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Have the extraordinary circumstances of the COVID-19 outbreak and the Russian–Ukrainian conflict impacted the efficiency of cryptocurrencies?

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Abstract

This study explores whether the COVID-19 outbreak and Russian–Ukrainian (R–U) conflict have impacted the efficiency of cryptocurrencies. The novelty of this study is the use of the Cramér-von Mises test to examine cryptocurrency efficiency. We used a sample of daily prices for the six largest cryptocurrencies, covering the period from September 11, 2017, to September 30, 2022. Cryptocurrencies are found to be weakly efficient but exhibit heterogeneous levels of efficiency across currencies. Extraordinary events (COVID-19 and R–U) play a vital role in the degree of efficiency, where a trend toward inefficiency appears in all cryptocurrencies except for Ethereum Classic and Ripple. During the COVID-19 pandemic, the degree of inefficiency was higher than the level of inefficiency during R–U. This study provides useful guidance for investors and portfolio diversifiers to adjust their asset allocations during normal and stressful market periods.

Keywords: Cryptocurrencies, Efficiency, Cramér-von Mises test, COVID-19, Russian–Ukrainian war

Introduction

Market informational efficiency, whereby all available information is reflected in the prices of financial assets, particularly stock prices (Fama 1970), is one of the more debatable concepts in finance literature. Weak efficiency signifies that stock prices cannot be predicted because current stock prices reflect the information conveyed by past stock prices. Although the literature is flooded with articles examining the efficiency of different financial markets such as stock, futures, and foreign exchange markets, very limited research has examined informational efficiency in cryptocurrency markets. The rapid increase in cryptocurrency price volatility, as well as the value arising from their detachment from the global financial system, has given cryptocurrencies the position to be very influential assets due to their risk management capabilities and their unique blockchain technology features compared to conventional assets. If cryptocurrencies are considered hedges, their efficiency remains relatively stable during various market conditions and crises. Otherwise, their valuable role in conventional assets could be endangered and their price predictability could be disguised. Thus, the recent popularity of cryptocurrencies has attracted the interest of researchers and practitioners alike, especially those seeking a better understanding of the dynamic behavior of efficiency in the cryptocurrency market.

A growing body of literature on the information efficiency of cryptocurrency markets has emerged in recent years. However, existing studies produce mixed results regarding the degree of market efficiency. Some of these studies have reported evidence of a weak form of efficiency (Nadarajah and Chi 2017; Yaya et al. 2019; Hawaldar et al. 2019; Kakinaka and Umeno 2022; Apopo and Phiri 2021), while others have found evidence of inefficiency (Urquhart 2016; Bariviera 2017; Brauneis and Mestel 2018; Tiwari et al. 2018; Mandaci and Cagli 2022; Zhang et al. 2018) and a few have resulted in no such evidence (Grobys and Sapkota 2019; Hua et al. 2019; Palamalai et al. 2021). The most common justification for this difference in results is that cryptocurrencies differ in their operating systems and functionalities (e.g., blockchain and digital); thus, their prices might have different levels of predictability.

Although prior studies have used different methodological approaches and procedures to test for the presence of efficiency evolution in cryptocurrencies markets such as time-varying Hurst exponent analysis (Bariviera 2017; Wei 2018; Jena et al. 2022), multifractal detrended-fluctuation-analysis (MF-DFA) (Al-Yahyaee et al. 2018; Zhang et al. 2020; Kakinaka and Umeno 2022), traditional unit root tests (Hawaldar et al. 2019; Yaya et al. 2019), the log-periodic power law (Ghosh et al. 2022) and long-range dependence, fractal dimension and entropy components (Kristoufek and Vosvrda 2019; Sensoy 2019), they have rarely used the most recently developed methodology, the Cramér-von Mises test statistic (CvM) which was created by Hill and Motegi (2019, 2020). Furthermore, while existing studies (e.g., Fernandes et al. 2022; Ghosh et al. 2022; Zhang et al. 2020) have examined the evolution of market efficiency during the COVID-19 outbreak, they have not used the most updated sample period that covers the COVID-19 vaccination offering and the Russian–Ukrainian (R–U) war. Thus, the evolution of the cryptocurrency market efficiency remains fertile for further research.

Our main motivation stems from the recent noticeable high volatility shown in global cryptocurrency markets in normal times as well as during recent crisis periods, such as the COVID-19 and R–U conflict. Higher volatility of cryptocurrency prices may affect market efficiency. Apart from the well-known significant drop in cryptocurrency prices after the Bitcoin crash in early 2018, the global cryptocurrency market's market capitalization has fluctuated greatly over the past several years.[1] For instance, directly after the confirmation of COVID-19 as a pandemic in March 2020, the market capitalization of the global cryptocurrency market started to rise, from 226.7 USD billion in March 2020 to 2,463.3 USD billion in mid-May 2021, an increase of approximately 11 times. However, after around two months, in July 2021, market capitalization began to decline significantly, reaching 1,285.5 USD billion, which could be due to the confirmation of the coronavirus vaccine. Once the R–U conflict started in the early months of 2022, market

[1] The empirical data about market capitalizations of the global cryptocurrency market were obtained from https://coinmarketcap.com/.

capitalization began to decline, reaching approximately 797 USD billion by the end of October 2022. Thus, the high volatility in global market capitalization that occurred during the recent crises may have influenced the degree of market efficiency.

The highly influential recent global crises, namely the COVID-19 pandemic and the R–U conflict, are considered very strong motives in the investigation of the efficient market hypothesis (EHM) in cryptocurrency markets. The COVID-19 pandemic has been regarded as one of the most significant global crises in more than a century, resulting in a significant increase in human deaths and casualties as well as a dramatic increase in global poverty and economic inequality. Thus, these negative consequences have created behavioral biases in cryptocurrency markets.

The ongoing conflict between Russia and Ukraine has generated political and economic tension worldwide. This conflict has caused financial market downturns and sharply increased uncertainty in the global economy, in which higher commodity prices are intensifying, long-term high inflation looms, and the risk of stagflation and social instability increases. Industry sectors such as automotive, transportation, and chemical spheres suffer the most.[2] This turbulence has influenced cryptocurrency traders' behavior. Thus, given the increase in the level of volatility in cryptocurrency prices during COVID-19 and the R–U war, examining the impact of these crises on market efficiency is an attractive topic for investigation.

Our main objective is to investigate the effect of the COVID-19 crisis and the Russian–Ukrainian (R–U) war on the dynamic behavior of evolving efficiency in cryptocurrency markets. Specifically, we aim to answer three questions. First, how has the efficiency of cryptocurrencies evolved over the last five years? Second, are there any noticeable differences in the efficiency of cryptocurrencies during extreme events such as the COVID-19 pandemic and the R–U war compared to non-crisis periods? Third, how did the efficiency of different cryptocurrencies vary during the COVID-19 pandemic and the R–U war, and did any specific cryptocurrencies exhibit unique patterns?

This study contributes to the existing literature in several ways. It provides a comprehensive analysis of the debate on the evolution of market efficiency for six cryptocurrencies (Bitcoin, Ethereum, Binance [BNB], Ripple [XRP], Ethereum Classic, and Litecoin)[3] and extends the body of knowledge on cryptocurrencies' evolving efficiency after most global events, such as the COVID-19 pandemic and the R–U war. In addition, our study is the first to use the CvM test statistic, created by Hill and Motegi (2019, 2020), to examine how efficiency changes during extraordinary circumstances. In contrast to other existing approaches,[4] this novel framework is based on blockwise wild bootstrapping in a rolling window (Shao 2011), thereby not being sensitive to the choice of block

[2] European countries have been most substantially affected, showing an increase in the inflation rate, reaching 8.5% in September 2022, while the GDP growth in Europe decreased by up to 4 percentage points (IFM 2022; Eurostat 2022).

[3] To enrich the analysis of market efficiency, we carefully selected this mix of cryptocurrencies due to their heavy use in previous studies, their higher liquidity and market coverage, and their well-established statuses (e.g., Bitcoin and Ethereum), older digital currencies with lower market capitalizations (Ripple and Litecoin), and younger ones with smaller market capitalizations (Binance and Ethereum Classic). For more details about the market capitalization of each cryptocurrency as a percentage of the total market capitalization of the global cryptocurrency market, as of October 2022, see Table 1.

[4] The most commonly used efficiency testing approaches are the variance ratio test by Lo and MacKinlay (1988), the bicorrelation test by Hinich (1996), the spectral test by Hong (1996), the sign/rank test by Wright (2000), the multifractal detrended-fluctuation-analysis (MF-DFA) by Kantelhardt et al. (2002), the generalized spectral test by Escanciano and Valasco (2006), and the robust automatic portmanteau test of Escanciano and Lobato (2009).

Table 1 The Sample cryptocurrencies by market capitalization

	Symbol	Total market capitalization	
		US$	Market share (%)
Bitcoin		370.568B	39.48
Ethereum		162.151B	17.27
Binance		21.049B	2.24
XRP		23.913B	2.55
Ethereum classic		3.781B	0.40
Litecoin		3.796	0.40
Total market		938.730B	62.35

The data is based on October 1, 2022. The data are obtained from https://coinmarketcap.com/

size for a large sample size and providing more reliable inference for testing white noise than the rolling window subsample techniques used in previous studies. In addition, the existing approaches are not genuine white noise tests because they do not asymptotically capture serial correlations at all lags (Hill and Motegi 2019).

The results reveal that cryptocurrencies are weak-form efficient and that their degree of efficiency evolves over time. The weak form of cryptocurrency efficiency is heterogeneous across currencies. This means that cryptocurrency prices are less predictable and that arbitrage opportunities are very limited in these markets. We also show that, during the extreme events, there was a trend toward inefficiency in all cryptocurrencies except for Ethereum Classic and Ripple. The COVID-19 crisis resulted in a higher degree of inefficiency than has the R–U war. Our study offers useful information to investors, governments, prudential regulatory authorities, and portfolio diversifiers.

The remainder of the paper is organized as follows: Section "Introduction" presents the introduction, and Section "Literature review" contains a literature review. Section "Methodology" presents the methodology and data. The results and analyses are discussed in Sections "Data and preliminary statistics" and "Results and analysis" concludes the paper.

Literature review

Existing studies suggest that market efficiency is not only a static phenomenon, but also one that evolves over time because market conditions and crises often have a strong influence on its behavior. Most prior studies have focused on the degree of evolving efficiency in different types of financial markets. For example, some studies have found evidence of evolving efficiency in stock markets (Al-Shboul and Alsharari 2019; Tiwari et al. 2019; Gaio et al. 2022; Ozkan 2021), while others have found evidence of evolving efficiency in foreign exchange markets (traditional currencies) (see Yamani 2021; Aslam et al. 2020; Yang et al. 2019). Evidence of evolving efficiency has also been found in other markets, such as oil and gold markets (Okoroafor and Leirvik 2022; Bariviera et al. 2019; Iwatsubo et al. 2018; Al-Yahyaee et al. 2018). These studies indicate that most conventional assets experience different levels of return predictability, supporting the adaptive market hypothesis.

Another group of studies examined the efficiency of Bitcoin and other large traded cryptocurrencies such as Ethereum, Litecoin, and Ripple. However, they reported different findings owing to differences in the functionalities of cryptocurrencies. Before addressing the literature, the differences between cryptocurrencies need to be discussed.[5] For example, Litecoin (LTC) is a cryptocurrency based on the Bitcoin protocol. However, the two currencies differ in terms of their algorithms, hard caps, block transaction times, transaction speeds, and levels of privacy. LTC provides fast, secure, and low transaction fees and is suitable for microtransactions and point-of-sale payments. Ethereum (ETH) allows for the creation of smart contracts and decentralized applications. ETH has its own cryptocurrency and functions as a platform for many other cryptocurrencies. In contrast, Ripple (XRP) provides a variety of open-source protocols and arranges for payments, including micropayments such as DeFi, tokenization, stablecoins, and NFTs. Ripple also supports tokens of fiat currencies, other cryptocurrencies, commodities, and other units of value. It enables secure and nearly free global financial transactions of any size at no charge. Given these differences between the above cryptocurrencies, investors' behavior and reactions to market changes may differ, leading to differences in the degree of market efficiency.

Hawaldar et al. (2019), when using the traditional efficiency tests (unit root and stationary tests) argue that cryptocurrencies (Bitcoin and Litecoin) exhibit random walk behavior, supporting the efficient market hypothesis. Using the detrended-fluctuation-analysis (DFA) method, Zhang et al. (2020) found that Bitcoin, Ethereum, and Litecoin are efficient in bull markets but inefficient in bear markets. Naeem et al. (2021) studied asymmetric multifractal DFA and found evidence of asymmetric efficiency in Bitcoin, Ethereum, Litecoin, and Ripple; in particular, upward trends exhibited stronger efficiency than did downward trends. However, during the COVID-19 crisis, there was a substantial increase in inefficiency; Bitcoin and Ethereum were the hardest-hit cryptocurrencies. Similarly, Kakinaka and Umeno (2022) used asymmetric MF-DFA and showed that the COVID-19 outbreak greatly changed the level of asymmetry in the cryptocurrency markets for Bitcoin and Ethereum. After the COVID-19 outbreak, stronger evidence of efficiency appeared in the short term and weaker evidence in the long term.

In addition to the popularly traded cryptocurrencies, recent studies have started focusing on a mix of cryptocurrencies with various functionalities and designs such as the Binance Coin (BNB), Cardano, NEM, Stellar, Dash, Monero, Verge, and EOS, among others. Cryptocurrencies can be classified into tokens and coins. For instance, by taking the 2017–2018 Bitcoin price crash, Yaya et al. (2019), employing the fractional integration approach, found that after the Bitcoin crash, Bitcoin and other digital coins and tokens (namely, Ethereum, Ripple, Litecoin, Dash, Digibyte, Doge, Maidsafecoin, Monero, Nem, Stellar, Verge, and Vertcoin) were highly efficient because of speculative transactions among cryptocurrency traders that caused non-mean reversions. Le Tran and Leirvik (2020) analyzed five cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, and EOS) and reported that before 2017, these cryptocurrencies were mostly inefficient but showed a trend toward efficiency during the Bitcoin crash, as in the 2017–2019 period.

[5] We have addressed these difference thanks to the suggestion by an anonymous referee.

Fernandes et al. (2022), by constructing the Shannon-Fisher causality plane (SFCP), argued that five cryptocurrencies (Bitcoin, Binance Coin, Cardano, Ethereum, and Ripple) exhibited high but slightly evolving efficiency behavior in the periods before and during the COVID-19 crisis, but Cardano was the most efficient. The researchers stated that the difference in evolution might be due to an increase in maturity and a low potential for price predictability. Zhang et al. (2018) used a battery of efficiency tests to confirm that cryptocurrency markets (Bitcoin, Ripple, Ethereum, NEM, Stellar, Litecoin, Dash, Monero, and Verge) are informationally inefficient. Using the Hurst exponent, Wei (2018) showed that while Bitcoin exhibits some evidence of efficiency, other cryptocurrencies (DASH, Litecoin, Monero, Ripple, and Stellar) exhibit signs of inefficiency. Within the 2007–2008 global financial crisis (GFC), Apopo and Phiri (2021) argued that the daily returns of cryptocurrencies (namely Bitcoin, Ethereum, Litecoin, Bitcoin Cash, and Ripple) supported the random walk hypothesis, that is, evidence of a weak form of efficiency, while weekly returns did not support the weak form of efficiency.

In another study using the 20 most liquid cryptocurrencies in September 2016, Brauneis and Mestel (2018) argued that the efficiency of cryptocurrencies was less predictable when liquidity rose because of the use of different cryptocurrencies operated by different mechanisms. Kristoufek and Vosvrda (2019), who utilized an Efficiency Index based on long-range dependence, fractal dimension, and entropy components, argue that historical currencies (e.g., Bitcoin, DASH, Litecoin, Monero, Ripple, and Stellar) were consistently inefficient over the full sample period. However, most coins and tokens were efficient only between July 2017 and June 2018. The weakest efficiency for digital coins was observed for Ethereum and Litecoin, whereas Dash was the most efficient.

Other studies examined the impact of anomalies (day-of-the-week, month-of-the-year, and calendar anomalies) on the level of efficiency for different cryptocurrency markets. Ahraron and Qadan (2019) found evidence of the day-of-the-week effect on returns and the volatility of Bitcoin, confirming its strong independence. By considering noneconomic events (calendar anomalies), Qadan et al. (2022) argued that anomalies (the day of the week) had an impact only on the Bitcoin market and made it inefficient. However, they report that the within-month effect affects all cryptocurrencies. Caporale and Plastun (2019) confirmed the impact of the day of the week on Bitcoin; the Bitcoin market remains somewhat efficient. However, they argue that other cryptocurrencies (Litecoin, Ripple, and Dash) are not affected by the day-of-the-week anomalies. Robiyanto et al. (2019) argued that the day of the week and month of the year led the Bitcoin and Litecoin markets to become inefficient. Nevertheless, Kinateder and Papavassiliou (2021) showed no evidence of the effects of the Halloween calendar and day-of-the-week anomalies in Bitcoin, indicating that cryptocurrency prices remain less predictable; that is, the Bitcoin market is efficient.

By comparing the degree of efficiency before and after the COVID-19 pandemic for a mix of 18 major traded digital cryptocurrencies during periods of extreme events, El Montasser et al. (2022) indicated that cryptocurrency efficiency strongly increased during the COVID-19 pandemic compared to before COVID-19. Using a set of 143 cryptocurrencies, Grobys and Sapkota (2019) found no evidence of a significant momentum payoff strategy in the cryptocurrency market, confirming that such a market is not efficient. Hua et al. (2019), allowing for cross-sectional dependence and considering possible structural breaks, showed no empirical support for the efficient market hypothesis for 31 of the top market-cap cryptocurrencies.

Palamalai et al. (2021), using non-parametric and parametric random walk testing methods with structural breaks and asymmetric effects, found no evidence to support the random walk hypothesis owing to the occurrence of asymmetric volatility clusters. Based on the time-varying generalized Hurst exponent, Jena et al. (2022) stated that although cryptocurrencies (Bitcoin, DASH, Litecoin, Monero, Ripple, and Ethereum) have different degrees of (in)efficiency, they exhibit evidence of evolving inefficiency owing to differences in their functionality; for example, privacy coins (Monero) and digital cash (DASH) use different technologies, such as zero-knowledge proofs, to ensure the privacy and confidentiality of transactions. Sensoy (2019) found that Bitcoin-US and Bitcoin-Euro have become more informationally efficient at the intraday level since the beginning of 2016, and Bitcoin-US was slightly more efficient than Bitcoin-Euro in the sample period. As these cryptocurrencies are pegged against the US dollar, which brings traditional currencies to blockchain technology, they could be subject to government prudential regulations; therefore, they might behave differently, leading to different levels of market efficiency.

Most recently, a noticeable shift in the literature has been directed toward examining the behavior of asset-linked cryptocurrencies during COVID-19 and the R–U war, such as energy cryptocurrencies, traditional cryptocurrencies, and energy-conserving cryptocurrency markets. For example, Mnif et al. (2023) provide different results regarding the efficiency of traditional cryptocurrencies (Ethereum and Bitcoin) and energy-conserving cryptocurrencies (Green Bitcoin, Cardano, SolarCoin, and Ripple). They argue that Bitcoin and SolarCoin had the lowest degree of inefficiency before COVID-19. However, Ethereum was the most effective after COVID-19. Similarly, Ripple was the most efficient cryptocurrency during the R–U crisis. This resulted from the energy crisis caused by the R–U conflict, which led to an increase in the efficiency of energy-conserving cryptocurrencies. Yousaf et al. (2023), using the TVP-VAR method, show that energy cryptocurrencies (POWR, GRID+, and SNC) are strongly connected only to Bitcoin. Conversely, the degree of connectedness changed rapidly during COVID-19 and the R–U war and was highly sensitive to shocks in uncertainty. By employing the QVAR approach, Le (2023) argues that stressful market periods, such as COVID-19 and the R–U war, influence the degree of connectedness between the cryptocurrency volatility index and renewable energy volatility (Green Bonds, Clean Energy, Wind Energy, Solar Energy, Natural Gas, and Crude Oil). This confirms that these crises affected the efficiency of both types of assets. These studies point out that asset-linked cryptocurrencies exhibit different levels of evolving efficiency.

Overall, while the studies cited above attempted to investigate the presence of evolution in the efficiency of cryptocurrency markets, they failed to provide convincing evidence as to whether such markets are clearly efficient or whether their efficiency evolves over time. Most importantly, although the aforementioned studies use different methodological approaches to examine efficiency and evolving efficiency, our study is the first to use the CvM test procedure created by Hill and Motegi (2019, 2020) to examine efficiency. Furthermore, given that the above studies used different and mixed types of cryptocurrencies with different operating systems, they missed the opportunity to use mixed types of digital and blockchain currencies (decentralized digital, tokens, altcoins, and coins), which have different operating systems and are older and well-established currencies (Bitcoin and Ethereum) or more liquid and new currencies (younger in age) with lower market capitalization (Ethereum Classic and Binance). While a few studies have examined the evolution of market efficiency during COVID-19 and the R–U war, they have not used the most updated sample period that covers the full R–U war period. This study examines the evolution of efficiency in cryptocurrency markets by covering the above research gaps. Thus, we tested the following hypothesis.

H1 Extraordinary circumstances (i.e., COVID-19 and the R–U war) have an impact on the evolution of cryptocurrency market efficiency.

By rigorously testing this hypothesis, we not only provide robust empirical evidence regarding the evolution of cryptocurrency efficiency over time but also examine whether notable variations in efficiency arise during extreme events such as the COVID-19 pandemic and the R–U war and whether specific cryptocurrencies exhibit distinctive patterns in such circumstances.

Methodology

In this study, the CvM developed by Hill and Motegi (2019, 2020) was applied to examine the impact of the COVID-19 pandemic and the R–U war on the dynamic evolution of cryptocurrency market efficiency. Compared to rolling window subsample methods, this novel framework is based on blockwise wild bootstrapping in a rolling window,[6] thereby being less sensitive to the choice of block size for a large sample size and providing a more reliable inference for testing white noise. In this section, we briefly describe the proposed method.[7]

Let r_t be a strictly stationary time series (i.e., cryptocurrency returns) at day $, t \in \{1, \ldots, n\}$. Consider that the mean, autocovariances, and autocorrelations are defined as $\mu = E(r_t), \gamma(h) = E\left[(r_t - \mu)\left(r_{t-h} - \mu\right)\right]$, and $\rho(h) = \frac{\gamma(h)}{\gamma(0)}$ for $h \in \{0, \ldots, N\}$, respectively. Weak-form efficiency (white noise hypothesis) can then be tested using the following two hypotheses:

$$H_0 : \rho(h) = 0, \text{ for } h \in \{0, \ldots, N\} \text{against } H_1 : \rho(h) \neq 0 \text{ for some } h \in \{0, \ldots, N\} \quad (1)$$

Acceptance of the null hypothesis (H_0) supports weak-form efficiency, whereas rejection is evidence against weak-form efficiency.

Likewise, writing the sample mean, autocovariances, and autocorrelations as $\hat{\mu}_n(h) = \frac{1}{n}\sum_{t=1}^{n} r_t, \hat{\gamma}_n(h) = \frac{1}{n}\sum_{t=h+1}^{n}\left(r_t - \hat{\mu}_n\right)\left(r_{t-h} - \hat{\mu}_n\right), and\ \hat{\rho}_n(h) = \frac{\hat{\mu}_n(h)}{\hat{\gamma}_n(0)}$ for $h \in \{0, \ldots, N\}$, respectively, the CvM statistic for testing white noise under general weak dependent assumptions is defined as spectral density $f(\lambda)$ by

[6] This method was initially proposed by Shao (2011).

[7] Most discussion and notation contained in this section follows Hill and Motegi (2019, 2020).

$$\mathrm{CvM}_n = n\int_0^{\pi}\left\{\sum\nolimits_{h=1}^{n-1}\hat{\gamma}_n(h)\psi_h(\lambda)\right\}^2 d(\lambda) \quad (2)$$

where $\psi_h(\lambda)=\frac{\sin(h\lambda)}{h\pi}forh\neq 0$. To perform the dynamic evolution of the CvM test for CvM_n, we use a blockwise wild bootstrap in a rolling-window framework. Following Hill and Motegi (2019, 2020), the blockwise wild bootstrap for CvM_n can be executed using the following steps:

1. Decide on block size b_n with $1 \leq b_n < n$. Indicate the blocks with $B_s=\left\{(s-1)b_n+1,\ldots,n/b_n\right\}$, where $s=1,2,\ldots,L_n$, $L_n=n/b_n$.
2. Generate *iid* random numbers such that $\left\{\xi_1,\ldots,\xi_{n/b_n}\right\}$ with $E[\xi_i]=0, E\left[\xi_i^2\right]=1$ and $E\left[\xi_i^4\right]<\infty$. Create auxiliary variables $\omega_t=\delta_s ift \in B_s$ for $t-1,\ldots,n$.
3. Calculate the bootstrapped autocovariance as: $\widehat{\gamma}_n^{COV}(h)=\sqrt{n}\sum_{h=1}^{n-1}\widehat{\gamma}_n^{*}(h)\psi_h(\lambda)$, where $\widehat{\gamma}_n^{*}(h)=\frac{1}{n}\sum_{t=h+1}^{n}\left(r_t-\widehat{\mu}_n\right)\left(r_{t-h}-\widehat{\mu}_n\right)-\widehat{\gamma}_n(h)$.
4. Then, compute the bootstrapped test statistic such that $CvM_n^{*}=\int_0^{\pi}\widehat{\gamma}_n^{COV}(h)$.
5. Repeat steps 2 and 3 M times, and label the results using $\left\{CvM_{n,i}^{*}\right\}_{i=1}^{M}$. The approximate p-values are $\widehat{p}_{n,M}^{*}=(1/M)\sum_{i=1}^{M}I(CvM_{n,i}^{*}\geq\widehat{\mathrm{CvM}_n})$. We then reject the null hypothesis of white noise at the significance level α if $\widehat{p}_{n,M}^{*}<\alpha$.

Finally, in order to capture time-varying market efficiency, we perform a rolling window analysis based on randomizing the block size for each bootstrap sample and window using window sizes of $n\in\{240,480,720\}$ days.[8] For the blockwise wild bootstrap (b_n), we chose $b_n=c\sqrt{n}$, where $c\in\{0.5,1,2\}$ so that$b_n\in\{15,21,61\}$.[9] A total of 5,000 replicates were performed using bootstrapping for each window.

Data and preliminary statistics

This study explores whether cryptocurrencies are weak-form efficient. Therefore, we choose the six largest cryptocurrencies in the market: Bitcoin, Ethereum, Binance, XRP, Ethereum Classic, and Litecoin. These six constitute approximately 62% of total cryptocurrency market capitalization (see Table 1).[10] Our cryptocurrency sample is priced in US dollars. The dataset consists of daily closing prices, spanning the period from September 11, 2017, to September 30, 2022, with 1786 observations.[11] The time span of the data includes the most recent crises, namely, the ongoing COVID-19 pandemic and the R–U war. Data were obtained from Thomson Reuters Datastream. The daily returns for each cryptocurrency are calculated as the natural logarithmic

[8] These window sizes were chosen for two reasons: (i) they represent short-term (1-year window), medium-term (2-year window), and long-term (3-year window) effects; and (ii) these sizes are mostly less sensitive to the choice of block size for a large sample size, which provides more reliable inference for testing white noise. Using window sizes higher than 240 blocks can cover the crisis periods, lead to smoother autocorrelations and confidence intervals, and avoid generating any periodicities like those reported when using a 240-block fixed window size.

[9] Hill and Motegi (2019, 2020) demonstrate that non-periodic and smooth confidence bands can be obtained using a blockwise wild bootstrap with block size $b_n=c\sqrt{n}$.

[10] See https://www.statista.com/statistics/1269013/biggest-crypto-per-category-worldwide/. In addition, these cryptocurrencies have recently triggered the attention of investors and academic researchers (e.g., Cui and Maghyereh 2022; Wang et al. 2022b; Maghyereh and Abdoh 2021; 2022; Pace and Rao 2023; Al-Shboul et al. 2022, 2023; among many others).

[11] The starting date of the sample was selected based on the data availability.

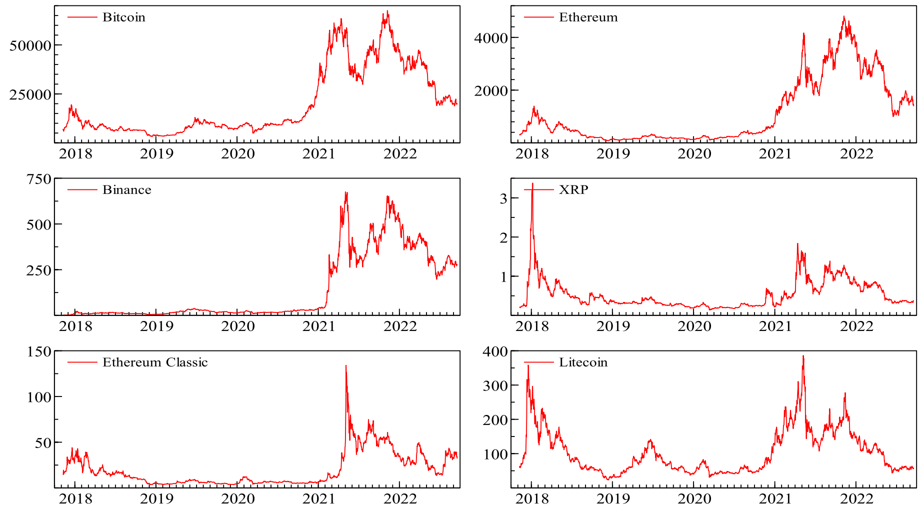

Fig. 1 Evolution of daily prices series. *Notes* the figures disply the sample cryptocurrencies' historical daily closing prices from September 11, 2017 through September 30, 2022. In the vertical axis, all cryptocurrencies are priced in US dollars

difference between two continuous price observations: $r_{it} = ln(p_{it}) - ln(p_{it-1})$, where r_{it} denotes the daily returns and p_{it} represents the i-th daily price.

Figure 1 shows the dynamic evolution of the daily cryptocurrency prices. The figure shows that all cryptocurrencies exhibit similar evolutionary features. The prices showed a sudden increase in December 2018, then fluctuated at lower levels in 2019 and 2020 (when the US–China trade war occurred and COVID-19 was confirmed as a pandemic on March 11, 2020), and then rose rapidly and reached an all-time high in April 2021 (when the COVID-19 vaccine was becoming widely available). The prices fell rapidly until rising again in July 2021 and peaked in November 2021 before falling again in March 2022 (the beginning of the R–U war). A graphical representation of the return series (Fig. 2) indicates high volatility in the cryptocurrency market, particularly during the COVID-19 crisis.

Table 2 displays descriptive statistics for the daily returns of cryptocurrencies. Binance has the highest mean positive value, followed by Ethereum, Bitcoin, Ethereum Classic, and XRP, while the mean value of Litecoin is negative. While XRP has the highest volatility, Bitcoin has the lowest standard deviation. Regarding the distribution properties of the cryptocurrencies, all of the series are right heavy-tail. In addition, all of the series exhibited excess kurtosis, indicating that they are leptokurtic. According to the Jarque–Bera test results, all return series are non-normal. The quantile–quantile (Q–Q) plots, which are shown alongside histograms in Fig. 3, confirm the result. The results of the ADF unit root test show that all return series are stationary. Even more importantly, as illustrated in Table 2, the Q(10) and $Q^2(10)$ test for autocorrelation of returns and squared returns, respectively, the Variance-Ratio test, R/S test, the Runs test, and the BDS test all reject the hypothesis of independence in cryptocurrency returns. This justifies the use of Hill and Motegi's (2019; 2020) white noise test, which assumes that weak dependence exists in return series.

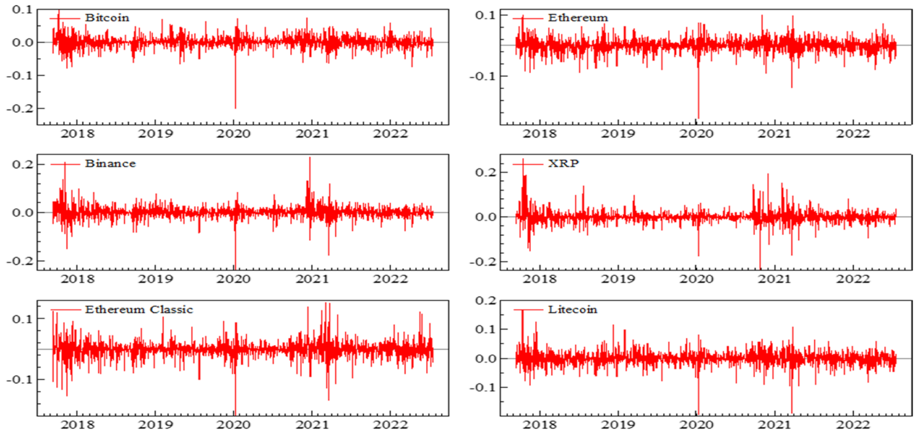

Fig. 2 Evolution of daily returns series. *Notes* the figures disply the sample cryptocurrencies' historical daily returns (%) calculated as the natural logarithmic difference between two continuous price observations.

Table 2 Summary descriptive statistics

	Bitcoin	Ethereum	Binance	XRP	Ethereum classic	Litecoin
Mean	0.00025	0.00036	0.00121	0.00014	0.0002	− 0.00003
Max	0.09777	0.10195	0.22984	0.26357	0.15308	0.16908
Min	− 0.20183	− 0.23918	− 0.23586	− 0.23908	− 0.21992	− 0.19503
Std. Dev	0.01778	0.02255	0.02596	0.02798	0.02792	0.02431
Skewness	− 0.80762	− 0.91065	0.38542	0.83215	− 0.10954	− 0.13829
Kurtosis	14.71101	12.50943	17.42898	19.39155	10.67991	11.52421
J-B	10,330.3***	6929.41***	15,433.04***	20,064.89***	4363.22***	5376.59***
ADF	− 43.450***	− 28.412***	− 27.64***	− 41.831***	− 42.879***	− 43.357***
Q(10)	18.6755**	26.1702***	41.3476***	20.4137**	16.0249*	18.0468**
$Q^2(10)$	46.0623*	52.262***	308.931***	191.534***	194.006***	143.824***
Variance-ratio test	0.19435	0.58274	0.70095	0.87198	0.40564	0.36437
R/S test	1.44376	1.50027	1.24291	1.26962	1.26338	1.21698
Runs test	2.37565**	2.80597***	3.2156***	4.20952***	3.61372***	2.61404***
BDS test						
Dimension						
2	5.0270***	3.9657***	10.1987***	10.9165***	8.5719***	5.6492***
3	6.6425***	5.7120***	12.7241***	12.6963***	11.3498***	7.3051***
4	7.5004***	6.7478***	14.1455***	13.8784***	12.7082***	8.1639***
5	8.6387***	7.4868***	15.4217***	15.4535***	13.5220***	9.1827***
6	9.5135***	8.3270***	16.5656***	16.6495***	14.2998***	9.8311***

The table show the summary descriptive statistics of the daily returns of cryptocurrencies. The Jarque–Bera statistic the normality test of the sample distribution. ADF is the Augmented Dickey-Fuller test of unit root. Q(10) and $Q^2(10)$ are Li and McLeod test for autocorrelation of returns and squared returns respectively. Variance-Ratio Test is the Lo and MacKinlay statistics for testing the random walk hypothesis (weak-form efficiency which are robust under homoscedasticity and heteroscedasticity. R/S (range over standard deviation) test is the Hurst-Mandelbrot statistics for testing the hypothesis of no long-range dependence. Runs Test (also called Wald-Wolfowitz test) is the Lo's statistic (a non-parametric statistic) that test the random walk hypothesis. BDS test (initiated by Brock, Dechert, Scheinkman and LeBaron) is a non-parametric statistic of testing the nonlinear serial dependence in time series using spatial dimensions from 2 to 6. ***, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is 11/09/2017–30/09/2022

Finally, Fig. 4 presents a correlation heatmap of the six studied cryptocurrencies. Stronger correlations correspond to warmer colors (red). The graph shows that the returns of all six cryptocurrencies are highly related to one another. This finding is

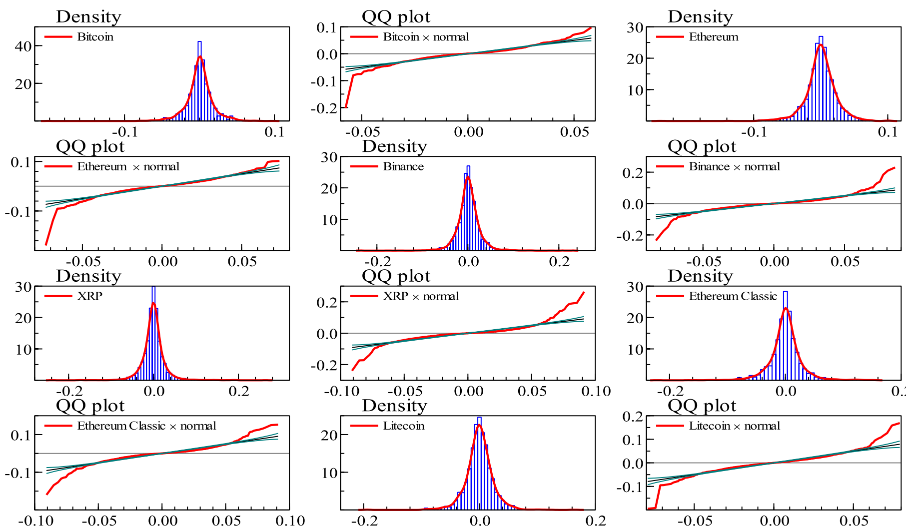

Fig. 3 Density distribution and Q–Q plots. *Notes* the figures disply the density empirical distribution and quantile-quantile (Q–Q) plots of the sample cryptocurrencies' historical daily returns

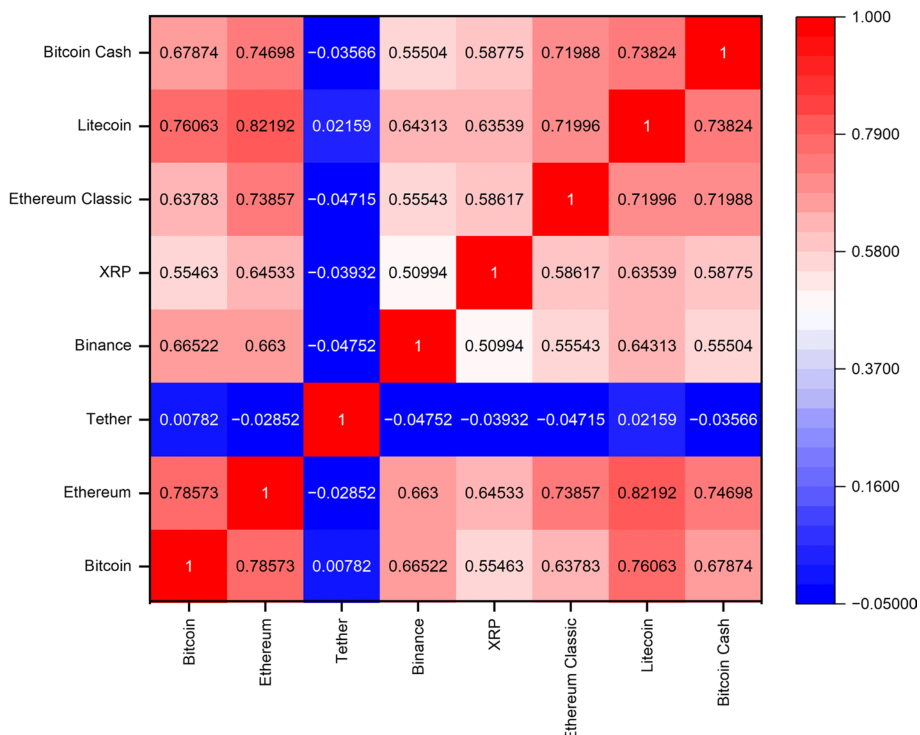

Fig. 4 Heatmap correlation matrix. *Notes*: The figure displays the correlation matrix heatmap between the sample cryptocurrencies' daily returns. Numbers in heatmap presents the correlation coefficients. The colors bar on the right-hand side of the plot presents the strength of correlation

consistent with previous research (i.e., Hu et al. 2019a, b; Ferreira et al. 2020; Zhang et al. 2021; Al-Shboul et al. 2022, among others), which shows that most cryptocurrency returns are positively correlated.

Table 3 Rejection ratio of cram´er-von mises test over rolling windows

	Bitcoin	Ethereum	Binance	XRP	Ethereum classic	Litecoin
n = 240	0.00404	0.00692	0.0060	0.0000	0.0000	0.0512
n = 480	0.00328	0.00407	0.0024	0.0000	0.0000	0.0000
n = 720	0.00273	0.00451	0.0009	0.0000	0.0000	0.0029

The table reports the ratio of rolling windows. At the 5% level, the null hypothesis of white noise is rejected

Results and analysis

This section reports the results of the CvM test statistic in different forms, such as autocorrelation with windows of different sizes (fixed and random block sizes), rolling windows of the value of the CvM test, and *p* values of the CvM test for selected window sizes (240, 480, and 720). Before reporting the results of this test, we report the efficiency rejection ratios of the CvM test statistics for all cryptocurrencies in Table 3. Interestingly, Table 3 shows evidence of very low rejection ratios for all currencies, providing strong evidence supporting the white noise hypothesis—the existence of weak-form efficiency in all currency markets.

Our main aim is to capture the potentially time-varying degree of cryptocurrency market efficiency using a rolling-window analysis of cryptocurrency price returns. To measure the time-varying degree of efficiency, autocorrelations with different window sizes (240, 480, and 720 days) are reported in Figs. 5, 6, and 7. In each graph of these figures, the autocorrelation series is drawn in black, solid lines, and 5% critical values (i.e., 95% confidence bands) in red dotted lines.

In general, the results show a periodic pattern that fluctuates rhythmically in every window, in contrast to the true *iid* data generation structure. In Fig. 5, where a 240 days window is used, the white noise hypothesis is accepted for all cryptocurrency markets, indicating that these markets are weak-form efficient, especially in non-crisis periods, but are often rejected during crisis periods such as the COVID-19 crisis and the R–U war. In addition, at the start of 2019, all cryptocurrencies (except Litecoin and Binance) showed signs of inefficiency (where the trade wars and crash in the Bitcoin market were clear). One possible reason for this rejection is the large negative autocorrelation of cryptocurrency prices. Our results contradict the findings of Urquhart (2016) and Bariviera (2017), who argued that cryptocurrencies are mostly inefficient, and are in line with the results of Brauneis and Mestel (2019) and Hawaldar et al. (2019). When weak-form efficiency is present, whereby public information is reflected in prices, there is limited cryptocurrency price predictability (i.e., fewer arbitrage opportunities) because of the difference in the degree of shocks in information transmission across investors within the market. Thus, cryptocurrencies can be considered beneficial investment tools that investors can use to reduce the risk of their portfolios under normal conditions, while they can be used as safe haven assets during crisis periods. During crises, investors may be less advantaged when investing in cryptocurrencies; thus, policymakers must follow certain regulatory reforms and prudential policies to stabilize cryptocurrency prices and implement effective risk controls during extreme conditions. In this case, the market may have regained efficiency quickly.

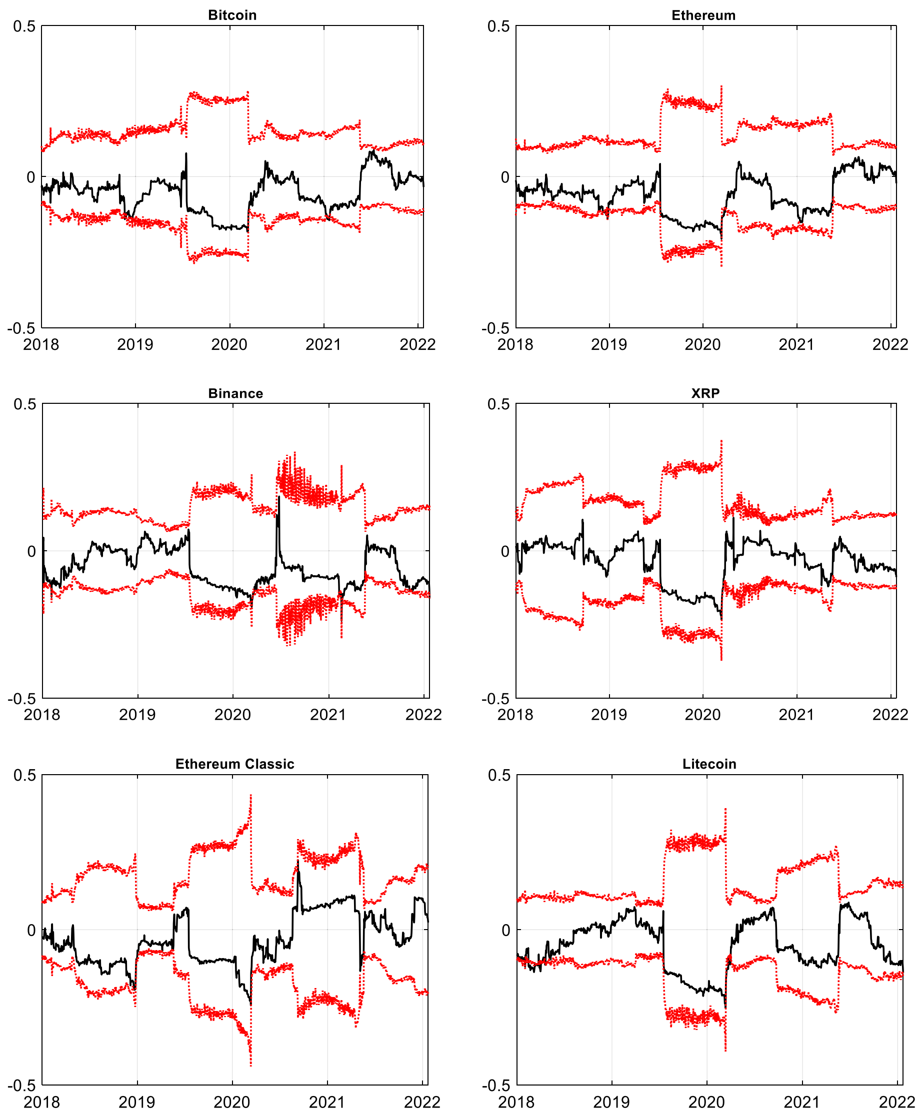

Fig. 5 Autocorrelations with Window Size n = 240 (Fixed Block Size). *Notes* The figure displays autocorrelations with lag h = 1 over rolling windows. Correlations are shown by solid black lines, while 95% confidence bands are represented by dotted red lines. Under the null hypothesis of white noise, the confidence band is produced using a blockwise wild bootstrap of 5000 iterations for each window. Each point on the horizontal axis represents the initial date of each window

When larger window sizes (480 and 720) are used, as shown in Figs. 6 and 7, evidence similar to that reported in Fig. 5 is observed. In general, negative autocorrelations shift over time, with the trend shifting from inefficiency to a weak form of efficiency. We found that all cryptocurrency markets are weakly efficient during non-crisis periods but inefficient during crisis periods. However, this does not apply to Binance and Ethereum Classic, which show evidence of a weak form of efficiency during the COVID-19 crisis and the R–U war. Thus, the increase in window size shows smoother autocorrelations and confidence intervals and does not generate any periodicities similar to those

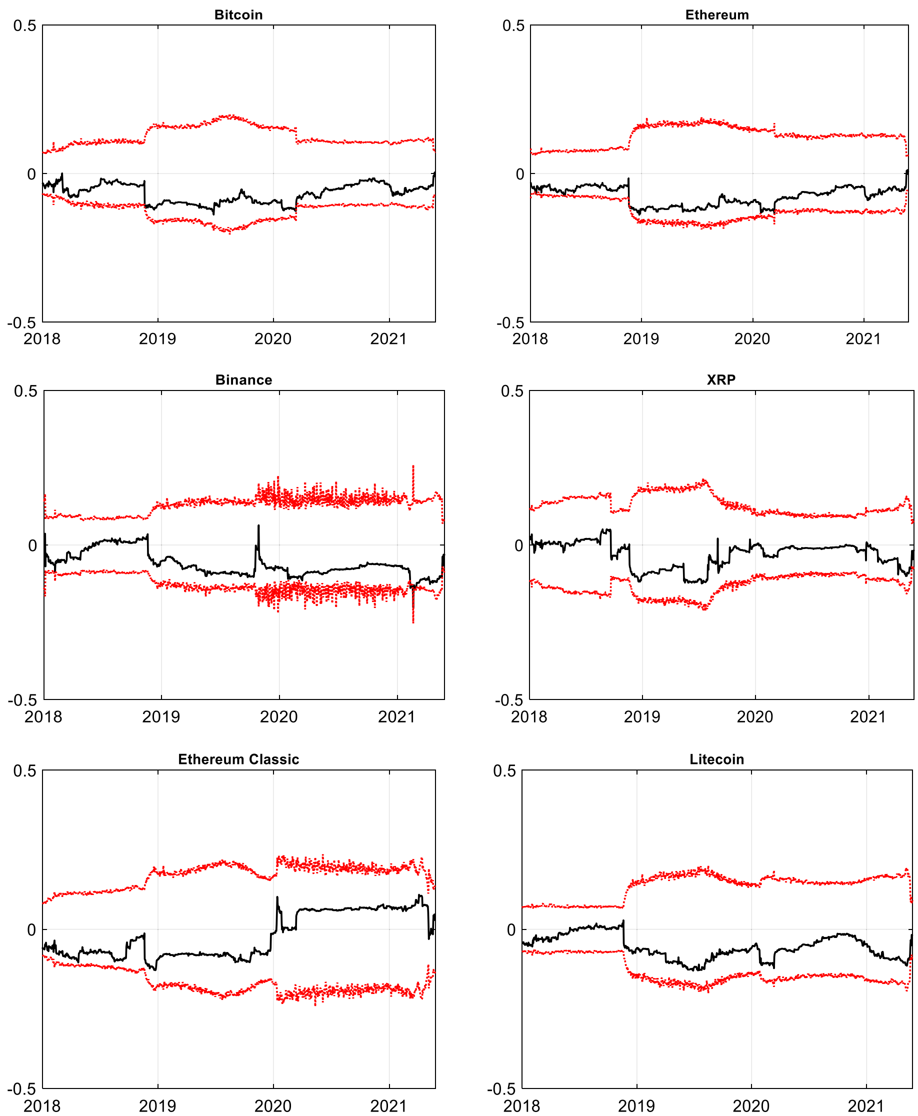

Fig. 6 Autocorrelations with Window Size n = 480 (Fixed Block Size). *Notes* The figure displays autocorrelations with lag h = 1 over rolling windows. Correlations are shown by solid black lines, while 95% confidence bands are represented by dotted red lines. Under the null hypothesis of white noise, the confidence band is produced using a blockwise wild bootstrap of 5,000 iterations for each window. Each point on the horizontal axis represents the initial date of each window

reported when using a 240-block fixed window size. The higher the window size, the smoother and less periodic the autocorrelations and their confidence bands. The same results were obtained using larger window sizes, providing empirical support for the EMH and confirming the presence of efficiency evolution in cryptocurrencies. In summary, although our analysis uses larger window sizes to avoid periodicity and smoothen autocorrelations, our results show similar benefits for investors. Based on our results, investors can reallocate their portfolio assets by adding cryptocurrencies to reduce the risk of their portfolios during normal market conditions and use cryptocurrencies as safe haven assets during crisis periods.

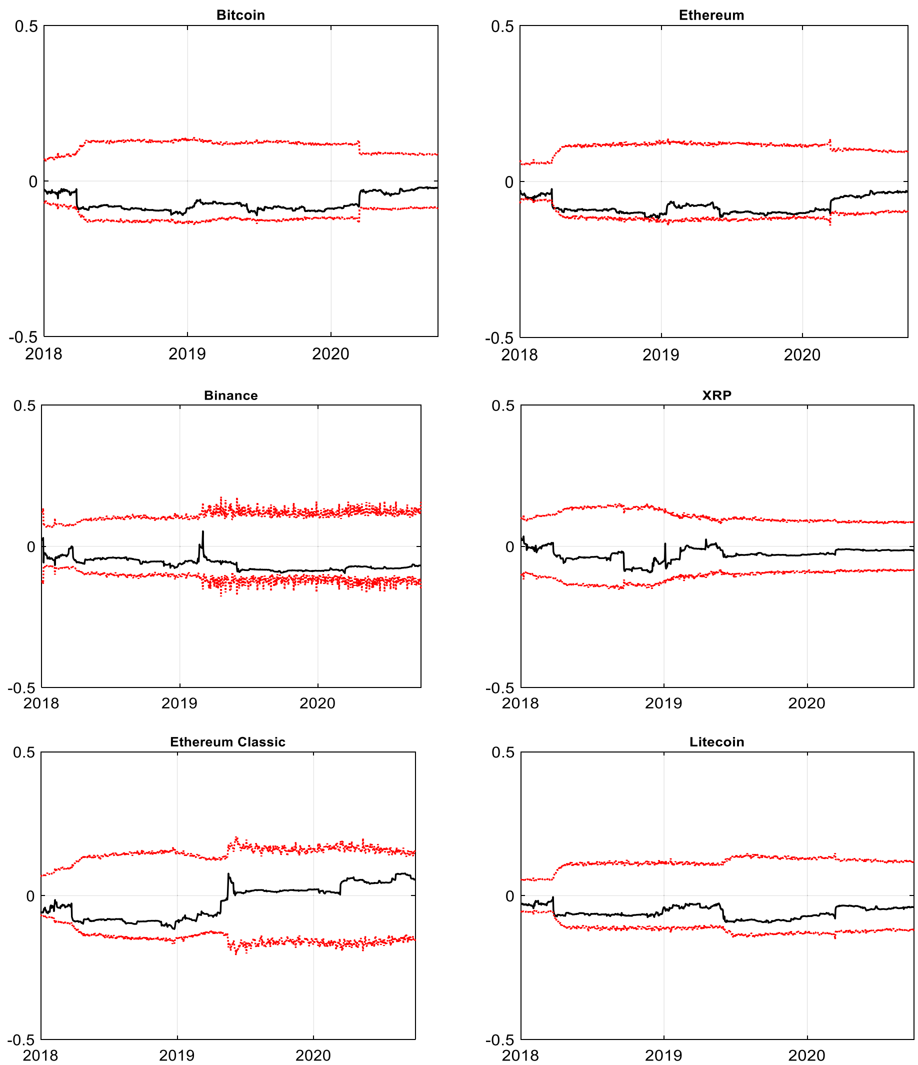

Fig. 7 Autocorrelations with Window Size n = 720 (Fixed Block Size). *Notes* The figure displays autocorrelations with lag h = 1 over rolling windows. Correlations are shown by solid black lines, while 95% confidence bands are represented by dotted red lines. Under the null hypothesis of white noise, the confidence band is produced using a blockwise wild bootstrap of 5000 iterations for each window. Each point on the horizontal axis represents the initial date of each window

Several possible reasons led to the presence of inefficiencies during the COVID-19 crisis and the R–U war. Despite their differences in nature, these crises negatively impacted cryptocurrency prices and the global economy. These negative consequences of COVID-19 include fear and sadness, negative sentiments, the application of social distancing, the long-term lockdown of business activities, and an increase in deaths and casualties. This led to a dramatic rise in global poverty and economic inequality, and ultimately, an increase in uncertainty across markets. Such consequences resulted in disparities in the degree to which cryptocurrency investors and policymakers responded to price changes, leading to market inefficiency. This is because of the delay in price adjustments within the cryptocurrency market, in which the flow of information is conveyed at the same time, speed, and quality. Although investors respond instantly to changes in cryptocurrency prices, policymakers and regulators take longer to respond to such changes during crises. The severe impact of the crisis led to a significant movement in cryptocurrency prices, which affected intraday price behavior. Furthermore, changes in the persistence of cryptocurrency price behavior caused market inefficiencies during these economic upheavals. James (2021) argues that the degree of efficiency in cryptocurrencies varies over time owing to less consistency in cryptocurrency price structural breaks.

Based on the negative impact of the R–U war, the high correlation and co-movement among cryptocurrencies as well as other financial assets resulted in a significant depreciation of the major global traditional currencies and an increase in interest rates. These effects led cryptocurrency investors to move intentionally and directly toward other financial markets that offer higher returns. Although there was a noticeable recovery in the cryptocurrency market at the end of 2020, particularly after the distribution of the coronavirus vaccine, investors' risk appetite could not lead to a price equilibrium in most cryptocurrencies because of the impact of the ongoing R–U war. This is because investors react more to the flow of information during periods of stress (Youssef and Waked 2022).

As cryptocurrencies are generally considered as "safe haven" tools (Al-Shboul et al. 2022; Melki and Nefzi 2022), they lose their value because of global negative sentiments, worry, and fear. In summary, the varying impacts of these crises on the degree of efficiency can also be explained by the structures of the markets and trader behavior. During both crises, media coverage, such as international news headlines, generated fear and sadness, negative sentiments, and uncertainty across markets. Thus, investors tended to reduce their trading activities to avoid financial losses, which adversely affected financial and cryptocurrency markets. These crises not only affected trading behavior but also led to complex issues associated with a low degree of information determinacy.

The other part of our analysis examines the evolution of market efficiency using the rolling window of the CvM test value based on various window sizes (fixed block sizes) (240, 480, and 720 days). The results are shown in Figs. 8, 9, and 10. In each graph, the solid black lines reflect the CvM test statistics, whereas the red dotted lines represent 5% critical values (95% confidence bands). In Fig. 8, where a 240 days window size is used, the time-varying values of CvM show evidence of evolving efficiencies during the crisis and non-crisis periods. Almost all cryptocurrencies are highly inefficient during a crisis. The value of the test shows a sudden jump in efficiency patterns during all crises (the COVID-19 crisis, the Bitcoin crash crisis after the beginning of 2018, and the trade wars between the US, China, and North Korea in 2019 and 2020). This finding suggests that during crises, there is a trend toward inefficiency. However, the efficiency evolution patterns differ across crises. The highest degree of evolving efficiency was noticed during the COVID-19 crisis for all currencies except for Bitcoin and Ethereum, where the degrees of inefficiency for these two currencies were higher during the trade wars between 2019 and mid-2020 and after the Bitcoin crash crisis. The R–U war showed the lowest degree of evolving efficiency for all currencies. Our results are consistent with the findings of Fernandes et al. (2022), who argue that cryptocurrency markets showed efficiency trends during the COVID-19 crisis.

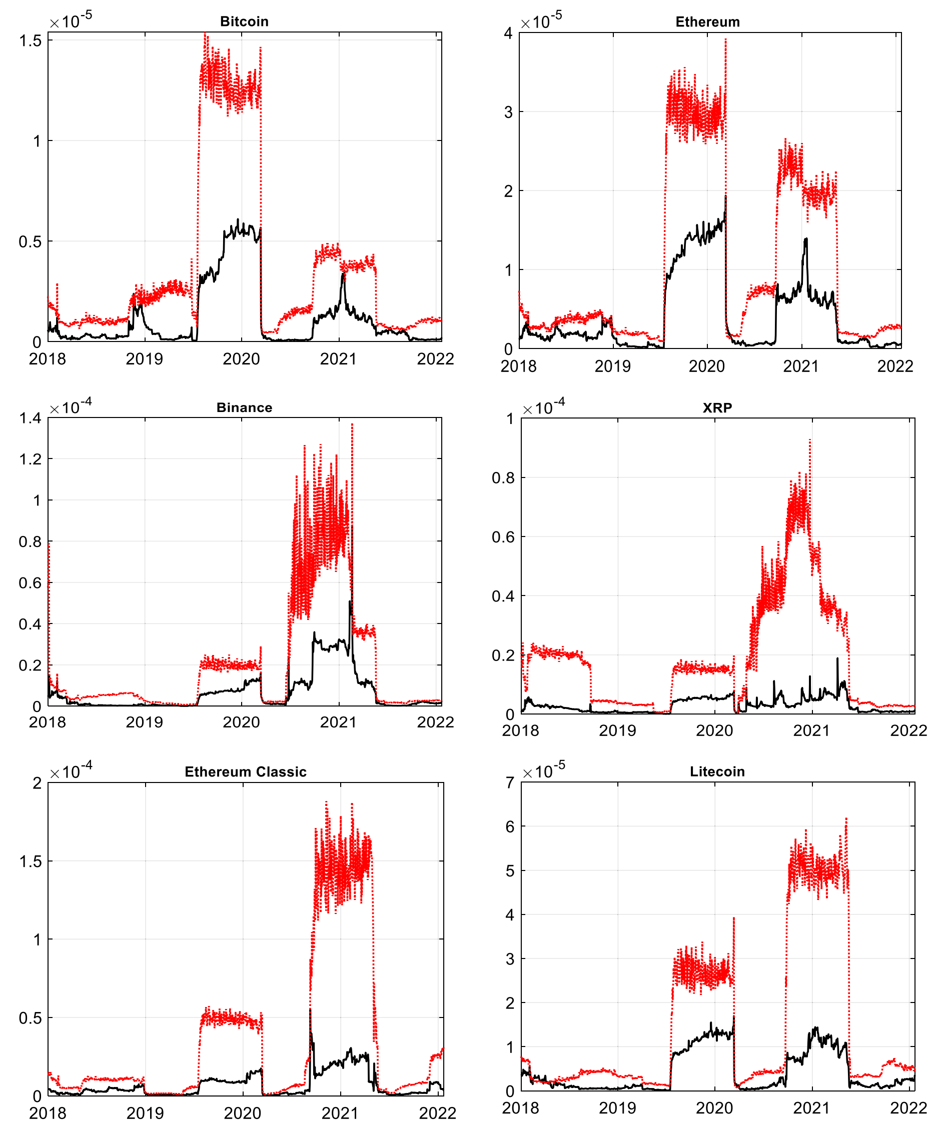

Fig. 8 Rolling window Cram´er-von Mises tests n = 240. *Notes* The figures display the Cram´er-von Mises (CvM) tests based on the blockwise wild bootstrap. Under the null hypothesis of white noise, the confidence band is produced using a blockwise wild bootstrap of 5000 iterations for each window. The solid black lines reflect the CvM test statistics, while red, dotted lines represent 5% critical values (95% confidence bands). Each point on the horizontal axis represents the initial date of each window

In addition, we observed a higher degree of inefficiency (higher correlation) during crisis periods than under normal conditions. This is due to changes in investors' responses to changes in cryptocurrencies as well as negative economic conditions across the globe. As there is a clear trend toward inefficiency during the COVID-19 period, one can argue that the slowness and delay in cryptocurrency price adjustments is one of the reasons for the higher changes in the level of (in)efficiency over time. The higher level of inefficiency during the COVID-19 pandemic was caused by the pandemic's negative impact, which was more devastating and lasted longer than other crises. Furthermore, compared with other crises, the COVID-19 crisis has had comprehensive socioeconomic

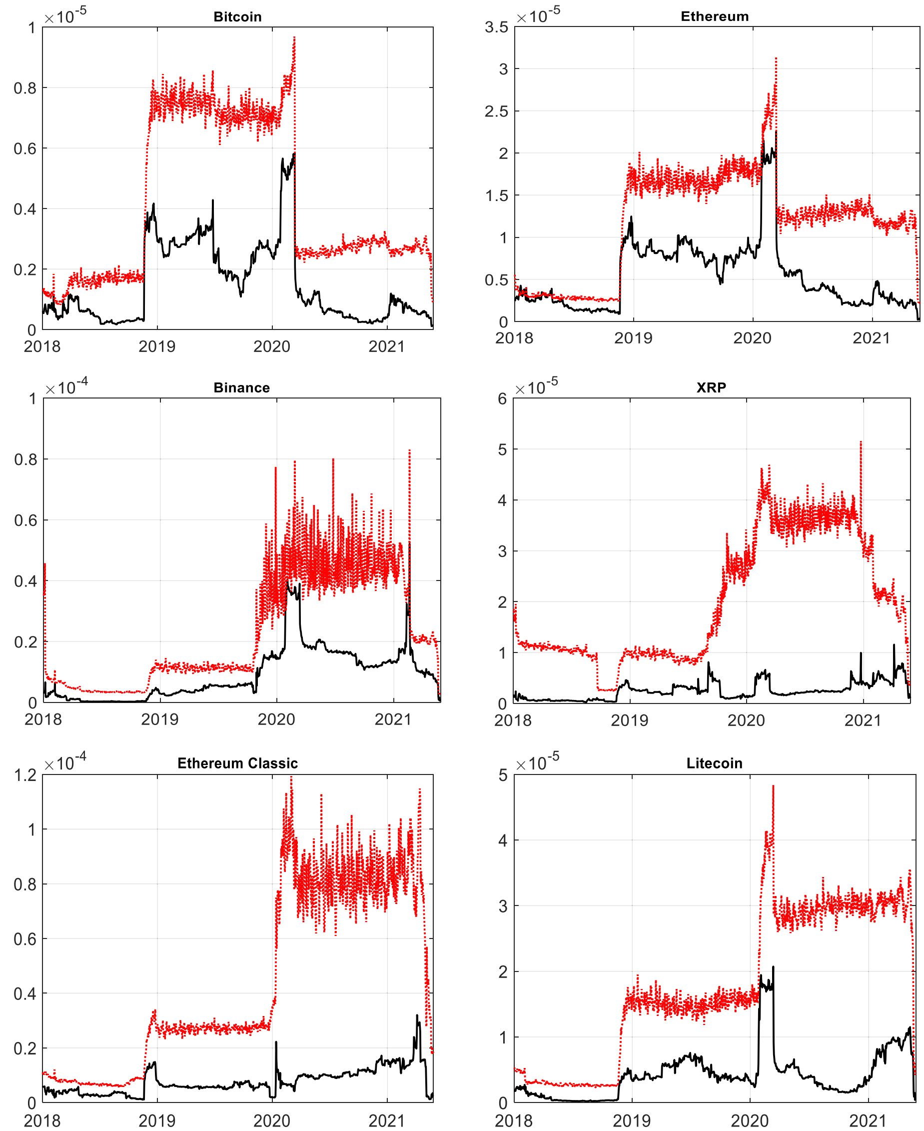

Fig. 9 Rolling window Cram´er-von Mises tests n = 420. *Notes* The figures display the Cram´er-von Mises (CvM) tests based on the blockwise wild bootstrap. Under the null hypothesis of white noise, the confidence band is produced using a blockwise wild bootstrap of 5000 iterations for each window. The solid black lines reflect the CvM test statistics, while red, dotted lines represent 5% critical values (95% confidence bands). Each point on the horizontal axis represents the initial date of each window

and humanitarian impacts. The delay in price adjustments also resulted from changes in market structure and trader behavior. During both crises, the massive number of deaths, abandonment of the entire global market, and media coverage such as international news headlines generated fear, sadness, negative sentiments, and uncertainty across markets. Thus, investors attempted to reduce their trading activities to avoid financial losses, which negatively impacted the cryptocurrency markets. The crises affected not only trading behaviors but also the complexity of information transmission from one currency to another.

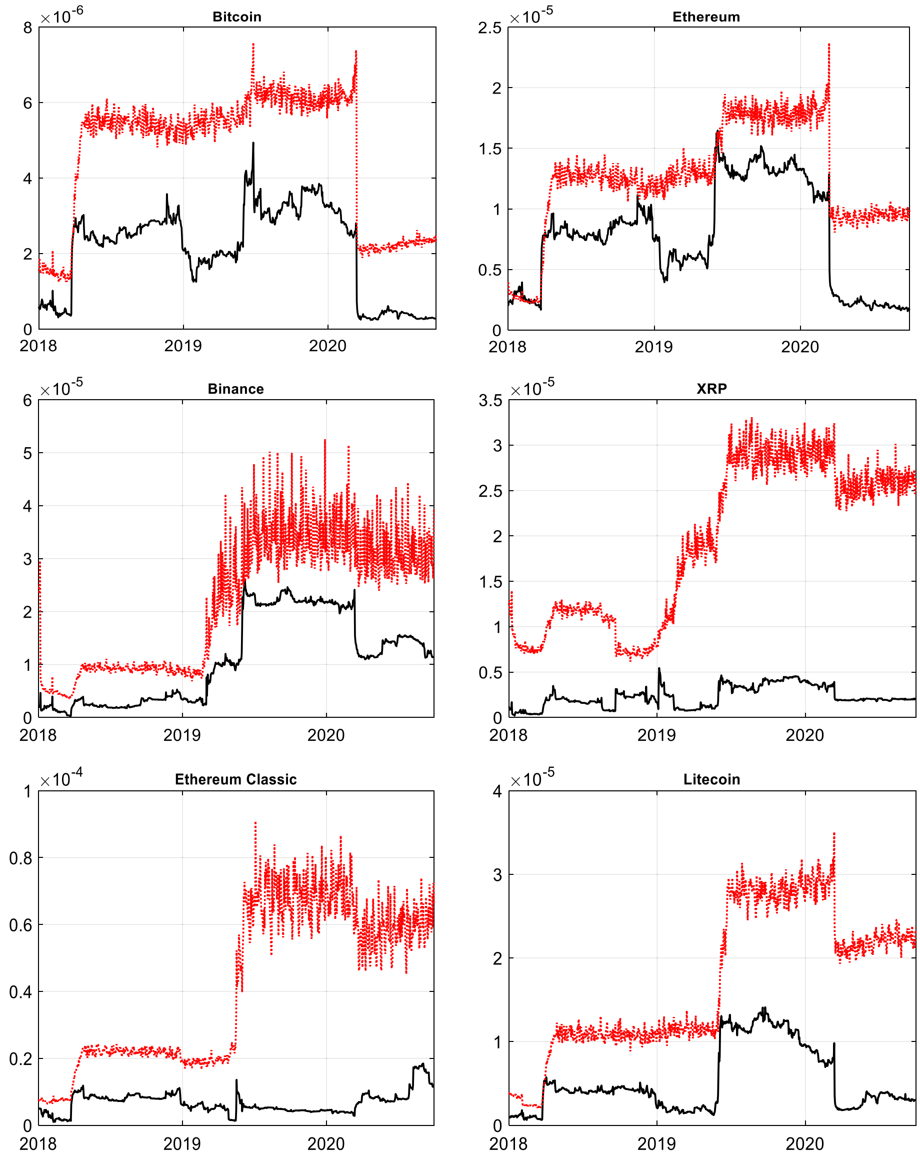

Fig. 10 Rolling window Cram´er-von Mises tests n = 720. *Notes* The figures display the Cram´er-von Mises (CvM) tests based on the blockwise wild bootstrap. Under the null hypothesis of white noise, the confidence band is produced using a blockwise wild bootstrap of 5000 iterations for each window. The solid black lines reflect the CvM test statistics, while red, dotted lines represent 5% critical values (95% confidence bands). Each point on the horizontal axis represents the initial date of each window

Looking at Bitcoin and Ethereum, where the degree of inefficiency during trade wars and the Bitcoin crash crisis was higher than that during the COVID-19 period, we argue that because these currencies are well established with a longer period of market survival and are decentralized currencies, their investors may behave differently than investors in other currencies during other crisis periods. Investors in such currencies may have shown more variability in their responses to price adjustments during the Bitcoin crash crisis and trade wars. Furthermore, because these cryptocurrencies have different operating systems, investors in one currency (i.e., Bitcoin) may have different trading behaviors than investors in another (i.e., Ethereum) because of their investment preferences and needs. Thus, different investor responses to changes in prices would lead to different degrees of market efficiency across different periods of crisis.

Figures 9 and 10 show the time-varying efficiencies based on the CvM test when larger window sizes (420 and 720) were used. In general, these results are similar to those reported in Fig. 8. The degree of inefficiency increased during crisis periods. Although these larger window sizes with fixed blocks allow for less periodicity and smoother bands, the evidence of evolving efficiency remains quantitatively similar to those with lower window sizes during periods of crisis and non-crisis for all currency markets but with different degrees of efficiency evolution. We observe a higher degree of inefficiency during the COVID-19 crisis for almost all currencies, except for Bitcoin and Ethereum, which show a higher degree of inefficiency between 2019 and the end of 2020 (during the Bitcoin crash crisis and the trade war period) compared to the COVID-19 crisis. However, during the R–U war, they exhibited less inefficiency. The lower degree of inefficiency during the R–U conflict is a result of the reduced impact of our sample period, which does not cover the entire period of the ongoing conflict and could be due to the slight impact of the R–U war on the price adjustments of cryptocurrencies.

To further examine the evolving efficiency in cryptocurrency markets, we report the patterns of p values associated with the CvM test results. The p values are shown in Figs. 11, 12 and 13. These figures show the patterns of the p values for different window sizes (240, 420, and 270) using block size randomization. In each figure, the solid black lines show the p values of the CvM tests, while the shaded regions represent the 5% critical values (95% confidence bands). Our results in these figures are consistent with our findings in Figs. 8, 9 and 10. In Fig. 11, our results show evidence of evolving efficiency for all cryptocurrencies. The "white noise" hypothesis is accepted in most cases for almost all cryptocurrencies in periods of non-crisis while being rejected in periods of crises. During non-crisis periods, the p values rise dramatically, whereas during crisis periods, they fall precipitously, sometimes below the 5% confidence level. This means that there was a trend toward inefficiencies during the crisis period, confirming the results reported in Figs. 6, 7, 8, 9 and 10. However, the degree of inefficiency is heterogeneous across cryptocurrencies.

Given the serious political and trade tensions between the US and North Korea at the time, as well as the US–China trade war between mid-2017 and early 2019, Bitcoin, Litecoin, Binance, and Ethereum Classic showed a trend toward inefficiency. During the great cryptocurrency crash in early 2018, Ethereum and Litecoin showed evidence of a trend toward inefficiency. The COVID-19 outbreak and the R–U war had a negative effect on the degree of efficiency, leading cryptocurrency markets except for Ethereum Classic and Ripple to be inefficient.

When larger sizes of windows are taken, (e.g., 420 days and 720 days), the p value series of the CvM test for each cryptocurrency are shown in Figs. 12 and 13. We report evidence of evolving efficiency for almost all cryptocurrency markets except during the COVID-19 crisis. We can see that the larger the window size, the smoother the p values. Thus, a larger window size makes p values smoother, increasing the possibility that they will remain weakly efficient across almost all cryptocurrency markets and making the evaluation of efficiency more noticeable, even during a crisis. Evidence of inefficiency has been reported for almost all cryptocurrencies during crisis periods, whereas weak

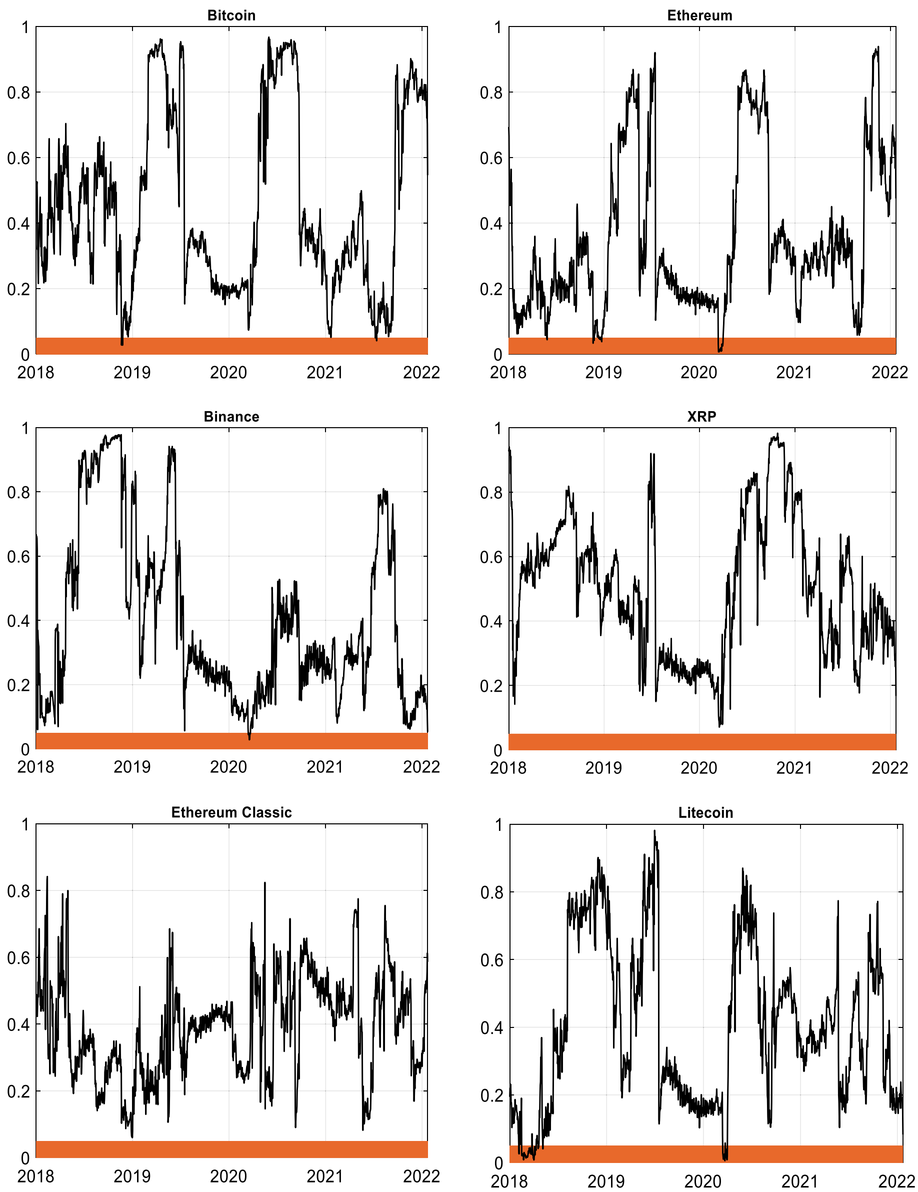

Fig. 11 *P* values of Cram´er-von Mises Test with Fixed versus Randomized Block Sizes n = 240, *Notes* The figures display the rolling window *p* values of Cram´er-von Mises tests (solid black lines) based on the blockwise wild bootstrap under the null hypothesis of white noise. The shaded areas represent 5% critical values (95% confidence bands). Each point on the horizontal axis represents the initial date of each window

efficiency is clearly visible during non-crisis periods. However, Ethereum and Binance showed a higher degree of inefficiency during the COVID-19 period. In general, the results in Figs. 12 and 13 provide evidence of inefficiencies during crisis periods, particularly during COVID-19 and the trade wars. This confirms our results shown in Figs. 8, 9, 10 and 11. Kristoufek and Vosvrda (2019) argue that the tendency of these cryptocurrencies to become less efficient could be attributed to anomalies (Qadan et al.

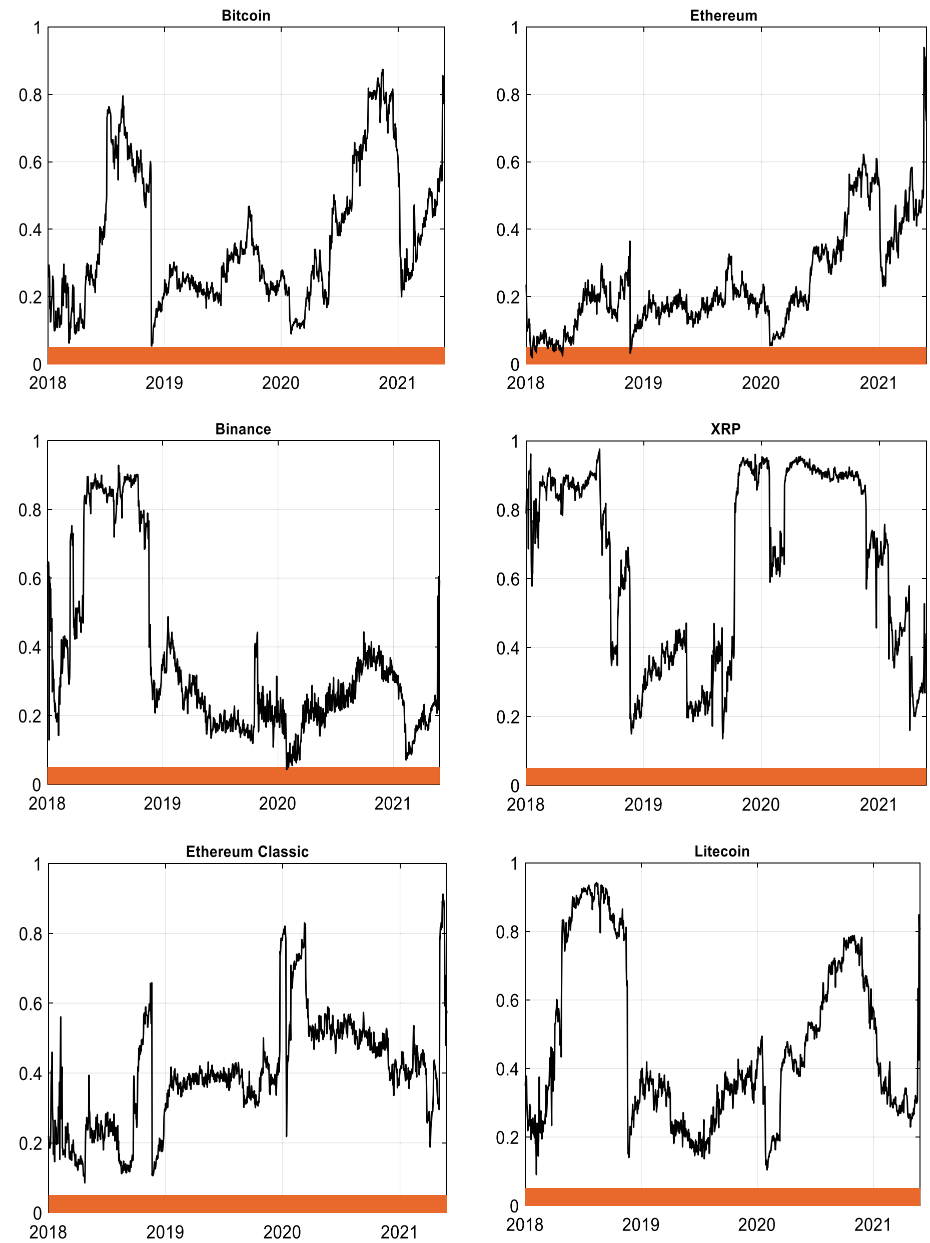

Fig. 12 *P* values of Cram´er-von Mises Test with Fixed versus Randomized Block Sizes n = 480. *Notes* The figures display the rolling window *p* values of Cram´er-von Mises tests (solid black lines) based on the blockwise wild bootstrap under the null hypothesis of white noise. The shaded areas represent 5% critical values (95% confidence bands). Each point on the horizontal axis represents the initial date of each window.

2022; El Montasser et al. 2022). To interpret our results, trade wars and COVID-19 have had a greater negative impact on investor behavior, leading to a higher degree of inefficiency. Our results help investors construct their portfolios and opt for risk diversification among the cryptocurrencies studied.

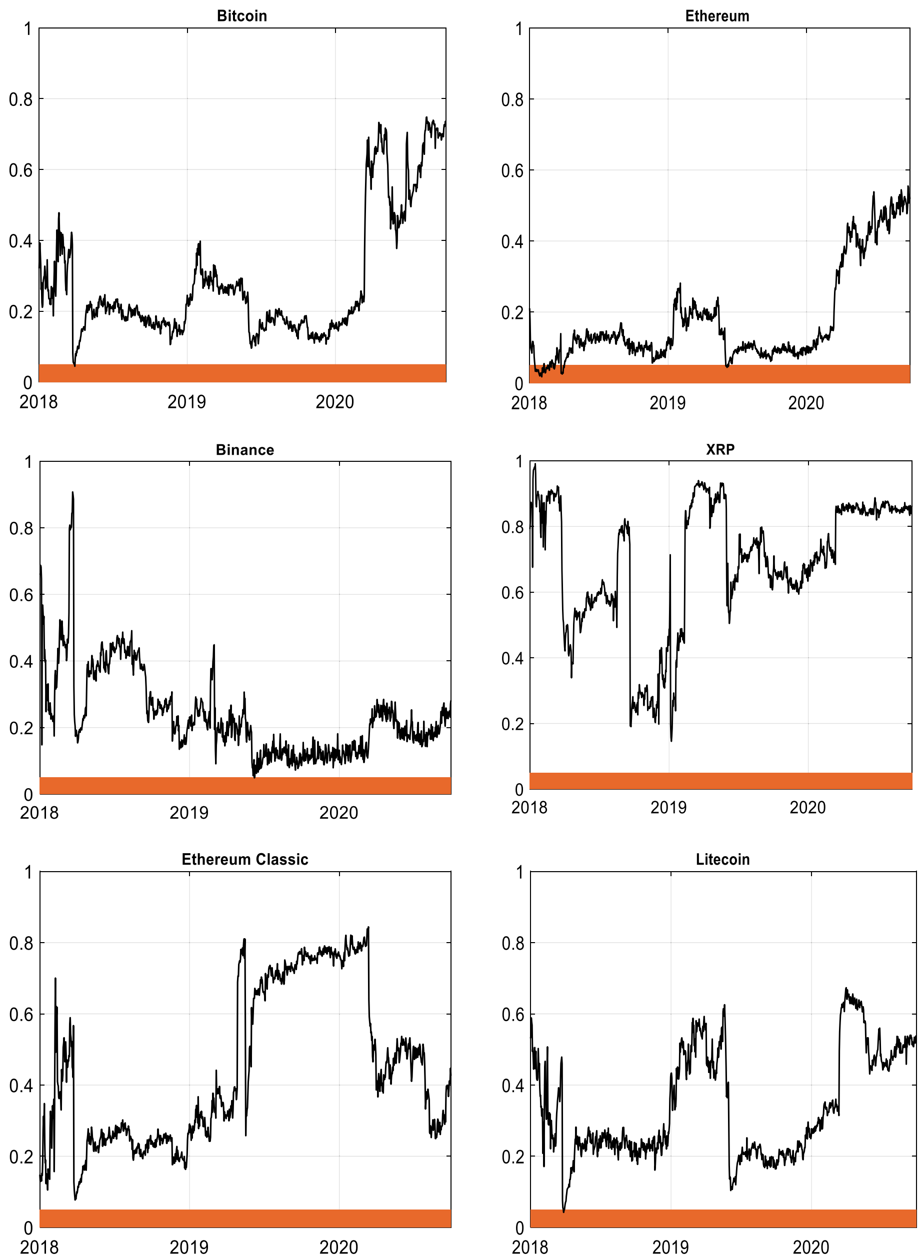

Fig. 13 *P* values of Cram´er-von Mises Test with Fixed versus Randomized Block Sizes n = 720. *Notes* The figures display the rolling window *p* values of Cram´er-von Mises tests (solid black lines) based on the blockwise wild bootstrap under the null hypothesis of white noise. The shaded areas represent 5% critical values (95% confidence bands). Each point on the horizontal axis represents the initial date of each window

Conclusions

This study examines the evolution of cryptocurrency efficiency and whether it is affected by extreme events such as the COVID-19 pandemic and the R–U war. Using the CvM, our analysis reveals that all cryptocurrencies followed a weak form of efficiency in the non-crisis period, while during COVID-19 and the R–U war, the cryptocurrency markets became inefficient. Efficiency was heterogeneous across currencies. This confirms that cryptocurrency prices are less predictable and arbitrage opportunities are very limited in these markets. Our analysis also found evidence that the efficiency of cryptocurrency markets (except for Ethereum Classic and Ripple) changes over time, with a tendency toward less efficiency during times of crisis. The COVID-19 crisis shows a higher degree of inefficiency than the R–U war. This trend appears not only during the COVID-19 breakout and R–U war but also during periods of high political tension and trade war such as the conflict between the United States and North Korea and the US–China trade war in the middle of 2017 and early 2019 as well as during the Bitcoin crash in early 2018.

This study has several policy implications. First, digital currency investors can better understand risk-diversification strategies during normal and crisis periods. Second, our findings shed light on the benefits of cryptocurrency market behaviors, which would allow central banks and regulators to adopt certain regulatory laws, supervision, and prudential policies to stabilize cryptocurrency market forgery and run effective risk controls during extreme conditions such as the COVID-19 pandemic and the R–U war. These policies may strengthen oversight and enact laws and reforms to increase the efficiency of cryptocurrencies compared to other financial and commodity markets. Third, although efficiency in cryptocurrency markets relates to price predictability and arbitrage opportunities, our results provide researchers and regulators with deeper insight into the profitability mechanism in trading strategies as well as the determinants of cryptocurrency prices. Fourth, given the degree of connectedness among cryptocurrencies, investors and market participants may use our results to distinguish between the short- and long-run effects of their transmission, leading to a better evaluation of systematic risk. Finally, as cryptocurrencies are highly volatile, the findings of our study offer investors and portfolio managers valuable advice on how to understand cryptocurrency market efficiency, which plays a crucial role in adjusting their portfolios, and explores the importance of negative and positive shocks coming in or out of each cryptocurrency.

Further research can be conducted in the domain of cryptocurrency market efficiency. For example, an interesting area for future research is testing for momentum, where researchers can clarify why price anomalies such as momentum payoffs appear in cryptocurrency markets. This can explore the profitability of risk-managed momentum in cryptocurrency markets. The efficiency of cryptocurrency markets can be further explored with respect to investor sentiment, liquidity risk, and the macroeconomic determinants of cryptocurrency prices.

Abbreviations

CvM	Cramér-von Mises test statistic
COVID-19	The COVID-19 pandemic crisis
R–U	Russian–Ukrainian war
Q–Q	Quantile–quantile
ADF	Augmented Dickey–Fuller test

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Author contributions
AM: Initiated the subject, contributed to the methodologies, collected data, analyzed the data in MATLAP and interpretation and discussion of results. MAS: Review of literature, and wrote the first manuscript. The author(s) read and approved the final manuscript.

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All data are obtained from Thomson Reuters Datastream database. The models and data analysis are applied through computer software such as MATLAB. All data and codes will be available from the authors upon request upon request.

Declarations

Competing interests
The authors declare that they have no competing interests.

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