Mokni *et al. Financial Innovation* (2024) 10:39
https://doi.org/10.1186/s40854-023-00566-3

Financial Innovation

RESEARCH

Open Access

On the efficiency and its drivers in the cryptocurrency market: the case of Bitcoin and Ethereum

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Abstract

Most previous studies on the market efficiency of cryptocurrencies consider time evolution but do not provide insights into the potential driving factors. This study addresses this limitation by examining the time-varying efficiency of the two largest cryptocurrencies, Bitcoin and Ethereum, and the factors that drive efficiency. It uses daily data from August 7, 2016, to February 15, 2023, the adjusted market inefficiency magnitude (AMIMs) measure, and quantile regression. The results show evidence of time variation in the levels of market (in)efficiency for Bitcoin and Ethereum. Interestingly, the quantile regressions indicate that global financial stress negatively affects the AMIMs measures across all quantiles. Notably, cryptocurrency liquidity positively and significantly affects AMIMs irrespective of the level of (in) efficiency, whereas the positive effect of money flow is significant when the markets of both cryptocurrencies are efficient. Finally, the COVID-19 pandemic positively and significantly affected cryptocurrency market inefficiencies across most quantiles.

Keywords: Bitcoin, Ethereum, Time-varying efficiency, AMIMs, Quantile regression, Drivers of efficiency

JEL Classification: C58, G14

Introduction

Following the inception of Bitcoin in early 2009, the cryptocurrency (CC) market expanded rapidly in size and number of cryptocurrencies (CCs), exceeding $1 trillion as of March 2023.[1] This digital asset class has gained huge attention and interest from speculators and investors due to its rapid price appreciation, without ignoring its hedging and diversification opportunities (see, among others, Bouri et al. 2020; Shahzad et al. 2022; Hatemi et al. 2022), despite its extreme volatility. However, in addition to market booms, the CC market has been subjected to several stress periods, suggesting that CCs should be treated as assets (Noda 2021). Accordingly, several studies have examined the dynamics of major CCs across various crisis periods, making inferences about their return characteristics and, importantly, their market (in)efficiency and return

[1] Bitcoin and Ethereum dominate the cryptocurrency scene, with a combined market capitalization exceeding 60% of the total market capitalization of all cryptocurrencies.

predictability (see among others, Wei 2018; Vidal-Tomás et al. 2019; Chu et al. 2019; Kyriazis 2019; Aslan and Sensoy 2020; Kakinaka and Umeno 2021; Kang et al. 2021; El Montasser et al. 2022). Interestingly, these results are mixed. Many studies show that the Bitcoin market is generally efficient (Urquhart 2016; Nadarajah and Chu 2017; Bariviera 2017; Khuntia and Pattanayak 2018; Kristoufek 2018; Dimitrova et al. 2019), while others support the inefficiency of this young and volatile market (Cheah et al. 2018; Al-Yahyaee et al. 2018; Vidal-Tomás et al. 2019). This points to the time-varying feature of efficiency, indicating that the efficiency in the CC markets can be present over one period but not over another (Keshari Jena et al. 2020; Khursheed et al. 2020; Noda 2021).

In young and immature CC markets, market (in)efficiency attracts the attention of practitioners and academics, mostly because of the lack of evaluation models for CC and because market participants are highly driven by emotion and irrationality and often exhibit fear of missing out. In this regard, investors operating in CC markets appreciate detailed information about (in)efficiency in these markets, given its implications for asset allocation and the decision-making process (Al-Yahyaee et al. 2020). Cryptocurrency market efficiency is evolving and time-varying. The CC market has developed better over time, and market participants have become more experienced, suggesting that the efficiency level has gradually improved. Therefore, investigating the efficiency of the CC markets within a time-varying framework is crucial. Indeed, the CC market is very emotional, and investors in this market have a dynamic character, dealing with continuous and smooth changes in the behavior of CC prices. This feature can only be captured through analysis in a time-varying framework rather than splitting the period into sub-periods selected a priori. Modeling efficiency in a time-varying manner depicts market efficiency as a continuous process that depends on the market's conditions and events. In addition, such a procedure allows the data to detect periods of efficiency and inefficiency for which investigators can proceed to identify the associated events. However, the literature remains silent on the factors driving major CCs' (in)efficiency. Thus, providing insights into the factors that can affect market (in)efficiency should be useful not only for market participants regarding the variables that should be monitored when making trading or investment decisions involving the level of (in)efficiency but also for policymakers concerned with the functioning of this digital asset. In this regard, some studies suggest growing linkages between major CCs such as Bitcoin and Ethereum, and thus, the possibility of risk spillover from the latter to the former can put the financial system's stability at risk.

The objectives of this study were twofold: First, we examine the (in)efficiency of the two largest CCs (Bitcoin and Ethereum) in a time-varying setting based on the recent econometric procedure of Adjusted Market Inefficiency Magnitudes (AMIMs) proposed by Le Tran and Leirvik (2019). Second, we examined the potential factors affecting (in)efficiency using quantile regression (QR). Unlike ordinary least squares (OLS) regressions, QR analysis provides a more comprehensive picture of the determinants of (in)efficiency in the Bitcoin and Ethereum markets by differentiating between efficiency and inefficiency based on the quantile order.

Notably, considering the different factors driving market (in)efficiency is a crucial complement to academic debate. Recent studies show that CCs are somewhat related to the global financial system and, thus, to conventional assets such as equities. For example, Kumar et al. (2022) applied a spillover approach, showing that the interconnectedness across large CCs is unstable. Importantly, they consider conventional assets in the spillover analysis and present evidence challenging the decoupling hypothesis between CCs and financial markets after the pandemic, which challenges the safe-haven properties of CCs. Wang et al. (2022) applied a multivariate GARCH model and showed that Bitcoin is positively correlated with stocks, bonds, and commodities and negatively correlated with the US dollar index, which challenges the safe-haven role of Bitcoin. Notably, during crisis periods such as COVID-19, the positive correlation intensifies, reducing diversification benefits.[2] Elsayed et al. (2022) highlight the risk spillover effect between Bitcoin and other financial markets during the pandemic and the importance of global uncertainties. Furthermore, empirical evidence on market efficiency highlights the importance of crisis periods such as the COVID-19 pandemic (Naeem et al. 2021) and market liquidity (Wei 2018; Al-Yahyaee et al. 2020). However, each of these factors is conducted separately in individual studies, and the corresponding studies focus mostly on boom periods, which are not necessarily transferable to the bust period from November 2021 to the end of 2022, during which Bitcoin and major CCs declined by more than 75%.

This study focused only on Bitcoin and Ethereum, commonly used in the related literature for several reasons. Bitcoin and Ethereum are the two largest CCs in terms of market capitalization. They constitute more than 65% of the market value of all CCs (https://coinmarketcap.com). They have held top positions for a long time, and their market dominance has persisted over the past few years. Bitcoin has traditionally been viewed as the most established and widely recognized CC. In contrast, Ethereum has gained prominence because of its smart contract capabilities and decentralized applications (dApps) development. Second, Bitcoin and Ethereum have the highest trading volumes and liquidity levels compared to smaller CCs. This makes buying and selling CCs easier without significantly affecting the market prices. Higher liquidity attracts more institutional and retail investors. Third, Bitcoin and Ethereum often serve as bellwethers in broader CC markets. Price movements and market trends can also substantially impact other CCs. Therefore, studying Bitcoin and Ethereum can provide valuable insights into overall market sentiment and potential price patterns in CC markets. Fourth, regarding infrastructure and ecosystems, these two CCs have well-developed infrastructures, including established exchanges, wallets, and other supporting services. They also have extensive communities and ecosystem developers. This infrastructure and ecosystem contribute to CCs' overall stability and reliability, making them attractive subjects for academic studies.

This study contributes to existing literature in several ways. First, we proceed to the efficiency analysis using a time-varying procedure over a relatively long period from August 7, 2016, to February 15, 2023, including the boom periods around 2017 and 2020, the COVID-19 pandemic, and the bust periods of 2022, unlike previous studies based on the boom period of 2017 or the early stage of the pandemic in 2020. This allows

[2] Banerjee et al. (2022) show that COVID-19 news sentiment significantly impacts the returns and volatility of cryptocurrencies. Khalfaoui et al. (2023) highlight the influence of the Russia-Ukraine war attention on cryptocurrency markets, whereas Gemici et al. (2022) reflect the importance of social-media posts, as captured by Twitter-based economic uncertainty, for the pricing of safe-haven assets like Bitcoin. On a related front, some studies (Yousaf et al. 2022; Mensi et al. 2023) consider the relationship between cryptocurrencies and conventional assets.

us to consider a more comprehensive period that can better reflect the time evolution of market (in)efficiency and its potential drivers. Second, we add to previous studies considering only one-factor influencing efficiency in the CC markets, such as liquidity (Wei 2018; Al-Yahyaee et al. 2020). We capture the effect of various variables on the efficiency of Bitcoin and Ethereum, such as the global financial and monetary-policy factors (financial stress, world stock market, and Fed fund rates), the investment substitutes (energy and gold investments), uncertainty factors (Economic Policy Uncertainty and Chicago Board Options Exchange (CBOE) implied volatility index), and CC-related factors (return volatility, liquidity, and money flow). Third, the investigation of the effect of these factors is based on a quantile regression model, allowing the distinction of the effect of these factors on various levels of CC (in)efficiency.

The main findings of this study indicate that the level of market (in)efficiency, measured by AMIMs values, is time-varying for both Bitcoin and Ethereum. Moreover, financial stress negatively affects the efficiency level, regardless of whether the markets are efficient or inefficient. Cryptocurrency liquidity positively and significantly affects AMIMs irrespective of the level of (in) efficiency, whereas the positive effect of money flow is significant when the markets of both CCs are efficient. Finally, the COVID-19 pandemic positively and significantly affected CC market inefficiencies across most quantiles.

The remainder of this paper is organized as follows. Section Literature review presents previous studies on CC market efficiency. Section Data and methodology presents the data used. Section The data presents and discusses the empirical results. Finally, Sect. Empirical methodology concludes the paper and discusses policy implications.

Literature review

Fama's (1965, 1970) seminal work introduced the concept of efficiency in financial markets. Following a simple definition, the market is efficient if the available information is completely reflected in prices. Market efficiency is investigated by distinguishing between three forms (weak, semi-strong, and strong) in different financial markets, including stock markets (Abraham et al. 2002; Ben Rejeb and Boughrara 2013; Smith 2012; Obalade and Muzindutsi 2018; Bianchi and Pianese 2018; Tiwari et al. 2019; Mensi et al. 2022), exchange rates (Shah et al. 2018; Kumar 2018; Yang et al. 2019; Aslam et al. 2020), commodity markets (Jebabli and Roubaud 2018; Ghazani and Ebrahimi 2019; Kuruppuarachchi et al. 2019; Shahid et al. 2020; Okoroafor and Leirvik 2022).

CC markets and blockchain technology have been studied extensively. For instance, Xu et al. (2019) provide detailed reviews of current academic research on blockchain and CC trading. Sebastião and Godinho (2021) examined the predictability of three major CCs (Bitcoin, Ethereum, and Litecoin) and analyzed the profitability of trading strategies devised by machine learning techniques. Regarding the CC market efficiency, several studies have been conducted on the particular price behaviors of these assets. However, previous studies have provided mixed results regarding this issue despite most of the literature supporting the inefficiency of CC markets.

Earlier studies on the efficiency of CC markets were initiated by Urquhart (2016), who considered the Bitcoin market the most popular CC. Using the runs test, Brock, Dechert, and Scheinkman (BDS) test, and the rescaled range (R/S) Hurst exponent method, the results provided evidence of an inefficient market that decreased over time and moved toward an efficient market. Al-Yahyaee et al. (2020) investigated the multifractality and efficiency features of the Bitcoin market compared with conventional assets. The results show that Bitcoin is characterized by long-range dependence and multifractality, supporting the inefficiency of Bitcoin market properties compared to other financial assets. Similar results are obtained by Caporale et al. (2018) when examining the persistence of some of the main CCs, including Bitcoin, Litecoin, Ripple, and Dash. These results indicated that the main CC market was inefficient. By employing a battery of efficiency tests and the Multifractal Detrended Fluctuation Analysis (MF-DFA) and Multifractal Detrended Cross-Correlation Analysis (MF-DCCA) approaches, Zhang et al. (2018) illustrate that the nine most popular CC markets were inefficient. Similar results were suggested by Hu et al. (2019), who analyzed the efficient market hypothesis (EMH) for the top 31 CCs in terms of market capitalization. Charfeddine and Maouchi (2019) analyzed breaks and long memory in the main CC markets (Bitcoin, Litecoin, Ripple, and Ethereum). They confirm the inefficiency of the CCs considered, except for Ethereum. In the same context, Bouri et al. (2019) show that Bitcoin's volatility persists, suggesting inefficiency in the Bitcoin market. The inefficiency of the CC markets was also verified in Bitcoin and Ethereum price returns. More recently, Rambaccussing and Maribas (2020) used the log periodogram bias test and skip sampling test to investigate the presence of long memory in the returns and volatility of five CCs (Bitcoin, Litecoin, Ethereum, Bitcoin Cash, and XRP) and report the inefficiency of these markets. Zhang et al. (2020) examine the market efficiency and liquidity of Bitcoin, Ethereum, and Litecoin based on high-frequency data. The findings of this study show that the (in)efficiency of these markets depends on the market conditions. Specifically, they documented that the investigated cryptos were efficient during bull market periods and were more inefficient over bear market periods. Ghazani and Jafari (2021) investigate market efficiency using daily data on three CCs (Bitcoin, Ethereum, and Ripple), gold, and West Texas Intermediate (WTI) crude oil. These results support the adaptive-market hypothesis (AMH) in these markets.

Another strand of literature shows contradictory results and supports the efficiency of CC markets. For instance, Khuntia and Pattanayak (2018) examined the efficiency of the Bitcoin market using the Dominguez–Lobato consistency test and the generalized spectral test. They conclude that dynamic efficiency in the Bitcoin market follows the adaptive market hypothesis (AMH). Chu et al. (2019) analyzed the efficiency of the high-frequency markets of the two largest CCs, Bitcoin and Ethereum, versus the euro and US dollar by investigating the existence of the AMH.

Many studies have employed a dynamic approach to test the efficiency in each period. For example, Alvarez-Ramirez et al. (2018) implemented the DFA method to estimate the long-range dependence of Bitcoin. Using a time-varying generalized Hurst exponent, they found that the Bitcoin market exhibited alternating efficiency periods. In the same context, Jiang et al. (2018) used the rolling-window approach to investigate the time-varying long-term memory in the Bitcoin market. The results indicate long-term memory and a degree of inefficiency in this market. Le Tran and Leirvik (2020) showed that the level of market efficiency in the five largest CCs cannot be constant but exhibits a time-varying feature, and CCs were generally more inefficient before 2017. Based on the adaptive market hypothesis (AMH), Noda (2021) analyzed the time-varying characteristics of efficiency for Bitcoin and Ethereum. The empirical results suggest that the degree of market efficiency varies with time and that Bitcoin is more efficient than Ethereum. Another study by Khursheed et al. (2020) examined the AMH concerning time-varying market efficiency using three tests, namely, Generalized Spectral (GS), Dominguez-Lobato (DL), and automatic portmanteau (AP) tests on four digital currencies: Bitcoin, Monaro, Litecoin, and Steller, over the sample period of 2014–2018. The results indicate that Bitcoin, Monaro, and Litecoin have the longest efficiency periods, whereas Steller has the longest inefficient market period. Tiwari et al. (2020) reported that the top six CC markets exhibited time-varying efficiency throughout the study period. Bitcoin is the third most inefficient market; the first and second most inefficient markets are DASH and NEM, respectively. Therefore, they provide the most abnormal profit opportunities. However, according to their rankings, the most efficient crypto markets are Ethereum and Ripple. Recently, Noda (2022) studied the joint degree of market efficiency using the approach of Ito et al. (2014, 2016), which is based on the Generalized Least Squares-based time-varying vector auto-regression (VAR) model.[3] Noda (2022) finds that the joint degree of market efficiency is time-varying and that market efficiency increased during the pandemic, intensifying the correlation between markets. Further evidence shows that the Bitcoin market efficiency has deteriorated since the bubble emerged in late 2020. These results seem to counter previous findings, except for the consensus on the time variation in the degree of market efficiency.

One of the advantages of a time-varying efficiency approach is accounting for the effect of crisis periods on market (in)efficiency and the possibility of examining the factors driving the level of (in)efficiency. However, related literature exists on the important factors for CC (in)efficiency dynamics. For example, Wei (2018) examined the relationship between liquidity and efficiency in 456 CC markets and provided evidence of a positive relationship, particularly for Bitcoin. Naeem et al. (2021) investigated the efficiency hypothesis in the main CCs and showed that this behavior was affected by the COVID-19 pandemic. Fernandes et al. (2022) highlight the resilience of CC market efficiency during a pandemic. Similarly, El Montasser et al. (2022) showed that CC market efficiency is largely affected by COVID-19. Al-Yahyaee et al. (2020) investigate the multifractality, long-memory process, and efficiency hypotheses of six major CCs (Bitcoin, Ethereum, Monero, Dash, Litecoin, and Ripple) using the time-rolling MF-DFA approach. They used a quantile regression approach to examine the determinants of the efficiency of these markets. Specifically, they support the significant impacts of volatility and liquidity as potential determinants of CC market efficiency.

Data and methodology

The data

We collected the daily closing prices of the two largest CCs by market capitalization, Bitcoin and Ethereum, from https://coinmarketcap.com. The sample period is from 08/07/2016 to 02/15/2023, yielding 2384 daily observations for each CC. The period considered is suggested by data availability and accounts for various events that potentially

[3] See also the recent work of Ito et al. (2022).

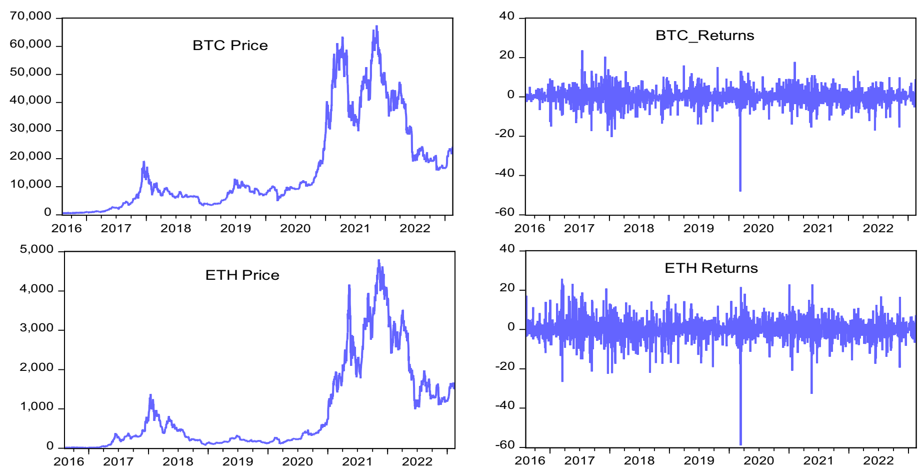

Fig. 1 Daily prices and log returns of Bitcoin and Ethereum

Table 1 Descriptive statistics and preliminary tests of the returns of Bitcoin and Ethereum

	Mean	Std. Dev	Skewness	Kurtosis	J–B prob	AFD	PP
BTC	0.1551	4.0365	− 0.7890	14.2828	0.0000	− 51.2593***	− 51.2000***
ETH	0.2142	5.4116	− 0.5427	11.9024	0.0000	− 51.0701***	− 51.1700***

This table reports the descriptive statistics and preliminary tests of BTC and ETH daily returns. The sample period is 08/07/2016–02/15/2023. J–B (Jarque–Bera) statistics p-values are related to the normality test. ADF and PP are the statistics of Dickey–Fuller and Phillips–Perron related to the unit root tests

***Indicates statistical significance at the 1% level

affect the CC market, such as the 2017 boom, the Bitcoin crash at the end of 2017, and the COVID-19 pandemic.

Figure 1 shows the daily prices and log returns of Bitcoin and Ethereum over the study period. Both CCs exhibit a set of upward and downward phases. Specifically, the price evolution shows a large increase from the beginning of the study period until the end of 2017, followed by a drop from the beginning of 2018. Prices generally remained stable until the end of 2019, when upside movements and large price corrections had to occur. Subsequently, the price trend shows a sharp increase in the price level after the end of 2020, with the beginning of the COVID-19 pandemic followed by a considerable drop from approximately $60,000 to about $20,000. Figure 1 also shows the behavior of the return series and highlights some variations in the two CCs considered, especially during the COVID-19 pandemic. Moreover, a large increase followed by a decrease in returns indicates volatility clustering.

Table 1 presents summary statistics and preliminary tests for the daily return series. The mean returns show positive values for both CCs, indicating beneficial investment opportunities characterizing the two assets, especially for Ethereum, which has the highest value at 0.2142%. According to the standard deviation, Ethereum was, on average, more volatile than Bitcoin. Both return series are negatively skewed and have excess kurtosis values, and the normality hypothesis is strongly rejected, as the null p-values of the Jarque–Berra statistics show. Unit root testing is performed by applying the ADF of the Dickey and Fuller (1979), and Phillips and Perron (1988) tests, and the results show that both return series are stationary at the 1% significance level.

Empirical methodology

Our empirical methodology consists of two parts. First, we conduct an efficiency testing procedure on the Bitcoin and Ethereum markets, following Le Tran and Leirvik's (2019) approach. Second, we investigate market (in)efficiency determinants using quantile regression.

Testing efficiency in a time-varying framework

Le Tran and Leirvik (2019) proposed a measure of the level of Adjusted Market Inefficiency Magnitudes (AMIMs) within a time-varying framework. This procedure begins by representing the returns on each CC, $R_t, t = 1, 2, \ldots, T$, following an Autoregressive AR(p) model, as follows:

$$R_t = \alpha_0 + \sum_{i=1}^{p} \alpha_1 R_{t-1} + \epsilon_t \tag{1}$$

Then, if the market is efficient, the parameters $(\alpha_1, \alpha_2, \ldots, \alpha_p)$ are zero or statistically insignificant. By contrast, when this vector of parameters is statistically significant, the market is inefficient.

Let be the $\widehat{\alpha} = \left(\widehat{\alpha}_1, \widehat{\alpha}_2, \ldots \widehat{\alpha}_p\right)\prime$ obtained after estimating the coefficients of Eq. (1) by OLS. Asymptotically, we have

$$\widehat{\alpha} \sim N(\alpha, \Sigma). \tag{2}$$

Here Σ is the covariance matrix of the vector $\widehat{\alpha}$. We can apply the Cholesky decomposition to this matrix as follows: $\Sigma = LL\prime$ where L and L' are two triangular matrices. Le Tran and Leirvik (2019) recommended using such a decomposition in the first stage of constructing their proposed measures for market efficiency. Accordingly, this decomposition ensures standardization of the estimated coefficients, which can be obtained as follows:

$$\widehat{\alpha}^{standard} = L^{-1}\widehat{\alpha}. \tag{3}$$

Asymptotically, this standardized vector defined above is normal. More explicitly, we have

$$\widehat{\alpha}^{standard} \sim N(0, I), \tag{4}$$

where I denotes the identity matrix. Second, Le Tran and Leirvik (2019) introduce the magnitude of market inefficiency (MIM_t), defined as follows:

$$MIM_t = \frac{\sum_{h=1}^{p} \left|\widehat{\alpha}_{h,t}^{standard}\right|}{1 + \sum_{h=1}^{p} \left|\widehat{\alpha}_{h,t}^{standard}\right|}. \tag{5}$$

MIM_t provides the inefficiency levels for different times t. By construction, MIM_t smoothly varies in the interval [0,1]. This measure equals 0 when the market is very efficient. It tends toward 1 when the market is inefficient.

The MIM_t has several advantages. For example, it does not depend on the frequency of data in the sample. Furthermore, it does not set the number of autocorrelation lags as a priori. The MIM_t measure considers standardized coefficients and works with their absolute values in Eq. (5). Nevertheless, it has a drawback arising from the possibility of several lags p in Eq. (1) is positively correlated with the MIM. To solve this, Le Tran and Leirvik (2019) employed Monte Carlo simulations in a third step to determine the 95 percent quantile of MIM_t under the null hypothesis of market efficiency. The difference between this quantile and zero represented the range of the interval. Finally, Le Tran and Leirvik (2019) defined the adjusted market inefficiency magnitude ($AMIM_t$) as follows:

$$AMIM_t = \frac{MIM_t - R_{CI}}{1 - R_{CI}} \tag{6}$$

The market is inefficient when $AMIM_t$ is higher than zero, but when $AMIM_t$ is less than or equal to zero, the market is efficient. As Le Tran and Leirvik (2019, 2020) advised, we use an overlapping one-year window to construct the AMIM measures.

Determinants of efficiency

We use a quantile regression (QR) to identify the factors driving the (in)efficiency of Bitcoin and Ethereum. Unlike OLS estimators in linear regressions, the QR model allows us to investigate the effect of certain factors on the (in)efficiency measured by the AMIM variable at different distributional levels of the AMIM variable. Therefore, QR has the advantage of distinguishing the effect of explanatory variables on various levels of efficiency, notably in the case of efficiency (low quantiles) and inefficiency (high quantiles).

Following the existing literature, we found that some factors can influence investor behavior and potential efficiency in the Bitcoin and Ethereum markets. These include global financial and monetary policy (GF), investment substitutes (IS), uncertainty (U), and CC internal and specific factors (INT). Additionally, we accounted for the COVID-19 pandemic by adding a dummy variable equal to one for the crisis and zero otherwise.

Therefore, for each considered CC, the QR model is specified as:

$$\begin{aligned} Q(AMIM)_{\tau,t} =& \theta_0(\tau) + \sum_{i=1}^{I} \theta_i(\tau) GF_{i,t} + \sum_{j=1}^{J} \theta_j(\tau) IS_{j,t} \\ &+ \sum_{k=1}^{K} \theta_k(\tau) U_{k,t} + \sum_{h=1}^{H} \theta_h(\tau) INT_{h,t} + \theta_l(\tau) COVID_t + \epsilon_t \end{aligned} \tag{7}$$

where $Q(AMIM)_{\tau,t}$ denotes the conditional quantile of efficiency measure (AMIM) at the order τ ($\tau \in [0,1]$). GF is a global financial and monetary policy factor that includes the Financial Stress Indicator (FSI), Morgan Stanley Capital International World Stock Market Index (MSCI), and Fed Fund rates (FFR).[4] The investment substitutes (IS) are the Goldman Sachs Commodity Index (GSCI) energy index and the Gold Bullion index (Gold). The uncertainty factor includes the economic policy uncertainty (EPU) and CBOE volatility index (VIX). Internal factors are specific to the CC market and include the volatility of CCs (VOL), measured by squared returns; liquidity (LIQ), measured by

[4] Wang et al. (2022) study the interaction between Bitcoin and US economic variables such as consumer price index and money supply, which are available at the monthly frequency.

Table 2 Summary statistics of AMIM for Bitcoin and Ethereum

	Mean	Min	Max	Std. Dev	Skewness	Kurtosis	ADF	PP
Bitcoin	0.0255	− 1.2907	0.4742	0.2909	− 0.9034	3.6816	− 3.9997***	− 3.9997***
Ethereum	0.1012	− 1.5201	0.5112	0.2936	− 1.6531	6.9687	− 2.9012**	− 8.0242***

The table shows the descriptive statistics of the one-year- AMIM series of Bitcoin et Ethereum. Given that we retain a window size of one year, the sample period of the AMILM variable is between 08/08/2017 and 02/15/2023. J–B (Jarque–Bera) statistics p-values are related to the normality test. ADF and PP are the statistics of Dickey–Fuller and Phillips–Perron related to the unit root tests

*** and ** indicate statistical significance at the 1 and 5% levels, respectively

dividing the value traded by the market capitalization of CCs (Al-Yahiya et al., 2020); and money flow to cryptocurrencies (MFC). We account for the pandemic using a dummy variable (COVID) equal to one during the COVID-19 period (after the date of deflation on the pandemic on 03/11/2020 by the World Health Organization) and zero otherwise.

Results and discussion

Testing efficiency results

To test efficiency in the Bitcoin and Ethereum markets, we follow Le Tran and Leirvik (2019) by estimating the daily AMIM values based on Eq. (6) using overlapping window data for one year.[5] The results of the descriptive statistics for daily AMIM are presented in Table 2. They show that the mean values of AMIM are positive and statistically significant (suggested by small standard error values) for the two assets, indicating that both the Bitcoin and Ethereum markets are inefficient on average. Bitcoin has the smallest mean value, implying that the Bitcoin market is less inefficient than Ethereum.

To provide a more in-depth analysis of (in)efficiency in a time-varying framework, we assessed the quantiles of AMIM at different orders ranging from 0.1 to 0.9. Table 3 shows that the efficiency of the Bitcoin and Ethereum markets is lost from the quantile order exceeding 0.4 and 0.2, respectively. In other words, the Bitcoin (Ethereum) market is efficient in over 40% (20%) of the data sample, suggesting that Bitcoin is more efficient than Ethereum. This finding is consistent with that of Noda (2021), who reported that Bitcoin's market efficiency level was higher than Ethereum over most periods. A plausible explanation for this finding is that Bitcoin is the oldest and largest CC.

Figures 2 and 3 show the AMIM plots for Bitcoin and Ethereum, respectively. For a clearer illustration of the periods of efficiency and inefficiency, we highlight the area (light gray) when the market is efficient, as reflected by the negative values of AMIM. As these two figures show, the level of market (in)efficiency varies substantially over time, corroborating a large strand of literature suggesting that CC market efficiency changes over time and reacts to events and crisis periods (Alvarez-Ramirez et al. 2018; Jiang et al. 2018; Le Tran and Leirvik 2020; Khursheed et al. 2020; Tiwari et al. 2020; Al-Yahyaee et al. 2020; Naeem et al. 2021; Noda 2021).

The Bitcoin market was inefficient from the beginning of the study period, especially from August 2017 to the end of 2017. Long periods of efficiency were observed in this market in 2018, especially during April, May, June, and the first half of July. In June and July 2017, Bitcoin prices increased, and the resulting high returns led to the availability

[5] For robustness, we r-estimate the AMIM using over-lapping windows data with different sizes of 3 months, 6 months, 18 months, and 2 years. The results are mostly similar in the common date range. See Appendix Fig. 4.

Table 3 Empirical quantiles and market conditions for Bitcoin and Ethereum

Quantile's order	Bitcoin		Ethereum	
	Quantile	Condition	Quantile	condition
0.1	**− 0.3843**	**Efficiency**	**− 0.2052**	**Efficiency**
0.2	**− 0.2056**	**Efficiency**	**− 0.0796**	**Efficiency**
0.3	**− 0.0813**	**Efficiency**	0.0043	Inefficiency
0.4	**− 0.0006**	**Efficiency**	0.0730	Inefficiency
0.5	0.0679	Inefficiency	0.1795	Inefficiency
0.6	0.1400	Inefficiency	0.2277	Inefficiency
0.7	0.2139	Inefficiency	0.2667	Inefficiency
0.8	0.2987	Inefficiency	0.3366	Inefficiency
0.9	0.3631	Inefficiency	0.4126	Inefficiency

The table shows the results of the quantiles of the AMIM at different orders ranging from 0.1 to 0.9. Bolds indicate the cases of efficiency

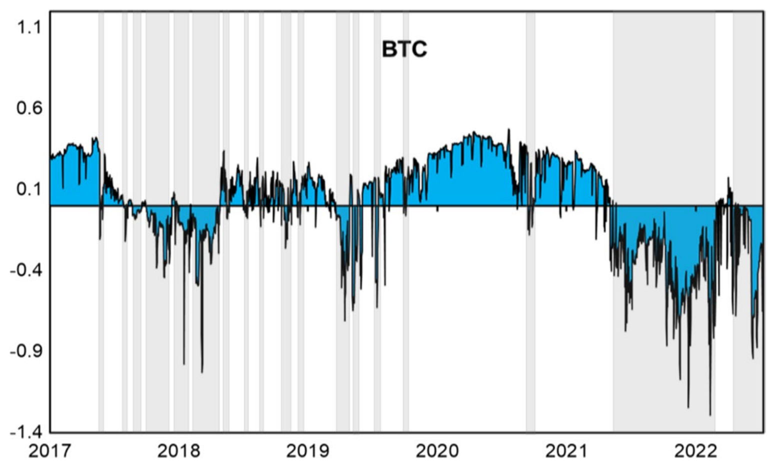

Fig. 2 Time series AMIM for Bitcoin. *Notes*: The figure shows the time evolution of the AMIM series, defined by Eq. (6). Negative (positive) values indicate market efficiency (inefficiency). The vertical shades (in light gray) indicate the periods of efficiency

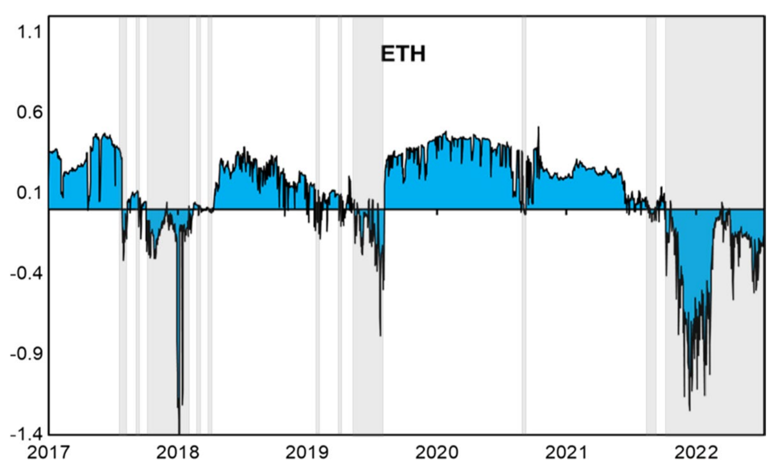

Fig. 3 Time series AMIM for Ethereum. *Notes*: The figure shows the time evolution of the AMIM series defined by Eq. (6). Negative (positive) values indicate market efficiency (inefficiency). The vertical shades (in light gray) indicate the periods of efficiency

of more information in the market (Yu et al. 2019). Similarly, the longest period of efficiency in the Bitcoin market is from late December 2021 to early October 2022. This market also finds another period of efficiency from December 2022 to the end of the study period on February 15, 2023.

The situation for the Ethereum market is somewhat similar, but the number of observations corresponding to efficiency is lower than that for Bitcoin. Specifically, a relatively long period of efficiency was observed in the Ethereum market in 2018. This period lasted from May 11 to September 2018. Other long periods of efficiency were observed from May 30, 2022, to October 14, 2022, and November 9, 2022, until the end of the study period.

Our findings confirm those of Le Tran and Leirvik (2020), who report that the efficiency of CCs changes over time. In addition, our findings are comparable to those of Noda (2021), who finds that the degree of market efficiency varies with time for Bitcoin and Ethereum. Notably, our results support the AMH for the two CCs.

Determinant of efficiency

We investigated the determinants of the (in)efficiency using the QR model specified in Eq. (7), which involves a set of financial, investment substitute, uncertainty, CC-specific, and COVID-19 pandemic factors. We used the logarithmic changes of the different explanatory variables covering GF (FSI, MSCI, and FFR), IS (CSCI and GOLD), U (EPU and VIX), and INT (VOL, LIQ, and MFC), as described in Sect. Data and methodology Descriptive statistics and preliminary tests are provided in Table 4, where the Jarque–Bera test strongly rejects the null hypothesis of normality. Moreover, the ADF and PP tests show that all considered series are integrated in the order of zero I(0). The correlations among these variables are presented in Table 10 in the Appendix.

Tables 5 and 6 present the estimation results of the QR model for Bitcoin and Ethereum, respectively. For clarity and readability purposes, Table 7 provides a simple representation of the sign and significance of the impact of different variables on the (in) efficiency of the two considered CC markets. Bearing in mind that based on previous results in Table 3, Bitcoin is efficient at the quantile orders from 0.1 to 0.4, while the efficiency of the Ethereum market is verified at quantile orders 0.1 and 0.2.

Starting with the Bitcoin market, we observe that financial stress is statistically significant at all quantile orders, indicating that this factor is a driver of both the efficiency and inefficiency of Bitcoin. Moreover, the negative sign of the estimated parameter shows that an increase in global financial stress leads to a decrease in AMIM values. However, the results show that AMIM is significantly and positively affected by the MSCI world stock market only when the Bitcoin market is efficient (low quantiles of the order 0.2). Additionally, we found that investment substitutes have an insignificant effect on AMIM. A plausible explanation for this finding is that investors look at substitutes such as gold and crude oil to hedge their portfolios. Policy uncertainty measured by EPU and VIX was found to have no significant effect on the efficiency of Bitcoin, indicating that Bitcoin market efficiency is not influenced by economic or market uncertainty.

Bitcoin market efficiency is significantly affected by volatility at a high quantile order of 0.7. This result implies that Bitcoin market efficiency is affected only by Bitcoin volatility when it is inefficient. We find that liquidity positively and significantly affects the AMIM variable, whether the market is efficient or inefficient. Finally, the COVID-19

Table 4 Descriptive statistics and preliminary analysis of the (in)efficiency drivers

	Mean	Std. Dev	Skewness	Kurtosis	J-B p-value	ADF	PP
Global financial and monetary policy (GF)							
FSI	− 1.651	2.320	1.695	6.658	0.000	− 2.998**	− 2.968**
MSCI	0.025	1.100	− 1.092	19.226	0.000	− 37.538***	− 39.652***
FFR	0.093	7.509	1.147	212.652	0.000	− 41.352***	− 41.135***
Investment substitutes (IS)							
GSCI	0.034	2.589	− 1.779	25.895	0.000	− 35.602***	− 36.416***
GOLD	0.027	0.933	− 0.234	8.016	0.000	− 33.005***	− 35.145***
Uncertainty factors (U)							
EPU	0.067	51.938	0.126	7.815	0.000	− 20.209***	− 174.397***
VIX	− 0.005	4.945	1.124	8.851	0.000	− 33.820***	− 40.240***
Internal factors (INT)							
VOL_BTC	16.755	61.922	26.159	941.306	0.000	− 41.220***	− 42.531***
VOL_ETH	27.123	96.668	23.970	814.212	0.000	− 39.810***	− 40.992***
LIQ_BTC	0.090	0.071	2.235	10.979	0.000	− 3.369***	− 9.516***
LIQ_ETH	0.203	0.227	2.040	8.521	0.000	− 3.786***	− 4.660***
MFC	0.008	11.900	0.160	4.337	0.000	− 20.257***	− 41.442***

This table reports the descriptive statistics of the potential drivers of (in)efficiency of Bitcoin and Ethereum. J–B (Jarque–Bera) statistics p-values are related to the normality test. ADF and PP are the statistics of Dickey–Fuller and Phillips–Perron related to the unit root tests. GF is the global financial and monetary policy factor, which includes the Financial Stress Indicator (FSI), the MSCI world stock market index (MSCI), and Fed Fund rates (FFR). The investment substitutes (IS) are represented by the GSCI Energy index (GSCI) and Gold Bullion index (Gold). The uncertainty (U) factor includes the economic policy uncertainty (EPU) and the CBOE volatility index (VIX). The internal (INT) factors are specific to the cryptocurrency market and include the volatility of the cryptocurrency (VOL), liquidity (LIQ), and money flow to cryptocurrencies (MFC)

*** and ** indicate the statistical significance at 1%, and 5%, respectively

pandemic positively affected market inefficiency, suggesting that the pandemic pushed the market into inefficiency. This result supports the findings of Naeem et al. (2021), El Montasser et al. (2022), and Aaasf et al. (2022), who reported that the efficiency level of CC markets was affected by the COVID-19 pandemic.

Table 6 shows similar results for the global financial factors of Ethereum. FSI is a significant driver of efficiency in the Ethereum market, regardless of whether the market is efficient or inefficient. The MSCI world stock market generally affects the Ethereum market when it is efficient, whereas FFR negatively affects AMIM. In addition, we find slightly different results from the Bitcoin case concerning the investment substitute factors. EPU and VIX generally do not affect the efficiency measure for Bitcoin or Ethereum, irrespective of the level of (in)efficiency. We also report a significant impact of Ethereum volatility on efficiency, particularly when the market is efficient. Finally, while MFC affected Bitcoin AMIM, it did not affect Ethereum.

In summary, the variables affecting the efficiency of CC markets are (1) global financial stress, which negatively and significantly affects their AMIM measures. This can be interpreted by the relative immunity of CC markets to the global financial index in times of uncertainty; see Zhang and Wang (2021). (2) The effect of investment substitutes and uncertainty are marginal, especially for Bitcoin. (3) Liquidity positively and significantly affects efficiency, regardless of whether the cryptocurrency market is efficient or inefficient. This result is expected because the lack of liquidity reflects underlying market imperfections, such as asymmetric information, different forms of trading costs, and funding constraints (Vayanos and Wang 2012). (4) The money flow index has a positive

Table 5 Determinants of the Bitcoin market's efficiency

	OLS	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Constant										
C	− 0.2092***	− 0.5184***	− 0.4177***	− 0.3436***	− 0.2622***	− 0.1959***	− 0.1193***	− 0.0623***	0.0133	0.0963**
	(0.0149)	(0.0273)	(0.0159)	(0.0208)	(0.0230)	(0.0243)	(0.0259)	(0.0253)	(0.0329)	(0.0345
Global financial and monetary policy										
FSI	− 0.0636***	− 0.0905***	− 0.0862***	− 0.0765***	− 0.0694***	− 0.0645***	− 0.0689***	− 0.0703***	− 0.0599***	− 0.0532***
	(0.0033)	(0.0114)	(0.0074)	(0.0072)	(0.0078)	(0.0072)	(0.0061)	(0.0050)	(0.0064)	(0.0063)
MSCI	0.0043	− 0.0108	− 0.0120	0.0033	− 0.0026	0.0092	0.0114	0.0166*	0.0125	0.0070
	(0.0079)	(0.0233)	(0.0261)	(0.0161)	(0.0151)	(0.0145)	(0.0109)	(0.0102)	(0.0079)	(0.0076)
FFR	− 0.0013	0.0014	− 0.0013	− 0.0024	− 0.0013	− 0.0010	− 0.0016	− 0.0009	− 0.0007	− 0.0013***
	(0.0009)	(0.0050)	(0.0076)	(0.0054)	(0.0020)	(0.0018)	(0.0010)	(0.0009)	(0.0005)	(0.0004)
Investment substitutes										
GSCI	− 0.0007	− 0.0071	− 0.0033	0.0011	0.0047	0.0025	0.0005	− 0.0034	− 0.0017	− 0.0011
	(0.0029)	(0.0141)	(0.0078)	(0.0072)	(0.0055)	(0.0043)	(0.0031)	(0.0037)	(0.0032)	(0.0014)
GOLD	0.0034	0.0078	0.0026	0.0118	0.0116	0.0067	0.0046	0.0040	− 0.0028	− 0.0035
	(0.0075)	(0.0196)	(0.0171)	(0.0145)	(0.0118)	(0.0116)	(0.0100)	(0.0081)	(0.0061)	(0.0047)
Uncertainty factors										
EPU	− 1.6E−04	− 3.1e−05	− 1.0e−04	7.1e−05	− 1.7e−04	− 1.5e−04	− 2.8e−04	− 1.5e−04	− 1.4e−04	− 5.9e−05
	(1.5e−04)	(2.6e−04)	(1.8e−04)	(1.8e−04)	(1.9e−04)	(2.0e−04)	(2.0e−04)	(1.8e−04)	(1.7e−04)	(1.5e−04)
VIX	5.8e−04	6.3e−04	4.3e−04	2.1e−03	− 9.8e−04	1.3e−03	8.7e−04	1.1e−03	1.0e−03	9.8e−04
	(5.8e−04)	(4.1e−03)	(3.3e−03)	(2.9e−03)	(2.7e−03)	(2.4e−03)	(2.3e−03)	(1.8e−03)	(1.4e−03)	(1.0e−03)
Internal factors										
VOL	6.7e−04	4.7e−05	− 9.7e−05	1.6e−05	1.9e−05	− 5.4e−05	− 2.1e−04	− 3.1e−04***	− 1.2e−04	− 1.1e−04
	(1.6e−03)	(1.9e−04)	(1.3e−04)	(3.9e−04)	(4.1e−04)	(3.9e−04)	(3.4e−04)	(7.1e−05)	(3.4e−04)	(2.7e−04)
LIQ	− 0.0001	0.7755***	1.1085***	1.3647***	1.3839***	1.4334***	1.5266***	1.6466***	1.5911***	1.4302***
	(0.0001)	(0.5194	(0.2123)	(0.1406)	(0.1380)	(0.1642)	(0.1896)	(0.2038)	(0.2268)	(0.2389)

Table 5 (continued)

	OLS	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
MFC	1.4454***	− 7.6e−04	7.2e−04	1.4e−04	5.6e−04	1.4e−03*	2.5e−04	4.4e−04	5.2e−04	7.5e−05
	(1.1e−01)	(1.2e−03)	(7.1e−04)	(7.2e−04)	(7.4e−04)	(8.5e−04)	(8.7e−04)	(6.9e−04)	(6.3e−04)	(5.3e−04)
COVID-19 factor										
	0.0380	0.0609*	0.1322***	0.1755***	0.1862***	0.1789***	0.1442***	0.0869***	0.0021***	0.0380***
	(0.0498)	(0.0366)	(0.0263)	(0.0155)	(0.0120)	(0.0118)	(0.0160)	(0.0234)	(0.0250)	(0.0498)

The table reports the coefficients on the drivers of Bitcoin market efficiency estimated based on the OLS and quantile regressions specified in Eq. (7). The Bitcoin market is efficient for quantiles' orders between 0.1 and 0.4. Standard errors are given in parentheses

***, **, * denote the statistical significance at the 1, 5, and 10% levels, respectively

Table 6 Determinants of the Ethereum market's efficiency

	OLS	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Constant										
C	− 0.1566***	− 0.5283***	− 0.3663***	− 0.2735***	− 0.1724***	− 0.1262***	− 0.0589***	0.0206	0.0963***	0.2036***
	(0.0175)	(0.0341)	(0.0223)	(0.0257)	(0.0182)	(0.0169)	(0.0201)	(0.0202)	(0.0198)	(0.0288)
Global financial and monetary policy										
FSI	− 0.0626***	− 0.1305***	− 0.0955***	− 0.0737***	− 0.0574***	− 0.0530***	− 0.0473***	− 0.0456***	− 0.0444***	− 0.0446***
	(0.0036)	(0.0126)	(0.0074)	(0.0103)	(0.0045)	(0.0038)	(0.0036)	(0.0036)	(0.0039)	(0.0074)
MSCI	− 0.0041	− 0.0595**	− 0.0245	− 0.0028	− 0.0008	− 0.0013	− 0.0003	0.0005	0.0028	0.0056
	(0.0081)	(0.0279)	(0.0198)	(0.0234)	(0.0132)	(0.0112)	(0.0068)	(0.0063)	(0.0067)	(0.0062)
FFR	− 1.5e−03	− 4.2e−03	− 1.7e−03	1.8e−04	− 2.4e−04	− 2.0e−05	− 1.8e−04	− 5.0e−05	− 5.8e−04	− 8.1e−04*
	(9.3e−04)	(3.4e−03)	(2.2e−03)	(1.7e−03)	(1.5e−03)	(5.2e−04)	(3.9e−04)	(3.6e−04)	(4.0e−04)	(4.8e−04)
Investment substitutes										
GSCI	0.0042	0.0120	0.0149*	0.0086	0.0021	0.0043	0.0027	− 0.0005	− 0.0005	− 0.0003
	(0.0030)	(0.0136)	(0.0077)	(0.0058)	(0.0039)	(0.0038)	(0.0032)	(0.0019)	(0.0014)	(0.0013)
GOLD	0.0140*	0.0333	0.0110	0.0150	0.0139*	0.0158**	0.0086	0.0041	0.0089	0.0037
	(0.0078)	(0.0209)	(0.0113)	(0.0111)	(0.0073)	(0.0069)	(0.0075)	(0.0076)	(0.0061)	(0.0046)
Uncertainty factors										
EPU	5.3e−05	− 5.2e−05	7.0e−05	1.4e−04	7.2e−05	1.0e−06	− 3.0e−05	− 3.9e−05	− 1.9e−04	− 3.6e−05
	(1.5e−04)	(2.2e−04)	(1.4e−04)	(1.4e−04)	(1.3e−04)	(1.4e−04)	(1.5e−04)	(1.5e−04)	(1.4e−04)	(1.8e−04)
VIX	− 9.2e−04	− 8.4e−03*	1.0e−03	1.2e−03	3.8e−04	− 3.5e−04	− 8.7e−04	− 9.2e−04	4.4e−04	3.1e−04
	(1.7e−03)	(4.8e−03)	(3.4e−03)	(2.8e−03)	(2.2e−03)	(1.9e−03)	(1.6e−03)	(1.5e−03)	(1.4e−03)	(9.2e−04)
Internal factors										
VOL	− 2.9e−06**	2.5e−04	1.7e−04***	4.2e−05	− 6.7e−05	− 1.2e−04**	− 8.8e−05	− 4.2e−05	8.3e−05	1.9e−05
	(6.6e−05)	(1.6e−04)	(4.7e−05)	(7.1e−05)	(5.0e−05)	(4.5e−05)	(2.1e−04)	(1.3e−04)	(2.7e−04)	(1.4e−04)
LIQ	0.4044***	− 0.0244	0.1181*	0.3279***	0.4172***	0.4742***	0.4991***	0.5035***	0.5260***	0.4743***
	(0.0339)	(0.0694)	(0.0633)	(0.1028)	(0.0520)	(0.0475)	(0.0415)	(0.0430)	(0.0611)	(0.1282)

Table 6 (continued)

	OLS	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
MFC	2.1e−04	3.5e−04	2.1e−04	2.7e−04	− 3.7e−05	− 1.4e−04	− 2.1e−05	− 3.7e−04	3.4e−04	− 4.0e−04
	(6.0e−04)	(1.1e−03)	(6.4e−04)	(6.0e−04)	(5.5e−04)	(5.2e−04)	(5.0e−04)	(5.3e−04)	(5.7e−04)	(5.8e−04)
COVID-19 factor										
COVID-19	0.1259***	0.1349***	0.1793***	0.1811***	0.1565***	0.1594***	0.1338***	0.0844***	0.0443***	− 0.0016
	(0.0158)	(0.0301)	(0.0186)	(0.0205)	(0.0144)	(0.0137)	(0.0140)	(0.0168)	(0.0168)	(0.0274)

The table reports the coefficients on the drivers of Ethereum market efficiency estimated based on the OLS and quantile regressions specified in Eq. (7). The Ethereum market is efficient for quantiles' orders between 0.1 and 0.2. Standard errors are given in parentheses

***, **, * denote the statistical significance at the 1%, 5%, and 10% levels, respectively

Table 7 Sign and significance of the drivers' effects

	OLS	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Panel A: Bitcoin										
Global financial and monetary policy										
FSI	(−)	(−)	(−)	(−)	(−)	(−)	(−)	(−)	(−)	(−)
MSCI								(+)		
FFR										(−)
Investment substitutes										
GSCI										
GOLD										
Uncertainty factors										
EPU										
VIX										
Internal factors										
VOL								(−)		
LIQ		(+)	(+)	(+)	(+)	(+)	(+)	(+)	(+)	(+)
MFC	(+)					(+)				
COVI-19 pandemic										
COVID-19		(+)	(+)	(+)	(+)	(+)	(+)	(+)	(+)	
Panel B: Ethereum										
Global financial and monetary policy										
FSI	(−)	(−)	(−)	(−)	(−)	(−)	(−)	(−)	(−)	(−)
MSCI		(−)								
FFR										(−)
Investment substitutes										
GSCI			(+)							
GOLD	(+)				(+)	(+)				
Uncertainty factors										
EPU										
VIX		(−)								
Internal factors										
VOL	(−)		(+)			(−)				
LI	(+)		(+)	(+)	(+)	(+)	(+)	(+)	(+)	(+)
MFC										
COVID-19 pandemic										
COVID-19	(+)	(+)	(+)	(+)	(+)	(+)	(+)	(+)	(+)	

Signifiance at 1% level
Signifiance at 5% level
Signifiance at 10% level

impact only when CCs are efficient, suggesting that money flow can only improve efficiency and is unrelated to inefficiency. (5) Finally, the COVID-19 pandemic had a positive and significant effect on CC market inefficiencies. This result is consistent with previous studies. One probable explanation for this finding is herding behavior, which was observed in the early months of the containment of the pandemic; see, inter alia, Ali et al. (2021), Arsi et al. (2021), Guzman et al. (2021), and Maouchi et al. (2021).

Robustness analysis

We split the sample period, considered the periods before and after the COVID-19 pandemic, and re-analyzed the drivers of the efficiency of Bitcoin and Ethereum. The results are reported for Bitcoin (Table 8) and Ethereum (Table 9), considering the lower, middle, and upper quantiles. Overall, the results provide evidence that the levels of market (in)efficiency, measured by AMIMs values before and after COVID-19, are still negatively impacted by financial stress for both Bitcoin and Ethereum, regardless of whether the markets are efficient. Moreover, CC liquidity positively and significantly affects AMIMs. In addition, we found that the parameter estimates changed remarkably after the COVID-19 pandemic compared with the period before the crisis, indicating that the pandemic affected the different factors. Thus, the change in the effect of different values

Table 8 Determinants of the Bitcoin market's efficiency before and after the COVID-19 crisis

	Before COVID-19 crisis			**Post COVID-19 crisis**		
	0.1	0.5	0.9	0.1	0.5	0.9
Constant						
C	− 0.1123***	− 0.0448	0.2624***	− 0.7083***	− 0.3205***	− 0.0731***
	(0.0323)	(0.0279	(0.0218)	(0.0428)	(0.0303)	(0.0254)
Global financial and monetary policy						
FSI	− 0.0352***	− 0.0249***	− 0.0310***	− 0.1338***	− 0.1092***	− 0.0753***
	(0.0098)	(0.0077)	(0.0053)	(0.0160)	(0.0053)	(0.0043)
MSCI	0.0083	− 0.0066	− 0.0077	− 0.0507*	− 0.0032	0.0029
	(0.0282)	(0.0142)	(0.0102)	(0.0281)	(0.0106)	(0.0090)
FFR	− 0.0067**	− 0.0014	0.0002	0.0017	0.0004	− 0.0003
	(0.0028)	(0.0023)	(0.0014)	(0.0091)	(0.0007)	(0.0004)
Investment substitutes						
GSCI	− 0.0038	− 0.0003	− 0.0015	0.0019	− 0.0024	− 0.0044
	(0.0079)	(0.0050)	(0.0030)	(0.0162)	(0.0060)	(0.0029)
GOLD	− 0.0108	0.0138	0.0044	0.0209	− 0.0026	0.0025
	(0.0263)	(0.0123)	(0.0077)	(0.0265)	(0.0089)	(0.0042)
Uncertainty factors						
EPU	− 0.0002	0.0002	0.0001	− 0.0002	− 0.0002	− 0.0001
	(0.0003)	(0.0002)	(0.0002)	(0.0007)	(0.0002)	(0.0001)
VIX	− 0.0004	− 0.0002	0.0007	− 0.0055	0.0003	0.0003
	(0.0058)	(0.0021)	(0.0014)	(0.0065)	(0.0020)	(0.0016)
Internal factors						
VOL	0.0009**	0.0004**	0.0003***	− 0.0006	− 0.0006***	− 0.0007***
	(0.0004)	(0.0002)	(0.0001)	(0.0017)	(0.0001)	(0.0001)
LIQ	0.4764**	0.2706**	− 0.8490***	3.1974***	3.2716***	2.8215***
	(0.2106)	(0.1345)	(0.0902)	(0.4344)	(0.2371)	(0.2100)
MFC	0.0021**	0.0008	− 0.0004	0.0012	0.0006	− 0.0001
	(0.0009)	(0.0009)	(0.0006)	(0.0019)	(0.0008)	(0.0006)

The table reports the coefficients on the drivers of Bitcoin market efficiency estimated based on quantile regressions before and after the COVID-19 crisis. Standard errors are given in parentheses

***, **, * denote the statistical significance at the 1, 5, and 10% levels, respectively

indicates that the (in)efficiency of the two main CCs was widely affected by the COVID-19 pandemic, confirming the robustness of our analysis.

Conclusions

Market efficiency is a well-investigated topic in the financial literature, and several empirical blueprints are used to test the efficient market hypothesis in several assets and markets. Recently, the efficiency of CC markets has been the subject of an increasing number of studies. However, it remains largely unclear which factors and variables drive the level of (in)efficiency in this young market. This study examines the time-varying adjusted magnitude market inefficiency (AMIM) measure, recently introduced by Le Tran and Leirvik (2019), to study the two largest CCs, Bitcoin and Ethereum. Second, we apply the quantile regression (QR) model to understand the drivers of AMIMs, using a large set of explanatory variables reflecting the internal and external characteristics of the CC markets. We use the QR model to account for the evolution of AMIM measures

Table 9 Determinants of the Ethereum market's efficiency before and after the COVID-19 crisis

	Before COVID-19 crisis			Post COVID-19 crisis		
	0.1	**0.5**	**0.9**	**0.1**	**0.5**	**0.9**
Constant						
C	− 0.1982***	0.1585***	0.3288***	− 0.5537***	− 0.0693***	0.1096***
	(0.0313)	(0.0416)	(0.0262)	(0.0352)	(0.0196)	(0.0120)
Global financial and monetary policy						
FSI	− 0.0250**	− 0.0207*	− 0.0323***	− 0.1439***	− 0.0719***	− 0.0538***
	(0.0100)	(0.0120)	(0.0060)	(0.0082)	(0.0045)	(0.0027)
MSCI	− 0.0172	0.0022	− 0.0061	− 0.0434*	− 0.0039	0.0005
	(0.0255	(0.0210)	(0.0124)	(0.0261)	(0.0075)	(0.0068
FFR	− 0.0015	0.0011	0.0011	− 0.0037	0.0012***	− 0.0001
	(0.0030)	(0.0055)	(0.0041)	(0.0024)	(0.0004)	(0.0003))
Investment substitutes						
GSCI	0.0027	0.0054	− 0.0009	0.0166	0.0005	− 0.0017
	(0.0071)	(0.0064)	(0.0056)	(0.0139))	(0.0022)	(0.0022)
GOLD	0.0090	0.0041	0.0000	0.0234*	0.0093	0.0047
	(0.0137)	(0.0155)	(0.0153)	(0.0136	(0.0084)	(0.0046)
Uncertainty factors						
EPU	− 0.0004*	0.0001	0.0001	0.0002	0.0001	− 0.0001
	(0.0002)	(0.0002)	(0.0001)	(0.0003)	(0.0002)	(0.0002)
VIX	− 0.0021	0.0010	− 0.0005	− 0.0065	− 0.0004	− 0.0007
	(0.0043)	(0.0038)	(0.0013)	(0.0081)	(0.0017)	(0.0012)
Internal factors						
VOL	0.0001	0.0002	0.0001	− 0.0004	− 0.0003***	− 0.0001
	(0.0002)	(0.0002)	(0.0001)	(0.0005)	(0.0000)	(0.0001)
LIQ	− 0.1123***	− 0.3049***	− 0.3338***	1.1722***	0.9282***	0.7982***
	(0.0336)	(0.0539)	(0.0732)	(0.1096)	(0.0566)	(0.0501)
MFC	0.0008	− 0.0005	− 0.0001	− 0.0010	− 0.0006	− 0.0006
	(0.0009)	(0.0009)	(0.0008)	(0.0021)	(0.0005)	(0.0005)

The table reports the coefficients on the drivers of Ethereum market efficiency estimated based on quantile regressions before and after the COVID-19 crisis. Standard errors are given in parentheses

***, **, * denote the statistical significance at the 1, 5, and 10% levels, respectively

and their recurrent shifts from a situation in which the markets studied are efficient to one in which these markets are inefficient.

The results suggest that the two CC markets exhibit a time-varying efficiency pattern, as indicated by an alternation between periods of efficiency and inefficiency. The Bitcoin market is generally more efficient than Ethereum in terms of the length of the efficiency period. Furthermore, the analysis shows that global financial stress has significant negative effects on the AMIMs of Bitcoin and Ethereum, which concurs with Zhang and Wang (2021), who find that, in comparison to conventional financial markets, crypto markets are relatively insensitive to financial stress. Furthermore, CC liquidity appears to be a major driver of AMIMs, irrespective of the level of CC (in)efficiency, consistent with previous findings (Wei 2018; Al-Yahyaee et al. 2020). As documented by Naeem et al. (2021), the impact of the COVID-19 pandemic was positive and significant in both CC markets. This observation was strengthened because herding behavior was observed, particularly during confined periods.

As the concept of financial market efficiency is yet to be fully understood in our reliance on AMIM, our results should be interpreted with caution. However, they can be a starting point for investors looking to track their financial plans in CC markets. Our study had some limitations. Despite the underlying assumption under the AMIM approach of Le Tran and Leirvik (2019) that time-varying estimates follow a standard normal distribution, Le Tran and Leirvik (2020) apply the AMIM approach to CC markets whose returns do not necessarily follow a normal distribution. This shortcoming should be addressed in future research while extending the approach of Le Tran and Leirvik (2019) to account for the fat-tailed return distribution of CCs.

Appendix

See Fig. 4 and Table 10.

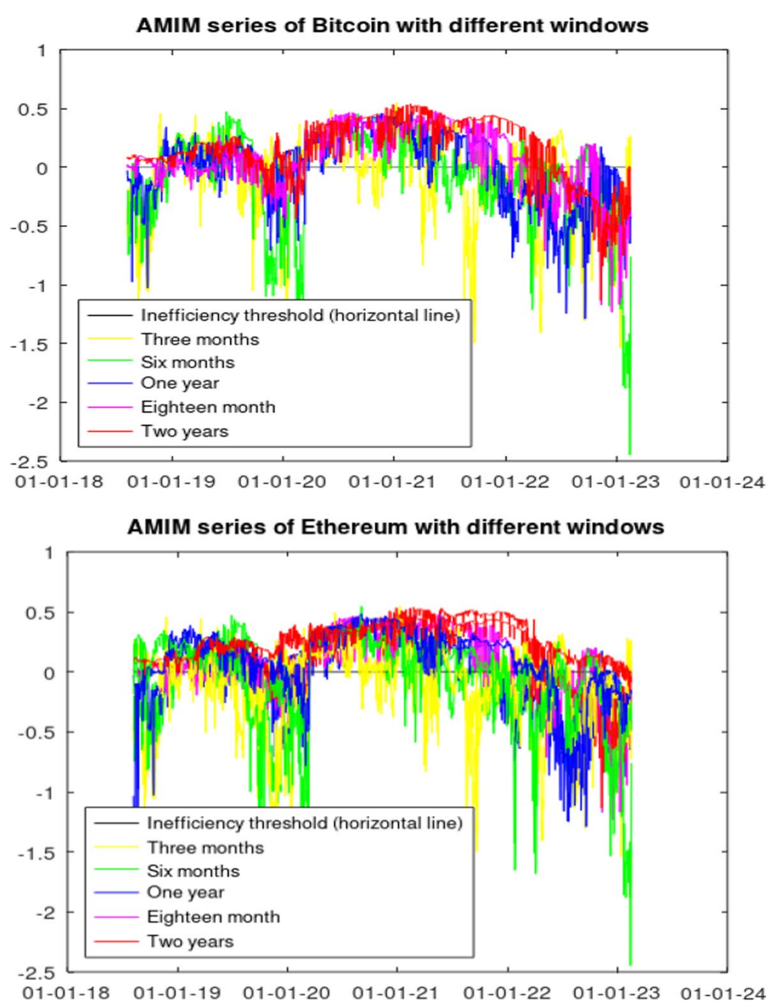

Fig. 4 AMIM variable for different window sizes

Table 10 Correlation matrix between independent variables used in the analysis of efficiency drivers

	FSI	MSCI	FFR	GSCI	GOLD	EPU	VIX	VOL_BTC	VOL_ETH	LIQ_BTC	LIQ_ETH	MFC	AMIM_BTC	AMIM_ETH
FSI	1.000													
MSCI	− 0.071	1.000												
FFR	− 0.078	0.095	1.000											
GSCI	− 0.086	0.353	0.117	1.000										
GOLD	0.021	0.138	0.032	0.140										
EPU	0.017	0.033	− 0.037	0.028	− 0.005	1.000								
VIX	− 0.022	− 0.523	− 0.033	− 0.190	− 0.039	− 0.041	1.000							
VOL_BTC	0.069	− 0.241	− 0.001	− 0.058	− 0.069	− 0.034	0.085	1.000						
VOL_ETH	0.083	− 0.228	0.000	− 0.071	− 0.069	− 0.008	0.083	0.895	1.000					
LIQ_BTC	0.435	− 0.040	− 0.155	− 0.069	− 0.006	0.026	0.027	0.210	0.220	1.000				
LIQ_ETH	0.335	− 0.046	− 0.145	− 0.069	− 0.002	0.016	0.031	0.171	0.187	0.930	1.000			
MFC	0.014	0.144	0.062	0.104	0.123	0.003	− 0.106	− 0.022	− 0.025	− 0.015	− 0.003	1.000		
AMIM_BTC	− 0.355	0.038	− 0.047	0.018	0.003	− 0.023	0.021	0.008	− 0.016	0.133	0.166	0.002	1.000	
AMIM_ETH	− 0.304	0.032	− 0.040	0.064	0.035	0.008	0.002	0.042	0.016	0.117	0.145	0.012	0.693	1.000

This table shows the Pearson correlation coefficient between the variables used on the right side of Eq. (7). Financial Stress Indicator (FSI), MSCI world stock market index (MSCI), Fed Fund rates (FFR), GSCI Energy Index (GSCI), Gold Bullion Index (Gold), economic policy uncertainty (EPU), CBOE volatility index (VIX), volatility of the cryptocurrency (VOL), liquidity (LIQ), money flow to cryptocurrencies (MFC), and adjusted market inefficiency magnitude

Abbreviations

AMIMs	Adjusted market inefficiency magnitudes
CC	Cryptocurrency
QR	Quantile regression
OLS	Ordinary least squares
CBOE	Chicago Board Options Exchange
BDS	Brock, Dechert, and Scheinkman
R/S	Rescaled range
WTI	West Texas Intermediate
AMH	Adaptive market hypothesis
AP	Automatic portmanteau
VAR	Vector auto-regression
MF-DFA	Multifractal Detrended Fluctuation Analysis
BTC	Bitcoin
ETH	Ethereum
AR	Autoregressive
MIM	Magnitude of market inefficiency
AMIM	Adjusted market inefficiency magnitude
GF	Global financial
IS	Investment substitutes
U	Uncertainty
INT	Internal
FSI	Financial Stress Indicator
MSCI	Morgan Stanley Capital International
FFR	Fed Fund rates
GSCI	Goldman Sachs Commodity Index
EPU	Economic policy uncertainty
VIX	Volatility index
VOL	Volatility
LIQ	Liquidity
MFC	Money Flow to Cryptocurrencies

Acknowledgements
There are no acknowledgements to declare.

Author contributions
The work is solely the contribution of authors. All authors contribute equally to the realization of the manuscript.

Funding
There is no funding for this work.

Availability of data and materials
Data will be made available upon request.

Declarations

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

Received: 5 October 2022 Accepted: 24 November 2023
Published online: 08 January 2024

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