocurrencies may serve as leading indicators of market sentiment, potentially providing early signals of policy transmission effects.

6.2 Economic Mechanisms

Policy sentiment affects cryptocurrency markets primarily through the risk appetite channel. Hawkish policy reduces risk appetite, leading to capital outflows from high-risk assets (smaller cryptocurrencies) and inflows to safer assets (Bitcoin, major stablecoins). This mechanism explains the negative correlation between policy sentiment and smaller cryptocurrency returns.

Traditional financial markets' liquidity conditions spill over into cryptocurrency markets through institutional investors and market makers. During periods of tight monetary policy, reduced liquidity in traditional markets affects cryptocurrency market depth, particularly for smaller assets with limited institutional backing.

Policy announcements create regulatory uncertainty that differentially affects cryptocurrencies based on their regulatory status. Centralized stablecoins with clear regulatory frameworks benefit from reduced uncertainty, while decentralized and algorithmic designs face increased regulatory risk.

6.3 Market Microstructure Effects

The 24/7 nature of cryptocurrency markets creates unique arbitrage opportunities during policy announcements. Market makers adjust their strategies based on policy sentiment, affecting bid-ask spreads and market depth. Centralized stablecoins benefit from more efficient arbitrage mechanisms, contributing to their peg stability.

Policy sentiment affects institutional adoption of cryptocurrencies. Hawkish policy may accelerate institutional adoption of Bitcoin as a store of value, while dovish policy may increase interest in high-growth cryptocurrencies. This mechanism explains the differential responses across cryptocurrency types.

6.4 Limitations and Caveats

Our analysis covers a period of significant market evolution, including the COVID-19 pandemic and subsequent monetary policy responses. The results may reflect specific market conditions rather than fundamental relationships. Future research should examine longer time periods and different market regimes.

Our LLM-based sentiment analysis, while innovative, may not capture all nuances of policy communications. Central bank communications are complex and context-dependent, requiring careful interpretation. The model's performance, while strong, may miss subtle policy signals that affect markets.

Cryptocurrency markets continue to evolve rapidly, with new assets, technologies, and regulatory frameworks emerging. Our findings may not apply to future market conditions or newly developed cryptocurrencies. Ongoing research is needed to track these developments.

7 Policy and Market Implications

7.1 Implications for Central Banks

Our findings suggest that cryptocurrency markets represent a new channel for monetary policy transmission. While the effects are currently limited compared to traditional financial markets, they may grow as cryptocurrency adoption increases. Central banks should monitor these developments and consider their implications for monetary policy effectiveness.

The resilience of major stablecoins to policy shocks reduces immediate financial stability concerns. However, the vulnerability of algorithmic stablecoins and the sensitivity of smaller cryptocurrencies suggest potential risks during periods of market stress. Central banks should develop frameworks for monitoring cryptocurrency market stability.

Our results highlight the importance of regulatory clarity for market stability. Centralized stablecoins with clear regulatory frameworks exhibit greater resilience, suggesting that regulatory certainty benefits market participants. Central banks should work with regulators to develop comprehensive frameworks for cryptocurrency oversight.

7.2 Implications for Stablecoin Issuers

Stablecoin issuers should prioritize robust peg mechanisms, particularly for algorithmic designs. Our results suggest that algorithmic stablecoins face increased stress during policy announcements, highlighting the importance of sufficient collateral backing and transparent mechanisms.

Issuers should develop risk management frameworks that account for policy-driven market stress. The differential responses across stablecoin types suggest that issuers should consider their regulatory status and institutional backing when designing risk management strategies.

Transparent communication about peg mechanisms and risk management practices may enhance market confidence. Our results suggest that market participants value clarity about stablecoin operations, particularly during periods of market stress.

7.3 Implications for Investors

Investors should consider cryptocurrency sensitivity to policy sentiment when constructing portfolios. Bitcoin's resistance to policy shocks makes it suitable for diversification, while high-beta cryptocurrencies may provide exposure to policy-driven cycles.

Understanding cryptocurrency sensitivity to policy sentiment can inform risk management strategies. Investors should monitor policy developments and adjust their cryptocurrency allocations accordingly, particularly during periods of heightened policy uncertainty.

Our results suggest that policy sentiment may provide signals for cryptocurrency market timing. Hawkish policy may present opportunities to accumulate Bitcoin, while dovish policy may favor high-growth cryptocurrencies. However, investors should consider transaction costs and market impact when implementing such strategies.

7.4 Implications for Regulators

Regulators should develop frameworks for monitoring cryptocurrency market stability, particularly during periods of policy uncertainty. Our results suggest that different cryptocurrency types require different monitoring approaches based on their sensitivity to policy shocks.

International coordination on cryptocurrency regulation may enhance market stability. Our results suggest that regulatory clarity benefits market participants, highlighting the importance of coordinated regulatory approaches across jurisdictions.

Regulators should assess the systemic risk implications of cryptocurrency market growth. While current risks appear limited, the rapid growth of cryptocurrency markets may create new systemic risks that require ongoing monitoring and assessment.

8 Conclusion

This paper provides comprehensive evidence on the relationship between central bank policy sentiment and cryptocurrency market dynamics. Our analysis of 43 policy events from 2020-2025 reveals fundamental differences in how stablecoins and non-stablecoin cryptocurrencies respond to monetary policy communications.

8.1 Key Findings

Our results demonstrate that stablecoins exhibit remarkable resilience to policy sentiment shocks, with peg stability averaging above 99.7% across all sentiment regimes. This resilience reflects the robust design mechanisms of centralized stablecoins and the "flight-to-quality" effect during hawkish policy periods. However, algorithmic stablecoins show greater vulnerability, highlighting the importance of sufficient collateral backing.

Non-stablecoin cryptocurrencies display heterogeneous sensitivity to policy sentiment, with correlations ranging from -0.023 (`BTC`) to +0.156 (`ADA`). This heterogeneity reflects different roles in the financial system: Bitcoin serves as "digital gold" with policy resistance, while high-beta cryptocurrencies act as amplifiers of policy shocks.

8.2 Methodological Contributions

Our LLM-based sentiment analysis represents a significant methodological advancement, achieving 94.2% accuracy in classifying policy communications. This approach provides a scalable framework for analyzing central bank communications and their market effects, with applications extending beyond cryptocurrency markets.

The integration of event study methodology with cryptocurrency market characteristics addresses unique challenges posed by 24/7 trading and high volatility. Our flexible event window approach and robust statistical methods provide a template for future cryptocurrency market research.

8.3 Policy Implications

Our findings have important implications for monetary policy transmission and financial stability. While cryptocurrency markets currently represent a limited channel for policy transmission, their rapid growth suggests increasing importance for monetary policy effectiveness.

The resilience of major stablecoins reduces immediate financial stability concerns, but the vulnerability of algorithmic designs and sensitivity of smaller cryptocurrencies warrant ongoing monitoring. Regulatory clarity emerges as a key factor in market stability, supporting coordinated regulatory approaches.

8.4 Limitations and Future Research

Several limitations warrant acknowledgment. Our sample period covers significant market evolution, potentially limiting generalizability. The rapid pace of cryptocurrency market development requires ongoing research to track emerging trends and relationships.

Future research should expand in several directions: **Extended Time Series** (longer sample periods to examine stability across different market regimes), **Cross-Jurisdictional Analysis** (comparative studies across different central banks and regulatory frameworks), **Intraday Analysis** (high-frequency analysis of policy transmission mechanisms), **DeFi Integration** (analysis of decentralized finance protocols and their sensitivity to policy sentiment), and **Machine Learning Enhancement** (development of more sophisticated sentiment analysis models).

8.5 Broader Implications

Our research contributes to the growing literature on cryptocurrency markets and monetary policy. The findings suggest that cryptocurrency markets are becoming increasingly integrated with traditional financial markets, with important implications for both monetary policy and financial stability.

The differential responses across cryptocurrency types provide insights into their evolving roles in the financial system. As these markets mature, understanding their sensitivity to policy sentiment becomes increasingly important for policymakers, investors, and market participants.

This paper demonstrates that LLM-based sentiment analysis provides a powerful tool for bridging qualitative policy communications with quantitative market responses. As central bank communications become more sophisticated and cryptocurrency markets continue to evolve, such analytical frameworks will become increasingly valuable for understanding policy transmission mechanisms.

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