Good versus Bad COVOL in Cryptocurrency Markets: A Measure of Asymmetric Common Volatility

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Abstract

Founded on the newly developed measure of common volatility (COVOL) by Engle and Campos-Martins (2023), we propose distinguishing the COVOL of twenty-five cryptocurrencies into “good” and “bad” COVOL, which track the effects of common volatility shocks associated with positive and negative returns, respectively. We find that the difference between good and bad crypto COVOL is statistically and economically significant. Constructing the Relative COVOL Index (RCI) to represent this *asymmetry*, we demonstrate that dynamic RCI-based trading strategies remarkedly improves both portfolio returns and risk management. Further validation tests affirm COVOL’s effectiveness in predicting market volatility and correlations among returns.

JEL Classification Codes: C58, F31, G11, G15

Keywords: Common volatility; COVOL; Asymmetry; Cryptocurrency; Bitcoin; Portfolio optimization

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1. Introduction

The increasing popularity of cryptocurrencies, driven by the desire for decentralised financial systems that are secure and efficient[1], has significantly increased the sector's influence on the global economy. A recent report by CoinGecko revealed that the total cryptocurrency market capitalisation surpassed $3 trillion in November 2021, showcasing its tremendous growth compared to previous years.[2] The cryptocurrency market's growth, securitisation, and breadth have solidified its role in the global economy. With increasing institutional adoption, regulatory clarity, and innovative applications, cryptocurrencies are poised to play a more significant role in shaping the future of finance.

The growing importance of cryptocurrencies in global finance urges risk managers and policymakers to systematically understand which shocks, and to what extent, collectively affect the volatility of the sector. Types of shocks are diverse, ranging from economic, regulatory, geopolitical, societal, and technological. Their intensity and frequency can vary across years and across types. A recent World Economic Forum survey[3] highlighted that the top risks have evolved rapidly in recent years, with the collapse of prominent exchanges like FTX in 2022 and regulatory crackdowns being major events that significantly impacted market stability. In the cryptocurrency sector, shocks such as exchange collapses, regulatory changes, technological vulnerabilities, and macroeconomic shifts have proven to be significant contributors to market volatility. For instance, the implosion of the Terra ecosystem and the subsequent failure of crypto hedge fund Three Arrows Capital in 2022 triggered a series of

[1] https://www.forbes.com/advisor/in/investing/cryptocurrency/advantages-of-cryptocurrency

[2] This impressive growth has attracted a diverse range of investors, from retail to institutional, and has transformed cryptocurrencies into a viable asset class. Moreover, the number of cryptocurrencies has expanded exponentially, with over 10,000 distinct digital assets listed on CoinGecko. This breadth reflects the rapid pace of innovation in the industry, with new projects and decentralized applications continuously being developed to cater to various use cases, from decentralized finance (DeFi) to non-fungible tokens (NFTs). Binance Research highlighted that the DeFi market alone has a total value locked (TVL) exceeding $50 billion, illustrating the sector's potential. Securitization of cryptocurrencies, through the emergence of exchange-traded funds (ETFs) and derivatives, has further legitimized the market.

[3] See https://intelligence.weforum.org/monitor/latest-knowledge/5125d4ef3e3d4e7b9c6c622fe4182f30

cascading effects that led to substantial market corrections. Similarly, the rapid interest rate hikes by the Federal Reserve in response to inflation affected liquidity in the crypto market, leading to widespread asset sell-offs and heightened volatility. Therefore, it is essential for the risk management practice to have a comprehensive measure of risk that systematically captures the collective impacts of all shocks, and further identifying which assets are the most sensitive to these shocks at any given time. Motivated by this need, Engle and Campos-Martins (2023) propose the common volatility measure (COVOL, hereafter) to capture the time-varying collective volatility of all considered assets in the sample. In the context of cryptocurrency market, understanding COVOL could be particularly valuable in identifying systemic events that cause widespread market disruption and in better predicting risk and return.

In this study, we firstly explore the COVOL of the cryptocurrency sector, discern the events that exert the most significant influence over time and examine variations in COVOL across different sub-sectors such as decentralised finance (DeFi), non-fungible tokens (NFTs), and layer-one blockchains. We assess how insights into COVOL can inform better predictions of risk and return for crypto assets. By utilising the COVOL metric,[4] which quantifies the extent to which simultaneous shocks impact all assets within a system, our analysis offers a comprehensive assessment of these shocks' effects. Predicated on the assumption that asset prices integrate all relevant information necessary for forecasting future cash flows, COVOL provides a broader and potentially gauges better overall market dynamics compared to other measures that capture only specific types of shocks, such as economic policy uncertainty or geopolitical risk indices, offering a unique perspective on the interconnected nature of financial markets and their susceptibility to systemic risks.

[4] Engle and Campos-Martins (2023) argue that news-based measures might only represent concerns about potential or past events. In comparative analyses of global equity markets, they found that the COVOL measure provides more valuable information for predicting asset returns than other news-based uncertainty measures.

More importantly, cryptocurrencies are known for their extreme volatility and susceptibility to market sentiment, regulatory news, and macroeconomic factors. These characteristics often lead to asymmetrical reactions in the market, where positive and negative news or events can have disproportionate effects on crypto returns and their dynamics (Gkillas et al., 2022; Naeem et al., 2022; Pham et al., 2022; Suleman et al., 2023). In this regard, we hypothesise that the effects of common volatility shocks driven by negative news might substantially differ from those driven by positive news in the cryptocurrency market. This hypothesis is also motivated by a large strand of literature exploring the good and bad volatility dynamics in financial markets and their role in risk management or forecasting including Patton and Sheppard (2015), Baruník et al. (2016), BenSaïda (2019), Bollerslev et al. (2020), Yu et al., (2022), among others. As the cryptocurrency market is characterised by powerful herding behaviour (Bouri et al., 2019; Choi et al., 2022; Vidal-Tomás et al., 2019; and Papadamou et al., 2021), the asymmetric herding could be a source of asymmetric common volatility of good and bad returns (Park, 2011).

Our paper, therefore, proposes to separate the COVOL of cryptocurrency market into good and bad COVOL to account for asymmetry in COVOL. Good COVOL quantifies the magnitude of positive return shocks shared among cryptocurrencies, suggesting a collective upward trend or a bullish market sentiment. Conversely, bad COVOL captures the extent of negative return shocks, reflecting widespread declines or bearish sentiment. We capture the COVOL's asymmetry information by constructing Relative COVOL Index (RCI, hereafter), defined as the difference between good and bad COVOL. This index represents asymmetric COVOL and serves as a relative strength indicator, providing a dynamic measure of market sentiment and identifying periods when the effects of positive shocks (in terms of magnitude) on market's common volatility outweigh negative ones or vice versa. This insight proves invaluable for dynamic portfolio management, allowing investors to adjust their strategies based on prevailing market conditions and anticipated volatility trends.

To highlight the importance of the asymmetric COVOL measure and its practical implications for investors and policymakers, we further examine the benefits of incorporating asymmetric COVOL information into a dynamic investment strategy when managing cryptocurrency portfolios. By simulating the performance of two hypothetical portfolios—one using a static buy-and-hold approach (i.e., benchmark portfolio) and the other adjusting weight invested in the cryptocurrency market based on the RCI from the asymmetric COVOL model (i.e., RCI-based portfolio)—we demonstrate that the dynamic rebalancing strategy can significantly enhance returns and risk-adjusted performance compared to the static strategy. Specifically, the RCI-based portfolio consistently outperforms the benchmark portfolio in terms of monthly return and both Sharpe and Sortino ratios. Between March 2017 and April 2024, the RCI-based portfolio achieved an accumulated return of 141.98%, compared to 45.58% for the benchmark portfolio, with its Sharpe ratio and Sortino ratio outperforming by 42% and 47%, respectively. These findings underscore the crucial role of incorporating COVOL-based adjustments in investment strategies, allowing investors to optimise their portfolios by mitigating risks associated with common market volatility. For investors, this emphasises the necessity of active portfolio management in the volatile cryptocurrency market, while for policymakers, it reinforces the need for frameworks that support sophisticated risk management practices.

Our study makes two main contributions to the literature. First, our study advances the asset pricing literature by demonstrating the explanatory power of COVOL in predicting the risk and correlation of cryptocurrencies. This aligns with Engle and Campos-Martins' (2023) findings on global equity markets and underscores the importance of COVOL in understanding systemic risk within the cryptocurrency sector. By illustrating that COVOL effectively captures the co-movement of cryptocurrency returns and their shared volatility, our analyses validate the use of COVOL as an essential tool for financial analysts and researchers in assessing the broader implications of market-wide volatility on cryptocurrency-related portfolios.

Second, we introduce an innovative framework for distinguishing between good and bad COVOL, accompanied by the development of the Relative Common Volatility Index (RCI). This framework considers individual cryptocurrencies' exposure to these distinct volatility types, identifying which are most vulnerable to positive and negative market shocks. Such insights enrich the financial literature that distinguishes the impacts of good and bad volatility on market price dynamics (e.g., Patton and Sheppard, 2015; Baruník et al., 2016; BenSaïda, 2019; Bollerslev et al., 2020). Moreover, the RCI, as a gauge of the relative strength of good versus bad volatility, proves essential for dynamic portfolio management. It empowers investors to make well-informed decisions and strategically manage risk, particularly during periods of significant market volatility. Our work adds to the evolving body of research that indexes risk exposures in the cryptocurrency market, contributing novel insights alongside studies by Wang (2022), Wang et al. (2022a, 2022b), and Lucey et al. (2022).

The remainder of this paper is structured as follows. Section 2 provides a brief literature review. Section 3 presents the modelling framework used to estimate COVOL in the cryptocurrency sector as well as methodology to construct the RCI measure to capture the asymmetric COVOL. Section 4 details the data and discusses the estimation results of COVOL. Section 5 explores COVOL and asymmetric COVOL dynamics. Section 6 illustrates the portfolio implications which compare the portfolio management and risk management effectiveness between the buy-and-hold strategy (benchmark) and the RCI-based trading strategies. Section 7 concludes the paper with implications to investors, risk managers and policy makers.

2. Literature review

The literature on the cryptocurrency market can be broadly categorised into three strands: (1) trading characteristics, including return, volatility, and liquidity; (2) market efficiency and investor trading behaviour; and (3) the relationship between the cryptocurrency market and other markets, providing hedging and portfolio diversification implications.

The first strand of literature focuses on the trading characteristics of cryptocurrencies, particularly their return, volatility, and liquidity dynamics. Cryptocurrencies typically yield higher average daily returns than traditional assets (Lee et al., 2018; Trimborn et al., 2020; Petukhina et al., 2021). Given the superior return, several studies explored the predictability of cryptocurrency market returns, pointing out several determinants of cryptocurrency pricing including technical patterns (Bianchi et al., 2022), cross-cryptocurrency return (Guo et al., 2024); trading volume (Bouri et al., 2019), and speculative activities (Koutmos and Payne, 2021). In addition to superior returns, the cryptocurrency market is characterised by high volatility, which is determined by several factors including trading volume, global uncertainties, Google search volumes, and stock market returns (Bouri et al., 2021; Wang et al., 2023b). Moreover, numerous papers examine the volatility connectedness across cryptocurrencies and document significant spillover effects (Yi et al., 2018; Ji et al., 2019a; Bouri et al., 2021). Liquidity is another aspect of the cryptocurrency market that attracts the attention of researchers (Amihud, 2002; Brauneis et al., 2021; Zhang and Li, 2021; Bianchi et al., 2022).

The second strand of literature delves into market efficiency and investor trading behaviour. Specifically, a number of papers document the inefficiencies amid cryptocurrency market, indicated by abnormal returns (Gregoriou, 2019), directional predictability (Fousekis and Grigoriadis, 2021), among others. On the other hand, the existing literature argues that factors such as herding behaviour driven by social media (King and Koutmos, 2021), social influence and financial literacy (Gupta et al., 2021; Nadler and Guo, 2020), and the status of market development (Petukhina et al., 2021; Vidal-Tomás, 2021).

The final strand investigates the relationship between the cryptocurrency market and other markets, focusing on their connectedness, hedging, and diversification benefits. To illustrate, recent research suggests that the connectedness between Bitcoin and traditional assets is weak (Zeng et al., 2020), along with significant spillover effects (Andrada-Félix et al., 2020). Subsequently, an increasing number of studies argue that cryptocurrencies can offer hedging abilities against downside risks in stock market (Bouri et al., 2020a), which is superior to gold and commodities (Bouri et al., 2020b), and this effect is also robust during turbulent market (Corbet et al., 2020; Koutmos et al., 2021; Mariana et al., 2021). The diversification benefits of cryptocurrencies are also highlighted in numerous studies when they are combined with other asset classes such as equity (Demiralay and Bayraci, 2021; Anyfantaki et al., 2021; Petukhina et al., 2021), energy commodities (Ji et al, 2019b; Okorie and Lin, 2020; Pham et al., 2022), and gold (Kumah et al., 2022). Moreover, different sub-sectors of cryptocurrency market can also improve the portfolios' risk-adjusted returns (Huang et al., 2023).

Despite the extensive research on the cryptocurrency market, crucial questions about its volatility remain unanswered. One fundamental aspect that remains unclear is whether there exists a common volatility factor influencing all cryptocurrencies across the market. Identifying this factor is vital for understanding systemic risks and market dynamics impacting these digital assets collectively. Moreover, it is crucial to rigorously investigate the drivers behind this common volatility. Specifically, to what extent do macroeconomic factors, investor sentiment, market regulations, or global financial risks contribute to these dynamics? Additionally, comprehending how different cryptocurrencies vary in their exposure to this common volatility factor is essential. Gaining insights into the vulnerability of specific cryptocurrencies to sector-wide shocks is vital for investors managing risk and for policymakers striving to stabilise the market. Such an analysis will deepen the understanding of financial behaviours within crypto markets and aid in formulating more robust financial and regulatory strategies tailored to their unique characteristics.

3. Methodology

3.1. COVOL measure

Let (r_t) be the vector of cryptocurrency excess daily returns $r_t = \left(r_{1,t}, \dots, r_{N,t}\right)^{'}$, where ($r_{i,t} = \tilde{r}_{i,t} - r_{f,t}$). Here, $\tilde{r}_{i,t}$ is the observed return, and $r_{f,t}$ is the risk-free return for $i = 1, \dots, N$ and $N = 25$. The risk-free rate benchmark is the yields on the U.S. one-year Treasury notes. Daily risk-free rate is calculated dividing annualised risk-free rate by 360.

The first step in calculating common volatility involves a factor model with GARCH(1,1) errors for each series of excess returns $r_{i,t}$ as follows:

$$r_{i,t} = c_i + \delta_i r_{i,t-1} + \beta_i^{'} f_t + u_{i,t} \tag{1}$$

$$u_{i,t} = \sqrt{h}_{i,t} e_{i,t} \tag{2}$$

$$h_{i,t} = \omega_t + \alpha_{i,t} u_{i,t-1}^2 + \beta_{i,t} h_{i,t-1} \tag{3}$$

where i, t denotes a specific cryptocurrency and time, respectively. $c_i, \delta_i, \beta_i^{'}, \omega_t, \alpha_{i,t}, \beta_{i,t}$ are parameters to be estimated from the GARCH(1,1) model and we have $\left(|\delta_i| < 1;\ \omega_t > 0;\ \alpha_{i,t} > 0;\ \beta_{i,t} \geq 0;\ \alpha_{i,t} + \beta_{i,t} < 1\right)$. f_t is a factor vector that includes the first principal component of cryptocurrencies' excess return series.

From the estimation of GARCH(1,1) model for cryptocurrencies' excess returns, we get the vector of standardised residuals $e_t = \left(e_{1,t}, \dots, e_{N,t}\right)^{'}$. According to Engle and Campos-Martins (2023), even though the standardised residuals have unit variance and zero covariance, their squared term or absolute values are likely to be correlated in the cross-section.

Therefore, the comovement of volatilities is most likely caused by the positive correlation between shocks to those volatilities, since volatility is partly predictable. Assume that the variance shock to cryptocurrency i is:

$$\varphi_{i,t}^{\sigma} \equiv \frac{u_{i,t}^2 - h_{i,t}}{h_{i,t}} = e_{i,t}^2 - 1 \tag{4}$$

where $\varphi_{i,t}^{\sigma}$ is the proportional difference between the squared idiosyncrasy $e_{i,t}^2$ and its expectation 1. If many cryptocurrencies have larger squared idiosyncrasies than usual at the same time, this can be viewed as a common volatility shock to the entire cryptocurrency market. Let x_t^{σ} be the variance (latent) factor that captures the common volatility (COVOL) in the cryptocurrency market and $x_t^{\sigma} > 0; E[x_t^{\sigma}] = 1$.

To test whether the common volatility (x_t^{σ}) of the cryptocurrency market exist, we conduct the following test proposed in Engle and Campos-Martins (2023). Let ρ_{e^2} be the equicorrelation of the squared standardised residuals. The test-statistics for the existence of common volatility among the selected cryptocurrencies is given as follows:

$$T_{e^2} = \frac{\sqrt{\frac{NT}{(N-1)/2}}\sum_{i>j,j=1}^{N}\sum_{t=1}^{T}(e_{i,t}^2 - 1)(e_{j,t}^2 - 1)}{\sum_{i=1}^{N}\sum_{t=1}^{T}(e_{i,t}^2 - 1)^2} \tag{5}$$

T_{e^2} follows a normal distribution under the null hypothesis of no common volatility within the cryptocurrency market or $\rho_{e^2} = 0$.

If we reject the null hypothesis of the test shown in Eq. (5), Engle and Campos-Martins (2023) suggest that we can represent standardised residuals under the following specification:

$$e_{i,t} = \sqrt{g(s_i, x_t^{\sigma})}\epsilon_{i,t} \tag{6}$$

$$g(s_i, x_t^{\sigma}) = s_i(x_t^{\sigma} - 1) + 1 \tag{7}$$

where $\epsilon_{i,t}$ is independently and identically normally distributed with zero mean and unit variance, $\epsilon_{i,t} \sim IIN(0,1)$ with $i = 1, \dots, N$. Moreover, vector $\epsilon_t = (\epsilon_{i,t}, \dots, \epsilon_{N,t})'$ is independent of x_t^σ. In Eq. (7), s_i is the factor loading for cryptocurrency i. The estimation of x_t^σ and s_i is conducted using maximum likelihood method. x_t^σ indicates the time-varying common volatility or COVOL of the cryptocurrency market and s_i represents the sensitivity of cryptocurrency i to COVOL of the cryptocurrency market. The higher the value of s_i, the more susceptible cryptocurrency i is to systematic risk within the crypto market.

3.2. Good and bad COVOL and the Relative Common Volatility Index (RCI)

To capture the "good" and "bad" COVOL of the cryptocurrency market, we decompose the return series of each cryptocurrency ($\tilde{r}_{i,t}$) into positive and negative components, denoted as $\tilde{r}_{i,t}^{+}$ and $\tilde{r}_{i,t}^{-}$, respectively. $\tilde{r}_{i,t}^{+}$ and $\tilde{r}_{i,t}^{-}$ are defined as follows,

$$\tilde{r}_{i,t}^{+} = \begin{cases} \tilde{r}_{i,t} \; if \; \tilde{r}_{i,t} > 0 \\ 0 \; otherwise \end{cases} \tag{8}$$

$$\tilde{r}_{i,t}^{-} = \begin{cases} \tilde{r}_{i,t} \; if \; \tilde{r}_{i,t} \leq 0 \\ 0 \; otherwise \end{cases} \tag{9}$$

The positive and negative return series of cryptocurrencies are then processed following the similar steps as described in subsection 3.1 to estimate the good COVOL ($\hat{x}_t^{\sigma,+}$) and bad COVOL ($\hat{x}_t^{\sigma,-}$) and their corresponding factor loadings ($\hat{s}_i^{+}$ and $\hat{s}_i^{-}$). Under this approach, the good COVOL measures the common volatility driven by the positive return shocks among the selected cryptocurrencies. By contrast, the bad COVOL quantify common volatility due to the negative return shocks that affect the cryptocurrencies. Therefore, the difference between good COVOL and bad COVOL ($\hat{x}_t^{\sigma,+} - \hat{x}_t^{\sigma,-}$) can be interpreted as a relative strength index for the cryptocurrency market. When the good COVOL is greater than the bad COVOL, it suggests that a unit of positive return shock has a larger impact on market's COVOL in terms of magnitude compared to that of a negative shock, which could indicate bullish market sentiment. Conversely, when the bad COVOL exceeds the good COVOL, it implies that the market's COVOL is affected by negative shocks to a larger extent, pointing towards bearish market sentiment. This difference can thus serve as a useful indicator for traders and investors to gauge the overall health and direction of the cryptocurrency market.

To implement this concept, we define the relative COVOL index (d_t) as follows:

$$d_t = \hat{x}_t^{\sigma,+} - \hat{x}_t^{\sigma,-} \tag{10}$$

A positive d_t would suggest a favourable market condition with predominant positive shocks, while a negative d_t would indicate unfavourable conditions with predominant negative shocks. We employ a 20-day moving average of d_t to smooth short-term fluctuations and highlight the underlying trend.[5] Specifically, the 20-day moving average ($dma_{20,t}$) of the d_t is calculated as follows:

$$dma_{20,t} = \frac{1}{20}\sum_{k=0}^{19} d_{t-k} \tag{11}$$

Finally, normalization is conducted to rescale the $dma_{20,t}$ to a common range, typically between 0 and 100, to make it easier to interpret and compare across different time periods. The normalisation, which leads to the relative volatility commonality index of the crypto market (RCI_t) can be performed using the following formula:

$$RCI_t = 100 \times \frac{dma_{20,t} - \min(dma_{20,t})}{\max(dma_{20,t}) - \min(dma_{20,t})} \tag{12}$$

Values of RCI_t around 50 indicate that the $dma_{20,t}$ is at a midpoint relative to its historical range, suggesting a balanced sentiment where neither positive nor negative return

[5] A window size of 20 days is suggested by Engle and Campos-Martins (2023).

shocks are dominant. If the RCI_t is above 50, it generally signifies that positive shocks are more prevalent than negative shocks, hinting at a bullish trend and potential opportunities for long positions. On the other hand, if the RCI_t is below 50, it suggests that negative shocks are more prevalent, indicating a bearish trend and potential opportunities for short positions or risk reduction strategies.

Notably, when the RCI_t is close to 100, it indicates that the $dma_{20,t}$ is near its historical maximum, suggesting a strong predominance of positive return shocks in the cryptocurrency market, indicative of a climax of herding behaviour and a bubble environment. Conversely, when the RCI_t is close to 0, it implies that the $dma_{20,t}$ is near its historical minimum, indicating a strong predominance of negative return shocks, reflective of widespread panic selling and a potentially buying opportunity.[6]

4. Data

To estimate the COVOL of the cryptocurrency market, we collect daily price series of 25 largest cryptocurrencies based on their market capitalisation as of 10th April 2024 from the website coingecko.com. Coingecko.com is trusted source of cryptocurrency prices, volumes and market capitalisation that aggregates information from over 400 major cryptocurrency exchanges (Han et al., 2023). In addition, we exclude stable coins from the sample as their values are mostly anchored to fiat currencies and hardly fluctuate. The sample period is set from 25 January 2015 to 23 April 2024, covering significant events in global financial markets including the cryptocurrency market. The start date is chosen to ensure our sample has at least two cryptocurrencies at a point of time. As cryptocurrencies have different launching dates, our sample is an uneven panel data of 25 cryptocurrencies and each cryptocurrency has at least one year of price history. The list of the cryptocurrencies and their respective ticker,

[6] Please see Appendix 3A for a graphical display of the thresholds of the RCI.

description, and market capitalisation in the sample is shown in Appendix A1. As shown in Appendix 1, Bitcoin (BTC) and Ethereum (ETH) are the two largest cryptocurrencies with dominant market capitalisation compared to others.

From the daily price series, we compute the daily logarithmic return for each cryptocurrency. Then excess returns ($r_{i,t}$) are calculated by taking the difference between daily returns of cryptocurrencies and daily risk-free interest rate (r_f), proxied by the yields of the U.S. 1-year Treasury notes. Data on the yields of U.S. 1-year Treasury notes is sourced from the website of St. Louis Fed.[7]

Descriptive statistics of excess returns are shown in Table 1. First, it is noticeable that all cryptocurrencies have positive mean excess returns for the sample period. This indicates that investing in these cryptocurrencies generally provided positive returns during this time frame. Second, the maximum and minimum values give insight into the wild volatility of cryptocurrency investing. The maximum and/or minimum excess returns exceed 10% for most cryptocurrencies, except Toncoin (TON). Notably, Stacks (STX) stands out with the highest maximum return of 144.91% and the lowest minimum return of -60.32%, demonstrating extreme fluctuations.

The standard deviation further quantifies the volatility of the cryptocurrencies' excess returns. It is notable that the standard deviation of the largest cryptocurrencies, including Bitcoin (BTC), Ethereum (ETH), and Binance Coin (BNB), is relatively low compared to other cryptocurrencies. One possible explanation is that these are more established cryptocurrencies, offering greater stability because of their widespread adoption and market size. The skewness values reveal the asymmetry of the return distributions, with Dogecoin (DOGE) having the highest skewness (4.72), indicating the prevalence of extreme positive price movements. Similarly, DOGE shows the highest kurtosis (97.06), reflecting sporadic yet significant spikes.

[7] See https://fred.stlouisfed.org/series/DGS1

In addition, Table 1 includes diagnostic tests. The Jarque-Bera (JB) statistics indicate that all cryptocurrencies significantly reject the null hypothesis of a normal distribution. The Augmented Dickey-Fuller (ADF) tests confirm stationarity for all cryptocurrencies, and the Ljung-Box Q and Q^2 tests reveal significant autocorrelation in returns and squared returns.

[Please insert Table 1 about here]

5. Empirical results

5.1. COVOL estimation and extreme values

To assess the common volatility of the cryptocurrency market, we apply the GARCH(1,1) model outlined in Eqs. (1), (2), and (3) to each series of excess returns. In Eq. (1), the factor model regresses excess returns against the first principal component, as described in Section 3. Each factor model incorporates a lagged dependent variable to capture the temporal dependence evident in the first moment. Given the significant presence of ARCH effects, a GARCH(1,1) model is employed to model the second moment. The average correlation of the standardised residuals from the factor models is -0.059, indicating a slight negative relationship. For detailed test statistics and p-values from the AR(1) and ARCH(1) tests of individual cryptocurrencies, refer to Appendix A2.

To be concise, we only present the average standardised residuals and volatilities across all cryptocurrencies in the study. Figure 1a displays the daily cross-sectional mean standardised residuals, derived by averaging standardised residuals across individual cryptocurrencies. Figure 1b shows the cross-sectional mean cryptocurrency conditional volatilities, calculated as the square root of the cross-sectional mean variance from the GARCH(1,1) model. For comparison, we also plot the conditional volatility of the returns of the S&P 500 index, the WTI crude oil futures, and the gold futures, obtained from applying a GARCH(1,1) model to these variables. As shown in the figure, there are significant discrepancies in the pattern of volatility between the cryptocurrency market and other traditional asset classes. The correlations between the cross-sectional mean cryptocurrency conditional volatility and those of the SP 500 Index, WTI oil futures, and gold are -0.07, -0.04, and 0.01, respectively. These low correlations emphasise the unique volatility characteristics of the cryptocurrency market, underlining the necessity of a distinct metric for measuring its common volatility.

[Please insert Figures 1 and 2 in here]

After estimating the factor pricing models, we retain the standardised volatility residuals from the GARCH(1,1) model for each major cryptocurrency. Prior to estimating the market's common volatility, we test the null hypothesis of no common variance shocks, as detailed in Eq. (5). For this sample, the correlation of the squared standardised residuals is $\rho_{e^2} = 0.043$ with the test statistic of $T_{e^2} = 20.67$ and a p-value of 0. This leads to a strong rejection of the null hypothesis, allowing us to proceed with estimating the common volatility of the cryptocurrency market using the standardised residuals.

As the test statistics indicate the existence of COVOL, we proceed to estimate COVOL (x_t^σ) of the cryptocurrency market and factor loadings (s_i) of individual cryptocurrencies using the process outlined in section 3. Following Campos-Martins and Hendry (2024), 15 iterations were used in the logarithm to compute x_t^σ and s_i. In addition, to evaluate the goodness-of-fit of the model, we calculate the test statistic in Eq. (5) using $\hat{\epsilon}_{i,t}^2 = \frac{\hat{e}_{i,t}^2}{g(\hat{s}_i, \hat{x}_t^\sigma)}$. The realised correlation $\hat{\rho}_{e^2} = 0.0013$ and the test statistic is $\hat{T}_{e^2} = 0.635$, with a p-value of 0.2627. The test results indicate that the squared standardised residuals become uncorrelated after removing the common volatility, which lends support to the decomposition method in Eqs. (6) and (7). This also implies that the estimated common volatility (x_t^σ) can capture the volatility co-movement in the cryptocurrency market.

The largest estimates of common volatility (COVOL) in the cryptocurrency market shown in the Panel A of Table 2. For comparative analysis, we also present the returns on the S&P 500 index, WTI crude oil futures, and spot gold corresponding to the dates of the highest cryptocurrency COVOL values. The results in Panel A reveal several interesting patterns when examined in detail. First, the highest COVOL value, 52.06, recorded on March 2, 2015, occurred in the wake of a substantial $75 million investment in Coinbase and a significant leadership change at JP Morgan. These developments fostered optimism and rapid growth in the cryptocurrency market, driving widespread speculation and leading to heightened volatility. Subsequent high values, such as those seen after the DAO hack recovery (September 15, 2016) and the 2021 cryptocurrency bubble (January 28, 2021), show that security incidents and speculative bubbles significantly increase market volatility. To conclude, the COVOL values illustrate that while global economic markets remained relatively stable, cryptocurrencies are uniquely impacted by sector-specific events.

A notable exception is the COVID-19 pandemic. On March 12, 2020, cryptocurrency COVOL reached 29.06 amidst a broader financial market meltdown, with the S&P 500 index plunging by 10%, WTI by 4.6%, and gold by 3.6%. This event highlighted how cryptocurrency volatility aligns with global financial instability during extreme circumstances. Moreover, categorising these events shows the susceptibility of the cryptocurrency market to regulatory actions, speculative bubbles, and legal rulings. For instance, the COVOL peak on July 13, 2023, followed Ripple XRP's legal victory, exemplifying how court decisions shape investor confidence and subsequent market movements. Similarly, SEC's rejection of the first Bitcoin ETF and New York State's regulatory approvals reflected significant impacts, proving the sensitivity of cryptocurrencies to government policies.

In Panel B of Table 2, the factor loadings offer a granular view of the market's risk profile. Focuses on the largest cryptocurrencies reveal key insights into their varying degrees of sensitivity to market-wide volatility. Bitcoin (BTC) and Ethereum (ETH), the most prominent cryptocurrencies by market capitalisation, have factor loadings of 0.2311 and 0.2145, respectively, suggesting moderate sensitivity to market-wide shocks. These values of factor loadings illustrate that while these cryptocurrencies are not immune to common volatility, their larger size and greater adoption provide a degree of stability compared to those of smaller coins. To illustrate, Bitcoin, often considered a "digital gold," has a broad investor base and is increasingly used as a store of value. Its factor loading reflects significant exposure to systemic risk but is cushioned by strong institutional investment and the relatively mature nature of its market.

Ethereum, with its slightly lower factor loading, presents a similar but nuanced picture. As a platform that supports decentralised applications and smart contracts, Ethereum is integral to the broader blockchain ecosystem. Its exposure to market-wide volatility is partially mitigated by its utility and strong developer community. However, recent technological upgrades like Ethereum 2.0 and increased competition from other layer-1 blockchains suggest that Ethereum remains susceptible to rapid sentiment shifts.

Other leading cryptocurrencies like Litecoin (LTC) and Bitcoin Cash (BCH) have factor loadings of 0.2268 and 0.2503, respectively, indicating higher sensitivity to common volatility. Their susceptibility could be linked to their positioning as Bitcoin derivatives, making them inherently more volatile. Ripple (XRP), with a factor loading of 0.2885, stands out due to its distinct legal troubles and regulatory scrutiny.[8] Its high exposure demonstrates the heightened risks that legal challenges can introduce. Cryptocurrencies like XRP, DOGE, and SHIB, with the highest loadings (0.2885, 0.2792, and 0.2653 respectively), show extreme sensitivity to market-wide volatility. This may be due to their speculative nature and high social

[8] In 2020, the U.S. SEC accused Ripple of selling its cryptocurrency in an unregistered security offering. The lawsuit could change the regulatory outlook of the cryptocurrency industry. The SEC and Ripple are appealing the court outcome over remedies for the dispute. See https://www.nasdaq.com/articles/xrp-news-today:-ripples-latest-market-report-amidst-sec-lawsuit-tensions for details.

media exposure, which amplifies volatility shocks.[9] In contrast, TON and MNT, with loadings of 0.0856 and 0.0822 respectively, exhibit greater stability, possibly due to their diversification strategies or market positions that shield them from sector-wide shocks.

The implications of these results are significant for investors and policymakers. High loading assets may offer rapid gains but require vigilant risk management. On the other hand, lower loading cryptocurrencies provide more stability, serving as a hedging tool against volatility. Investors should be aware of these patterns to balance potential rewards against systemic risks. Policymakers, in understanding these dynamics, can better anticipate market reactions to regulatory changes and develop frameworks that promote stability while allowing for growth in this rapidly evolving sector.

[Please insert Table 2 in here]

Figure 2 displays the time-varying common volatility (COVOL) of the cryptocurrency market, with its 20-day moving average presented alongside individual daily COVOL values. It is apparent that COVOL experiences substantial fluctuations over time, ranging from minimal values close to zero up to extreme spikes nearing 60. This variation underscores the volatile nature of COVOL in the cryptocurrency market, highlighting its sensitivity to changes in macroeconomic conditions, regulatory shifts, or significant developments within the sector. The graph reveals several major spikes in COVOL that can often be traced back to pivotal global economic or financial events. For example, the pronounced surge in early 2020 coincides with the onset of the COVID-19 pandemic, which introduced unprecedented volatility across financial markets, including the cryptocurrency sector. This event drastically influences market dynamics, correlating with sharp increases in COVOL as investors

[9] As explained above, the high factor loading of XRP is due to the uncertainty in its legal disputes with the SEC. DOGE and SHIB are two popular meme coins, cryptocurrencies originated from Internet memes or trends, and are typically characterized by their high volatilities.

responded to the uncertainty and rapid changes in market conditions. This finding corroborates with previous findings of extreme market movements during the COVID-19 financial crisis (for example, Engle and Campos-Martins, 2023; Pham et al., 2023; Yousaf et al., 2023; Yousaf et al., 2024).

The moving average line smoothed these fluctuations, providing a clearer view of the underlying trends in market volatility over time. This smoothed line helps to identify periods of relatively stable volatility as well as those of heightened uncertainty, which are critical for understanding the market's reaction to external shocks or internal developments. Additionally, the high values of COVOL during specific periods may reflect reactions to regulatory announcements, significant changes in cryptocurrency adoption rates, or macroeconomic adjustments. Each spike in COVOL represents a period where the collective market is significantly more susceptible to external shocks, indicating higher risk for investors during these times. Table 2 presents the dates with the highest COVOL and the events around those dates.

[Please insert Figure 2 in here]

Overall, a visual inspection of COVOL in the cryptocurrency market not only enhances our understanding of cryptocurrency market behaviour but also assists investors and policymakers in making informed decisions by pinpointing periods of high vulnerability and potential market instability.

5.2. Validation tests

In this subsection, we follow Engle and Campos-Martins (2023) and conduct two validation tests to check the validity of our COVOL measure for the cryptocurrency market. First, we examine if our COVOL measures help explain the volatility of the broad cryptocurrency market. We employ the S&P Cryptocurrency Broad Digital Market Index (BMD) to proxy the cryptocurrency market. The BMD index is one of the most comprehensive indices for the cryptocurrency market, covering the fluctuations of 276 digital assets including all cryptocurrencies in our sample.[10] In line with Engle and Campos-Martins (2023), we take the BMD squared standardised residuals (average over the calendar month) derived from the GARCH(1,1) model and denote them by $\vartheta_m^{BMD} = (e_m^{BMD})^2 - 1$. We then regress this realised cryptocurrency market volatility measure on different risk measures including i) the realised cryptocurrency market common volatility ($COVOL_m^2$), ii) the monthly change in the Global Economic Policy Uncertainty Index (Δ_m^{GEPU}), iii) the monthly change in the implied volatility of the US stock market measured by VIX (Δ_m^{VIX}), and iv) the monthly change in the global geopolitical risk index by Caldara and Iacoviello (2022) (Δ_m^{GOPRX}). As the purpose of our COVOL measure is to quantify the common volatility of the cryptocurrency market, we expect it to be positively affect the volatility of the broad cryptocurrency market, proxied by ϑ_m^{BMD}.

Continuing from the setup of the first validation test of the COVOL measure for the cryptocurrency market, the regression results from Table 3 Panel A provide significant comprehension. In Column (1) of the table, the coefficient for the squared common volatility measure ($COVOL_m^2$) is 0.42 with a standard error of 0.17, indicating a statistically significant positive relationship at the 5% level between the common volatility in the cryptocurrency market and the market volatility measured by ϑ_m^{BMD}. This result supports our hypothesis that higher common volatility within the cryptocurrency market contributes to greater overall market volatility. Further, the monthly changes in the Global Economic Policy Uncertainty Index and the implied volatility of the US stock market measured by VIX (Δ_m^{VIX}) also exhibit interesting relationships with ϑ_m^{BMD}. For instance, in Column (2) GEPU has a coefficient of 0.02 with a standard error of 0.01, significant at the 5% level, suggesting that a one-unit

[10] The index was launched S&P Global on February 28, 2017.

increase in economic policy uncertainty are associated with a 2% higher cryptocurrency market volatility. Similarly, Column (3) shows that changes in the VIX have a strong positive effect on cryptocurrency market volatility with a coefficient of 0.19 and a standard error of 0.06, significant at the 5% level. This underscores the sensitivity of the cryptocurrency market to shifts in broader financial market volatility. Conversely, the global geopolitical risk index (Δ_m^{GOPRX}) does not show a statistically significant impact on cryptocurrency market volatility, as evidenced by the coefficients in Columns (4) being -0.01 with standard errors of 0.01. This might indicate that although economic and financial volatility have clear impacts on cryptocurrency volatility, geopolitical risks might not have a direct or immediate effect. The insignificant effect of GPRD on cryptocurrency COVOL can stem from the diverse relationships between individual cryptocurrencies and geopolitical risks, thus, geopolitical risks do not cause all cryptocurrencies to move synchronously in the same direction. For example, Long et al. (2022) study the relationship between geopolitical risk and the cross-section of cryptocurrency returns. They find that the geopolitical risk betas of cryptocurrencies can be negative, close to 0, or positive, which implies diverse reactions of cryptocurrencies to geopolitical risks. As COVOL is a measure of the common volatility risks in the cryptocurrency market, the heterogeneous responses of individual cryptocurrencies to geopolitical risks implies that the GPRD has a statistically insignificant significant relationship with the cryptocurrency COVOL measure.

The overall fit of the models, as indicated by the R-squared values, shows a reasonable level of explanatory power, particularly in Column (5) where the combined effects of all predictors explain approximately 21.4% of the variation in the cryptocurrency market volatility. The regression results illustrate the significant role of COVOL in explaining the volatility of the broad cryptocurrency market. In the most comprehensive model (Column 5 of Table 3 Panel A), COVOL retains its statistical significance with a positive coefficient (0.38), indicating that as common volatility in the cryptocurrency market increases, so does the overall market volatility. This underscores COVOL's robustness as a predictor of broad market volatility within the cryptocurrency sector.

Conversely, GEPU exhibits statistically significant effect in the single regression models, but it does not maintain its explanatory power in the full multiple regression model. This suggests that that GEPU’s influence on cryptocurrency volatility may be less direct or overshadowed by more dominant market-specific volatility factors like COVOL. These findings are vital for investors and policymakers within the cryptocurrency space. First, understanding that COVOL significantly influences market volatility can aid in better risk assessment and strategic planning. It highlights the necessity for investors to monitor common market volatilities closely as part of their risk management practices. On the other hand, for policymakers, acknowledging the pivotal role of COVOL could assist in developing targeted regulatory measures that address systemic risks inherent in the cryptocurrency markets without stifling innovation and growth. Overall, the results emphasise the importance of COVOL in capturing the systemic risks affecting the cryptocurrency market, thereby providing a valuable tool for predicting significant movements and potential disruptions within this highly volatile and evolving market sector.

In the second validation test, we examine whether our common volatility measure could help explain the average correlation of cryptocurrency returns. From the daily return series of cryptocurrencies in our sample, we estimate all pairwise correlation coefficients on a monthly basis. Then, we compute the monthly average pairwise correlation series and denote them as ρ_m , where m denotes the calendar month. Since high volatility periods are usually accompanied by high correlations, we thus expect higher correlations among cryptocurrencies when the COVOL of the cryptocurrency market is high. To test this hypothesis, we regress ρ_m on the cryptocurrency COVOL and other measures of global uncertainties. In addition, a one-period lagged variable of ρ_{m-1} is added to the regression model to account for the persistent characteristics of correlations. The regression results of the second validation test are shown in Table 3 Panel B. The coefficients for $COVOL_m^2$ in models 1 and 5 (β=0.02 with p < 0.05) suggest a consistent positive relationship between COVOL and the average correlation among cryptocurrencies. Specifically, a one-unit increase in squared cryptocurrency COVOL leads to 2% increase in the average return correlation among cryptocurrencies. Thus, an increase in common volatility in the cryptocurrency market is associated with the synchrony among individual cryptocurrency movements. We note that such effect remains robust even when other variables are introduced in the regression, highlighting the dominant influence of common market volatility on the correlation structure within the cryptocurrency sector.

The results from various models also indicate that the Global Economic Policy Uncertainty (Δ_m^{GEPU}) has a minimal and statistically insignificant effect. The stock market implied volatility (Δ_m^{VIX}), on the other hand, shows a small (with a factor loading of 0.05%) but significant influence, suggesting that increasing volatility in the U.S. stock market slightly enlarges the correlations among cryptocurrencies. The Global Geopolitical Risk Index (Δ_m^{GOPRX}) appears to have a negligible impact (-0. 1%). Nevertheless, our study also highlights the significance of lagged correlations, demonstrating a strong persistence in the correlation patterns and its crucial usage for predicting future interconnections among cryptocurrencies.

These findings emphasise that compared to broader economic and geopolitical uncertainty measure, the common volatility measure (COVOL) plays a more essential role in understanding cryptocurrency market dynamics. The persistence of cryptocurrency serial correlations indicates that past correlation patterns are predictive of future trends, underscoring the importance for investors and policymakers to consider these dynamics for effective risk management and regulatory development. This analysis highlights that COVOL is a valuable tool for anticipating shifts in market behaviour and for strategic planning in the evolving landscape of digital assets.

[Please insert Table 3 in here]

5.3. The drivers of cryptocurrency COVOL

5.3.1. Full sample analysis

Given the significant variations and volatility observed in the COVOL measures, it is crucial for investors and policymakers to understand their key drivers. To uncover the factors influencing the COVOL measures, we employ both daily and monthly specifications. Our daily specification is specified by the following equation:

$$COVOL_t = \beta + \alpha_1 RAI_t + \alpha_2 SP500_t + \alpha_3 DXY_t + \alpha_4 Term10Y2Y_t + \alpha_5 DGS2_t + \varepsilon_t \quad (13)$$

where $COVOL_t$ is the daily COVOL measure for the broad cryptocurrency market or for sub-sectors; β denotes the intercept; ε_t represents the error term; and α_1 to α_5 are estimated coefficients. The explanatory variables identified in Eq. (13) include i) the daily measure of risk aversion index (RAI) as a sentiment indicator (Bekaert et al., 2022); ii) the return on the S&P 500 index ($SP500$); iii) the US Dollar index (DXY); iv) the term spread as the difference between the yields of the U.S. 10-Treasury notes and that of the 2-year Treasury notes ($Term10Y2Y$); and v) the yields of the U.S. 2-year Treasury notes ($DGS2$).

These explanatory variables are chosen as the extant literature suggests they could influence the return and volatility of the cryptocurrency market and hence, its common volatility. First, the RAI is a global investor sentiment index (Bekaert et al., 2022) that significantly influences the cryptocurrency market dynamics (Huynh and Phan, 2023). In addition, Wang et al. (2023a) document that fluctuations in the S&P 500 index and the US Dollar index help predict the volatility of Bitcoin. Moreover, monetary policies are known to impact cryptocurrency volatility through changes in interest rates, liquidity, and overall economic conditions, as central bank actions often lead to shifts in investor risk appetites and speculative trading behaviours (Claeys et al., 2018; Nguyen et al., 2019; Elsayed and Sousa, 2022; Che et al., 2023). For instance, when central banks implement expansionary policies such as lowering interest rates or quantitative easing, they increase the money supply, which can lead to lower returns on traditional assets like bonds. As a result, investors may seek higher returns in more speculative assets like cryptocurrencies, thus driving up their volatility.

The regression results of Eq. (13) for the broad cryptocurrency market are presented in the first column of Table 4. The dependent variable in this model is the daily COVOL measure for the entire cryptocurrency market. The coefficient for the RAI is positive (0.25) but not statistically significant, suggesting that variations in market sentiment, as captured by RAI, do not have a strong direct effect on the common volatility of the cryptocurrency market. The return on the S&P 500 index ($SP500$) also shows a negative but insignificant coefficient (-0.02), indicating that the overall performance of the equity market does not significantly influence cryptocurrency volatility in this broad context.

The US Dollar Index (DXY) is negatively associated with COVOL, with a statistically significant coefficient of -0.05 at the 5% level. This implies that an appreciation in the US dollar generally leads to lower volatility in the cryptocurrency market, possibly reflecting the inverse relationship between the dollar's strength and the attractiveness of alternative assets like cryptocurrencies. The term spread ($Term10Y2Y$), with a positive coefficient of 0.68 and significant at the 1% level, indicates that a steeper yield curve, typically a sign of economic optimism, is associated with increased volatility in the cryptocurrency market. Lastly, the yields of the 2-year Treasury notes ($DGS2$) also show a positive and significant relationship (0.26) with COVOL, suggesting that higher short-term interest rates contribute to greater cryptocurrency market volatility. The significant relationship between cryptocurrency COVOL and $DGS2$ and $Term10Y2Y$ suggests the pronounced impacts of the US monetary policy on the cryptocurrency market dynamics, which is consistent with Elsayed and Sousa (2022) and Nguyen et al. (2019).

Overall, the results emphasise the complex interplay between macroeconomic factors and market sentiment in influencing cryptocurrency volatility. Understanding these relationships is crucial for investors and policymakers aiming to navigate the dynamic and often volatile cryptocurrency market effectively.

[Please insert Table 4 in here]

5.3.2. Analyses across crisis periods

Understanding the drivers of common volatility (COVOL) in the cryptocurrency market during global crisis periods is even more crucial for investors and policymakers to tackle uncertainty. Crisis periods often lead to heightened market uncertainty and can amplify the sensitivity of financial markets to various economic indicators. Analysing the COVOL measures during such times provides insights into how different factors impact the volatility of cryptocurrencies, thereby aiding in the development of more robust risk management and investment strategies. In this section, we focus on analysing the determinants of cryptocurrency COVOL during the most recent two crises: the *COVID-19 crisis* and the *Russia-Ukraine conflict*.[11]

The COVID-19 pandemic, starting in early 2020, brought unprecedented global economic disruptions, significantly impacting financial markets, including cryptocurrencies. During the COVID-19 period (January 30, 2020, to December 31, 2021), the COVOL measures for the broad cryptocurrency market and its sub-sectors reveal distinct patterns affected by various economic factors. For example, at the start of the pandemic, investor demand for

[11] We followed Abdullah et al. (2023) to specify the COVID-19 crisis and Russia-Ukraine war periods.

cryptocurrencies such as Bitcoin skyrocketed, pushing Bitcoin's value by more than 200% by the end of 2020. This period of extreme upward price movements was followed by a subsequent price crash, which further increased cryptocurrency market volatility. Another major crisis period is the Russia-Ukraine war which started in February 2022. Both countries view cryptocurrencies as an alternative source of funding for their war efforts have accelerated the rate of adoption for cryptocurrencies.[12]

Column (2) of Table 4 presents the analysis of the determinants of cryptocurrency COVOL during the COVID-19 period. For the broad cryptocurrency market, the RAI shows a significant positive coefficient (0.34) during the COVID-19 pandemic period. This suggests that augmented investor risk aversion, as captured by the RAI using bond and stock market data, contributed significantly to the increasing common volatility in the cryptocurrency market. The $SP500$ exhibits a negative but insignificant coefficient (-0.07), indicating that the overall performance of the equity market had a lesser impact on cryptocurrency volatility during this period. The DXY has a negative and significant relationship with COVOL (-0.23), suggesting that an appreciation in the US dollar generally led to lower common volatility in the cryptocurrency market. The $Term10Y2Y$ is not significant, indicating that this macroeconomic factor had a subdued impact on volatility during the pandemic. Lastly, the impact of $DGS2$ on the cryptocurrency market COVOL is positive and statistically significant, which is consistent with the results for the whole period. This indicates that increases in the 2-year U.S. Treasury yield are associated with heightened volatility in the cryptocurrency market. The significance of this relationship suggests that as short-term interest rates rise, likely reflecting changes in economic conditions or monetary policy, there is a corresponding increase in market uncertainty or risk in the crypto space.

[12] The Global Crypto Adoption Index ranked Ukraine and Russia as #5 and 13 in terms of cryptocurrency adoption rates in 2023. See more at https://www.chainalysis.com/blog/2023-global-crypto-adoption-index/.

The Russia-Ukraine war, starting on February 24, 2022, introduced new geopolitical risks and economic uncertainties, affecting global financial markets, including cryptocurrencies. Analysing the COVOL measures during this period (February 24, 2022, to March 16, 2023) helps understand how different factors influenced market volatility. During the Russia-Ukraine war, as show in column (3) of Table 4, the RAI shows a positive but insignificant coefficient (0.19), indicating that investor risk aversion had a minimal direct effect on broad market common volatility. The $SP500$ has a significant negative relationship with COVOL (-0.28), suggesting that declines in the equity market increased cryptocurrency common volatility during the conflict. The $Term10Y2Y$ is significantly positive (1.26), indicating that economic optimism increased volatility. The $DGS2$ also shows a positive and significant relationship (0.72), reflecting that higher short-term interest rates contributed to increased volatility.

5.3.3. Drivers of COVOL using monthly data

Due to the unavailability of daily data for many potential drivers of COVOL, this subsection utilises monthly data to investigate the determinants of cryptocurrency COVOL. We derive monthly variables for all factors in Equation (10) and enhance the model by incorporating three additional explanatory variables: the U.S. monetary policy uncertainty index (MPU) by Baker et al. (2016), and two indices specifically for the cryptocurrency market—cryptocurrency policy uncertainty ($UCRY_{Policy}$) and cryptocurrency price uncertainty ($UCRY_{Price}$). These latter indices are text-based measures of uncertainty developed by Lucey et al. (2022) using data from LexisNexis Business.

The regression results of the monthly model are presented in column (4) of Table 4. For the broad cryptocurrency market (column 1), several significant relationships emerge. The RAI has a positive and significant coefficient (0.07), suggesting that increased investor risk aversion contributes to higher volatility in the cryptocurrency market. The DXY shows a negative and significant relationship (-0.02), indicating that a stronger dollar leads to reduced volatility. The $Term10Y2Y$ is significantly positive (0.63), implying that economic optimism, as signalled by a steeper yield curve, increases market volatility. The $DGS2$ also exhibit a positive and significant relationship (0.14), suggesting that higher short-term interest rates contribute to greater volatility. Notably, the $UCRY_{Price}$ also shows a significant positive coefficient (0.017), suggesting that higher price uncertainty in the cryptocurrency market increases overall volatility. By contrast, the cryptocurrency policy uncertainty index ($UCRY_{Policy}$) does not significantly influence the cryptocurrency COVOL.

5.4. Good and bad COVOL and the Relative Common Volatility Index (RCI)

In this subsection, we provide further insights into the common volatility of negative return shocks (bad COVOL) and positive return shocks (good COVOL) of the cryptocurrency market. This decomposition of COVOL into good and bad COVOL is crucial because it allows us to differentiate between the impact of negative and positive market events on the overall volatility structure. Understanding these distinctions is vital for developing targeted risk management strategies and optimizing trading decisions.

Following the procedure described in subsection 3.2, we estimate the good and bad COVOL and present their extreme values in Table 5 Panel A. The results indicate that spikes in good and bad COVOL happened at different periods, implying distinct episodes of market stress and exuberance. For example, the highest good COVOL value of 58.9349 on September 15, 2016, suggests a period of strong positive shocks, possibly due to favourable developments that boosted market optimism.[13] In contrast, the highest bad COVOL value of 98.4933 occurred on April 3, 2017, reflecting a period of significant market distress, likely driven by adverse

[13] This includes the Bitcoin halving event in 2016 and the increasing recognition of Bitcoin as a legitimate asset class.

news or market downturns. This marked the beginning of the 2017-2018 cryptocurrency market bubble and crash.

The temporal separation of these spikes highlights that periods of high market volatility are not always symmetrically distributed between positive and negative shocks. Instead, they can be driven predominantly by either positive or negative events. This asymmetry is crucial for investors and risk managers, as it underscores the need for differentiated strategies to handle positive and negative market conditions effectively. High-bad-COVOL periods may warrant more conservative approaches and hedging strategies to mitigate downside risks, whereas high-good-COVOL periods could present opportunities for more aggressive trading strategies to capitalize on upward market movements.

In Table 5 Panel B, we further report the factor loadings of the cryptocurrencies, showing their vulnerability to common good and bad volatility. A comparison of the top and bottom 5 factor loadings for good and bad COVOL estimates highlights key similarities and differences. The top and bottom 5 lists for good and bad COVOL include major cryptocurrencies, indicating that these assets play significant roles in influencing market volatility, regardless of whether the shocks are positive or negative. Cryptocurrencies such as DOGE and XRP appear prominently in both good and bad COVOL rankings, suggesting that they are consistently influential in the market's overall volatility. However, the specific cryptocurrencies that top the lists for good and bad COVOL differ. For instance, BTC has the highest factor loading in bad COVOL, indicating its significant susceptibility to market negative shocks, whereas its factor loading is only ranked 7th in good COVOL. In a similar vein, ETH, another major cryptocurrency, shows a higher factor loading in bad COVOL compared to good COVOL, highlighting its greater exposure to negative market events.

Additionally, the cryptocurrencies with the lowest factor loadings also show similarities and discrepancies. For example, TON and LEO are both in the bottom 5 for both good and bad

COVOL, indicating their relatively lower influence on overall market volatility. However, APT and UNI, which appear in the bottom 5 for good COVOL, do not appear in the bottom 5 for bad COVOL, reflecting their different levels of influence depending on the nature of the market shocks. These insights suggest that the response of cryptocurrencies to positive and negative return shocks is not uniform, and different assets may play varying roles depending on the market conditions. Some cryptocurrencies exhibit symmetrical vulnerability to both negative and positive shocks, such as DOGE and XRP, while others have more pronounced exposure to one type of shock. Overall, most cryptocurrencies show a distinct behaviour towards good and bad COVOL, emphasizing the need for differentiated strategies based on the prevailing market conditions. For investors, this means adopting tailored strategies that consider these differences can enhance trading and risk management decisions. During periods of high bad COVOL, focusing on assets like BTC for risk management might be prudent, while periods of high good COVOL could present opportunities to capitalize on assets like SHIB and BCH for potential gains. Understanding these dynamics helps in optimizing portfolio strategies to align with the market's specific volatility patterns.

[Please insert Table 5 about here]

To reveal more insights into the good and bad COVOL, we plot their 20-day moving average in Figure 3. First, consistent with the results in Table 10 Panel A, the spikes in good and bad COVOL occurred at different times, emphasizing that periods of market stress and positive market developments are driven by distinct events. For instance, the highest spike in good COVOL appeared around September 2016, indicating a period of strong positive shocks, whereas the highest spike in bad COVOL occurred around April 2017, reflecting significant market distress. The timing of the peaks in good and bad COVOL in Figure 3 is consistent with the findings in Table 5, as discussed above. Second, the spikes in bad COVOL are usually stronger than those in good COVOL, indicating that negative market events tend to cause more intense volatility compared to positive events. This suggests that the market reacts more sharply to negative news, which is often associated with heightened risk aversion and panic selling. Investors and risk managers need to be particularly cautious during these periods, as the potential for significant losses is greater when bad COVOL spikes. Yet, good COVOL occurs more frequently than bad COVOL throughout the observed period.[14] This indicates that, while negative shocks can be more intense, the market experiences positive return shocks more consistently. This trend suggests a generally optimistic market sentiment, with positive developments occurring more often, albeit with less intensity compared to negative events. This is consistent with the upward trend of the cryptocurrency market over the research period.

[Please insert Figure 3 about here]

Based on the moving average of good and bad COVOL, we compute the Relative Common Volatility Index (RCI) of the cryptocurrency market following the procedures outlined in subsection 3.2. The RCI of the cryptocurrency market is displayed in Figure 4. By construction, the RCI fluctuates between 0 and 100. An RCI of 0 reflects total dominance of bad COVOL. This often corresponds to market crashes or severe downturns, where prices drop sharply, and investor confidence is at its lowest. An RCI between 0 and 30 indicates strong dominance of bad COVOL, signalling strong bearish market conditions. An RCI that is between 30 and 50 signals moderate to weak dominance of bad volatility, signalling moderate to weak bearish market conditions. An RCI of 50 indicates a perfect balance between good and bad COVOL. An RCI between 50 and 70 indicates weak to moderate bullish market conditions with weak to moderate dominance of good volatility over bad volatility. An RCI of more than 70 indicates strong bullish market conditions, with strong dominance of good volatility over

[14] During the research period, good (bad) COVOL is greater than bad (good) COVOL in 1,754 (1,588) days.

bad volatility.[15] Finally, an RCI of 100 indicates the total dominance of good COVOL, suggesting an environment of strong optimism and possibly a market bubble with herding behaviour and speculative buying. This scenario may lead to significant market gains but also warrants caution as it could precede sharp corrections or increased bad volatility if the optimism fades. Understanding these extreme conditions helps investors and risk managers prepare for potential market reversals and implement strategies to protect their portfolios during periods of heightened volatility.

[Please insert Figure 4 about here]

To illustrate the practical application of the RCI, in Figure 5, we plot the RCI index along with the performance of cryptocurrency market, proxied by the logarithm of the S&P Cryptocurrency Broad Digital Market Index (BDM).[16] Figure 5 illustrates that bull markets are accompanied by several instances where the index crossed above the bullish line (70) and rarely touched the bearish line (30). These market conditions are characterized by strong positive sentiment and herding behaviour among crypto investors, leading to a significant commonality of positive return shocks among cryptocurrencies. By contrast, during bear markets, the RCI more frequently dips below the bearish line, indicating prevalent negative sentiment and increased risk aversion among investors, resulting in common negative return shocks.

In addition, it is observable that most spikes or troughs in the RCI coincide with market peaks or bottoms, irrespective of whether they are minor or significant. This suggests that the RCI reflects the asymmetry and extreme movements in the cryptocurrency market. Notably, some extreme values near the lower bound (0) or upper bound (100) serve as warnings or early warnings of significant market bottoms or peaks. For example, the extremely low values of the

[15] The 30 and 70 thresholds are used as these thresholds are frequently employed to interpret momentum technical indicators in technical analysis such as Relative Strength Index (RSI) or Moving Average Convergence Divergence (MACD).

[16] As the BDM index commenced in February 2017, the figure begins from that date.

RCI in March 2017 and March 2020 align with two major downturns in the BDM index. This observation is consistent with the contrarian view in financial markets that when fear and negative sentiment reach extreme levels, it often signals a market bottom and a potential buying opportunity. Conversely, when positive sentiment and exuberance reach extremes, it can indicate a market peak and a potential selling opportunity, as shown in the market peaks at the end of 2017, in April 2021, or recently, in March 2024.

[Please insert Figure 5 about here]

In summary, the decomposition of COVOL into good and bad components provides critical insights into the behaviour of the cryptocurrency market. By distinguishing between positive and negative return shocks, investors can tailor their risk management and trading strategies to better align with the market's current state, thereby enhancing their ability to navigate volatility and capitalize on market opportunities. The RCI, as demonstrated, is an effective tool for identifying market sentiment and potential turning points, enabling more informed investment decisions. By integrating these insights, investors can improve their risk-adjusted returns and better manage their exposure to market risks.

6. Portfolio Implications

In this section, we present the results of two simulations to illustrate the implications of our findings for cryptocurrency investors and portfolio managers. The second simulation incorporates insights from the RCI to rebalance a hypothetical cryptocurrency portfolio. The benchmark portfolio is fully invested in the S&P Cryptocurrency Broad Digital Market Index (BDM index) from March 2017 to April 2024. The RCI is used to dynamically adjust the allocation in the RCI momentum portfolio. If the RCI is above 70, indicating a strongly bullish market, the portfolio is leveraged to invest 125% in the BDM index. Conversely, if the RCI is below 30, indicating a strongly bearish market, the allocation to the BDM index is reduced to 75% of the portfolio. When the RCI is between 30 and 70, the RCI momentum portfolio remains fully invested (100%) in the BDM index, mirroring the allocation of the benchmark portfolio.

Table 6 presents the simulation results for two portfolio strategies—RCI momentum and a benchmark portfolio—over the period from March 2017 to April 2024. The RCI momentum portfolio, which dynamically adjusts its exposure to the BDM index based on the RCI, demonstrates a higher average monthly return of 2.48% compared to 1.91% for the benchmark portfolio, which follows a static buy-and-hold strategy. Despite its higher volatility, as indicated by a standard deviation of 11.38% versus 10.89% for the benchmark, the RCI momentum portfolio achieved a substantially higher accumulated return of 141.98%, far outperforming the benchmark's 45.58%. The Sharpe and Sortino ratios, which measure risk-adjusted returns, are also higher for the RCI momentum portfolio at 0.5648 and 0.3584, respectively, compared to 0.3971 and 0.2695 for the benchmark, suggesting that the RCI Momentum strategy offers superior performance on both an absolute and risk-adjusted basis. These results demonstrate the effectiveness of using the RCI to dynamically adjust portfolio allocations based on market sentiment, thereby enhancing returns and managing risk more effectively.

[Please insert Table 6 and Figure 6 about here]

These findings suggest that incorporating the RCI into a cryptocurrency investment strategy can provide substantial benefits. By leveraging periods of strong positive sentiment and reducing exposure during periods of heightened negative sentiment, investors can significantly improve their risk-adjusted returns. The proactive rebalancing based on the RCI allows for more responsive and adaptive portfolio management, which is crucial in the highly volatile cryptocurrency market. This approach not only boosts returns but also provides a more robust framework for navigating market fluctuations, ultimately leading to a more resilient investment strategy.

In summary, our simulation confirms that the RCI momentum strategy outperforms a traditional buy-and-hold approach. By integrating market sentiment indicators like the RCI into portfolio management, investors can better navigate the complexities and volatilities inherent in the cryptocurrency market. This adaptive strategy, which increases exposure during bullish periods and reduces it during bearish times, demonstrates a significant improvement in performance and risk management, providing a compelling case for the inclusion of sentiment-based metrics in investment strategies.

7. Conclusion

Diverse types of shocks in cryptocurrencies accompanied by their varying intensity and frequency in both dimensions, time and cross-section, necessitate an understanding of the collective effects of shocks on the market. At the same time, it is crucial to identify which shock plays a major role. Our paper significantly contributes to this area in two ways. First, we quantify the common volatility (or COVOL) of twenty-five cryptocurrencies and discuss its important role in risk management practices. Second, we introduce a new concept called asymmetric COVOL, which captures the asymmetry in COVOL, and demonstrate its significant role in enhancing portfolio performance alongside risk management.

More specifically, our analyses confirm the existence of common volatility factor in the cryptocurrency. This implies that cryptocurrencies are highly interconnected, therefore, diversification within the cryptocurrency market does not lead to substantial risk reduction. Thus, investors should consider diversification across different crypto and non-crypto asset classes to mitigate risks. For policymakers, this highlights the need to focus on systemic risks within the cryptocurrency market. Implementing policies that enhance transparency and monitor systemic risks can help stabilise the market during periods of high common volatility.

We further show that the cryptocurrency COVOL measure can effectively predict market volatility and correlation. Specifically, high COVOL values are associated with greater market volatility and correlation, while broader economic and geopolitical factors have a less pronounced impact. Investors should incorporate COVOL as a key indicator in their risk assessment and portfolio management strategies. Monitoring COVOL can provide ex ante warnings of potential market volatility. On the other hand, policymakers can use the COVOL measure to better anticipate market reactions to regulatory changes and develop frameworks that promote stability. By focusing on COVOL, regulators can address systemic risks more effectively without stifling innovation.

Our study reveals distinct volatility characteristics of cryptocurrencies compared to traditional assets. The relatively low correlation of cryptocurrency COVOL with the stock, oil, and gold markets indicates that cryptocurrency volatility is driven by factors different from traditional financial assets. Investors can leverage this distinction for portfolio diversification, benefiting from the uncorrelated volatility patterns of cryptocurrencies, though they must remain aware of the unique risks posed by these assets. Additionally, significant sector-specific events, such as the DAO hack recovery, have been found to cause notable spikes in COVOL. Unlike global economic markets, which remain relatively stable, the cryptocurrency market is uniquely impacted by such events. Therefore, it is crucial for investors to closely monitor sector-specific news and developments, as these can significantly affect cryptocurrency volatility. Developing strategies to respond swiftly to such news can help manage risks effectively. Policymakers should consider the sector-specific nature of cryptocurrency volatility when formulating regulations, creating frameworks that address specific events and issues within the cryptocurrency market to help mitigate extreme volatility.

In a more granular view, the study highlights the variation in COVOL sensitivity across different cryptocurrencies. Major cryptocurrencies like Bitcoin and Ethereum exhibit moderate sensitivity to market-wide shocks, while others like Litecoin and Ripple show higher sensitivity. Cryptocurrencies with high social media exposure, such as DOGE and SHIB, exhibit extreme vulnerability to market-wide volatility. Investors should differentiate their strategies based on the sensitivity of individual cryptocurrencies to market-wide volatility. High-sensitivity cryptocurrencies may offer rapid gains but also pose higher risks, necessitating vigilant risk management. Policymakers, by understanding the varying degrees of sensitivity among different cryptocurrencies, can prioritise their focus—policies aimed at stabilising the more sensitive cryptocurrencies can prevent broader market disruptions.

Most importantly, our paper highlights the distinct impacts of good and bad common volatility (COVOL) of the cryptocurrency market. By decomposing COVOL into positive (good) and negative (bad) return shocks, it becomes evident that these spikes occur at different times, driven by unique market events. By capturing the asymmetric COVOL, a difference between good and bad COVOL, our RCI measure proves its superior effectiveness in summarizing market sentiment, with high RCI indicating bullish conditions and low RCI indicating bearish conditions. Simulations demonstrate that using the RCI to dynamically adjust portfolio allocations significantly outperforms traditional buy-and-hold strategies, enhancing returns and managing risks. These findings imply that investors can leverage the RCI for better portfolio management, while policymakers can use the extreme values as early warnings to anticipate and mitigate systemic risks, promoting market stability and sustainable growth in the cryptocurrency sector.

In summary, our study establishes crucial implications for investors and policymakers by emphasising the importance of understanding and managing common volatility in the cryptocurrency market. Investors can use these insights for more informed decisions regarding asset allocation and risk assessment, while policymakers can understand COVOL dynamics to craft policies that stabilise the crypto market, thus fostering long-term investment. These contributions significantly advance the understanding of financial risks in cryptocurrency, supporting the growth of this sector.

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Figure 1. Residuals from AR(1)-GARCH(1,1) model and average conditional volatility

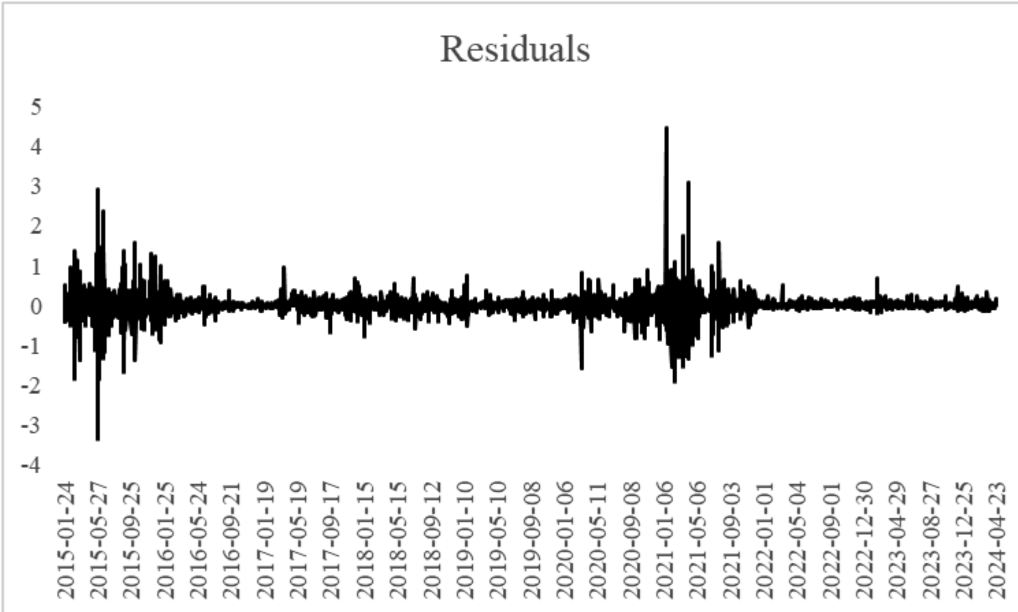


Figure 1a. Residual

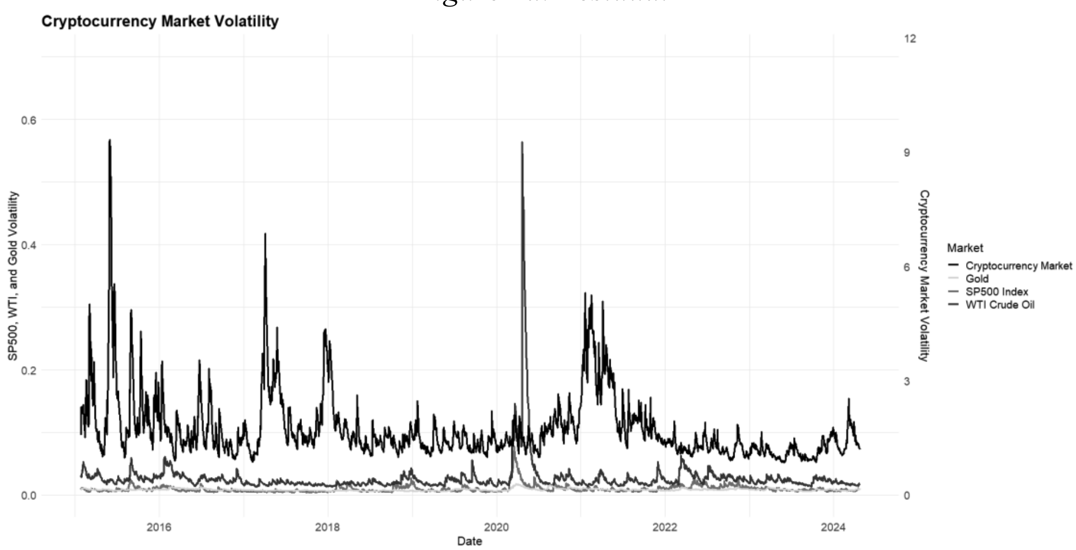
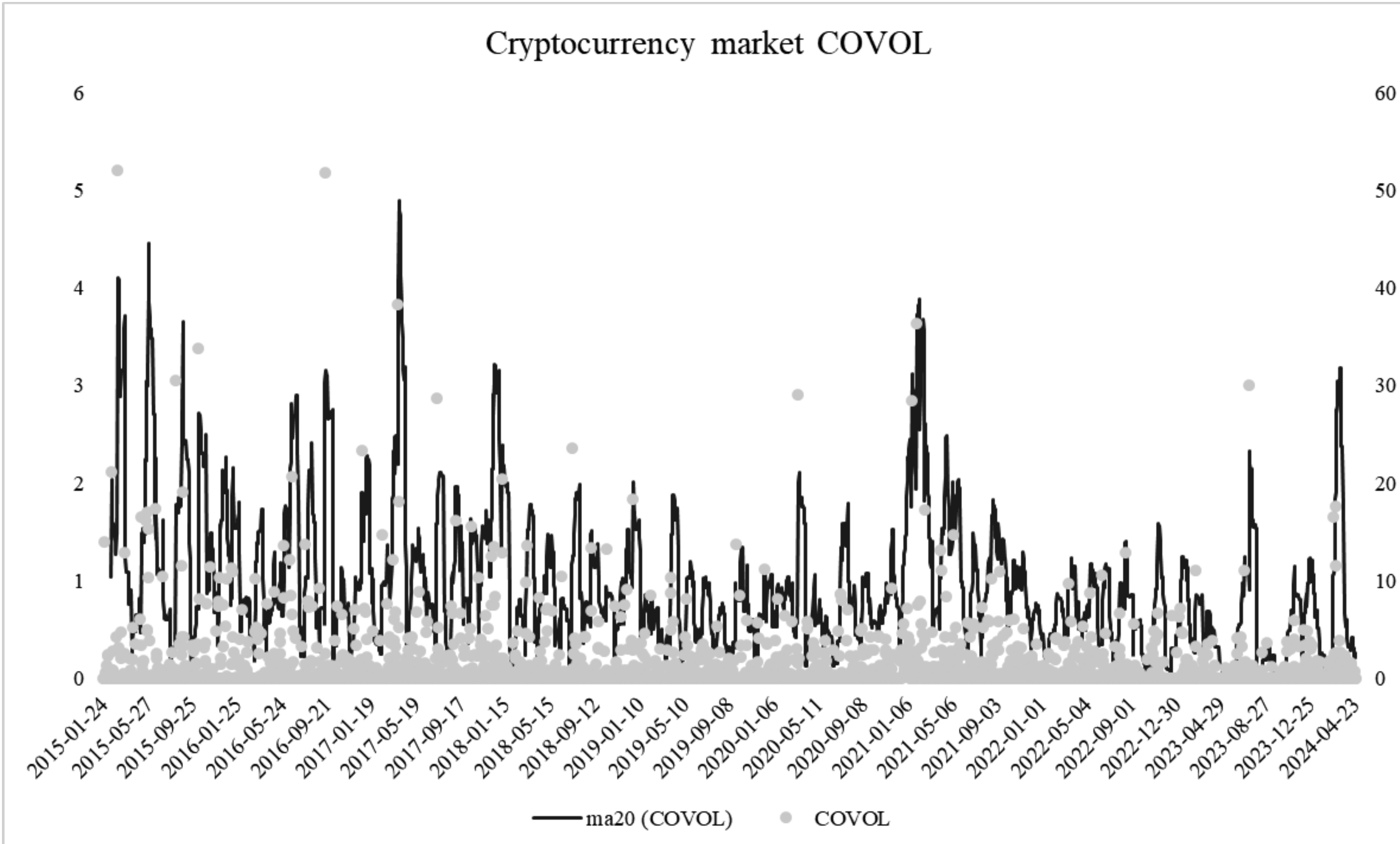


Figure 1b. Volatility

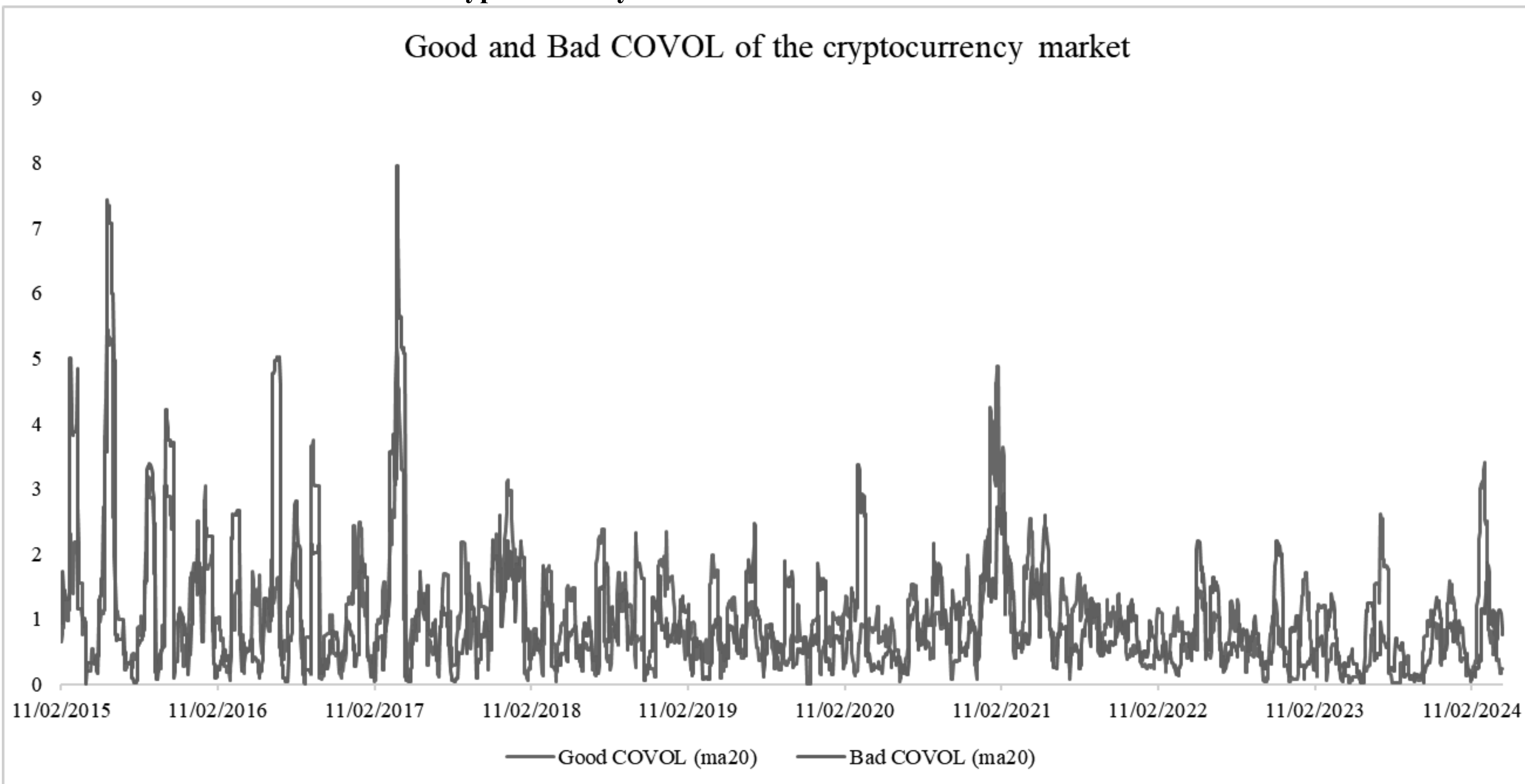
Note: Figure 1a presents the cross-sectional mean standardised residuals of 25 cryptocurrencies in the sample, which are obtained from the AR(1)-GARCH (1,1) model for each series. Figure 1b present the cross-sectional mean conditional volatilities of the cryptocurrency market and the conditional volatilities of the gold, stock market (S&P 500 index) and crude oil (WTI) markets.

Figure 2. Estimation of the cryptocurrency COVOL



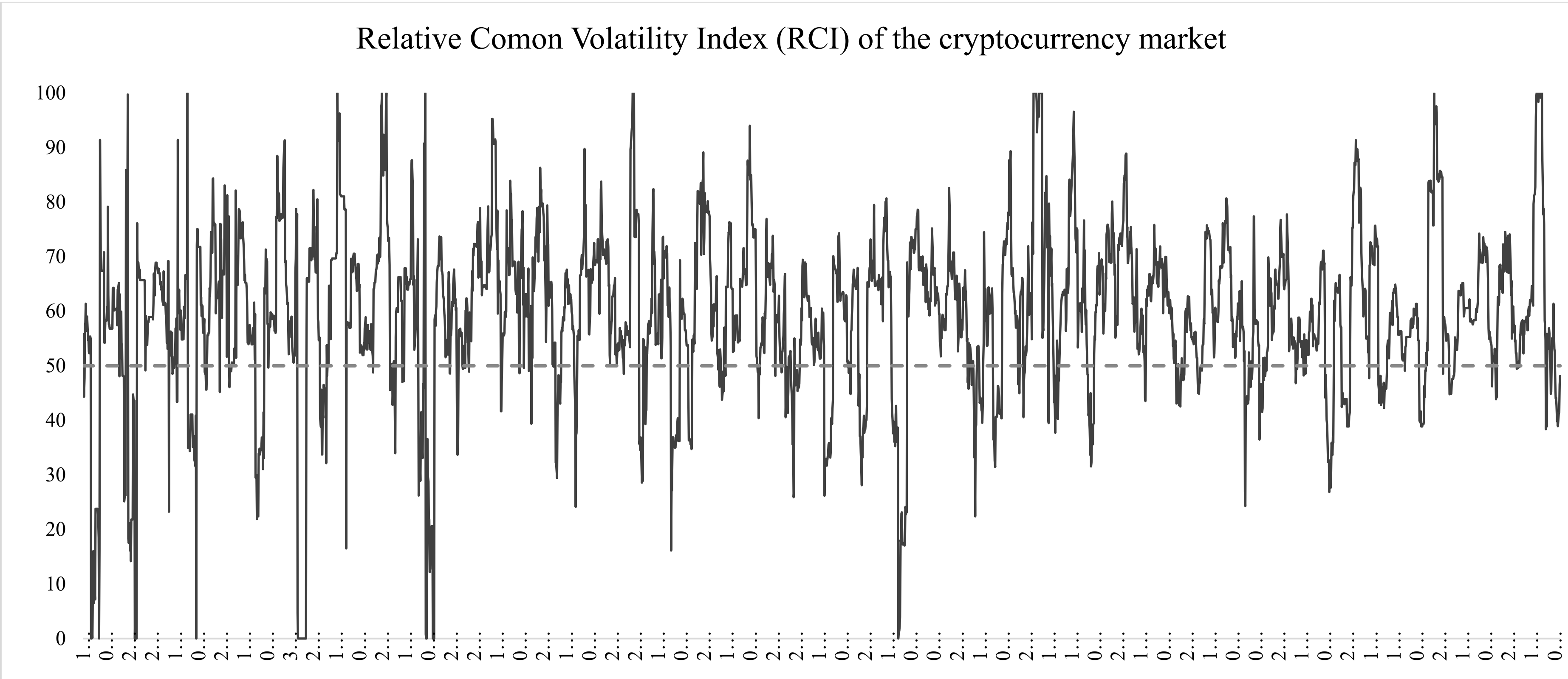
Note: Figure 2 presents the COVOL of the cryptocurrency market (blue dotted) and its 20-day moving average (black line), estimated from the empirical model described in subsection 3.1 for all cryptocurrencies in the sample.

Figure 3. Good and Bad COVOL for the Cryptocurrency Market



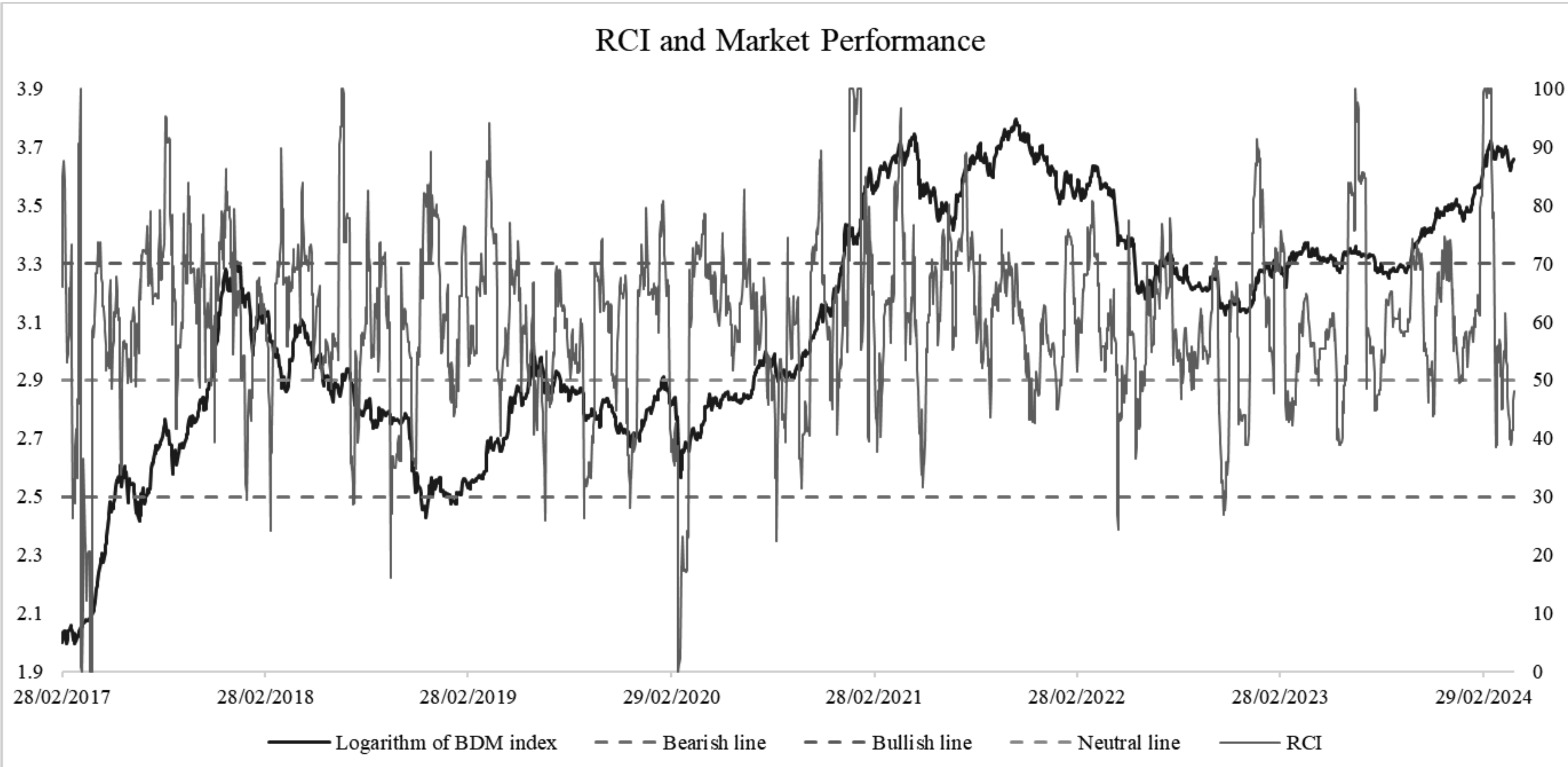
Note: Figure 3 presents the 20-day moving of the good COVOL (blue line) and bad COVOL (red line) of the cryptocurrency market, estimated from the empirical model as described in subsection 3.2 for all cryptocurrencies in the sample.

Figure 4. Relative Common Volatility Index



Note: Figure 4 presents the Relative Common Volatility Index (RCI) of the cryptocurrency market, estimated from the empirical model as described in subsection 3.2. The dashed orange line is at the neutral level (50).

Figure 5. The RCI and cryptocurrency market performance



Note: Figure 5 presents the Relative Common Volatility Index (RCI) of the cryptocurrency market (grey) along with the S&P Cryptocurrency Broad Digital Market Index (BDM index) (black) between February 2017 and April 2024.

Figure 6. Accumulated Return: RCI Momentum Portfolio vs. Benchmark Portfolio

Note: Figure 6 presents the accumulated returns of the RCI Momentum strategy and the benchmark portfolio that is fully (100%) invested in the S&P Cryptocurrency Broad Digital Market Index (BDM index).

Table 1. Descriptive statistics

Ticker	N. Obs.	Mean	Max	Min	SD	Skewness	Kurtosis	JB	ADF	Q	Q2
BTC	3361	0.07	9.88	21.59	1.60	0.819	16.17	24671***	13.99**	17.14*	96***
ETH	2955	0.0789	11.22	25.60	2.26	0.590	12.24	10705***	12.571**	23.78***	209***
BNB	2347	0.0989	23.04	25.24	2.38	0.261	21.37	33052***	11.171**	45.22***	407***
SOL	1367	0.1502	21.71	23.93	3.10	0.033	10.41	3134***	9.83**	26.34***	179***
XRP	3361	0.0406	44.64	43.57	3.54	1.110	34.96	143657***	14.02**	517.47***	1695***
DOGE	2505	0.0624	68.78	21.81	3.20	4.715	97.06	932768***	12.56**	45.00***	50***
TON	490	0.0618	9.16	6.16	1.66	0.835	7.00	384***	8.71**	7.65	77***
ADA	2294	0.0107	15.14	23.33	2.44	0.109	9.71	4308***	11.72**	26.89***	140***
SHIB	1074	0.0091	21.99	23.43	2.88	1.217	18.90	11586***	10.17**	48.72***	133***
AVAX	1203	0.0792	24.13	20.20	2.91	0.432	10.93	3195***	9.54**	24.09***	114***
DOT	1167	0.0503	11.33	21.06	2.284	0.764	11.53	3654***	10.13**	43.09***	238***
BCH	1966	0.0145	19.93	26.58	2.46	0.048	20.13	24046***	12.55**	29.73***	56***
TRX	2131	0.0156	14.78	24.67	2.11	0.854	17.14	18021***	12.70**	36.08***	115***
LINK	1762	0.0405	12.27	27.67	2.57	0.860	14.36	9693***	12.40**	29.96***	97***
NEAR	1283	0.0554	15.24	19.73	3.03	0.052	7.38	1026***	10.63**	12.29	54***
MATIC	1752	0.0842	20.36	31.97	3.13	0.310	18.61	17822***	11.39**	45.48***	103***
ICP	1073	0.1316	15.10	15.36	2.64	0.233	8.30	1268***	10.24**	13.14	124***

LTC	2788	0.0405	26.35	21.14	2.43	0.640	17.05	23123***	13.25**	28.85***	175***
LEO	1752	0.0212	19.57	9.50	1.29	1.966	39.77	99873***	12.87**	75.06***	136***
UNI	1261	0.0321	18.75	17.91	2.60	0.557	10.39	2941***	10.41**	43.47***	107***
STX	2262	0.027	144.91	60.32	7.48	3.862	87.56	679567***	13.729**	202.49***	70***
APT	550	0.0071	17.17	13.39	2.53	0.896	12.34	2072***	6.7094**	22.56**	57***
ETC	2815	0.0345	23.14	24.38	2.68	0.233	12.71	11098***	13.95**	24.03***	230***
MNT	267	0.1176	12.73	4.71	1.82	1.632	11.91	1002***	6.38**	10.56	9
FIL	1093	0.1332	15.00	18.49	2.53	0.259	10.59	2639***	9.71**	26.98***	58***

Note: This table reports the descriptive statistics of excess return series of 25 cryptocurrencies in the sample between January 2006 and April 2024. LB-Q(10) and LB-Q(20) represent the Ljung-Box Q-statistics up to the 10^{th} and 20^{th} order autocorrelation. Jarque-Bera statistics indicate the test for the normality of sample data. ERS test represent the Elliot, Rothenberg, and Stock's (1996) unit root test. denotes the cases where the null hypothesis of no autocorrelation (for LB Q test), and normal distribution (for JB test), and a presence of a unit root (for ERS test) is rejected at the 1% significance level.

Table 2. The largest estimated common volatility for the cryptocurrency market

Panel A. Twenty largest COVOL values (x_t^σ)

Date	x_t^σ	r_{SP500}	r_{WTI}	r_{Gold}	Event
02/03/2015	52.0557	0.61	-0.34	-0.50	Coinbase received USD 75 million for development; JP Morgan exec took CEO at bitcoin trading platform Digital Assets Holdings
15/09/2016	51.8267	1.01	0.75	-0.66	Cryptocurrency market recovery from Dao hack event
30/03/2017	38.3263	0.30	1.68	-0.73	Cryptocurrency market bubble in 2017
28/01/2021	36.3489	0.97	-0.97	-0.20	Cryptocurrency market bubble in 2021
10/10/2015	33.7644	NA	NA	NA	Bitcoin featured on the front cover *The Economist*
08/08/2015	30.4657	NA	NA	NA	Augur, the first token launch on the Ethereum network takes place
13/07/2023	30.0138	0.84	1.49	0.16	Ripple XRP climbed as high as 96% intraday after U.S. judge rules the sale of XRP tokens on exchanges did not constitute investment contracts
12/03/2020	29.0627	-10.00	-4.59	-3.61	COVID-19 global sell-offs
12/07/2017	28.7249	0.73	0.99	0.19	At trough of sharp correction in cryptocurrency market (BTC fell from 3,000 in June to 2,000 USD in mid-July 2017)
15/01/2021	28.4892	-0.72	-2.28	-1.08	Cryptocurrency market bubble 2021
11/07/2018	23.6286	-0.71	-5.16	-1.08	Google bans all crypto-related advertising
23/12/2016	23.2953	0.12	0.13	0.42	Bitcoin all-time high after a soar of more than 30% in December 2016
14/02/2015	21.1061	NA	NA	NA	Stripe initiates bitcoin payment integration for merchants

17/06/2016	20.6959	-0.33	3.76	1.51	DAO hack resulting in loss over USD 50 million worth of Ether, sparkling a sharp correction of cryptocurrency market
03/01/2018	20.4114	0.64	2.07	-0.40	Cryptocurrency market crash in January 2018 (“Great crypto crash”)
28/08/2015	19.1318	0.06	6.06	0.73	Augur, the first token launch on the Ethereum network takes place
21/12/2018	18.4067	-2.08	-0.63	-0.33	G20 decided on regulating the crypto sector
02/04/2017	18.1535	NA	NA	NA	SEC rejection of the first bitcoin exchange-traded fund
02/03/2024	17.6627	NA	NA	NA	Record fund inflows to Bitcoin ETFs
16/06/2015	17.3605	0.57	0.75	-0.38	New York State Department of Financial Services (NYDFS) approved regulatory framework for digital currency companies

Panel B. Estimated factor loadings of each cryptocurrency

Cryptocurrency	Factor loading	Cryptocurrency	Factor loading	Cryptocurrency	Factor loading
XRP	0.2885	APT	0.2066	SOL	0.1367
DOGE	0.2792	MATIC	0.2036	LINK	0.1303
SHIB	0.2653	ADA	0.1978	LEO	0.122
ETC	0.2546	NEAR	0.1819	TON	0.0856
BCH	0.2503	TRX	0.1784	MNT	0.0822
UNI	0.2327	STX	0.1757		
BTC	0.2311	AVAX	0.1708		
LTC	0.2268	DOT	0.165		

FIL	0.2267	ICP	0.1586
ETH	0.2145	BNB	0.1388

Note: Panel A of Table 2 presents the dates with the largest common volatility of the cryptocurrency market. x_t^{σ} denotes the common volatility. r_{SP500}, r_{WTI}, and r_{Gold} denotes the returns on the S&P 500 index, the WTI crude oil futures, and the gold futures. Panel B lists the cryptocurrencies and their factor loadings, estimated from the empirical model described in subsection 3.1.

Table 3. Validation tests

Panel A. Using cryptocurrency market volatility as dependent variable (ϑ_m^{BMD})

	(1)	(2)	(3)	(4)	(5)
$COVOL_m^2$	0.42**				0.38**
	(0.17)				(0.16)
Δ_m^{GEPU}		0.02**			0.01
		(0.01)			(0.01)
Δ_m^{VIX}			0.19**		0.16**
			(0.06)		(0.06)
Δ_m^{GOPRX}				-0.01	-0.01
				(0.01)	(0.01)
Observations	84	84	84	84	84
R^2	0.0663	0.0591	0.1235	0.0037	0.214
Adjusted R^2	0.05491	0.0476	0.1128	-0.0085	0.1742
F Statistic	5.823**	5.147**	11.55***	0.304	5.376***

Panel B. Using average correlation of cryptocurrencies in the sample as dependent (ρ_m)

	(1)	(2)	(3)	(4)	(5)
$COVOL_m^2$	0.02**				0.02**
	(0.01)				(0.01)
Δ_m^{GEPU}		0.0005			0.0002
		(0.0004)			(0.0004)
Δ_m^{VIX}			0.005*		0.005*
			(0.003)		(0.003)
Δ_m^{GOPRX}				-0.001	-0.001
				(0.001)	(0.001)
ρ_{m-1}	0.34***	0.41***	0.44***	0.44***	0.36***
	(0.11)	(0.09)	(0.09)	(0.09)	(0.11)
Observations	83	83	83	83	83
R^2	0.1426	0.2058	0.226	0.2207	0.231
Adjusted R^2	0.1203	0.1860	0.207	0.2012	0.1791
F Statistic	6.404***	10.37***	11.68***	11.33***	4.45***

Note: Table 3 presents the regression results (estimated coefficients and their standard errors) of validation tests, with Panels A and B using the cryptocurrency market's volatility (ϑ_m^{BMD}) and mean correlation (ρ_m) as dependent variable, respectively. $COVOL_m^2$ is the squared common volatility of the cryptocurrency market; Δ_m^{GEPU} denotes the monthly log-differenced Global Economic Policy Uncertainty Index (GEPU); Δ_m^{VIX} indicates the monthly log-differenced of the CBOE Volatility Index (VIX); Δ_m^{GOPRX} represents the monthly log-differenced of the Global Geopolitical Risk Index (GOPRX). Newey and West's (1987) robust standard errors are used. *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

Table 4. Drivers of COVOL in the cryptocurrency market

	Whole Sample	COVID-19	R-U War	Monthly data
	(1)	(2)	(3)	(4)
RAI	0.25	0.34^{**}	0.19	0.07^{**}
	(0.21)	(0.14)	(0.43)	(0.03)
$SP500$	-0.02	-0.07	-0.28^{**}	-0.28
	(0.13)	(0.19)	(0.14)	(0.41)
DXY	-0.05^{**}	-0.23^{**}	-0.08^{**}	-0.02^{*}
	(0.03)	(0.09)	(0.03)	(0.01)
$Term10Y2Y$	0.68^{***}	0.06	1.26^{*}	0.63^{***}
	(0.25)	(0.43)	(0.71)	(0.11)
$DGS2$	0.26^{**}	1.02^{***}	0.72^{**}	0.14^{**}
	(0.11)	(0.32)	(0.36)	(0.06)
MPU				-0.29
				(0.32)
$UCRY_{Policy}$				-0.01
				(0.01)
$UCRY_{Price}$				0.017^{*}
				(0.09)
Intercept	4.43^{**}	20.99^{***}	6.69^{**}	2.43^{*}
	(2.13)	(8.55)	(2.94)	(1.36)
N. Obs.	2,219	480	254	102
Adj. R-Squared	0.0105	0.0437	0.016	0.1657
F-statistics	5.71^{***}	5.38^{***}	1.82^{*}	3.51^{***}

Note: This table presents the regression results of Eq. (13) to investigate the daily determinants of the COVOL of the cryptocurrency market and sub-sectors for the whole research period. Eq. (13) is estimated using OLS estimation with t-statistics computed using Newey and West's (1987) robust standard errors. *, **, and **** indicate statistical significance at 10%, 5%, and 1% level, respectively. The first three columns present the estimated results of models using daily data for the whole sample, COVID-19 period, and Russia-Ukraine War period, respectively. The last column presents the estimated result of model using monthly data for the whole period to enhance the model specification with additional explanatory variables, whose data are only available in monthly frequency.

Table 5. Good and bad COVOL

Panel A. Extreme values of bad and good COVOL

$Bad\ COVOL$		$Good\ COVOL$	
Date	$x_t^{\sigma,-}$	Date	$x_t^{\sigma,+}$
03/04/2017	98.4933	15/09/2016	58.9349
28/05/2015	93.7393	23/05/2015	53.5099
17/06/2016	73.6695	15/01/2021	48.7105
02/03/2015	73.2973	10/10/2015	42.7339
11/10/2015	72.4438	30/03/2017	40.6846
28/08/2015	45.6582	28/01/2021	36.0338
12/03/2020	43.5893	11/07/2018	34.5149
16/09/2016	39.5258	13/07/2023	31.967
11/10/2018	31.5467	29/08/2015	28.5413
30/01/2021	30.697	10/01/2016	28.1495
14/03/2016	29.6513	25/12/2015	25.6165
24/09/2019	25.0515	23/12/2016	23.9475
27/06/2019	25.002	27/05/2015	22.5612
18/03/2017	24.5435	03/01/2018	20.9656
20/07/2018	22.9549	05/04/2021	20.6142

Panel B. Estimated factor loadings of cryptocurrencies

$Bad\ COVOL$		$Good\ COVOL$	
Cryptocurrency	$Loading\ factor$	Cryptocurrency	$Loading\ factor$
BTC	0.243	XRP	0.24
DOGE	0.2357	DOGE	0.24
TRX	0.2317	SHIB	0.24
XRP	0.231	BCH	0.23
ETH	0.2297	ETC	0.23
ETC	0.2251	FIL	0.23
BNB	0.2195	LTC	0.23
LTC	0.2154	BTC	0.22
SOL	0.2148	TRX	0.21

BCH	0.2146	UNI	0.21
FIL	0.2123	ETH	0.21
AVAX	0.2103	MATIC	0.21
SHIB	0.2048	DOT	0.20
ADA	0.1971	ADA	0.20
ICP	0.1911	ICP	0.19
NEAR	0.1897	APT	0.19
DOT	0.1873	NEAR	0.19
LINK	0.1823	LINK	0.19
MNT	0.1782	BNB	0.18
STX	0.1737	AVAX	0.17
MATIC	0.1717	STX	0.16
APT	0.1631	SOL	0.16
UNI	0.1587	LEO	0.15
LEO	0.1463	MNT	0.13
TON	0.1123	TON	0.11

Note: Panel A of this table presents the dates with the largest common bad and good volatility of the cryptocurrency market, estimated from the empirical model described in subsection 3.2. $x_t^{\sigma,-}$ and $x_t^{\sigma,+}$ denote the common bad and good volatility, respectively. Panel B lists the cryptocurrencies and their factor loadings.

Table 6. Portfolio Simulation Results

	Avg. Monthly Return	Std Dev.	Accumulated Return	Sharpe Ratio	Sortino Ratio
RCI Momentum	2.48	11.38	141.98	0.5648	0.3584
Benchmark Portfolio	1.91	10.89	45.58	0.3971	0.2695

Note: This table presents the different evaluation metrics between RCI momentum and benchmark portfolio for the period between March 2017 and April 2024. Benchmark portfolio is a buy-and-hold portfolio that fully invested (100%) in the S&P Cryptocurrency Broad Digital Market Index (BDM index). RCI momentum portfolio dynamically adjusts its weight invested in the BDM index. If the RCI is above 70, the portfolio is leveraged to invest 125% in the BDM index. If the RCI is below 30, the weight to the BDM index is reduced to 75% of the portfolio. When the RCI is between 30 and 70, the RCI momentum portfolio remains fully invested. Borrowing and investing rates are assumed to equal the risk-free rate, proxied by the yields on 1-year U.S. Treasury notes.

Appendix A1. Cryptocurrency description and market capitalisation

Rank	Ticker	Full Name	Description	Market Cap
1	BTC	Bitcoin	Decentralized digital currency, first and largest cryptocurrency	$1.2 trillion
2	ETH	Ethereum	Smart contract platform and cryptocurrency	$600 billion
3	BNB	Binance Coin	Utility token of the Binance exchange	$60 billion
4	SOL	Solana	High-performance blockchain platform	$25 billion
5	XRP	Ripple	Cryptocurrency for cross-border payments	$45 billion
6	DOGE	Dogecoin	Meme cryptocurrency, originally created as a joke	$28 billion
7	TON	Toncoin	Native cryptocurrency of The Open Network, a decentralized layer-1 blockchain	$8 billion
8	ADA	Cardano	Blockchain platform with proof-of-stake consensus	$43 billion
9	SHIB	Shiba Inu	Meme cryptocurrency, inspired by Dogecoin	$11 billion
10	AVAX	Avalanche	Scalable blockchain platform with consensus protocol	$10 billion
11	DOT	Polkadot	Multi-chain interoperability protocol	$18 billion
12	BCH	Bitcoin Cash	Fork of Bitcoin with larger block sizes	$9 billion
13	TRX	Tron	Blockchain-based decentralized content platform	$20 billion
14	LINK	Chainlink	Oracle network connecting smart contracts with real-world data	$8 billion
15	NEAR	NEAR Protocol	Scalable blockchain platform	$7.6 billion
16	MATIC	Polygon	Ethereum layer-2 scaling solution	$15 billion

17	ICP	Internet Computer	Blockchain platform for decentralized applications	$5.5 billion
18	LTC	Litecoin	Peer-to-peer cryptocurrency	$14 billion
19	LEO	UNUS SED LEO	Utility token of the Bitfinex exchange	$5.5 billion
20	UNI	Uniswap	Decentralized exchange protocol	$7.3 billion
21	STX	Stacks	Blockchain platform bringing smart contracts to Bitcoin	$3.2 billion
22	APT	Aptos	Layer-1 blockchain platform	$3.6 billion
23	ETC	Ethereum Classic	Ethereum fork focused on immutability	$4 billion
24	MNT	Mantle	Ethereum layer-2 scaling solution	$4.8 billion
25	FIL	Filecoin	Decentralized storage network	$3.1 billion

Note: This table presents the name, ticker, description, and market capitalisation as of 10 April 2024 of the 25 cryptocurrencies in our sample. The market capitalisation data is sourced from coingecko.com.

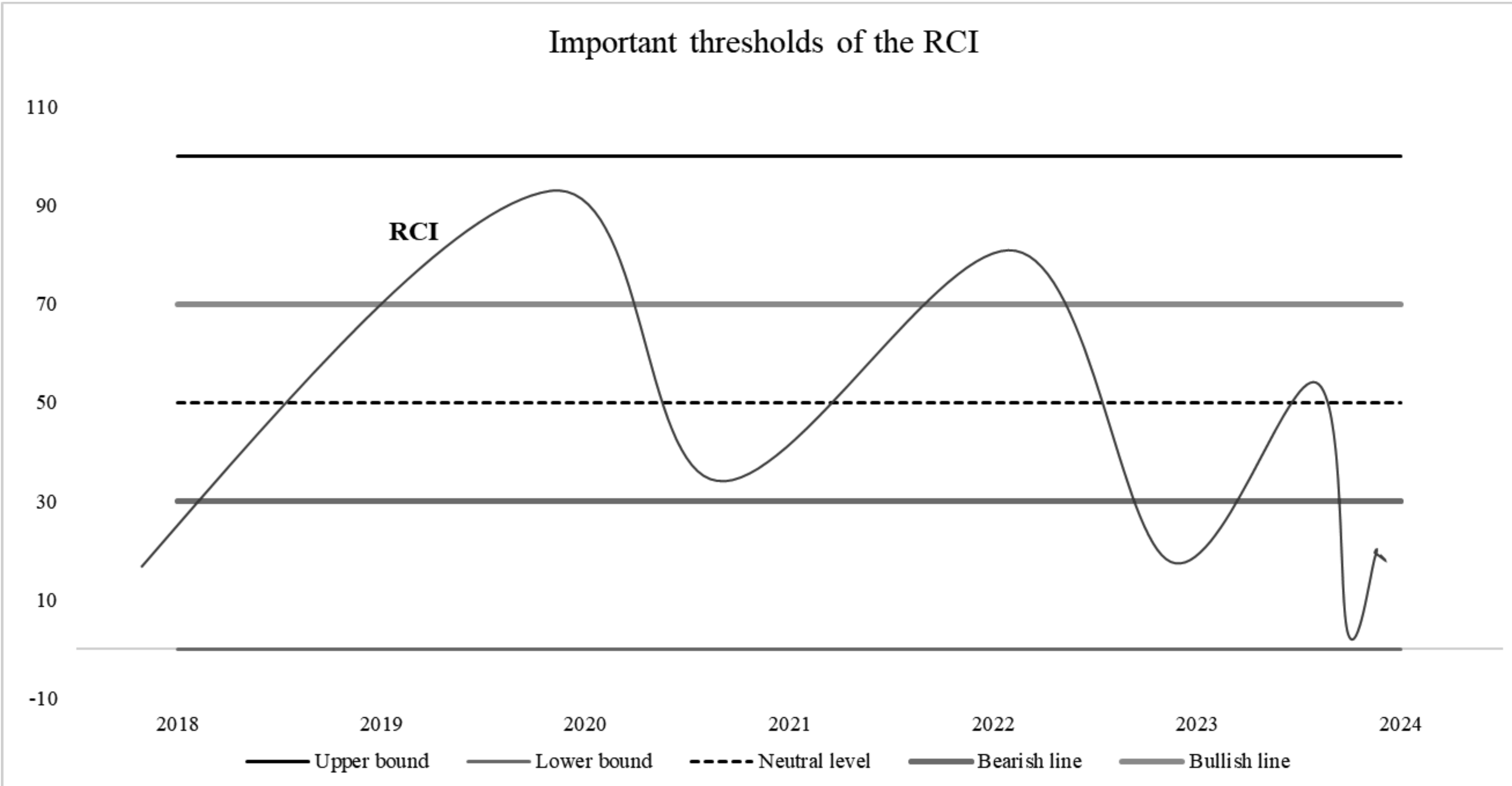
Appendix A2. AR (1) and ARCH (1) tests

Ticker	AR(1)	ARCH(1)
BTC	1.7183	38.021***
ETH	4.8433**	91.9574***
BNB	0.7715	152.5165***
SOL	4.7083**	100.1517***
XRP	25.9982***	943.1143***
DOGE	0.0088	8.2803***
TON	2.0922	30.7978***
ADA	0.2136	40.0668***
SHIB	14.8272***	27.3701***
AVAX	6.9465***	11.8597***
DOT	0.0752	14.7655***
BCH	6.0144**	19.0645***
TRX	5.8407**	30.0425***
LINK	1.1984	23.1341***
NEAR	0.2705	9.3923***
MATIC	9.4184***	21.3621***
ICP	2.7151*	39.0581***

LTC	0.0804	67.5175***
LEO	1.3662	15.3603***
UNI	1.8876	7.2326***
STX	49.4726***	17.0588***
APT	3.0712*	15.3004***
ETC	0.0054	130.8331***
MNT	0.0481	1.1491
FIL	0.0312	39.6173***

Note: This table presents the AR(1) and ARCH (1) test-statistics of the excess return series of the cryptocurrencies. *, **, and **** indicate statistical significance at 10%, 5%, and 1% level, respectively.

Appendix 3. RCI thresholds



Note: This figure shows the key threshold to interpret the variations of Relative Common Volatility Index (RCI) as described in subsections 3.2 and 5.4.