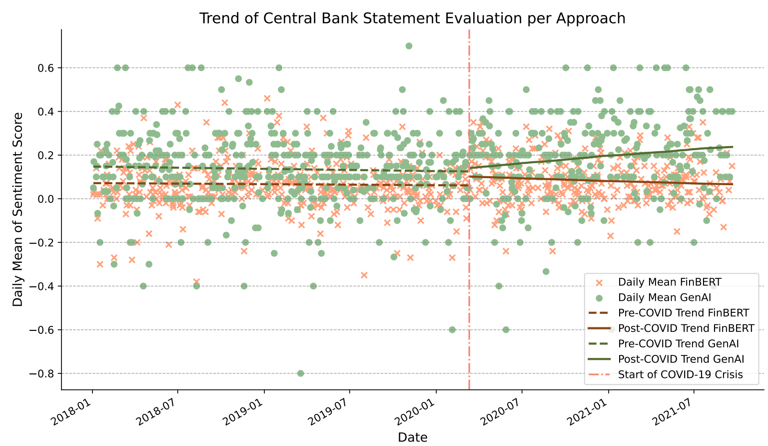
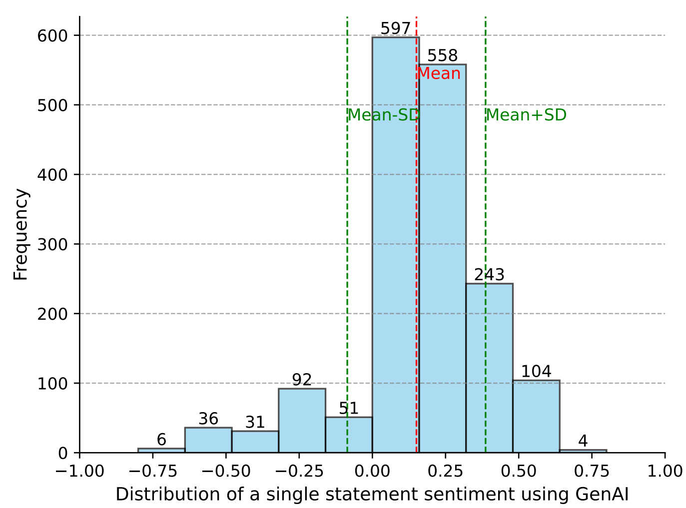
Graphical Abstract

Impact of ECB and FED Public Statements on Bitcoin Volatility through GenAI-powered Sentiment Analysis

Vilem Krejcar, Ladislav Kristoufek



Time-series analysis of both sentiment scoring approaches plotted with respective trend lines, with a special attention to the COVID-19 pandemic



Sentiment score distribution using Generative AI

Highlights

Impact of ECB and FED Public Statements on Bitcoin Volatility through GenAI-powered Sentiment Analysis

Vilem Krejcar, Ladislav Kristoufek

- Analyzed high-frequency Bitcoin data from 2018 to 2021.
- Extracted novel insights from unstructured central bank data (FED and ECB) using web scraping and advanced sentiment analysis techniques.
- Employed GPT-4 for sentiment analysis, outperforming traditional language models like FinBERT.
- Utilized the HAR model due to its robust performance in studies on realized volatility.
- Found that negative ECB statements during the Covid-19 period led to immediate and significant increases in Bitcoin volatility.
- Demonstrated the potential of Generative AI as a research tool to uncover previously inaccessible insights.

Impact of ECB and FED Public Statements on Bitcoin Volatility through GenAI-powered Sentiment Analysis

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Abstract

This study explores the impact of public statements from major central banks, the FED and the ECB, on Bitcoin volatility. We extract sentiment scores from the central banks' communications through two methods – the FinBERT language model and the state-of-the-art Generative AI GPT-4 – utilizing high-frequency data. Using the Heterogeneous Auto-Regressive (HAR) model for Bitcoin volatility as a benchmark, GPT-4 proved to be more effective. The findings indicate that negative sentiment from the ECB during the pandemic was associated with immediate and significant increases in Bitcoin volatility. The influence of central banks thus extends beyond direct market actions, affecting other markets through indirect mechanisms, here specifically the communications that can be qualitatively and quantitatively inspected and utilized via the Generative Artificial Intelligence instruments.

Keywords: Bitcoin volatility, Sentiment analysis, Generative AI, Unstructured data, Central bank communication, HAR, GPT, ECB, FED, FinBERT, Data mining

1. Introduction

Bitcoin (Nakamoto, 2009) emerged as a technological niche and proclaimed protest against the banking and monetary system in the aftermath

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of the Global Financial Crisis of the late 2000s. On its path towards maturity, it kept gaining interest and eventually has become a focal point for not only academia and media but also for retail and lately also institutional investors, leaving only public institutions reluctant to more open acceptance or support. The research on the interplay between Bitcoin and traditional financial markets goes back to its very beginnings (Kristoufek, 2015), through the 2016–2017 hikes (Corbet *et al.*, 2018), towards the reflection of monetary policies and FOMC (Federal Open Market Committee) statements into the Bitcoin price dynamics (Corbet *et al.*, 2020). While central banks are known to exert significant influence over traditional financial markets, shaping investor expectations and market sentiment through various instruments, their impact on Bitcoin has been less consistently observed. Although early investigations by Vidal-Tomás & Ibañez (2018), Cruz (2019) or Lundqvist & Olivefors (2022) did not find conclusive evidence of central bank interventions affecting Bitcoin, more recent studies by Karau (2023) and Pietrzak (2023) indicate that monetary policy can have a notable impact on Bitcoin prices, while Sila *et al.* (2024) find no evidence of interest rates or inflation expectations to have significant effects on a more general complex dynamics of the crypto-markets. We build and expand on these results and include a broader range of central bank communications–such as public speeches and press releases–while also employing experimental methods for data extraction to uncover deeper insights.

The use of Generative AI for generating novel insights remains relatively underexplored, as the technology is still in its early stages and is applied with caution. Korinek (2023) highlights its potential in economic research, particularly in extracting information from text. Krugmann & Hartmann (2024) further explore sentiment assessment by comparing large language models, finding that while Llama 2 and GPT-3.5 tend to assess texts positively, GPT-4 not only shows a tendency for negative assessments but also demonstrates superior overall performance.

Here we leverage a unique data source by generating sentiment scores from the public statements of the American and European central banks (FED and ECB, respectively) to inspect the relationship between the public communications of financial market regulators and Bitcoin price movements.

2. Methods

2.1. Sentiment Score

The unstructured data extraction, adjustments, and data cleaning are described in the Data section. The sentiment scoring has been performed in two ways – a benchmark analysis through the traditional FinBERT language model and a customized analysis using the state-of-the-art Generative AI technology.

For the benchmark analysis, we leverage the FinBERT language model (Araci, 2019), specifically tailored for financial text analysis based on transformers (Vaswani *et al.*, 2023). The unstructured texts were split on a sentence-by-sentence basis, assigning each split a sentiment score, which was then aggregated to produce an overall sentiment score for the entire text. Each sentence processed through FinBERT model yielded a sentiment classification, the likelihood of each sentiment category summing to one, and a numerical sentiment score ranging from -1 (negative) through 0 (neutral) to 1 (positive). The average sentiment score of a given text, $\bar{\mathbf{x}}$, was calculated using the formula $\bar{\mathbf{x}} = \sum(\mathbf{x})/\text{count}(\mathbf{x})$, where x represents the sentiment scores of individual sentences. The average sentiment score quantifies the overall sentiment of the text.

For the Generative AI approach, we employ the GPT-4 apparatus due to its flexibility and advanced capabilities (Radford *et al.*, 2018; OpenAI, 2023). A structured and optimized prompt was developed to generate the sentiment metric, a result of a thorough prompt engineering iterative exercise. It produces two main outputs – the sentiment score (ranging from 0 for negative sentiment to 1 for positive sentiment for performance stability), and an explanation of the decision to provide a layer of transparency and explainability. The sentiment scores from GPT-4 were rescaled to match the FinBERT scoring range. Several adjustments were made to this process due to the excessive length of certain statements (addressed through imputation in *.pdf* format) and additional data-related issues[1].

Furthermore, the modeling dataset was normalized (excluding Boolean variables and interaction terms) and differenced where necessary to achieve stationarity. For days with multiple public statements, a daily average was calculated for both approaches[2].

[1] These issues included duplicate entries and statements with low informational value.
[2] Sample output comparison of both scoring methods can be found in Appendix A.

2.2. Estimation

The volatility modelling builds on the Heterogeneous Auto-Regressive (HAR) model (Corsi, 2009), utilizing a realized volatility (RV) metric to capture Bitcoin price fluctuations, using the 5-min intra-day logarithmic price data. The HAR model is widely used in financial research for predicting the RV of assets using high-frequency data because of its ability to incorporate time-varying coefficients by using lagged RV at different time scales as predictors.

The traditional HAR-RV model is specified as HAR(1,5,22), which integrates daily volatility, weekly and monthly average volatility metrics within the model. Given that Bitcoin is traded every day of the week, we have opted for the HAR(1,7,30) specification. The model is specified as follows:

$$RV_t = \beta_0 + \beta_1 RV_{t-1}^{(1)} + \beta_2 RV_{t-1}^{(7)} + \beta_3 RV_{t-1}^{(30)} + \gamma\zeta_t + \varepsilon_t \tag{1}$$

where RV_t is the explained realized volatility at time t, $RV_{t-1}^{(1)}$ is its lagged derivative, $RV_{t-1}^{(7)}$ and $RV_{t-1}^{(30)}$ are the weekly and monthly rolling realized volatility averages, respectively; ζ_t represents the exogenous variables vector with corresponding parameters γ, and ε_t is the error term.

3. Data

High-frequency Bitcoin price data was sourced from the Kaggle G-Research Crypto Forecasting competition. Fundamental Bitcoin variables were obtained from CoinMetrics.io, while speculative variables were derived from Google Trends API and Wikipedia. Financial indicators were retrieved via the Yahoo! Finance API. The variable selection follows the current literature (Arratia & López-Barrantes, 2021; Fang *et al.*, 2020; Zhang *et al.*, 2022; Kukacka & Kristoufek, 2023). The unique unstructured central banks' public statements data was harvested through web scraping of ECB and FED websites. The entire data acquisition process is simplified into a data lineage graph in Figure 1. To provide a degree of transparency, research steps may be replicated by running the code stored in the thesis repository at *Github Repository*.

To understand the sentiment metrics, it is imperative to consider the cadence of released statements. Figure 2 illustrates the daily distribution of central bank public statements. A significant number of days, particularly

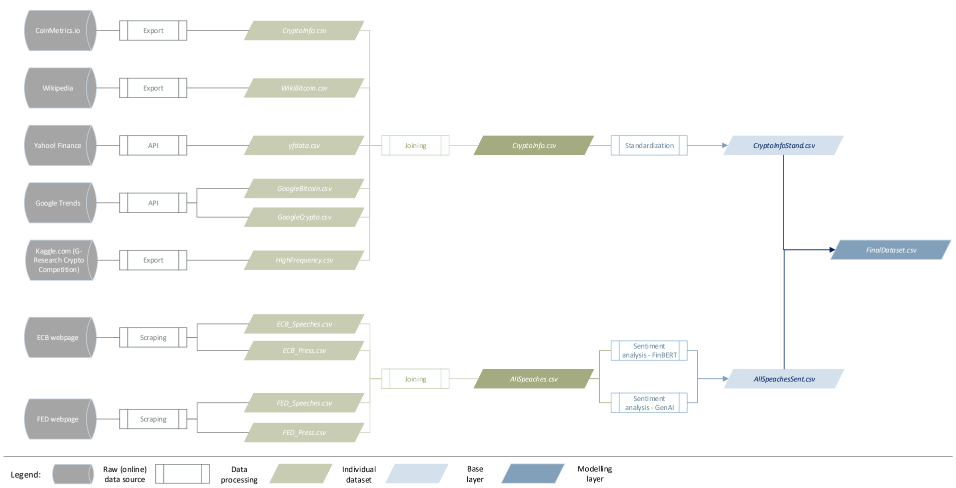

Figure 1: Data lineage representing the process of data acquisition.

weekends (when the central banks do not release statements but cryptomarkets are open), are characterized by the absence of statements. The decaying distribution peaks at eight emissions per day on several occasions, with a median of one speech per day. It is not uncommon that multiple statements are issued in a day.

Table 1 offers a quantitative overview of sentiment on a statement-level basis, complemented by a table highlighting the distribution of statement emissions per central bank in Table B.5. The sentiment distribution exhibits negative skew, indicating a general inclination towards positive values. Notably, Generative AI approach tends to produce a more optimistic sentiment compared to FinBERT. Central bank statements are typically written in a formal and measured tone. From a statistical point of view, we hypothesize that FinBERT may have captured only part of the sentiment. Both distributions show more outliers than a typical normal distribution, represented by leptokurtosis. The global means for both approaches reflect the overall Bitcoin market sentiment during the years 2018–2021, a period of rising Bitcoin prices. While the differences between the regulatory bodies are not pronounced, summary statistics suggest that FED news sentiment is generally slightly more conservative and less varied. In contrast, ECB's sentiment is marginally more positive with lower kurtosis, indicating lighter tails. This might be a reflection of the FED, being a sentiment setter on the global level, adopting a more conservative stance and tone. Those insights

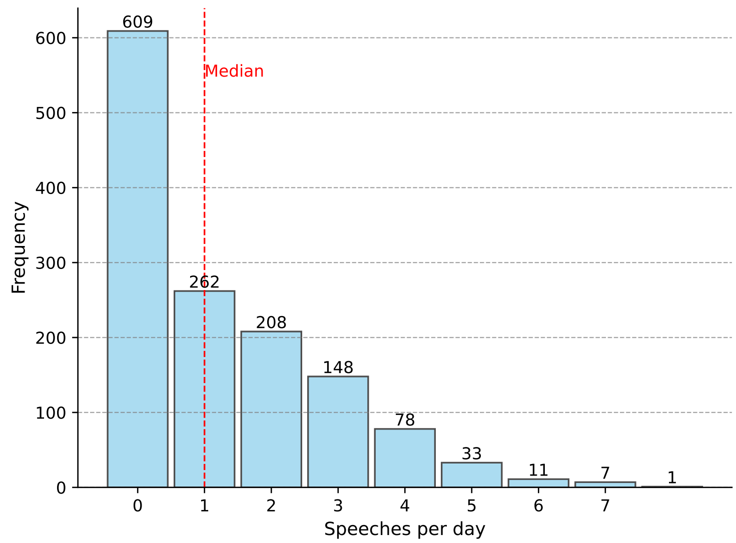

Figure 2: Histogram depicting the number of speeches per one day with highlighted median value.

are visually represented in Figure 3 and Figure 4, depicting the FinBERT and Generative AI sentiments, respectively.

Table 1: Distribution of both sentiment approaches

Variable	**Mean**	**Median**	**SD**	**Min**	**Max**	**Skew**	**Kurt**
SentimentFinBERT	0.073	0.053	0.148	-0.644	0.646	-0.055	1.782
SentimentGenAI	0.151	0.200	0.236	-0.800	0.800	-0.828	1.738
SentimentFinBERT_ECB	0.105	0.093	0.152	-0.567	0.646	-0.012	1.187
SentimentGenAI_ECB	0.173	0.200	0.208	-0.600	0.700	-0.392	0.637
SentimentFinBERT_FED	0.048	0.031	0.139	0.644	0.551	-0.215	2.507
SentimentGenAI_FED	0.133	0.120	0.255	-0.800	0.800	-0.938	1.715

An analysis of sentiment dynamics over time, as shown through simple daily averages in Figure 5, aligns with previously discussed findings. Generative AI sentiment consistently shows a more optimistic outlook compared to the FinBERT model, with a slight decline until March 11, 2020, the date the World Health Organization (WHO) formally declared the COVID-19

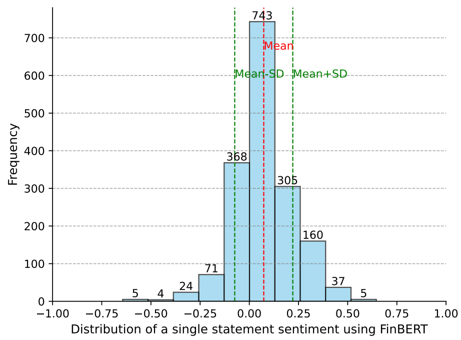

Figure 3: Sentiment score distribution using FinBERT ($n = 1727$).

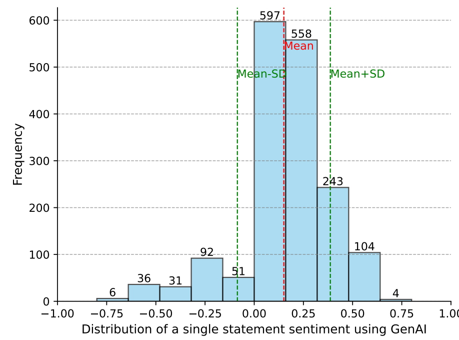

Figure 4: Sentiment score distribution using GenAI ($n = 1727$).

pandemic caused by the SARS-CoV-2 virus[3]. Interestingly, from this date onward, the average sentiment for both approaches increases, displaying a more positive outlook. This trend is counter-intuitive, as one would expect sentiment to drop significantly during a crisis. A plausible interpretation is that central banks, in their role of maintaining financial stability, aim to mitigate panic and stabilize the economic landscape. This optimism reflects the central banks' commitment to safeguarding the financial system and maintaining credibility as the guardians of financial stability.

The final dataset is formed by 12 variables with 1358 daily observations, covering the period between 2018-01-03 and 2020-09-21, including weekends. Summary statistics for these variables are present in Table 3, with a dictionary of variable definitions provided in Table 2. Correlation matrix is presented in Figure C.6 and does not uncover high correlations apart from the various volatility measures.

4. Results and Discussion

We now proceed to estimate the proposed HAR model, as specified in Equation 1, to investigate whether sentiment analysis affects Bitcoin's realized volatility. Specifically, we examine whether the inclusion of the sentiment variables – generated twofold using FinBERT and GPT-4 models –

[3]Source link with the announcement.

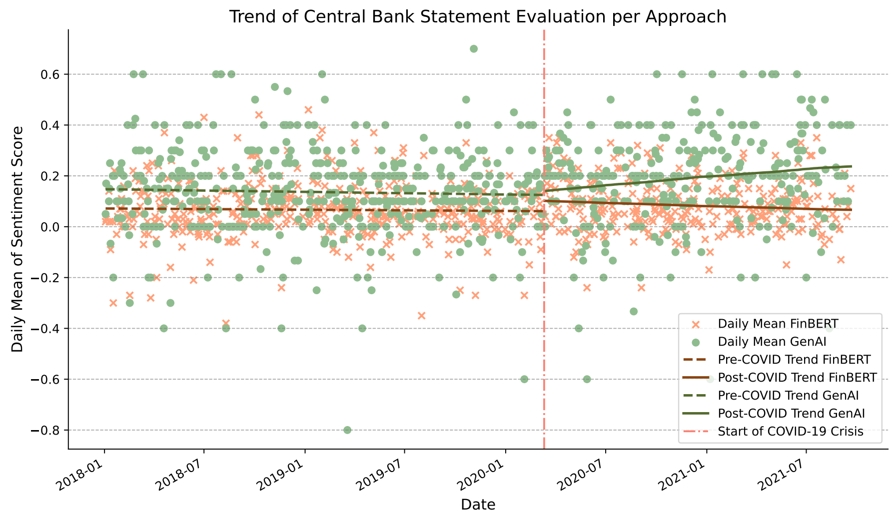

Figure 5: Time-series analysis of both sentiment scoring approaches plotted with respective trend lines, with a special attention to the COVID-19 pandemic.

Table 2: Summary of considered variables

Cluster	**Variable**	**Data Type**	**Short Description**
Key	*Date*	Date	Date in YYYY-MM-DD format
Bitcoin Price	*RealizedVolatility*	Numeric	Bitcoin realized volatility measure at time t
	DailyVolatility	Numeric	Bitcoin realized volatility measure at time $t-1$
	WeeklyVolatility	Numeric	Bitcoin past weekly realized volatility average
	MonthlyVolatility	Numeric	Bitcoin past monthly realized volatility average
Fundamental	*Inflation*	Numeric	Bitcoin annual inflation rate
	SP500Lret	Numeric	S&P500 Logarithmic Return
Speculative	*VIX*	Numeric	S&P500 Volatility index ("Index of Uncertainty")
	GoogleBitcoin	Numeric	Bitcoin-related Google search trends
	GoogleCrypto	Numeric	Cryptocurrency-related Google search trends
Sentiment	*NegFinBERTICovidECB*	Boolean	Dummy for negative daily ECB FinBERT sentiment during Covid
	NegGenAICovidECB	Boolean	Dummy for negative daily ECB GenAI sentiment during Covid

Table 3: Summary statistics of final data sample

Variable	Mean	Median	SD	Skew	Kurt	ADF	KPSS	Norm
RealizedVolatility	0.000	-0.240	1.000	3.291	21.665	0.000	0.100	0.000
Inflation	0.000	0.005	1.000	0.067	1.357	0.000	0.100	0.000
VIX	0.000	-0.001	1.000	0.163	5.179	0.000	0.100	0.000
SP500Lret	0.000	-0.007	1.000	-0.587	11.460	0.000	0.100	0.000
GoogleBitcoin	0.000	-0.017	1.000	1.589	20.200	0.000	0.100	0.000
GoogleCrypto	0.000	-0.011	1.000	2.167	58.295	0.000	0.100	0.000
DailyVolatility	0.000	-0.239	1.000	3.291	21.656	0.000	0.100	0.000
WeeklyVolatility	0.000	-0.272	1.000	1.818	4.660	0.000	0.100	0.000
MonthlyVolatility	0.000	-0.331	1.000	1.049	0.482	0.001	0.096	0.000
NegFinBERTCovidECB	0.032	0.000	0.175	5.349	26.614	0.000	0.010	0.000
NegGenAICovidECB	0.027	0.000	0.161	5.895	32.749	0.000	0.010	0.000

yields evidence of the aforementioned effect. The results are presented in Table 4.

Table 4: HAR Model Estimation Summary

Term	**Coefficient**	**(Std. Error)**
Constant	-0.0038	(0.016)
DailyVolatility	0.3917***	(0.026)
WeeklyVolatility	0.4870***	(0.031)
MonthlyVolatility	-0.0424*	(0.023)
Inflation	0.0298*	(0.015)
VIX	0.0296*	(0.016)
SP500Lret	-0.0438**	(0.015)
GoogleBitcoin	0.3207***	(0.019)
GoogleCrypto	0.0517***	(0.019)
NegFinBERTCovidECB	-0.0852	(0.099)
NegGenAICovidECB	0.2594**	(0.108)
Sample size		($n = 1358$)
Adjusted R-squared		0.685

Significance levels: *** $p \leq 0.01$, ** $0.01 < p \leq 0.05$, * $0.05 < p \leq 0.1$.

Significant dependencies are observed with short- and medium-term RV metrics, indicating a positive and substantial effect on Bitcoin's RV. This suggests a persistence in volatility and its clustering, with a change of nearly

0.5 standard deviations (SD) in Bitcoin's RV corresponding to a 1 SD increase in weekly volatility. In contrast, long-term volatility exhibits mean-reverting and stabilizing effects, although with a relatively lower magnitude. The serial shocks to volatility thus vanish quickly.

Among non-sentiment-based exogenous variables, the *GoogleBitcoin* metric shows the strongest effect, likely because public heightened interest translates into increased trading activity and volatility, highlighting its speculative and unstable nature. A similar, yet slightly reduced impact is observed with the *GoogleCrypto* variable, reflecting general cryptocurrency traffic. Additionally, three other variables have marginal effects on Bitcoin fluctuations. An increase in the *VIX* uncertainty index leads to higher Bitcoin volatility, as the risk-off sentiment tends to spread across speculative assets while also pointing towards the crypto and traditional market being at least partially affected by the same type of information translating into increased uncertainty in both. The Bitcoin issuance rate, referred to as the *Inflation* metric, measures the annual increase in new bitcoins relative to the current supply. This rate positively impacts Bitcoin fluctuations, emphasizing its appeal as a speculative asset. Lastly, the *S&P500* logarithmic returns have a slight negative effect on Bitcoin volatility, possibly because higher returns from traditional assets reduce Bitcoin's attractiveness as an alternative investment during bullish market conditions.

The sentiment-based variables offer intriguing insights. As shown in Figure 5, there is notable sensitivity to the Covid-19 period. Interestingly, significant evidence is found only for the ECB communications. This might be attributed to the individual approaches to public communication – in comparison with its European counterpart, FED statements tend to have a more neutral tone, as indicated by Table 1, which may explain the lack of evidence. Also, the FED announcements might have been used more as a political vehicle during the pandemic rather than vehicles of substance.

The FinBERT-based sentiment, represented by *NegFinBERTCovidECB* variable, has been found statistically insignificant. We hypothesize that this is due to the higher density of neutral sentiments captured by FinBERT, as illustrated in Figure 3.

In contrast, the sentiment metric obtained through Generative AI scoring, as captured by the *NegGenAICovidECB* variable, is associated with a statistically significant increase in Bitcoin volatility when the daily average sentiment for ECB emissions is negative during the pandemic. This finding aligns with empirical evidence that adverse negative shocks have a more pronounced impact on market dynamics, whereas positive sentiments tend to have a less significant effect. The results demonstrate the superiority of the Generative AI sentiment extraction method over FinBERT, which lacked explanatory power, likely due to its more neutral tone. Moreover, they underscore the crucial role of effective central bank communication during periods of distress, influencing not only traditional financial markets but also the cryptocurrency market. Other experiments with the sentiment estimation are present in Table D.6.

5. Conclusions

Our research provides compelling insights into the dynamics between major monetary authorities – the FED and the ECB – and the Bitcoin volatility. Notably, the Generative AI-based sentiment analysis outperformed the FinBERT language model, highlighting the potential of emerging technologies in financial modelling. Our findings confirm that central bank public statements significantly influence Bitcoin volatility, with negative daily ECB score during COVID-19 pandemic notably increasing market fluctuations.

Our key contribution lies in highlighting how central bank sentiment affects Bitcoin dynamics. Specifically, Bitcoin volatility tends to increase by more than a quarter of its standard deviation when the daily ECB average sentiment score during the pandemic is negative. Given that the Frankfurt-based institution typically releases positive statements, negative news signals market instability, potentially driving investment towards alternative assets like Bitcoin.

Such findings introduce hitherto unexplored variation in Bitcoin mechanics and suggest that emerging technologies like Generative AI can be valuable tools for financial modelling when applied responsively. Moreover, the results indicate that the influence of central banks extends beyond direct market interventions, impacting other markets through indirect channels as well.

Acknowledgments

This work was supported by the Cooperatio Program at Charles University, research area Economics. Support from the Czech Science Foundation (project 23-06606S "Deep dive into decentralized finance: Market microstructure, and behavioral and psychological patterns") is also highly appreciated.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used the generative AI system ChatGPT-4o and ChatGPT-o1 in order to improve readability and language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Appendix A. Output Examples

Appendix A.1. FinBERT

Given the machine learning-based nature of the FinBERT analysis, we lack the capacity to clarify the decision-making rationale behind the sentiment scores assigned by this model. To illustrate the algorithm's functionality through extreme case explanations, we present sentences with the maximum and minimum sentiment scores:

- **Maximum sentiment** (0.947): "*As the economic expansion in the euro area took hold after 2012, asset quality improved the fastest in real estate activities.*"
- **Minimum sentiment** (-0.969): "*To give some sense of the losses, employment in the leisure and hospitality sectors nationwide was down nearly 40 percent in the 12 months through May and still down about 25 percent through July.*"
- **Minimum sentiment** (-0.969): "*As a share of the total value of card transactions of 4.38 trillion EUR, fraud dropped by 0.001 percentage point to 0.041% in 2016, down from 0.042% in 2015.*"

It is crucial to note that the minimum value sentences have been randomly chosen from a set of 10 speeches, each sharing the identical sentiment score. In the second example of minimum sentiment, we can see that the model has captured rather incorrect extreme sentiment score. This may be caused by various factors, such as the model's processing of sentences in isolation without broader context, a limited representation of specific terms like "fraud" within the trained vocabulary, or the disproportionate influence of certain phrases like "dropped" and "down from."

Appendix A.2. Generative AI

Through the exercise of prompt engineering, we successfully extracted insights into the reasoning behind GPT's sentiment assessment, enabling a thorough analysis of model's consistency. Outcomes of this analysis, organized by sentiment level, offer a detailed perspective on the model's performance. These results, ranging from positive to negative sentiment scores, are summarized for an overview and are available for in-depth review within the disclosed dataset:

- **0.4 (Positive)**: *"The text presents a positive sentiment, focusing on the appointment of Silke Stapel-Weber as the new Director General in the Directorate General Statistics at the ECB. Her appointment, along with her professional background and qualifications (including her PhD in economics and her extensive experience at Eurostat), is presented in a positive light. The announcement reflects a successful career transition and a continuation of professional expertise in a significant role, contributing to the overall positive sentiment."*

- **0.2 (Moderately Positive)**: *"The release of the Federal Open Market Committee's meeting minutes discussing the economic impacts of the coronavirus pandemic indicates a moderately positive sentiment. The detailed consideration of financial markets and the economic outlook, despite the prevailing uncertainties and risks, demonstrates a commitment to transparency and a readiness to support economic stability."*

- **0.0 (Neutral)**: *"The ECB's press release on the consultation for a new euro unsecured overnight interest rate is purely informational and neutral in tone. It does not express any sentiment towards the economic or financial situation but rather invites stakeholders to participate in the consultation process. This fits the criteria for a neutral sentiment, as it simply communicates facts without emotional content or economic evaluation."*

- **-0.2 (Moderately Negative)**: *"The Federal Open Market Committee's economic projections and federal funds rate projections could also be viewed as slightly negative for cryptocurrency markets. These projections often reflect the broader economic outlook and monetary policy stance, which can influence investor sentiment and behavior in various asset classes, including cryptocurrencies. If the projections suggest a strengthening economy and tighter monetary policy (such as higher interest rates), this could lead to a preference for traditional investments over cryptocurrencies. Thus, in the context of its impact on cryptocurrency markets, the sentiment of this text could be considered slightly negative."*

- **-0.4 (Negative)**: *"The press release outlines the financial stability vulnerabilities posed by climate change, emphasizing the uneven impacts across regions, sectors, and firms. While it acknowledges the urgent* *need for climate policies and economic transitions, it also highlights the significant risks of inaction, including potential financial market repricing and long-term economic disruption. The focus on the concentration of risks and the potential for significant GDP decline in the absence of effective climate action conveys a more negative sentiment, stressing the importance of addressing these challenges promptly to mitigate long-term financial stability risks."*

Appendix B. Speech Variable Details

Appendix B.1. Speech Distribution per type and institution

Table B.5: Speech distribution per central bank

Institution	Type of speech	#	Sum institution	$\sum$
ECB	Press release	375	754 (43%)	**1722**
	Speech	379		
FED	Press release	751	968 (57%)	
	Speech	217		

Appendix C. Correlation Analysis

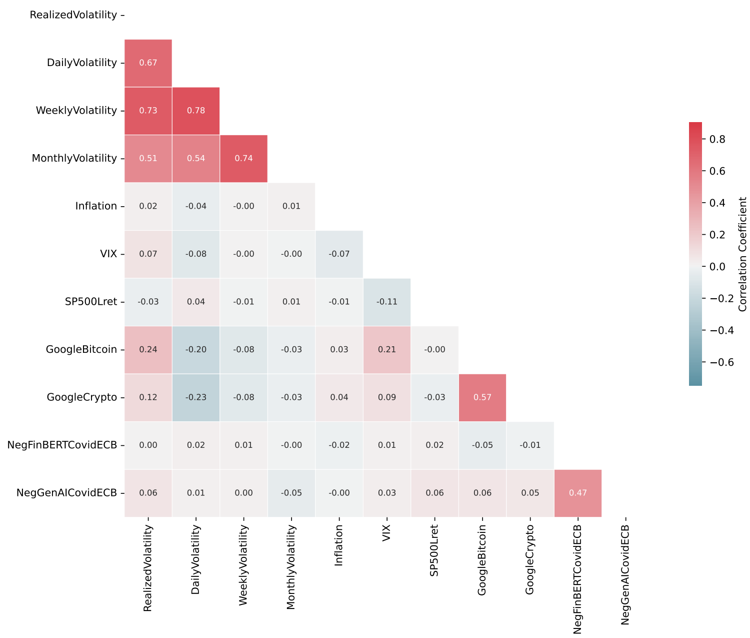

Figure C.6: Correlation matrix for the modelling dataset

Appendix D. Further Sentiment Estimation Coefficients

Variable	Coefficient	Standard Error	P-value	R^2
NegGenAICovidECB	0.215**	0.096	0.024	0.6871
NegGenAICovid	0.160**	0.076	0.035	0.6870
SentimentFinBERTNegative	0.072*	0.038	0.059	0.6868
NegFinBERTCovidFED	0.083	0.055	0.132	0.6865
SentimentGenAINegative	0.038	0.043	0.373	0.6861
NegFinBERTCovid	0.050	0.059	0.403	0.6861
PosGenAICovidECB	0.036	0.056	0.518	0.6860
NegGenAICovidFED	-0.036	0.073	0.620	0.6860
SentimentGenAIPositive	0.015	0.034	0.662	0.6860
SentimentFinBERTPositive	-0.011	0.034	0.754	0.6859
NegFinBERTCovidECB	0.026	0.087	0.765	0.6859
PosGenAICovidFED	0.011	0.043	0.805	0.6859
PosFinBERTCovidECB	0.010	0.055	0.850	0.6859
PosFinBERTCovid	-0.006	0.045	0.888	0.6859
PosFinBERTCovidFED	0.005	0.044	0.918	0.6859
PosGenAICovid	-0.002	0.039	0.964	0.6859

Table D.6: Summary of alternative sentiment variables, each included individually in the model and ranked by importance. Significant effects are highlighted according to common significance thresholds. While negative FinBERT sentiment demonstrates predictive power, the Generative AI-derived sentiment offers greater explanatory power, hence the decision to include this variable in the final model.