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Riding the Waves of Crypto Sentiment: Examining the Dynamics Between Returns and Sentiment in the Cryptocurrency Market

Peter ALBRECHT - Mendel University in Brno, Faculty of Business and Economics, Czech Republic, (peter.albrecht@mendelu.cz) *corresponding author*

Daniel PASTOREK - Mendel University in Brno, Faculty of Business and Economics, Czech Republic

David MAŇOUŠEK - Mendel University in Brno, Faculty of Business and Economics, Czech Republic

Abstract

This study examines the relationship between investor sentiment and market dynamics across the five largest cryptocurrencies—Bitcoin, Ethereum, Binance Coin, Ripple, and Cardano. Using the Crypto Fear & Greed Index as a proxy for market sentiment, we apply wavelet coherence to investigate the co-movement between sentiment and cryptocurrency returns across time and frequency domains. In parallel, impulse response functions from a vector autoregression framework are employed to assess how return shocks—particularly in Bitcoin—propagate through financial uncertainty, subsequently influencing sentiment and trading activity. Our findings reveal that sentiment functions as a robust leading indicator within an investment horizon of one week to one month, during which notable shifts in trading volume are observed. These results enhance our understanding of sentiment-driven behavior in crypto markets and provide actionable insights for short-term forecasting and investment strategy design across different time horizons.

1. Introduction

The burgeoning field of cryptocurrency research has recently turned its focus toward the nuanced interplay between investor sentiment and market dynamics. Pioneering studies, such as those by Polasik et al. (2015), Kyriazis et al. (2023), and Lin et al. (2023), have laid the groundwork by demonstrating the heightened

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sensitivity of crypto markets to investor sentiment. The sensitivity is primarily attributed to the dominant presence of retail investors in cryptocurrencies, as opposed to traditional markets (Bouteska et al., 2023). Such investors are often more susceptible to emotional extremes (Taleb, 2021). The impact of these emotional extremes is evident in market behaviors: a surge in cryptocurrency prices often triggers a wave of greed, propelling investors into a buying frenzy for fear of missing out. Conversely, price drops can incite panic selling as investors scramble to cut losses (Goodell and Goutte, 2021; Albrecht and Kočenda, 2024a). Recent studies delve into interactions between types of sentiment confirming the effect of sentiment from media news (Kulbhaskar and Subramaniam, 2023) as well as from Twitter (Shahzad et al., 2022). Such news affects the agents' emotions (Bouri et al., 2021) motivating them to rebalance cryptocurrency portfolios with a final effect on returns (Chowdhury et al., 2024).

Despite these advancements, a critical gap remains in our comprehension of the temporal aspects of sentiment-driven market reactions, particularly following market shocks. Previous literature has not sufficiently explored the specific time lags within which cryptocurrency prices react to sentiment changes. Aysan et al. (2023) examined the lead-lag relationship between crypto sentiment and bitcoin, but several questions remain. Despite bringing novel findings, the authors accounted only for the relationship between sentiment and bitcoin. Moreover, they examined the propagation of sentiment to returns on a lower frequency. Examination of higher frequencies, such as daily, is of crucial interest as cryptocurrencies are notably subject to speculative short-term trading strategies (Kulbhaskar and Subramaniam, 2023). Such oversight hinders the practical application of these findings, especially in developing effective trading strategies and short-term hedging techniques in the volatile crypto market.

In this study, we make three main contributions to current knowledge. First, we employ the VAR model to demonstrate that a price shock in crypto markets increases uncertainty, which leads to emotional behavior and subsequent reactions to sharp crypto trading movements up to one month ahead. Previous research brought notable insights into the relationship between uncertainty and cryptocurrencies (Elsayed et al., 2022; Hung et al., 2023; Xia et al., 2023), however, these studies did not delve into exploring the full transmission of the origins of the shocks. Moreover, employing wavelet coherence on crypto returns, we confirm cyclical behavior between the five most traded non-stablecoins and cryptocurrency sentiment. We build upon studies focusing on specific turmoil-linked periods (Goodell and Goutte, 2021; Gredojevic and Tsiakas, 2021; Karamti and Belhassine, 2022; Kyriazis et al., 2023; Li et al., 2023) and further investigate the relationship for a prolonged period of time from 2018 until 2023, including periods of distress as well as periods of greed. Using wavelet coherence enabled us to identify the length of a shock transmission from when the shock occurs until it is transmitted into crypto returns. In this context, we bring novel insights as we find that crypto sentiment was a robust leading indicator of returns of all selected cryptocurrencies from one week to one month ahead. Additionally, these insights are crucial for portfolio managers in the context that cryptocurrencies are appropriate as hedging tools for stocks and other financial assets (Bouri et al., 2020; Qureshi et al., 2020).

In an innovative move, we delve into the lead/lag structure of sentiment in the crypto market. Our study categorizes the market's response into immediate, short-term (one week to one month), and long-term (beyond one month) reactions. A key finding of our research is the role of the Fear & Greed index as a predictive tool for future cryptocurrency returns, observable in a time frame extending from one week to one month post-sentiment change.

Third and foremost, we argue that such a lag offers valuable information for portfolio managers using hedge strategies and traders watching the relationship between sentiment values and cryptocurrencies as they have an additional time window of up to one week to enter the position since the values of the Fear & Greed index reach either lower or higher extremes. These results are in line with research examining the impact of return frequency intervals on market efficiency, suggesting that intra-day traders are unlikely to beat the market, while weekly-based strategies can capitalize on market (in)efficiency (Kulbhaskar and Subramaniam, 2023).

In conclusion, our research extends the foundational work of leading studies exploring crypto-sentiment (e.g., Polasik et al., 2015; Sovbetov, 2018; Agyei and Bossman, 2023; Anamika et al., 2023) and takes a step further to enrich the academic discourse with a deeper, more nuanced understanding of investor behavior and market dynamics but also equips market practitioners with valuable insights.

2. Literature Review

Bitcoin, as the leading cryptocurrency by market capitalization and adoption, plays a central role in the cryptocurrency market. Its highly speculative nature and susceptibility to market news and external shocks (e.g., regulatory announcements or macroeconomic events) make it a dominant source of volatility within the cryptocurrency ecosystem (Mokni et al., 2022). The concept of risk propagation can be applied here, where significant price changes in bitcoin introduce conditions of immeasurable risk to other cryptocurrencies (Albrecht and Kočenda, 2024a). Such risk propagates through cryptocurrency markets as participants struggle to recalibrate expectations. The spillover effect from bitcoin to broader uncertainty is amplified in a market dominated by retail investors, who are more prone to behavioral biases like overreaction and herd behavior (Bouteska et al., 2023).

The Fear and Greed Index provides a quantitative measure of market sentiment, oscillating between the extremes of fear and greed based on underlying market conditions. Following a bitcoin-induced spike leading to the propagation of risk, heightened risk aversion fosters fear among investors, particularly in a market with a substantial retail base (Tran, 2019). Behavioral finance theories suggest that investors weigh losses more heavily than equivalent gains, leading to disproportionately larger fear responses during periods of market turbulence. The dynamic is further explained by Barberis et al. (1998), where the authors identified that fear amplifies itself through negative news cycles and social media, contributing to a reinforcing effect. Then, investors' sentiment reflects these emotional extremes, making it a valuable barometer for understanding market participants' reactions to uncertainty. As bitcoin shocks propagate through uncertainty channels, they shift the sentiment needle towards fear, signalling caution and risk aversion in the broader market.

Sentiment-induced fear or greed directly impacts trading activity, as evidenced by De Long et al. (1990). The model posits that irrational traders, influenced by sentiment rather than fundamentals, drive excess trading volume during periods of heightened market sentiment. When fear dominates, as triggered by uncertainty following a Bitcoin shock, investors tend to reduce positions or engage in panic selling, thereby increasing trading volumes. Conversely, during periods of greed, speculative buying spikes volume as traders seek to capitalize on perceived opportunities. Such bidirectional effect underscores the role of sentiment as a key determinant of trading activity. Furthermore, *Market Microstructure Theory* highlights that heightened volume during these periods contributes to liquidity shifts, further exacerbating price swings (O'Hara, 1995). As the Fear and Greed Index reflects these extremes, it not only captures market sentiment but also serves as a leading indicator for trading volume dynamics, linking emotional responses to tangible market outcomes. In this context, Albrecht and Kočenda (2024a) recently investigated transmissions of shocks among five major cryptocurrencies by using forecast error variance decompositions. Followingly, the authors bootstrapped the samples to confirm that cryptocurrency shocks are transmitted particularly from bitcoin to other cryptocurrencies. On the other hand, they did not investigate the transmissions via channels of uncertainty and sentiment. Further, they did not observe the lead-lag relationship between sentiment and crypto returns.

The cryptocurrency market, dominated by retail investors, is highly sensitive to sentiment due to its speculative nature and lack of centralized regulation. Aysan et al. (2023) found that Bitcoin-specific sentiment leads to market responses within shorter time horizons, particularly in speculative markets like cryptocurrencies. Sentiment changes influence investor behavior almost instantaneously, but the immediate market reaction (up to 4 days) is often noisy and lacks sustained directional trends. Behavioral finance theories suggest that initial reactions are driven by heuristic-based decisions rather than systematic assessments, limiting the strength of immediate correlations. As shown by Aysan et al. (2023) in the time-frequency domain, a period above a few days represents a functional lag for market participants to adjust trading strategies. Such horizon aligns with the business cycle of the cryptocurrency market, where weekly and monthly sentiment trends provide traders with sufficient lag to capitalize on market inefficiencies or hedge against volatility. The high-frequency nature of cryptocurrency trading amplifies this effect, as sentiment-driven speculative movements dominate price dynamics during this time frame. However, the authors only examined bitcoin reflections to sentiment excluding other cryptocurrencies, and further, they did not account for higher frequencies as they explored the relationship on weekly data.

On the other hand, the relationship between sentiment and bitcoin prices may reverse, with prices influencing sentiment in the long term. It may be due to the feedback loops inherent in speculative markets. Behavioral finance literature suggests that prolonged price trends can shape investor psychology, as individuals extrapolate historical returns to form future expectations (Barberis et al., 1998). The effect is particularly pronounced in cryptocurrency markets, where high volatility and retail dominance amplify the role of price signals in shaping collective sentiment (Bouri et al., 2021). Research by Kyriazis et al. (2023) highlights that sustained price increases in bitcoin often foster optimism and reinforce greed. Conversely, prolonged price declines exacerbate fear, leading to negative sentiment cycles that influence broader market behavior. These dynamics align with findings from Shahzad et al. (2022), who observe that sentiment is not only a leading indicator of short-term market reactions but also a lagging response to extended price movements, reflecting a bidirectional relationship over time. Such reversals in causality underscore the intricate interplay between price-driven expectations and sentiment, with prices acting as a barometer for market confidence and fear in speculative environments.

3. Methodology and Data

3.1. Data

The sentiment values are represented by the Fear & Greed index at a daily frequency from the index founders at Alternative.me. We use the data of five non-stablecoins with biggest market cap, namely bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Ripple (XRP), and Cardano (ADA). All data regarding cryptocurrencies are downloaded from Bloomberg using daily close prices. We chose five cryptocurrencies as they represent more than seventy percent of the entire cryptocurrency market capitalization (Coinmarketcap.com, 2023)[1]. VIX values as a proxy for financial uncertainty are obtained from Yahoo Finance. The timeframe analyzed starts in May 2018 and ends in February 2023, covering several critical events: the COVID-19 pandemic, the post-COVID inflation period, the invasion of Ukraine by Russian troops, and when cryptocurrencies reached their all-time highs within the observation period. The time span length was chosen since the beginning of the data series for the Fear & Greed index. The development of prices in more detail can be observed in Figure A1. We transform the data by logarithmic difference; descriptive statistics are presented in Table A1.

The Fear & Greed index, indicating sentiment in the cryptocurrency market (Mokni et al., 2022), ranges from 0 to 100, where 0 signifies extreme fear and 100

[1] All the cryptocurrencies are quoted against the US dollar. We use only the cryptocurrencies that are not stablecoins.

denotes extreme greed. It considers various factors in its calculation: Volatility (25%) gauges current market volatility by comparing bitcoin prices over the last 30 and 90 days, with increased volatility signaling higher fear. Market Volume (25%) includes momentum and traded volumes over 30 and 90 days. Social Media Analysis (15%) involves text analysis on Twitter, focusing on selected hashtags. Investor surveys (15%) assess market sentiment. Bitcoin Dominance (10%) as a factor measures bitcoin's market capitalization, reflecting increased fear. Google Trends (10%) gauges investor attention based on cryptocurrency-related internet searches (Alternative.me, 2023).

3.2. Methodology

In the paper, we employ the wavelet coherence method as it uncovers time-varying coherence between time series for different frequencies. Such identification is suitable to indicate strategies distinguishing between various types of investors based on their investment horizons (Albrecht et al., 2023). Moreover, we delve into the transmission mechanism of shocks on the cryptocurrency market as we employ the impulse response function. The method has its advantages in the identification of originations of transmissions based on the ordering of variables (Dibooglu and Kapounek, 2021).

We utilize wavelet analysis to examine time series in the time-frequency domain while preserving the overall time dimension by decomposing it into different frequencies (Kumar and Anandarao, 2019). Specifically, it helps to portray cyclicality at different time frequencies (Fidrmuc et al., 2020). Following Torrence and Webster (1999), we use the Morlet wavelet. The time variable is t, and the frequency variable is ω, expressed as:

$$\Psi_0(\mathrm{t}) = \frac{1}{\sqrt{2\pi}} e^{-i\,\omega_0 t}\, e\frac{-t^2}{2} \tag{1}$$

where ω_0 is the dimensionless frequency and t is the dimensionless time. According to Albrecht et al. (2023) and Pastorek et al. (2023), the parameter ω_0 is set to 6 for comparability with other studies. The continuous wavelet transforms functions as a series of filters sequentially applied to a time series (Albrecht et al., 2023), defined as follows:

$$W_n^X = \sqrt{\frac{\delta t}{s}} \sum_{n'=1}^{N} x_{n'}\, \Psi_0\left[(n'-n)\frac{\delta t}{s}\right] \tag{2}$$

Working with a finite-length time series introduces errors at the series' start and end. These errors stem from assuming cyclicity, resulting in missing values at these points. To address this, a "cone of influence" is employed to delineate significant data on the graph, excluding non-significant portions (Torrence and Compo, 1998). Wavelet strength is defined as follows:

$$W_n^{XY}(s) = W_n^X(s)W_n^{Y*}(s) \tag{3}$$

In the next step, we employ wavelet coherence to measure the degree of correlation between two-time series across different frequencies. Statistical significance, measured using the Monte Carlo method (Awada and Mestre, 2023; Pastorek et al., 2023), is applied to the different cryptocurrency prices and the differenced value of the Fear & Greed index (F&G index) as a sentiment variable. It reveals the relationship between cryptocurrency returns and sentiment at different time intervals and investment horizons, also assessing sentiment as a lagging or leading indicator. Wavelet coherence formula, as per Torrence and Webster (1999), is as follows:

$$R_n^2(s) = \frac{|\langle s^{-1}W_n^{XY}(s)\rangle|^2}{\langle s^{-1}|W_n^X(s)|^2\rangle \times \langle s^{-1}|W_n^Y(s)|^2\rangle} \tag{4}$$

The analysis adopts a 5% significance level and interprets relationships based on arrow directions in the graph. Arrows indicate phase shifts, determining whether variables move in the same or opposite directions and identify leading/lagging indicators. The circular average of arrow angles (Grinsted et al., 2004) reveals the nature of the phase shift. Right-pointing (left-pointing) arrows signify positive (negative) correlation. Downward (upward) arrows indicate the second (first) variable as the leading indicator, with the lagging indicator being the first (second) variable (Reboredo et al., 2017). The mathematical representation of the relationship is as follows:

$$a_m = arg(X,Y)\ s\ X = \sum_{i=1}^{n} cos(\, a_i)\ a\ Y = \sum_{i=1}^{n} sin(\, a_i) \tag{5}$$

To assess the extent and period to which the cryptocurrency market, including sentiment, responds to significant movements in crypto prices, we employ a Vector Autoregression (VAR) model to analyze the transmission of Fear (F&G index) triggered by sharp movements in bitcoin returns. We employ the VAR model as a suitable choice for our study due to its ability to capture dynamic interactions and feedback loops among multiple variables over time. In the context of the cryptocurrency market, where various factors such as bitcoin prices, volatility (VIX)[2], sentiment indicators (F&G), and trading volumes are expected to be interconnected (see Section 2), the VAR model allows us to model these relationships

[2] We interpret the volatility index (VIX) as computed from the volatility of S&P 500 options, which has been demonstrated to have an effect on cryptocurrencies (Wątorek et al., 2021). However, following previous research in the field (Tiwari et al., 2019; Albrecht and Kočenda, 2025), we interpret it as a proxy for financial uncertainty.

simultaneously. The results can offer insights into how changes in bitcoin returns can influence others in the short and long term.[3]

We propose a VAR model using Cholesky decomposition on daily data over the examined period. We specify the structure of our model as the log return of bitcoin price (the dominant cryptocurrency with a significant effect on the whole crypto market), VIX, F&G, and the log trading volume of selected currencies, including four lags of all variables. We report the responses of variables to a shock of one standard deviation in bitcoin price using response impulse functions with 90% confidence bands. The optimal lag length was determined using information criteria (AIC and BIC). The sharp movement in bitcoin price itself is expected to influence volatility due to increased uncertainty (VIX) reflecting changes in participants' sentiment (F&G). These changes are likely to lead to an increase in trading volumes as participants respond in the market.[4] Utilizing both the wavelet coherence and vector autoregression model enables us to empirically examine variables in the cryptocurrency market more comprehensively, offering diverse perspectives on their connectedness. The VAR model facilitates the capture of both direct and indirect shocks transmitted to modeled variables. Concurrently, the application of wavelet coherence allows us to pinpoint periods characterized by robust coherence patterns in the time-frequency domain, indicating instances where the analyzed variables are synchronized.

Our empirical approach allows us to discern not only whether and for how long the transmission of shock persists, originating from a sudden change in the price of bitcoin leading to a shift in sentiment to other cryptocurrencies, but also to identify the specific time-frequency horizon over which this synchronization between sentiment and other cryptocurrencies occurs. The information holds significance for investment strategies and can provide a nuanced understanding of the temporal dynamics in the market and offer valuable insights for strategic decision-making.

4. Results

We argue that crypto prices are more prone to extreme emotional behavior, exaggerated positive expectations, and excessive fear, as crypto markets involve more

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[3] Following previous studies (Corsi and Renò, 2012; Baruník and Ellington, 2024; Albrecht and Kočenda, 2025), we interpret a horizon until one month as a short-term, while the longer timeframe is interpreted as a long-term investment horizon from the trading perspective

[4] The ordering of variables in VAR models captures an economically intuitive transmission mechanism of shocks within speculative cryptocurrency markets (see Section 2). A price shock in bitcoin initiates the chain by influencing financial uncertainty, as represented by the VIX, due to bitcoin's dominant market position and its role as a leading indicator of volatility in cryptocurrencies. Increased uncertainty triggers emotional reactions, reflected in the Fear & Greed index, which quantifies market sentiment swings between optimism and pessimism. This shift in sentiment subsequently impacts trading activity, as fear or greed motivates changes in trading volumes. Finally, trading volumes drive price adjustments in other cryptocurrencies, reflecting the broader market's response to Bitcoin's initial price movement. The sequence aligns with behavioral finance theories that emphasize the role of sentiment in speculative markets, where price movements and emotional reactions reinforce each other through feedback loops, amplifying the market-wide impact of shocks.

retail investors (Mokni et al., 2022). Consequently, these markets are more affected by sentiment than macro fundamentals (Burggraf et al., 2020; Kraaijeveld and Smedt, 2020). Such market structure leads to higher spillovers between shocks and changes in crypto prices. However, these transmissions were observed without any definition of lag and no proxy for crypto sentiment (Kyriazis et al., 2023).

The VAR(4) model[5] results (Figure 1) indicate that a negative one-standard-deviation shock to Bitcoin returns leads to a significant increase in market uncertainty (proxied by the VIX), which triggers a decline in investor sentiment (increased fear), as reflected by the Fear & Greed Index. Crucially, the effect on trading activity among the other examined cryptocurrencies—Ethereum, Binance Coin, Ripple, and Cardano—becomes statistically significant and economically pronounced approximately two days after the initial shock. This delayed reduction in trading volumes is consistent with the notion of herding behavior, where market participants initially absorb the shock but subsequently retreat from trading due to elevated uncertainty and fear contagion (Bouri et al., 2021).

These findings uncover more insights about transmission of shocks induced by heightened fears. Moreover, the results suggest (Figure 1) that while uncertainty and fear exhibit an immediate reaction, the heightened fear persists beyond one month (approximately 30-40 days) after the negative shock (and vice versa in case of a positive shock). The transmission leads from a shock to bitcoin further propagated via increased uncertainty to heightened fear and decreased trading volumes of other cryptocurrencies. It indicates that increased fear prevents investors from opening new trades. The Forecast Error Variance Decomposition (FEVD) results (Table A5 in Appendix) highlight the dominant role of Bitcoin returns in driving forecast variance across all variables and horizons. Notably, Bitcoin returns explain nearly 100% of the variance at the shortest horizon, with a gradual decline over time, underscoring its central influence in crypto market dynamics. The Fear & Greed Index and Volatility Index exhibit significant but transient effects, particularly at shorter horizons, reflecting the behavioral nature of the market's response to shocks.[6]

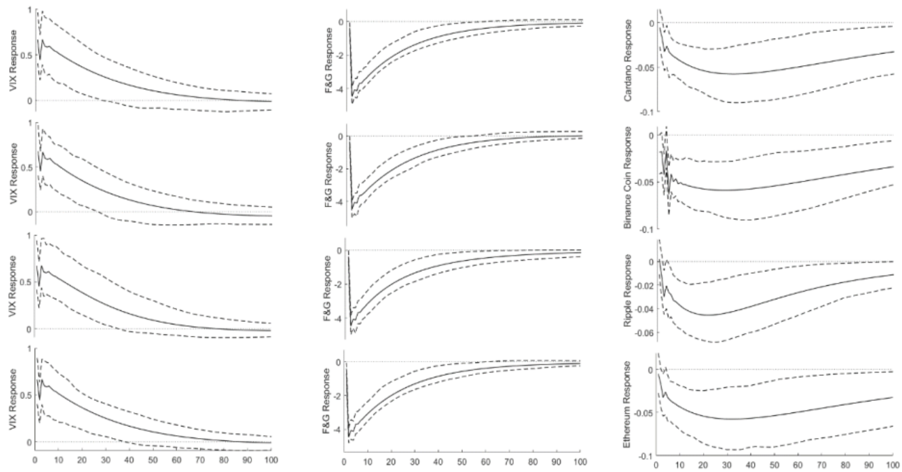
The impact of the uncertainty on cryptocurrencies has already been demonstrated in previous studies (e.g., Elsayed et al., 2022; Hung et al., 2023; Xia et al., 2023). However, these studies confirmed the relationship without providing evidence about direct transmission from a shock in bitcoin to uncertainty leading to a change in sentiment, which is further transmitted to other cryptocurrencies.

[5] The optimal lag length based on information criteria (AIC, BIC), was determined to be 3 or 4 depending on the specific model. To ensure consistency and comparability across models, we adopted a commonly used lag length of 4, which aligns with financial literature data analysis practices. For robustness, we also conducted additional analyses with a lag length of 3. The results remain stable and consistent regardless of whether lag 3 or lag 4 is used. Detailed results for lag specifications of 3 are provided in the appendix Figure A3.

[6] While the impulse responses of Bitcoin returns to VIX shocks appear limited (see Figure A5), this does not contradict the substantial contributions of VIX in the FEVD results. The IRFs reflect immediate directional effects, while the FEVD captures cumulative variance over time, including indirect transmission via sentiment and trading volume channels.

These results align with wavelet coherence results (Figure 2), which propose an investment horizon of up to one month. Notably, there is a statistically significant spillover from the bitcoin market through increased fear of other currencies after four days, with a long-term effect that gradually diminishes over time. To verify whether the transmission of this shock is not in the opposite direction—i.e., whether the shock in the Fear & Greed index causes a reaction in bitcoin and other cryptocurrencies—we repeated the exercise by reordering the variables as VIX, Fear & Greed index, bitcoin returns, and the trading volume of other selected cryptocurrencies. The results are available in Figure A2. However, this ordering did not reveal statistically significant effects. In Figure A3, we alternated the VAR lengths to confirm that the findings remain relatively stable.

Figure 1 Bitcoin Price Shock: Analyzing Responses to VIX, Sentiment, and Crypto Trading Volumes



Notes: The figure represents the response impulse functions of the Volatility Index (VIX), Fear and Greed Index (F&G), and trading volume of the four largest cryptocurrencies – Cardano, Binance Coin, Ripple, and Ethereum - to a negative shock of one standard deviation of bitcoin price returns. The results are presented using 90% confidence bands, and a VAR(4) model covers monthly data from May 2018 to February 2023. The y-axis is consistent across all subplots within each row, representing the magnitude of the response, while the x-axis indicates the time horizon.

Although the Fear & Greed (F&G) Index is a novel tool in financial analysis, its calculation methodology presents potential limitations, as it partially relies on components such as 30-day volatility and Bitcoin returns. To address concerns regarding the F&G Index's construction and its potential impact on our findings—particularly its reliance on market-based measures like volatility and trading volume—we conducted additional analyses to ensure the robustness of our results. While the F&G Index remains the primary focus of our study, we employed the Economic News Sentiment Index (DNSI) as an alternative sentiment measure (Shapiro et al., 2020). Unlike the F&G Index, the DNSI is constructed independently of market-based variables, drawing on sentiment derived from economics-related news articles. This approach provides a broader and less market-specific perspective, mitigating potential confounding effects while complementing our primary analysis. The VAR results using DNSI (Figure A4) are stable and consistent with our primary findings, reinforcing the validity of our analyses. Additionally, Variance Inflation Factor (VIF) values (Table A2) indicate no multicollinearity concerns across models using the F&G Index, while residual diagnostics (Table A3) confirm no serial correlation, ensuring the stability of the VAR estimates. Our robustness tests further confirm that a shock in Bitcoin triggers a surge in uncertainty, which, through heightened fear, prevents purchases on four additional cryptocurrencies.

These findings align with established economic theories in financial markets that emphasize the role of sentiment (Long et al., 1990; Barberis et al., 1998). Specifically, the results underscore how fear can intensify through feedback loops driven by negative news cycles and amplified by social media dynamics. To further validate our transmission framework, we examine how a shock in financial uncertainty—proxied by the VIX—affects returns, sentiment, and trading activity across major cryptocurrencies. As shown in Figure A5, the direct response of Bitcoin returns is modest and not statistically significant, but the Fear & Greed Index exhibits a strong and persistent decline, indicating that increased macro-level uncertainty is clearly reflected in market sentiment. Interestingly, trading volumes for the other cryptocurrencies (Cardano, Binance Coin, Ripple, and Ethereum) show a slight, though not statistically significant, increase.

While our main VAR model with a Bitcoin return shock shows a delayed decline in trading activity due to rising uncertainty and fear, the impulse responses to a VIX shock reveal a slightly different dynamic. This likely reflects the nature of the shock—external macroeconomic uncertainty versus internal market-driven stress. Prior research (Kumar and Goyal, 2015) suggests that macro shocks may trigger heterogeneous investor responses, where some reduce exposure, while others—particularly short-term traders—temporarily increase trading in search of volatility-driven opportunities.

Further, to examine the relationship more in detail, we distinguish three sub-horizons from the trading and hedging perspective. The first horizon is up to four days (covering immediate market reactions) without usable lag. We interpret the period above four days as a week as five days refer to one business week (Albrecht and Kočenda, 2024a). Then, we argue that the time frame from 5 to 31 days is a functional lag for the investors and traders to cover their positions based on a reasonable lag between sentiment values and cryptocurrencies (Baruník and Ellington, 2024). Also, a horizon below one month represents one business month in the cryptocurrency market, which has been confirmed as a reasonable window for hedging in the context of shocks (Albrecht and Kočenda, 2024b). Then, the third horizon represents a period longer than one month, as these fluctuations have a long-term impact on the fluctuations between financial assets (Corsi and Renò, 2012).

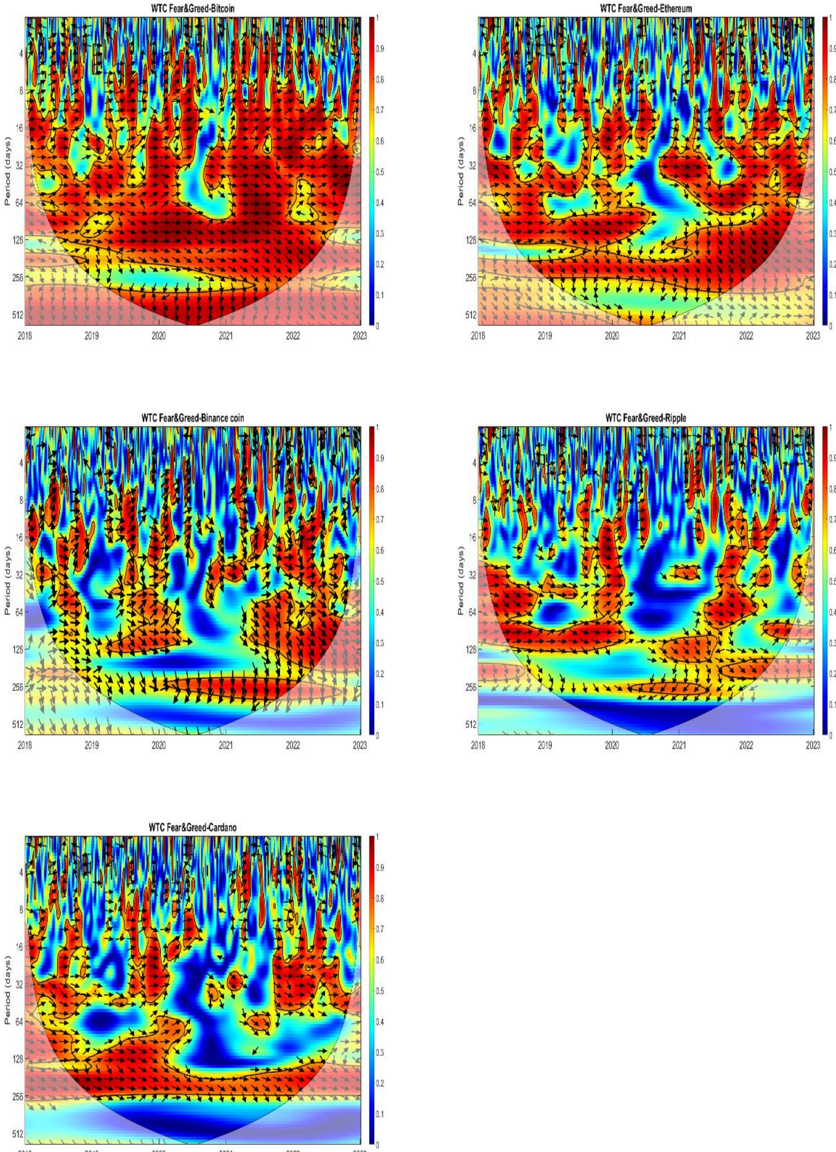
A VAR analysis allowed us to uncover the transmission of shocks, however, it did not identify, for what horizons the co-movement exists and to what extent sentiment could be a suitable prediction indicator for cryptocurrency returns. Previous findings (Aysan et al., 2023) demonstrated that sentiment specific to bitcoin prompts market reactions within shorter temporal frames, especially in speculative arenas such as cryptocurrency markets. Shifts in sentiment impact investor actions almost instantaneously; however, the immediate market response is frequently volatile and devoid of persistent directional movement. Theories in behavioral finance propose that these initial reactions are predominantly influenced by heuristic-driven choices rather than comprehensive evaluations, thereby constraining the robustness of short-term correlations (Hirshleifer and Subrahmanyam, 1998). However, the identification of concrete short-term horizons in cryptocurrency markets has not been observed in much detail. Asyan et al. (2023) suggested a potential short-term relationship, but the authors observed only bitcoin every week. Following the findings of these authors, we examine an extended sample of five cryptocurrencies on a daily basis. We employ wavelet coherence as it is a suitable tool to identify such relationships (Asyan et al., 2023; Pastorek et al., 2023).

In the case of bitcoin's instantaneous market return (Figure 2), no significant relationship has been demonstrated. The Fear & Greed index is not a suitable tool to predict future market developments in this trading horizon. However, the Fear & Greed index has the highest frequency of positive correlation and leading relationship from the Fear & Greed index to bitcoin from 5 to 31 days[7], suggesting a usable lag for price speculation. If the Fear & Greed index is rising (decreasing), investors can speculate on the rise (decline) in the price of bitcoin. It corresponds to the findings of Albrecht and Kočenda (2024a), who computed probabilities of a reaction of cryptocurrencies to ten endogenously chosen shocks. They found that the main propagation of returns occurred within one business month. However, the authors did not investigate the role of investor sentiment. We find that cryptocurrency investors tend to get overly greedy when the bitcoin price is rising. It is often the case that investors irrationally sell their cryptocurrencies after the price of bitcoin falls (Mokni et al., 2022). The causality moving from bitcoin to sentiment points to a highly speculative environment for cryptocurrencies (López-Cabarcos et al., 2021).

Nevertheless, over the long investment horizon, bitcoin predominantly acts as a leading indicator for Fear & Greed values (Figure 2). Therefore, past shocks to bitcoin returns may carry over to investor sentiment over a longer investment horizon. The result signals that bitcoin returns eventually determine the future investor behavior in the market. It aligns with economic theory that the relationship between sentiment and cryptocurrency prices may reverse over the long term, as prolonged price trends influence investor psychology and collective sentiment through feedback loops in speculative markets

[7] Corsi and Renò (2012) define the short-term horizon as a time until one month in the context of trading activity. The longer timeframe is interpreted as a long-term horizon. These assumptions are also supported by Baruník and Ellington (2024).

Figure 2 Wavelet Coherence Between Crypto Market Sentiment and Bitcoin, Ethereum, Binance Coin, Ripple, and Cardano



Notes: Wavelet coherence (WTC) for bitcoin, Ethereum, Binance coin, Ripple, and the Cardano. The color scales represent wavelet coherencies. The black contours denote insignificance at 5% against red noise, and the light shading shows the regions that are probably influenced by the edge effects. The direction of the relationship (the leading indicator) is represented by arrows—a left-hand arrow denotes an antiphase (180°), while a right-hand arrow denotes an in-phase (0° or 360°). A downward-pointing arrow indicates SVI as a leading indicator of stock market returns. Source: Own estimation

(Barberis et al., 1998; Bouri et al., 2021). Sustained price increases tend to amplify optimism and greed, while prolonged declines exacerbate fear, creating sentiment cycles that align with broader market behavior (Kyriazis et al., 2023). Such a bidirectional relationship highlights how prices can act as a barometer for market confidence and fear, reinforcing the dynamic interplay between sentiment and market movements (Shahzad et al., 2022).

In the case of Ethereum (Figure 2), for an immediate reaction up to a maximum of 4 days, we do not confirm a significant co-movement. For the lag between one week and one month, we can observe a change to a positive correlation, with the leading variable being the Fear & Greed index. Traders investing for 5 to 31 days can expect that if the Fear & Greed index values rise (greed rises), Ethereum returns will also rise. Also, in the long term, the relationship changes, and the correlation remains positive. However, the Fear & Greed index now acts as a lagging variable for Ethereum returns. In this case, the Fear & Greed index is no longer usable because its values are lagged. As with bitcoin, for investment horizons longer than one month, the evolution of cryptocurrency returns indicates changes in future market sentiment.

Binance coin shows less significant areas but with many similarities to bitcoin and Ethereum. We bring evidence about a lag from 5 to 31 days. During this period, traders can take advantage of the relationship and invest in the Binance coin in case of a rise in the Fear & Greed index (growth in greed). However, such a relationship is not usable for the longer term, which follows the results for previous assets under study and confirms robustness for the whole crypto market. Further, Ripple reports identical insights (Figure 2). Investment recommendations can be formulated only for an investment horizon of up to one month ahead as investors' fear (greed) indicates negative (positive) changes in Ripple values in a window from 5 to 31 days. Moreover, the co-movement of Ripple and sentiment values in wavelet coherence is inverse for the longer term without specific insights for trades. In Figure 2, we demonstrate these results to be robust for Cardano as well, suggesting that investors’ decisions in cryptocurrencies might be affected by sentiment within a window of one month. In the long term, cryptocurrency prices can influence sentiment through feedback loops, where prolonged price trends shape investor psychology, amplifying optimism during increases and fear during declines (Kyriazis et al., 2023; Shahzad et al., 2022).

The results of the conducted analyses confirm that a shock in the form of a bitcoin price change influences sentiment. The synchronization between sentiment and other cryptocurrencies in the time-frequency domain is subsequently further transmitted to the prices of other cryptocurrencies within a window of one week to one month. These findings suggest that investors may consider adjusting their investment horizons based on the described time-frequency patterns. By optimizing their positions to align with the expected synchronization between sentiment and other cryptocurrency prices, investors can potentially mitigate risk. Integrating sentiment analysis into their decision-making process may help in reducing exposure during periods of increased uncertainty or leverage these insights to formulate strategies that take advantage of the identified synchronization patterns, tailoring their approaches to the specific dynamics observed in the cryptocurrency market.

Our results support the notion that sentiment plays a crucial role in shaping cryptocurrency returns, as discussed in academic literature. While the previous research focuses on intraday findings in the cryptocurrency market, suggesting market inefficiencies (e.g., Mensi et al., 2019), the predictive power of sentiment is expected to be stronger on a daily level (Kraaijeveld and Smedt, 2020). It contrasts with intraday trading, where social media sentiment tends to react to market activities rather than predict them (Kraaijeveld and Smedt, 2020). The analysis of reaction patterns by Karalevičius (2017) shows that media sentiment can be utilized to predict semi-short-term bitcoin price movements, although the market's initial reaction is subject to several corrections, and a trader fully exploiting these movements cannot achieve abnormal returns. The study of the influence of social media, specifically the impact of tweets on bitcoin's realized volatility, trading volume, and returns by Shen et al. (2019), does not contradict these findings. It suggests that while the number of tweets from the previous day influences volatility and trading volume, there is only weak evidence that tweets might be associated with next-day returns. The study also notes the time variability and instability of these relationships. These outlined time windows align with our nuanced analysis, suggesting that traders can take advantage of sentiment as a leading indicator for price speculation within a range from one week to one month, demonstrating time periods where this relationship remains robust. Also, we do not provide evidence of its predictive power in the very first days when the market absorbs initial reactions.

5. Conclusions

This paper employs a comprehensive empirical framework to examine the dynamic interplay between investor sentiment and five major cryptocurrencies—Bitcoin, Ethereum, Binance Coin, Ripple, and Cardano. Drawing on recent literature (e.g., Sovbetov, 2018; Kyriazis et al., 2023; Lin et al., 2023), we extend prior findings by quantifying how sentiment—as proxied by the Fear & Greed Index—interacts with returns, trading volume, and financial uncertainty (VIX) over multiple time horizons and across both time and frequency domains.

Our wavelet coherence analysis reveals that sentiment exhibits a strong positive co-movement with returns specifically within the one-week to one-month horizon for all examined cryptocurrencies, with the most consistent lead-lag dynamics observed for Bitcoin and Ethereum. This co-movement is statistically significant and time-varying, suggesting that the Fear & Greed Index serves as a reliable short-term leading indicator. Over longer investment horizons (beyond one month), the relationship reverses direction, with cryptocurrency returns—particularly Bitcoin—becoming the dominant driver of sentiment, consistent with behavioral feedback mechanisms.

Complementing this, the VAR impulse response functions demonstrate a clear causal transmission path: a negative return shock in Bitcoin increases market uncertainty (VIX), exacerbates fear (lower Fear & Greed values), and will slow trading activity in the days following after the shock is priced in across the cryptocurrencies. These dynamics suggest behavioral contagion and volatility spillovers channeled through sentiment-driven expectations. Moreover, robustness checks using the DNSI sentiment measure (Shapiro et al., 2020) affirm the consistency of these findings.

Importantly, our results provide insights for investors and portfolio managers. The identified lag between sentiment shifts and market reactions enables short-term predictive positioning and supports the use of cryptocurrencies as tactical hedging tools (Bouri et al., 2020; Qureshi et al., 2020). Specifically, the one-week to one-month window highlighted by both wavelet and VAR approaches represents a functional horizon for managing exposure based on sentiment trends. These results also contribute to the broader discussion on market efficiency, revealing inefficiencies exploitable through sentiment-based strategies.

While our analysis focused on the five largest cryptocurrencies, future research could expand upon our findings by encompassing a broader range of cryptocurrencies, including stablecoins and emerging digital assets. Since the behavior of these cryptocurrencies towards sentiment can differ, it would be interesting to control for their technological characteristic and similarities.

Data availability statement

Data is available on the request.

APPENDIX

Table A1 Descriptive Statistics

Variable	*Obs.*	*Mean*	*SD*	*Skewness*	*Kurtosis*	*Min*	*Mdn*	*Max*	*ADF test*
BTC	1765	21093.00	17038.00	0.94	2.58	3236.80	11788	67567.00	0.44
ETH	1765	1185.40	1217.10	1.06	3.01	84.31	491.66	4812.10	0.36
BNB	1765	165.43	184.93	0.80	2.31	4.53	30.17	675.68	0.37
XRP	1765	0.48	0.29	1.58	5.25	0.14	0.38	1.84	0.08
ADA	1765	0.50	0.64	1.59	4.81	0.02	0.15	2.97	0.20
F&G	1765	42.51	22.42	0.59	2.34	5.00	39.00	95.00	0.00
VIX	1218	21.49	8.48	2.37	13.09	10.85	19.80	82.69	<0.001
ETH vol. log	1765	22.93	0.95	-0.51	2.40	20.67	23.11	25.15	<0.001
BNB vol. log	1765	19.80	1.52	-0.44	3.62	9.14	19.82	23.61	<0.001
XRP vol. log	1765	21.15	0.99	0.21	3.23	18.72	21.14	24.33	<0.001
ADA vol. log	1765	19.60	1.70	0.11	2.07	15.94	19.57	23.68	<0.001
BTC log diff	1764	0.00	0.04	-1.17	19.37	-0.46	0.00	0.17	<0.001
ETH log diff	1764	0.00	0.05	-1.09	14.71	-0.55	0.00	0.23	<0.001
BNB log diff	1764	0.00	0.05	-0.21	20.35	-0.54	0.00	0.53	<0.001
XRP log diff	1764	0.00	0.06	0.06	8.92	-0.55	0.00	0.45	<0.001
ADA log diff	1764	0.00	0.06	-0.25	18.25	-0.50	0.00	0.28	<0.001
F&G log diff	1764	0.00	0.21	0.02	12.78	-1.41	0.00	1.89	<0.001

Notes: Standard tickers represent descriptive statistics for cryptocurrencies before the transformation. Further rows represent time series transformed by logarithmic differences.

Table A2 Variance Inflation Factor (VIF) for Explanatory Variables Across Models

Cryptocurrency	*BTC*	*VIX*	*Fear and Greed Index*	*Volume*
Cardano	1.00	1.10	1.17	1.16
Binance Coin	1.00	1.10	1.09	1.09
Ripple	1.00	1.18	1.43	1.44
Ethereum	1.00	1.23	1.19	1.27

Notes: Multicollinearity Analysis. BTC represents logarithmic differences in Bitcoin prices. VIX represents the Volatility Index. The Fear and Greed Index serves as a proxy for market sentiment. Volume represents the trading volume of the respective cryptocurrency. The results indicate that VIF values for all variables across models are below the commonly accepted threshold of 10.

Table A3 Residual Diagnostics for VAR Models

Model	*Jarque-Bera Test (p-value)*	*Ljung-Box Test (p-value, lag 4)*	*ARCH Test (p-value)*
Cardano	0.000	1.10	0.000
Binance Coin	0.000	1.10	0.000
Ripple	0.000	1.18	0.000
Ethereum	0.000	1.23	0.000

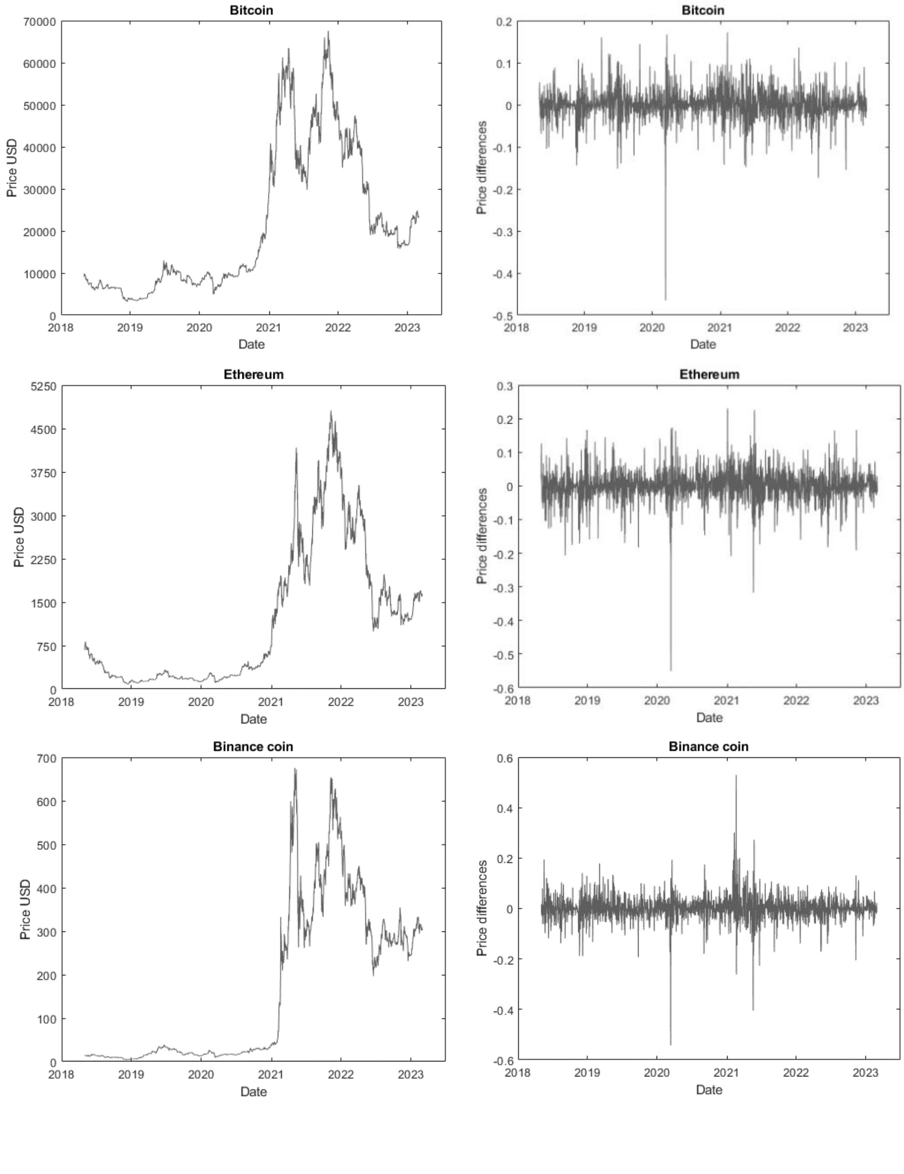
Notes: The table summarizes the results of residual diagnostics for the VAR models. The Jarque-Bera Test assesses the normality of residuals, the Ljung-Box Test checks for autocorrelation up to lag 4, and the ARCH Test examines heteroskedasticity in the residuals. The Jarque-Bera Test strongly rejects normality for all models (p-value = 0.000), a common result in financial time series due to the presence of fat tails and skewness. Despite this, the Ljung-Box Test indicates no serial correlation in the residuals (p-values > 0.05), and heteroskedasticity detected by the ARCH Test is accounted for using GARCH modelling in Table A4.

Table A4 GARCH Model Diagnostics for VAR Residuals

Model	*Log-Likelihood*	*AIC*	*BIC*	*α1 (p-value)*	*β1 (p-value)*	*Ljung-Box Test (p-value, lag 4)*
Cardano	-12404.7	24817.4	24843.6	0.045	0.000	0.951
Binance Coin	-12396.5	24800.9	24827.0	0.044	0.000	0.898
Ripple	-12405.9	24819.9	24846.0	0.042	0.000	0.953
Ethereum	-12403.0	24814.0	24840.1	0.044	0.000	0.948

Notes: The table presents the diagnostic results for GARCH models fitted to the residuals of the VAR models. The Log-Likelihood, AIC, and BIC provide measures of model fit, while α1 and β1 represent the GARCH parameters for volatility clustering. The Ljung-Box Test on the GARCH residuals confirms no significant autocorrelation (p-value > 0.05). The GARCH model captures the conditional heteroskedasticity in the residuals, as indicated by significant α1 and β1 coefficients. The Ljung-Box Test suggests that the residuals from the GARCH models are free from autocorrelation.

Figure A1 Time Domain Representation of the Analyzed Time Series (before and after Adjustment)



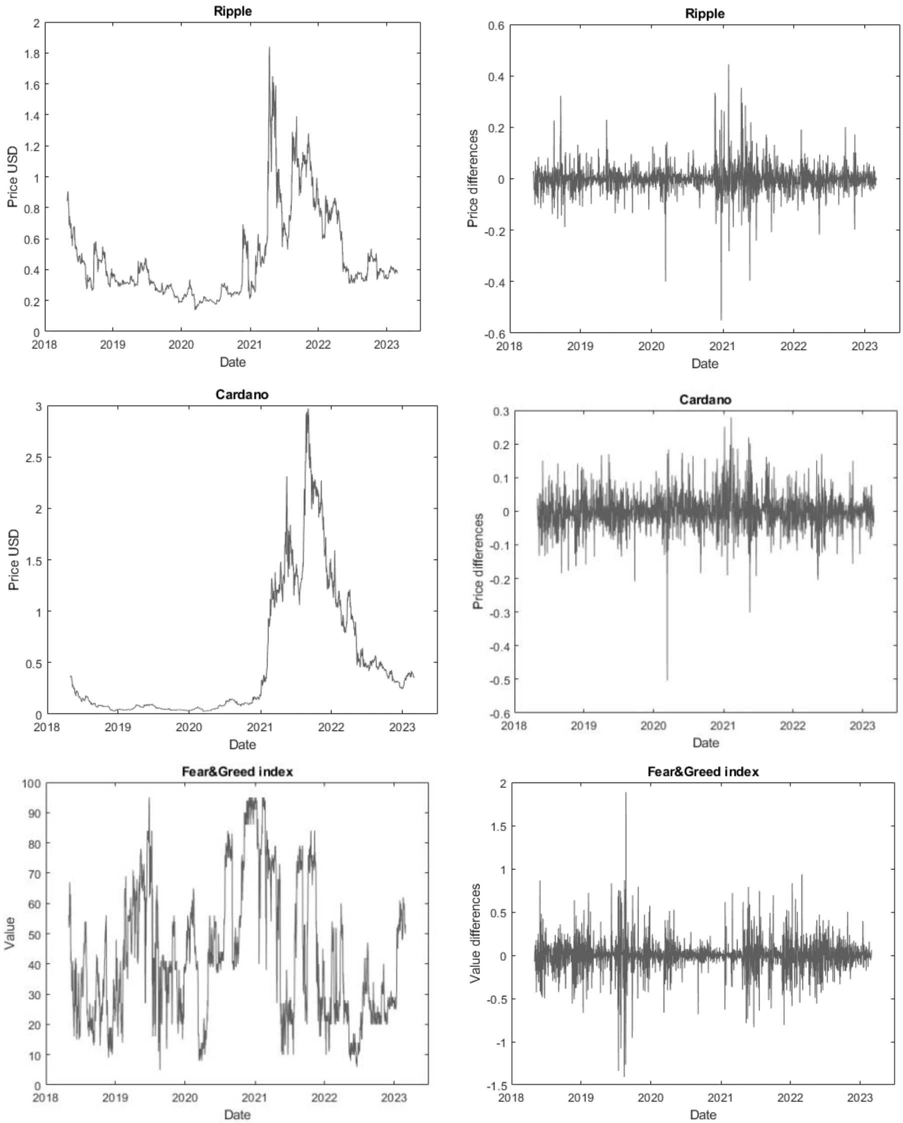
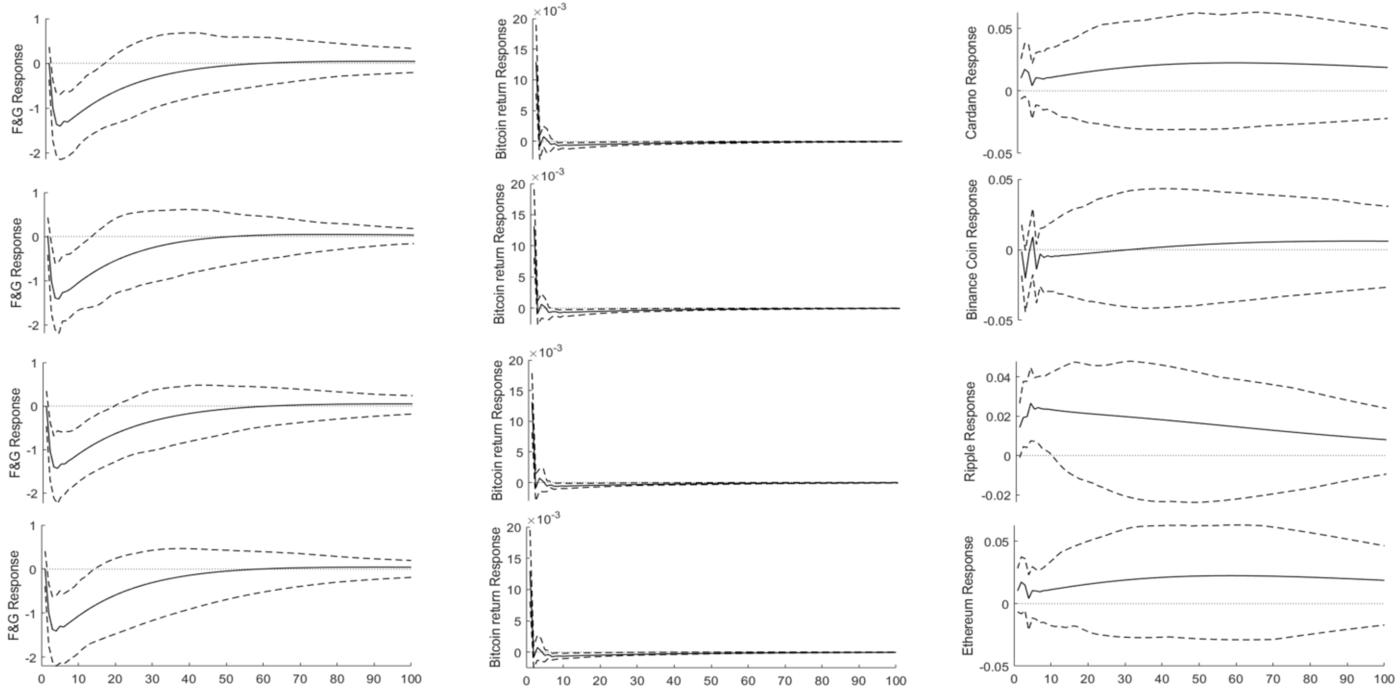
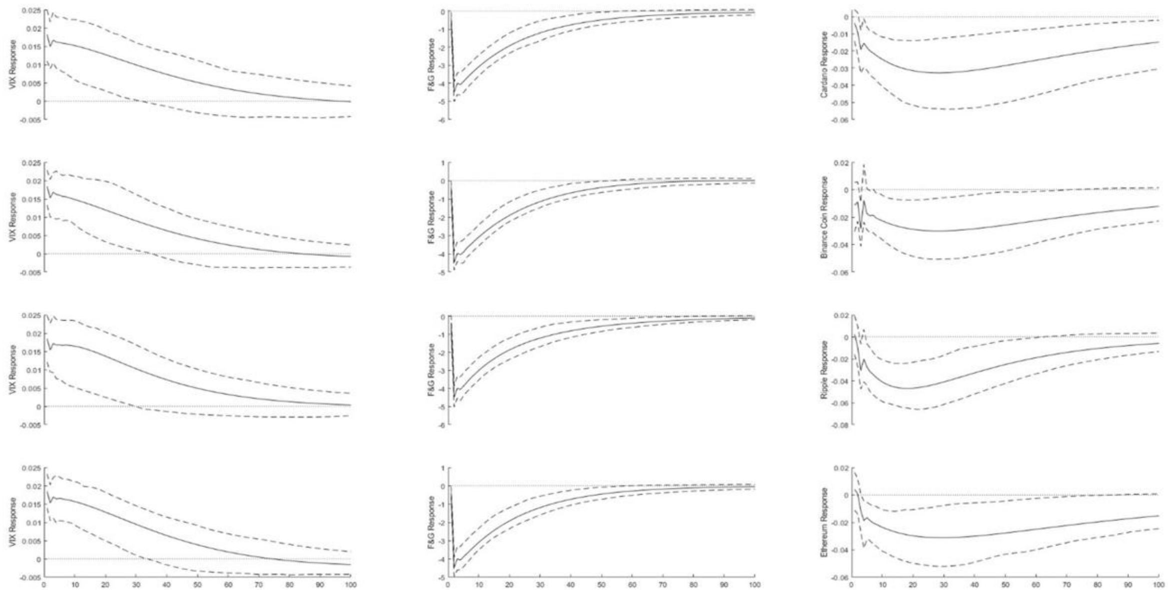

Ripple
Price USD
Date
Ripple
Price differences
Date
Cardano
Price USD
Date
Cardano
Price differences
Date
Fear&Greed index
Value
Date
Fear&Greed index
Value differences
Date

Figure A2 Responses to a Negative Market Movement Shock (Reordered Variables)



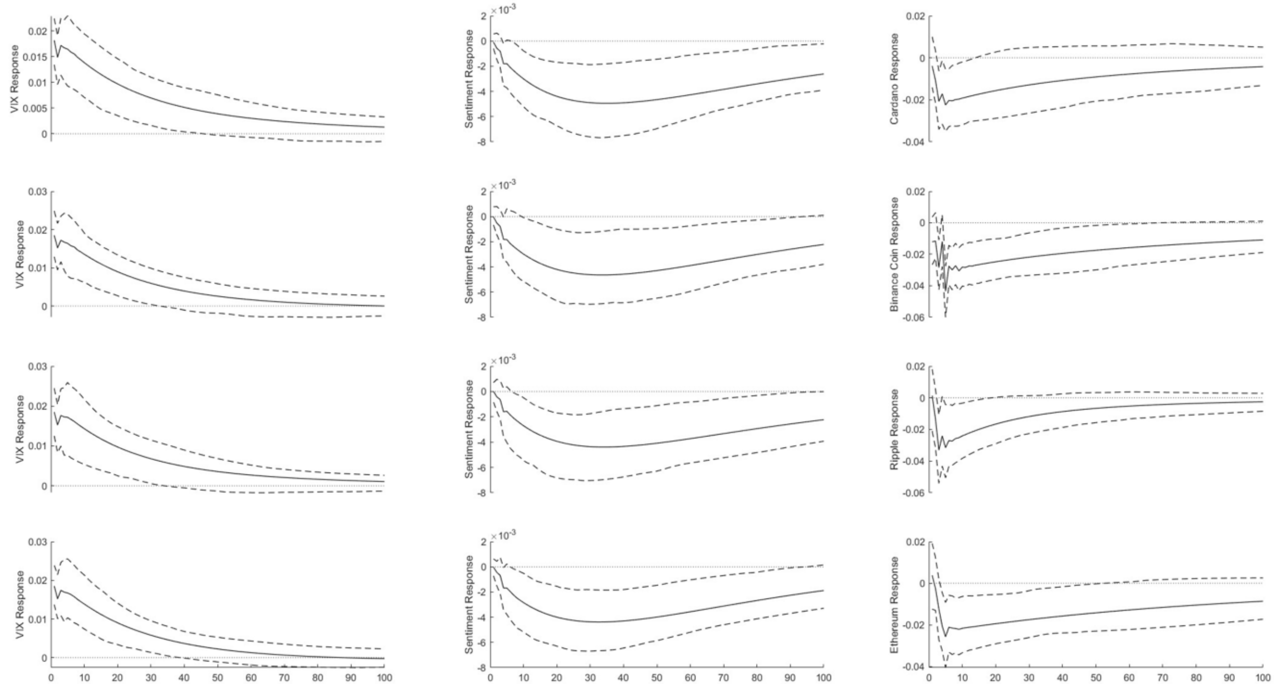
Note: The figure represents the response impulse functions of the reordered variables as Fear and Greed Index (F&G), bitcoin returns, and trading volume of the four largest cryptocurrencies – Cardano, Binance Coin, Ripple, and Ethereum - to a shock of one standard deviation of Volatility Index (VIX). The results are presented using 90% confidence bands, and VAR(4) covers monthly data from May 2018 to February 2023. The y-axis is consistent across all subplots within each row, representing the magnitude of the response, while the x-axis indicates the time horizon.

Figure A3 Responses to a Negative Market Movement Shock (*Alternated* VAR Lengths)



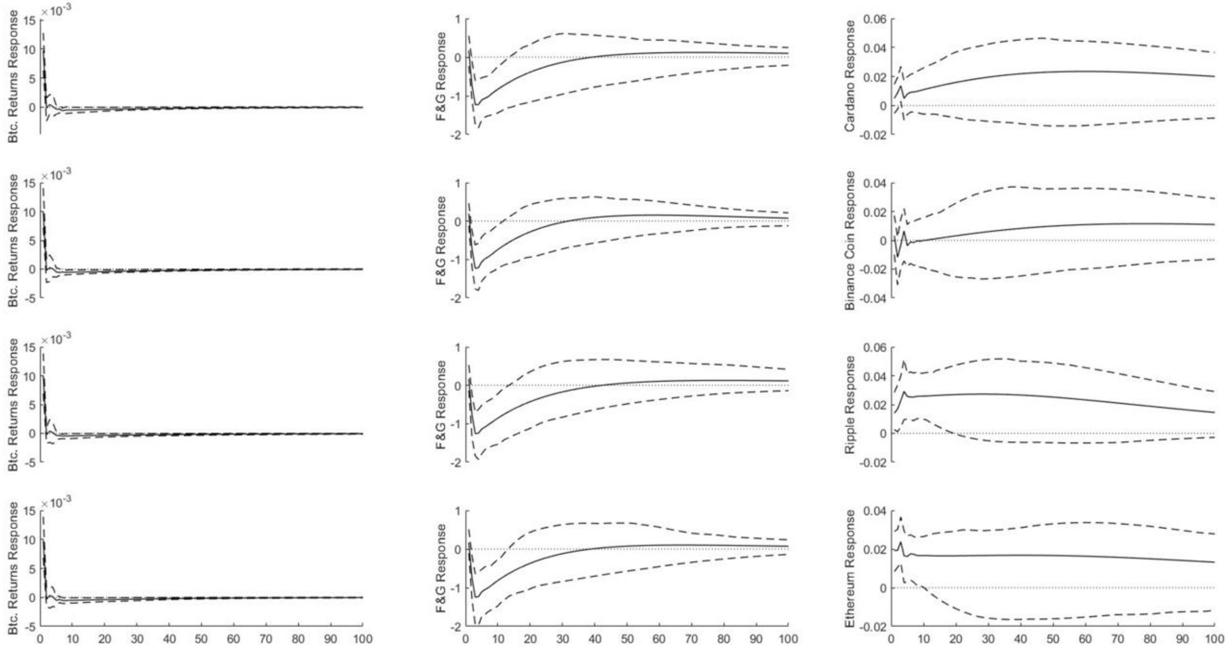
Notes: The figure represents the response impulse functions of the Volatility Index (VIX), Fear and Greed Index (F&G), and trading volume of the four largest cryptocurrencies – Cardano, Binance Coin, Ripple, and Ethereum - to a shock of one standard deviation of bitcoin price returns. The results are presented using 90% confidence bands, and a VAR(3) model covers monthly data from May 2018 to February 2023. The y-axis is consistent across all subplots within each row, representing the magnitude of the response, while the x-axis indicates the time horizon.

Figure A4 Responses to a Negative Market Movement Shock (F&G Index Replaced by Economic News Sentiment Index)



Notes: The figure represents use alternative proxy for investor sentiment and demonstrate the response impulse functions of the Volatility Index (VIX), News Sentiment Index, and trading volume of the four largest cryptocurrencies – Cardano, Binance Coin, Ripple, and Ethereum - to a shock of one standard deviation of Bitcoin price returns. The results are presented using 90% confidence bands, and a VAR(4) model covers monthly data from May 2018 to February 2023. The y-axis is consistent across all subplots within each row, representing the magnitude of the response, while the x-axis indicates the time horizon.

Figure A5 Responses to a Negative Volatility Index (VIX) Shock (Reordered Variables)



Notes: The figure represents the response impulse functions of the Bitcoin price returns, Fear and Greed Index (F&G), and trading volume of the four largest cryptocurrencies – Cardano, Binance Coin, Ripple, and Ethereum - to a shock of one standard deviation of Volatility Index (VIX). The results are presented using 90% confidence bands, and a VAR(4) model covers monthly data from May 2018 to February 2023. The y-axis is consistent across all subplots within each row, representing the magnitude of the response, while the x-axis indicates the time horizon.).

Table A5 Forecast Error Variance Decomposition (FEVD) Results

Cardano	***BTC Returns***	***VIX***	***F&G Index***	***Trading Volume***
Horizon 1	100.00	90.11	99.51	99.84
Horizon 5	99.18	89.23	58.58	98.40
Horizon 10	99.00	89.17	54.43	96.94
Horizon 20	98.77	89.21	52.69	93.68
Horizon 50	98.57	89.27	52.05	85.59

Binance Coin	***BTC Returns***	***VIX***	***F&G Index***	***Trading Volume***
Horizon 1	100.00	89.83	99.60	99.72
Horizon 5	99.43	89.35	58.73	97.21
Horizon 10	99.24	89.20	54.86	95.64
Horizon 20	98.99	89.14	53.49	92.90
Horizon 50	98.78	88.50	53.34	86.90

Ripple	***BTC Returns***	***VIX***	***F&G Index***	***Trading Volume***
Horizon 1	100.00	89.87	99.55	99.73
Horizon 5	99.62	88.64	58.50	97.01
Horizon 10	99.49	88.35	53.97	93.63
Horizon 20	99.31	87.94	51.67	86.77
Horizon 50	99.13	87.35	50.10	74.83

Ethereum	***BTC Returns***	***VIX***	***F&G Index***	***Trading Volume***
Horizon 1	100.00	89.90	99.56	99.05
Horizon 5	99.27	89.15	58.85	96.98
Horizon 10	99.09	88.82	54.65	95.06
Horizon 20	98.86	88.30	52.94	91.67
Horizon 50	98.69	86.44	52.43	84.24

Notes: The table represents the Forecast Error Variance Decomposition (FEVD) results for Bitcoin price returns, Volatility Index (VIX), Fear and Greed Index (F&G), and the trading volume of the four largest cryptocurrencies – Cardano, Binance Coin, Ripple, and Ethereum – following a one-standard-deviation shock to Bitcoin returns. The results are derived from a VAR(4) model using monthly data spanning from May 2018 to February 2023. Each horizon indicates the proportion of variance in the forecast error for each variable attributable to the shocks in the system.

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