Evaluating the Efficiency of the Global Cryptocurrency Market

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Abstract

Purpose : This study focused on evaluating the efficiency of the global cryptocurrency market under the efficient market hypothesis.

Methodology : The study explored the presence of calendar effects in the form of the day-of-the-week and the weekend effect in the top 25 global cryptocurrencies and a constructed index using autocorrelation corrected ARCH family models on the log-returns of prices. Non-normality is tackled through the use of a non-parametric bootstrapped approach in addition to parametric estimation. Additionally, rolling window regression is employed as a dynamic framework.

Findings : The findings of this study showed the presence of calendar effects in terms of higher returns for certain days over others, thereby concluding that the global cryptocurrency market as a whole was not efficient.

Practical Implications : As a result of its informational inadequacies, it was implied that cryptocurrency markets were not even efficient in the weak form. This had practical implications for investors, whose aggressive search and trading tactics appear warranted in the context of market anomalies, as well as other market players, like regulators attempting to comprehend the structure of the cryptocurrency market from an efficiency standpoint and researchers attempting to investigate the efficiency-related behavior and psychology of crypto markets.

Originality : This study is exceptional in that it uses a sample of cryptocurrencies that objectively covers the larger global cryptocurrency markets over the most extended amount of time possible, making it unique both for the participants in the crypto markets and for its contribution to the literature on market efficiency. The study employed an evolutionary methodology, taking into account the time-varying behavior of financial assets. As far as we can tell, this is one of the first studies to use this methodology and model formulation.

Keywords : ARCH modeling, cryptocurrency, calendar effects, EMH, market efficiency

JEL Classification Codes : G12, G14, G15, G17

Paper Submission Date : December 6, 2022 ; Paper sent back for Revision : September 18, 2023 ; Paper Acceptance Date : September 30, 2023 ; Paper Published Online : November 15, 2023

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DOI : https://doi.org/10.17010/ijf/2023/v17i11/173325

The efficient market hypothesis (EMH) (Fama, 1965) states that stock markets behave randomly, contending that in an efficient market, since information is rapidly spread among the market participants, excess returns based on such information cannot be continually earned. Malkiel and Fama (1970) put three conditions necessary for efficient markets, which are no transaction costs, costless and easily accessible information, and consensus on the effect of information on the present and future distributions of assets' prices.

Despite the assertion that financial markets are efficient, subsequent research has consistently shown that markets do not behave randomly as anomalies distort the notion of efficient markets, which create significant opportunities to generate excess returns using various patterns or information-based systems. Therefore, while, in theory, financial markets are considered efficient, there exists overwhelming evidence to prove otherwise. Three categories of market efficiency exist: weak, semi-strong, and powerful. A market is informationally inefficient overall if it is neither weak-form efficient nor semi-strong or strong-form efficient. The weak form of efficiency is evaluated through the presence of two calendar effects, namely, the day-of-the-week effect and the weekend effect. The day-of-the-week effect relates to significant differences in the mean returns of days for a given period. In the presence of a significant relation between asset returns and the day of the week, the weak form EMH is broken because it suggests that excess returns can be achieved by exploiting historical data (Cross, 1973).

Should the Cryptocurrency Market Be Considered Efficient?

As distributed assets, the intrinsic information of cryptocurrencies is publically[1] and costlessly accessible[2]. Cryptocurrencies are community-managed rather than corporate boards whose actions may influence the prices and have near-costless transactions. Unlike equity markets, where intrinsic information such as profitability or solvency follows a funneled path from the management to the markets, cryptocurrencies do not have intrinsic surprise elements in their informational content. External information, such as legislation or government actions on cryptocurrencies, is often available in advance and through public broadcast, unlike financial markets, where external information may emanate without prior intimation. Additionally, given the integration of social media, mainly dedicated online communities, there is a considerable spread of information and a somewhat familiar assessment of the risk and return perception of the underlying currency. Therefore, cryptocurrencies seem to fulfill the conditions for efficient markets as laid down by Malkiel and Fama (1970).

Should the Cryptocurrency Market Be Considered Inefficient? The Alternate Case for Inefficiency

While the preceding section puts arguments for considering crypto markets as efficient, arguments can be made for their inefficiency. Quiggin (2013) stated that the existence of cryptocurrencies itself is a refutation of the EMH. Unlike other financial instruments representing claims to potential income or assets, cryptocurrencies do not represent a claim. Changes to these incomes or institutions, as conveyed in informational and event contents, affect the prices of these assets. Yet, cryptocurrencies are traded as financial assets without any real value. The existence of meme cryptocurrencies such as Dogecoin, among the most actively traded cryptocurrencies, is a consideration of the market being inefficient.

Furthermore, a distinction can be made between the accessibility of information and its interpretability. While information on cryptocurrencies is publically and freely available, its interpretation requires an understanding of advanced mathematics and computer sciences. Therefore, despite informational availability, market participants

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[1] Available on market exchanges such as Binance.com or aggregators such as CoinMarketCap.com

[2] Available in the white paper of the cryptocurrencies.

may not have a homogeneous understanding. Also, the technological characteristics of these electronic cryptocurrencies put hackers at an informational advantage over other market participants. Events such as the failure of crypto exchanges, crypto frauds, or hacking highlight gaps in the informational content of the market and the informational advantage a set of market participants have over others. Furthermore, non-material events[3] such as tweets[4] of Elon Musk[5] have seen substantial price movements in cryptocurrencies. Given this background, the present research is focused on studying efficiency in global crypto markets.

Literature Review

While there is considerable research on the efficiency of traditional financial assets, comparatively less literature exists for evaluating the efficiency of crypto markets due to their relative modernity. Early research in this area was done by Bartos (2015), who suggested the efficiency of the Bitcoin market even in semi-strong form. By contrast, Urquhart (2016) found the bitcoin market is weak-form inefficient. This is confirmed by Kurihara and Fukushima (2017) and Wei (2018). Yet, Caporale and Plastun (2019) used parametric and non-parametric tests on the daily log returns of four cryptocurrencies and found them to be efficient. Using the same tests on odd-power converted Bitcoin returns, Nadarajah and Chu (2017) reexamined Urquhart's (2016) work and discovered that it was only marginally efficient. Using the event research technique, Vidal-Tomás and Ibañez (2018) further argued that Bitcoin may be efficient even in the semi-strong form. Similar results were obtained by Sensoy (2019). Yet, Al-Yahyaee et al. (2018) and Bundi and Wildi (2019) strongly contended that Bitcoins are not even efficient in the weak form. In recent times, Tran and Leirvik (2020) used adjusted market inefficiency magnitude[6] to evaluate weak form efficiency in five significant cryptocurrencies and found them to be inefficient. However, this study found that the efficiency of these markets is improving. Using the log-returns of the top six cryptocurrencies, López-Martín et al. (2021) applied Urquhart's (2016) technique. They discovered that while previous cryptocurrencies are efficient over time, the study's findings about their overall efficiency are still pending. Similarly, Apopo and Phiri (2021) found conflicting results, validating the daily returns of the cryptocurrency markets but not the weekly returns.

The examined literature thus far may be categorized into two distinct groups: the first group, which is usually made up of older studies (pre-2017–2018), supports the idea that cryptocurrency markets are inefficient, while the second group, which consists of more recent studies (post-2018), concludes that the cryptocurrency markets are efficient. The following are the conclusions drawn from the studied literature:

- There is no consensus as to whether the crypto markets are efficient.
- The efficiency of crypto markets is generally increasing over time.

The first gap emerges from the lack of detailed reasoning in many studies on why cryptocurrencies should even be considered efficient or not. Several studies have applied the EMH without considering the unique aspects of the crypto markets. As financial assets, cryptocurrencies possess entirely different attributes. Many early studies (pre-2017–2018) were done at a time when the crypto market was relatively nascent with few market participants, few crypto exchanges, and, accordingly, less volume and low market participation, therefore, not fulfilling the

[3] https://www.livemint.com/market/cryptocurrency/elon-musk-s-tweet-of-shiba-inu-sends-this-cryptocurrency-price-to-rally-nearly-1000-11631614701698.html
[4] https://www.analyticsinsight.net/elon-musks-grape-fuels-grapecoin-speculation-2/
[5] Elon Musk is neither a founder nor a major holder of the cryptocurrencies in question.
[6] See Tran and Leirvik (2019).

necessary conditions for market efficiency. Table 1 demonstrates that most cryptocurrencies were created after this time. The rise of the international cryptocurrency market raises the question of market efficiency—or lack thereof.

Regarding sample selection, most studies reviewed, among others, have either focused on the efficiency of only Bitcoin or a few cryptocurrencies as a proxy for the crypto market without considering the broader global market. The rationale for such a choice is also not presented. In terms of data, the efficiency in most studies is evaluated using returns computed from only the closing price[7], a choice rarely explained and debatable.

Some studies have chosen periods as small as one year to study market efficiency without explanation for such selection. In such studies, the results suggesting efficiency or inefficiency in the market of the sample cryptocurrencies may emanate due to their selection of the periods. There are also methodological considerations. While several studies use multiple methods for evaluating the market efficiency of their sample, these methods are employed on a priori belief of their application without considering the underlying properties of such tests or the assets' returns. Several studies apply models like ordinary least squares (OLS) or their "robust" variants without considering the unique properties of financial time series; therefore, the conclusion so drawn could be due to model misspecification. There is also a lack of diagnostic testing on the outcome of such models.

Rationale for the Present Study

Given the exponential growth of cryptocurrency as an alternative investment, the efficiency of the cryptocurrency market is an essential consideration for traders, investors, policymakers, and the general public. An inefficient financial market presents opportunities for both pattern-driven trades as well as scope for market manipulation. It validates active investment strategy and market timings to earn an excess rate of return over the market rate of return. The need and rationale for the present study are necessitated by the research gaps in the extant literature reviewed regarding the efficiency of cryptocurrencies.

Contribution of the Present Study

This study is unique in the following ways in its contribution to the literature on market efficiency and for the participants in crypto markets. First, in terms of the reasoning of research, this study provides clear arguments for this consideration. Secondly, data-wise, the present study employs a sample of cryptocurrencies objectively covering the broader global cryptocurrency markets. Furthermore, the data has been obtained for the maximum available period for each cryptocurrency in the sample. In terms of methodology, the study incorporates the time-varying behavior of financial assets using appropriate ARCH models. The use of ARCH family models is not based on a priori assumption but instead on an evolutionary approach. The study also evaluates the fit of these models through diagnostic testing. To the best of our belief, this is among the first studies to employ such an approach and model specification. The study also tackles non-normality through the use of a non-parametric bootstrapped approach in addition to the usual parametric estimation.

Additionally, the study does not limit itself to studying efficiency in a static context. The study contributes to the existing literature in terms of adding a dynamic framework to the study of cryptocurrency market efficiency. Finally, the study also considers the implications of the results for traders and other market participants.

[7] Except Sensoy (2019).

Research Objectives

Considering the propositions put forward in preceding sections and the gaps emerging from the literature reviewed, the objective of this study is to evaluate the weak form efficiency of the global cryptocurrency markets using static and dynamic frameworks.

Methodology

Model Specification

An evolutionary model technique is used in the study to investigate day-of-the-week effects. Using OLS as a starting point, this model may be described as:

$$r_t = \beta_1 + \sum_{i=2}^{n} \beta_i D_{it} + \varepsilon$$

Equation 1: Model 1

where, r_t represents the time returns (daily, weekly, or monthly) of the financial asset, D_{it} represents dummy variables of value 1 if the corresponding return for time t is the corresponding day (or week/month) and 0 otherwise. In this model, there is a dummy omitted for one day of the week or one month of the year. The term β_1 here captures the mean returns of the omitted day, with the other coefficients β_i capturing the mean excess daily returns for the rest of the days over the mean returns of the omitted day.

This model provides the best specification in the case where an *a priori* belief exists that one specific day of the week or month of the year may have a significantly different average return over others (Kumar & Dawar, 2017). Another model used by Borges (2009) estimated separate equations for each day of the week as given in Equation 2:

$$r_t = \alpha + \beta_i D_{it} + \varepsilon$$

Equation 2: Model 2

In model 2, the α captures the mean daily returns for other days, whereas β_i captures the excess returns of the specific day as compared to the remaining days. While the model does capture the effects of a particular day, as pointed out by Greene (2012), the use of a single independent variable where other variables exist may overstate the marginal impact of the said variable.

Given the shortcomings of the Model 2 specifications, where no such *a priori* expectations exist and to avoid the overstatement of any particular day, an alternate model specification is employed[8]:

$$r_t = \sum_{i=1}^{n} \beta_i D_{it} + \varepsilon$$

Equation 3: Model 3

The above specification considers a dummy for each unit of frequency in the time while also avoiding the dummy variable trap.

In the absence of the day-of-the-week effect, the mean daily returns of each day should not be significantly different from each other. Hence, using β_1 to β_7 to denote the mean daily returns of the seven days of the week, the null and the alternate hypothesis are framed as:

[8] See Kumar and Dawar (2017).

Hypothesis 1

H_{01}: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7$
H_{a1}: At least one β_i is different.

To test for the weekend effect, the hypothesis is framed as follows:

Hypothesis 2

H_{02}: $\beta_1 = 0$
H_{a2}: $\beta_1 \neq 0$

Estimation Procedures

Once the initial OLS model is fitted, a diagnostic analysis of residuals is done to evaluate the model fit. Here, as reported in the literature (Connolly, 1989, 1991), the characteristics of financial time series, such as non-normality, heteroskedasticity, autocorrelation, and non-constant variance of residuals are expected. As such, the ARCH test and Breusch–Godfrey serial correlation LM test are employed to check for homoskedasticity and autocorrelation in residuals, respectively, as done in contemporary financial literature (Parthasarathy, 2019; Ryaly et al., 2017). To correct for autocorrelation, if present, appropriate ARMA terms are added to the right side of the regression equation of Model 3. To handle non-normality, in addition to the parametric estimation, a non-parametric bootstrap approach (Borges, 2009; Khuntia & Pattanayak, 2017; Sullivan et al., 2001) is adopted with 1,000 replications for each regression output and then reapplied using the standard errors and confidence intervals from the resulting distribution from the bootstrapped estimation. Likewise, an ARCH family model is selected from the glossary of ARCH to account for heteroskedasticity (Bollerslev, 2008). For the selection of the appropriate ARCH family model, the Hannan and Quinn information criterion is employed (Hannan & Quinn, 1979).

As claimed in the literature reviewed, there may be time-varying efficiency in the crypto market, which could be efficient or inefficient for different periods. In addition to the aforementioned static estimation process, a dynamic framework that incorporates rolling window regressions on the results of the ARCH family estimations is used to evaluate the same. In each scenario, a window length of 1,000 days and a step size of 100 observations are used. This will allow the inquiry to determine whether the calendar effects found are only the result of sample selection, i.e., whether the day-of-the-week effects found are consistent throughout the study or not.

Data

To study efficiency in the global cryptocurrency market, first, a representative set of cryptocurrencies needs to be selected. As of December 2021, Coinmarketcap.com, considered to be the most referenced cryptocurrency price tracking website in the world,[9] reports about 8,554[10] cryptocurrencies in trade, with an average of three cryptocurrencies being added daily. These cryptocurrencies differ from each other in terms of factors such as their mineability, underlying technology, and use, among several others. The study of such a large number of cryptocurrencies would be a time-intensive and data-computationally challenging effort. A sample set of

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[9] https://coinmarketcap.com/about/ Accessed on December 15, 2021, at 5:30 PM.
[10] Accessed on December 27, 2021, at 3:17 AM.

cryptocurrencies having a vast and diverse representation of the global cryptocurrency market would, therefore, be better suited for the study. The study employs market capitalization,[11] defined as the circulating supply, which is the number of coins of a cryptocurrency that are freely circulating in the market and public hands, as the criterion used for the selection of this representative sample since it is common and applicable to all cryptocurrencies in the market.

There are two reasons for the choice of market capitalization as a selection criterion. First, market capitalization is an indicator of the size of a particular cryptocurrency's market, which is understood as a proxy for its acceptability and traceability. Second, market capitalization allows objective ranking of cryptocurrencies having different attributes on an everyday basis. The selected sample is shown in Table 1.

While there are over 8,500 cryptocurrencies, this sample of these top 25 cryptocurrencies accounts for 90% of the total market capitalization of the global cryptocurrency market. Therefore, this selected sample provides a

Table 1. ***Top 25 Cryptocurrencies in the Global Cryptocurrency Market***

Cryptocurrency	Symbol	Launch	Data Availability from	Market Capitalization ($)
Bitcoin	BTC	Jan-09	28-04-2013	915,736,776,207
Ethereum	ETH	Jul-15	07-08-2015	459,313,078,215
Binance Coin	BNB	Jul-17	25-07-2017	88,359,367,807
Tether	USDT	Oct-14	06-03-2015	76,421,446,531
Solana	SOL	Mar-20	10-04-2020	51,382,423,080
Cardano	ADA	Sep-17	01-10-2017	42,157,420,756
USD Coin	USDC	Sep-18	08-10-2018	41,722,201,252
Ripple	XRP	Jun-12	04-08-2013	38,067,205,512
Polkadot	DOT	May-20	20-08-2020	25,891,058,197
Dogecoin	DOGE	Dec-13	15-12-2013	23,995,866,558
Avalanche	AVAX	May-18	22-09-2020	22,236,760,412
Terra	LUNA	Apr-19	26-07-2019	22,072,825,314
Shiba Inu	SHIB	Aug-20	30-01-2021	18,635,766,094
Polygon	MATIC	Oct-17	28-04-2019	14,122,530,108
Binance USD	BUSD	Sep-19	20-09-2019	13,808,592,297
Crypto.com Coin	CRO	Nov-18	14-12-2018	13,730,722,020
Wrapped Bitcoin	WBTC	Jan-19	30-01-2019	12,529,011,521
Litecoin	LTC	Oct-11	28-04-2013	10,443,106,220
Uniswap	UNI	Nov-18	17-09-2020	9,425,862,588
Dai	DAI	Dec-17	22-11-2019	9,115,559,623
Chainlink	LINK	Sep-17	20-09-2017	9,241,941,822
TerraUSD	UST	Sep-20	25-11-2020	8,952,438,875
Algorand	ALGO	Jun-19	21-06-2019	8,815,725,859
Bitcoin Cash	BCH	Jul-17	23-07-2017	8,266,027,826
Tron	TRX	Sep-17	13-09-2017	8,228,858,052

[11] Market Capitalization of a cryptocurrency = Current Market Price of a cryptocurrency × circulating supply.

comprehensive representation of the overall cryptocurrency market and also allows the study of efficiency in both comparatively larger and smaller cryptocurrencies. Additionally, the sample is a mix of both older and newer cryptocurrencies.

After the sample selection, daily data about the price of each cryptocurrency in the sample from the earliest date of availability is obtained from CoinMarketCap.com. A total (T) of 35,356 daily data points organized from Monday to Sunday and used to investigate the equality of mean returns of the days are obtained up to the research period of December 2021. Since the global crypto market is an online market open 24 hours a day, there are no true opening or closing prices for cryptocurrencies. For analysis, the study employs the methodology used by Coinmarketcap.com,[12] where the opening price is defined as the price based on the earliest data in the range of the Coordinated Universal Time or UTC and the closing price is defined as the price based on the latest data in the range of the Coordinated Universal Time or UTC. Additionally, data can be collected for all seven days of the week. The market price is acquired in US Dollars ($) in order to guarantee that the impact of exchange rate translation in cryptocurrencies is eliminated.

A significant consideration in studies of market efficiency of financial assets pertains to the choice of the price itself. Prices in the financial markets are volatile, with frequent changes within the trading hours. A framework consisting of Open (O), High (H), Low (L), and Close (C) is utilized to get around this. While the majority of the literature uses close prices to approximate the daily prices, other works make use of indexes like C/O, O/H, or H/L. In spite of these estimates, it is asserted that:

- The close price is a single data point that happens to be the price at the time of closing of the market.
- Indices such as H/L or O/C are price relatives and not approximations.

As such, a closer approximation to daily price can be made by constructing a price composite. p_t^* computed as the simple average of the OHLC as:

$$p_{it}^* = \frac{(Open + High + Low + Close)}{4}$$

Equation 4: Price Composite

On computing the daily price composite, the daily return is then computed in Equation 5:

$$r_{it} = \ln \frac{p_{it}^*}{p_{it-1}^*}$$

Equation 5: Computation of daily logarithmic-return

where, r_{it} is the natural log return of the i^{th} cryptocurrency and p_{it}^* is the price composite for the corresponding date t.

Analysis and Results

Before formal testing, it would be helpful to explore the descriptive statistics of cryptocurrency returns, as shown in Table 2. Most cryptocurrencies (68%) in the sample have a positive mean daily return. The skewness and kurtosis of most of the cryptocurrencies deviate from the theoretical normal distribution parameters of 0 and 3, respectively, indicating non-normality of data with leptokurtic tails, which is confirmed through the Jarque–Bera normality test.

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[12] *Ibid.*

Table 2. ***Descriptive Statistics***

Particulars	Count	Mean	Max.	Min.	St. Dev.	Skewness	Kurtosis
BTC	3,157	0.19%	24.70%	–22.38%	0.03	–0.35	6.78
ETH	2,326	0.31%	32.92%	–88.36%	0.05	–2.56	49.52
BNB	1,608	0.53%	52.35%	–36.53%	0.06	1.44	16.38
USDT	2,480	0.00%	3.83%	–3.83%	0.00	–0.14	22.71
SOL	618	0.85%	26.63%	–27.53%	0.06	0.17	1.44
ADA	1,540	0.26%	65.96%	–23.35%	0.05	2.01	20.11
USDC	1,168	0.00%	29.11%	–24.93%	0.01	4.87	504.04
XRP	3,059	0.16%	71.65%	–39.83%	0.06	1.88	20.89
DOT	486	0.45%	28.01%	–23.80%	0.05	0.20	3.29
DOGE	2,926	0.20%	104.71%	–54.68%	0.07	4.23	60.43
AVAX	453	0.63%	37.70%	–31.96%	0.07	0.45	4.45
LUNA	877	0.43%	46.17%	–31.07%	0.06	0.73	7.44
SHIB	323	2.72%	179.18%	–48.01%	0.20	4.43	31.59
MATIC	966	0.64%	43.90%	–42.98%	0.07	0.44	8.24
BUSD	821	0.00%	2.74%	–2.54%	0.00	0.01	24.12
CRO	1,101	0.30%	62.38%	–23.44%	0.05	2.27	23.04
WBTC	1,054	0.25%	52.06%	–58.59%	0.04	–1.26	75.47
LTC	3,157	0.11%	58.97%	–35.89%	0.05	1.43	19.49
UNI	458	0.41%	85.13%	–22.03%	0.07	4.15	51.35
DAI	758	0.00%	50.86%	–39.31%	0.02	6.43	347.25
LINK	1,551	0.30%	33.14%	–29.46%	0.06	0.24	4.08
UST	389	0.00%	7.94%	–7.28%	0.01	1.01	97.29
ALGO	912	–0.09%	27.74%	–37.22%	0.05	–0.30	6.02
BCH	1,610	–0.01%	44.81%	–33.33%	0.06	0.90	10.76
TRX	1,558	0.24%	130.66%	–109.79%	0.08	2.30	84.11

The day-wise average returns and associated standard deviations are shown in Table 3. The percentage figures indicate the average daily returns for that specific day, while the bold digits show the average daily return's standard deviation.

Table 3. ***Day-Wise Average Returns and Standard Deviations of the Sample***

Particulars	Mon	Tue	Wed	Thu	Fri	Sat	Sun
BTC	0.39%	0.33%	0.13%	0.05%	0.01%	0.28%	0.08%
	0.03	**0.03**	**0.03**	**0.04**	**0.03**	**0.03**	**0.02**
ETH	0.24%	0.52%	0.50%	0.08%	0.35%	0.08%	0.40%
	0.05	**0.05**	**0.05**	**0.05**	**0.05**	**0.05**	**0.05**
BNB	0.45%	0.51%	0.35%	0.40%	0.54%	1.16%	0.27%
	0.06	**0.06**	**0.05**	**0.05**	**0.05**	**0.06**	**0.05**
USDT	–0.06%	0.01%	0.00%	0.00%	0.01%	0.04%	0.00%
	0.004	**0.003**	**0.004**	**0.004**	**0.004**	**0.004**	**0.004**

SOL	1.58%	0.39%	0.59%	0.91%	0.41%	1.13%	0.93%
	0.06	**0.06**	**0.06**	**0.06**	**0.07**	**0.06**	**0.06**
ADA	–0.02%	0.11%	0.13%	0.04%	–0.26%	1.37%	0.42%
	0.05	**0.07**	**0.05**	**0.06**	**0.05**	**0.05**	**0.05**
USDC	0.01%	0.19%	–0.17%	0.01%	0.01%	–0.04%	–0.01%
	0.003	**0.02**	**0.01**	**0.005**	**0.003**	**0.003**	**0.003**
XRP	0.07%	0.04%	0.12%	0.29%	0.26%	0.41%	–0.06%
	0.05	**0.06**	**0.05**	**0.06**	**0.06**	**0.05**	**0.05**
DOT	0.18%	0.11%	0.76%	1.14%	0.03%	0.96%	–0.05%
	0.05	**0.06**	**0.06**	**0.06**	**0.05**	**0.06**	**0.05**
DOGE	–0.25%	–0.05%	0.38%	0.55%	0.17%	0.48%	0.10%
	0.05	**0.07**	**0.06**	**0.09**	**0.07**	**0.06**	**0.05**
AVAX	0.14%	–0.11%	0.83%	0.88%	0.90%	1.76%	–0.01%
	0.06	**0.06**	**0.09**	**0.06**	**0.06**	**0.07**	**0.06**
LUNA	0.86%	0.80%	0.55%	0.28%	0.63%	–0.40%	0.35%
	0.06	**0.07**	**0.06**	**0.05**	**0.06**	**0.05**	**0.05**
SHIB	5.22%	0.40%	–0.36%	–0.02%	0.81%	5.37%	7.59%
	0.17	**0.14**	**0.15**	**0.10**	**0.16**	**0.28**	**0.29**
MATIC	0.52%	1.07%	0.91%	0.67%	0.23%	1.20%	–0.12%
	0.08	**0.09**	**0.07**	**0.06**	**0.06**	**0.05**	**0.05**
BUSD	–0.07%	0.01%	–0.01%	0.05%	–0.02%	–0.02%	0.06%
	0.003	**0.003**	**0.002**	**0.003**	**0.004**	**0.002**	**0.003**
CRO	0.09%	0.45%	0.57%	0.61%	0.75%	0.26%	–0.63%
	0.05	**0.07**	**0.06**	**0.05**	**0.06**	**0.04**	**0.04**
WBTC	0.20%	0.52%	0.42%	–0.06%	0.05%	0.61%	0.00%
	0.03	**0.04**	**0.06**	**0.06**	**0.03**	**0.02**	**0.02**
LTC	0.16%	0.13%	0.17%	–0.16%	–0.14%	0.44%	0.18%
	0.04	**0.05**	**0.05**	**0.05**	**0.05**	**0.05**	**0.05**
UNI	0.38%	–0.57%	0.02%	0.70%	1.17%	0.74%	0.41%
	0.06	**0.06**	**0.06**	**0.05**	**0.12**	**0.06**	**0.05**
DAI	0.02%	0.50%	–0.41%	–0.03%	0.05%	–0.07%	–0.05%
	0.02	**0.05**	**0.04**	**0.01**	**0.01**	**0.004**	**0.004**
LINK	–0.06%	0.24%	0.42%	0.33%	–0.09%	1.09%	0.18%
	0.05	**0.06**	**0.06**	**0.06**	**0.06**	**0.06**	**0.05**
UST	0.03%	–0.05%	–0.17%	0.04%	0.15%	0.02%	–0.02%
	0.003	**0.005**	**0.01**	**0.004**	**0.011**	**0.002**	**0.004**
ALGO	–0.45%	–0.94%	–0.22%	0.32%	0.35%	0.67%	–0.36%
	0.05	**0.05**	**0.05**	**0.06**	**0.06**	**0.05**	**0.04**
BCH	–0.22%	–0.19%	0.10%	–0.51%	–0.36%	0.97%	0.17%
	0.05	**0.06**	**0.06**	**0.06**	**0.07**	**0.05**	**0.04**
TRX	0.12%	0.23%	0.14%	0.48%	–0.44%	1.39%	–0.28%
	0.05	**0.09**	**0.01**	**0.07**	**0.06**	**0.1**	**0.07**

Looking at Table 3, two things become clear:

- While there is considerable variation in the day-wise average returns between cryptocurrencies, there seems to be a general pattern where the average return on Saturday is higher than the average returns of the rest of the days, and the average return on Friday is lower than the average returns of the rest of the days.
- The standard deviation of average return across all days in the week seems to be constant.

Table 4 provides a descriptive summary of the day-wise average returns, highlighting the higher price ranges on Monday, Saturday, and Sunday in comparison to the other four days.

A market-cap weighted index denoted by I is constructed using the sample cryptocurrencies as $I_i = w_i p_i$, where the individual weight of cryptocurrency (w_i) is given as $marketcap_i / \Sigma Total\ Marketcap$. The day-wise average returns of this index are presented in Figure 1. As can be observed, Saturday's average return on the index is significantly larger than the average return on other days. In the same vein, Monday and Sunday appear to have slightly greater average returns than the other days. Tuesday and Friday have relatively lower average returns as well. Significant fluctuations and outliers in the boxplots represent every day of the week.

The descriptive statistics provide a basis for further inferential analysis to confirm whether the observed differences in the average returns on different days of the week are actually calendar day-of-week anomalies or are merely due to chance or sample and data selection.

Before estimating the coefficients of Model 3, stationarity using the ADF test is checked, and returns of every individual cryptocurrency and the constructed index are found to be stationary at the level of intercept and trend.

Table 4. *Range in the Day-Wise Cryptocurrency Returns*

	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Max.	5.22%	1.07%	0.91%	1.14%	1.17%	5.37%	7.59%
Min.	–0.45%	–0.94%	–0.41%	–0.51%	–0.44%	–0.40%	–0.63%
Range	5.67%	2.01%	1.32%	1.65%	1.61%	5.77%	8.23%

Figure 1. *Barplot and Boxplot of Day-Wise Average Returns of the Index*

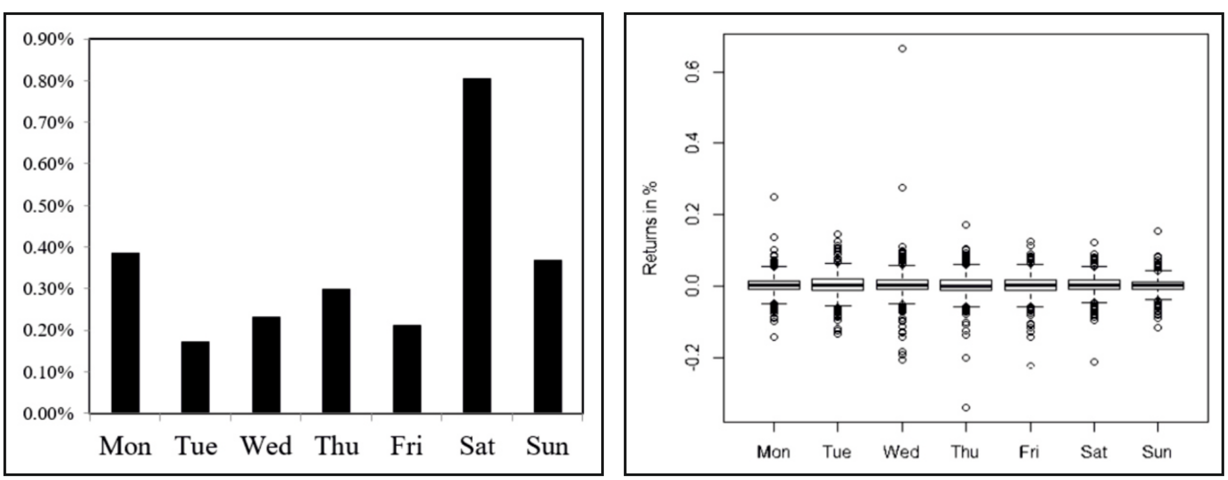

Table 5. *Results of OLS Regression*

Symbol	Beta							BGA		ALM	
	Mon	Tue	Wed	Thur	Fri	Sat	Sun	Obs. *F*	*P*-Val.	Obs. *F*	*P*-Val.
BTC	**0.004***	**0.003***	0.001	0.001	0.000	0.003	0.001	450.3	0	448.3	0
ETH	0.004	0.002	0.005	0.005	0.001	0.004	0.001	404.7	0	265.5	0
BNB	0.005	0.005	0.004	0.004	0.005	0.012	0.003	316.5	0	443.5	0
USDT	**–0.001***	0.000	0.000	0.000	0.000	0.000	0.000	9.3	0	487.2	0
SOL	**0.016***	0.004	0.006	0.009	0.004	0.011	0.009	72.3	0	48.6	0
ADA	0.000	0.001	0.001	0.000	–0.003	**0.014***	0.004	238.4	0	175.5	0
USDC	0.000	**0.002***	–0.002	0.000	0.000	0.000	0.000	179	0	359.2	0
XRP	0.001	0.000	0.001	0.003	0.003	0.004	–0.001	436.6	0	235.7	0
DOT	0.002	0.001	0.008	0.011	0.000	0.010	–0.001	65.6	0	34.1	0
DOGE	–0.002	–0.001	0.004	0.005	0.002	0.005	0.001	468.7	0	381.4	0
AVAX	0.001	–0.001	0.008	0.009	0.009	**0.018***	0.000	60.5	0	24.5	0
LUNA	0.009	0.008	0.005	0.003	0.006	–0.004	0.003	98.5	0	101.8	0
SHIB	0.052	0.004	–0.004	0.000	0.008	0.054	**0.076***	13.6	0	9.4	0
MATIC	0.005	0.011	0.009	0.007	0.002	**0.012***	–0.001	154.8	0	246.9	0
BUSD	**–0.001***	0.000	0.000	0.000	0.000	0.000	**0.001***	79.4	0	129.9	0
CRO	0.001	0.004	0.006	0.006	0.007	0.003	–0.006	101	0	108.1	0
WBTC	0.002	0.005	0.004	–0.001	0.000	0.006	0.000	11.1	0	308.2	0
LTC	0.002	0.001	0.002	–0.002	–0.001	**0.004***	0.002	487.3	0	792.9	0
UNI	0.004	–0.006	0.000	0.007	0.012	0.007	0.004	35.7	0	14.5	0
DAI	0.000	**0.005***	–0.004	0.000	0.000	–0.001	–0.001	95.3	0	203.5	0
LINK	–0.001	0.002	0.004	0.003	–0.001	**0.011***	0.002	174.2	0	120.1	0
UST	0.000	–0.001	–0.002	0.000	0.001	0.000	0.000	35.3	0	1	0
ALGO	–0.005	**–0.009***	–0.002	0.003	0.003	0.007	–0.004	106.9	0	162	0
BCH	–0.002	–0.002	0.001	–0.005	–0.004	**0.010***	0.002	260.9	0	413.6	0
TRX	0.001	0.002	0.001	0.005	–0.004	0.014	–0.003	0.3	0	250.9	0
I	0.003	0.004	0.003	–0.001	–0.001	0.003	0.001	450	0	440.3	0

Note. (* significant at 5% level of significance).

After that, our Model 3 is subjected to OLS regression, the findings of which are displayed in Table 5. OLS regression results indicate that for 12 cryptocurrencies, some days are noteworthy, although this could be the product of random fluctuations rather than any underlying cause. Also, the conditions of OLS are violated in the presence of autocorrelation and the ARCH effect, substantiated by the Breusch–Godfrey autocorrelation (BGA) LM test and the ARCH LM (ALM) test.

The presence of time-conditional heteroskedasticity necessitates the employment of ARCH family models. The choice of an appropriate ARCH model is done through HQIC. To control for autocorrelation, an autoregressive AR (1) term is included. Given the non-normality of data, the bootstrapping approach is applied to the ARCH family regressions with 1,000 replications. In this approach, regressions are executed 1,000 times, bootstrapping the β coefficient by resampling observations from the data with replacement. Since this is a non-parametric approach, the non-normality of the data is accounted for. A total of 182 (26×7) regressions are run.

Table 6. ***Results of the ARCH Family Regression***

Symbol	Higher Excess Returns than Other Weekdays				Lower Returns than Other Weekdays			
	OLS	Bootstrapped OLS	ARCH Family Model	Bootstrapped ARCH Family Regression	OLS	Bootstrapped OLS	ARCH Family Model	Bootstrapped ARCH Family Regression
BTC	Mon, Tue	Mon, Tue	Mon, Tue, Sat	Mon, Tue, Sat	–	–	–	–
ETH	–	–	Sat	Sat	–	–	–	–
BNB	–	–	–	Sat	–	–	–	–
USDT	–	Tue	Tue	Tue	Mon	Mon	Mon, Thu, Sun	Mon, Thu, Sun
SOL	Mon	–	Sat	Sat	–	–	–	–
ADA	Sat	Sat	Sat	Sat	–	–	–	–
USDC	Tue	Tue	–	–	–	–	Sat	Sat
XRP	–	–	–	–	–	Wed	Wed	Wed
DOT	–	–	–	–	–	–	–	–
DOGE	–	–	–	–	–	–	Mon, Tue, Sun	Mon, Tue, Sun
AVAX	Sat	Sat	Sat	Sat	–	–	–	–
LUNA	–	–	Sat	Sat	–	–	–	–
SHIB	Sun	–	Mon, Sun	Mon, Sun	–	–	–	–
MATIC	–	Sat	Sat	Sat	–	–	–	–
BUSD	Sun	–	Mon, Wed	Mon, Wed	Mon	–	Tue, Thu, Fri, Sun	Tue, Thu, Fri, Sun
CRO	–	–	Thu, Fri, Sat	Thu, Fri, Sat	–	–	–	–
WBTC	–	–	Mon, Tue, Wed	Mon, Tue, Wed	–	–	–	–
LTC	Sat	Sat	Sat	Sat	–	–	–	–
UNI	–	–	–	–	–	–	–	–
DAI	Tue	–	Tue, Fri	Tue, Fri	Tue	–	Mon, Sun	Mon, Sun
LINK	Sat	Sat	Sat	Sat	–	–	–	–
UST	–	–	–	–	–	–	Mon, Fri	Mon, Fri
ALGO	Tue	–	–	–	–	–	–	–
BCH	Sat	Sat	Sat	Sat	–	–	–	–
TRX	–	Sat	Sat	Sat	–	–	–	–
I	–	Mon, Tue, Sat	Mon, Tue, Wed	Mon, Tue, Wed	–	–	–	–

Note. (* significant at the 5% level of significance).

Avoiding cumbersome tabular representation of results, only days-of-the-week significant at a 5% level for different estimation procedures are shown in Table 6.

The results show that there exist day-of-the-week effects in all cryptocurrencies except for Uniswap and Algorand and the market index, allowing the rejection of the null hypothesis 1 (H01) in these cases; 13 out of 25 cryptocurrencies (52%) exhibit a positive Saturday Effect, followed by a positive Monday and Tuesday Effect. Except for Dai, TerraUSD, Dogecoin, and Tether, the remaining cryptocurrencies and the market index do not exhibit a traditional weekend effect in terms of lower Monday returns, leading to a rejection of the null hypothesis 2 (H02) for these cryptocurrencies and market index.

These results confirm that calendar anomalies exist in most of the cryptocurrencies, thereby challenging the notion of efficiency in global crypto markets. The existence of such day effects provides a basis for trading strategies, with some days providing higher or lower-than-average returns. Furthermore, it also highlights behavioral and informational gaps/lags in the market participants.

In a static situation, the findings above are usually accurate. A rolling regression is used on the returns of the constructed index with a window length of 1,000 days and a step size of 100 observations in each case. This means that the first regression uses observations from 1 to 1,000, the second regression uses observations from 101 to 1,100, and so on, to support the time stability of the coefficients and assess the efficiency in a dynamic context. Figure 2 shows the results of rolling-window regression. It can be seen that the coefficients for days fluctuate significantly. The significant days for the index, i.e., Monday, Tuesday, and Wednesday, follow a slightly different path as compared to other days. For Mondays, the coefficients have been positive before a significant drop in 2019, following which they became positive again. Similarly, for Tuesday and Wednesday, the coefficients are majorly positive, except for a window between 2018 and 2019. This shows that there is comparable stability in the day-of-the-week effects throughout the study period, implying that the market commenced and continues to be inefficient, which contradicts the idea posited by previous studies of market efficiency evolving.

Figure 2. ***Coefficient Graph in Rolling-Window Regressions***

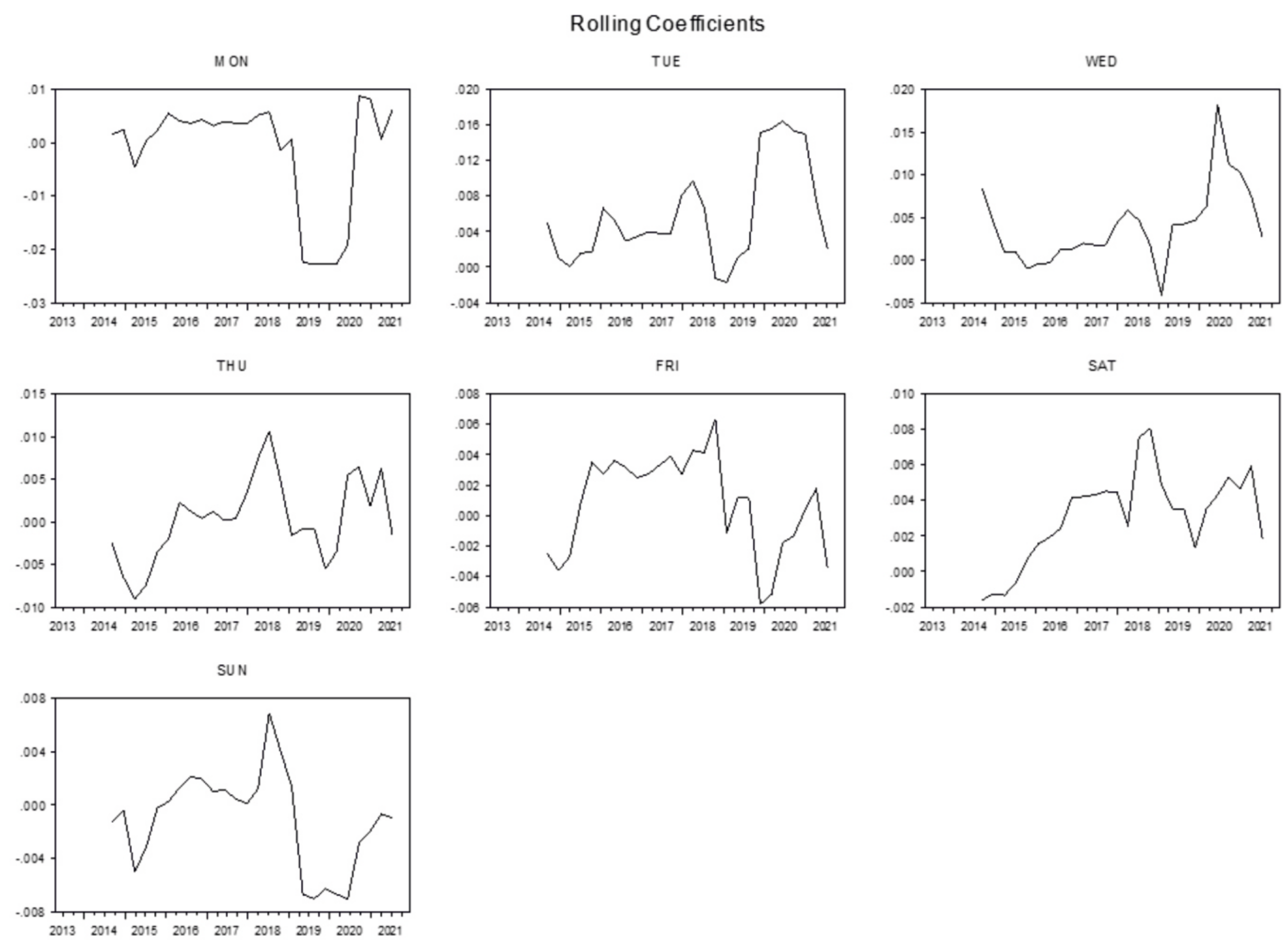

Table 7. *A Comparison of Annualized Returns Generated by Different Trading Strategies*

Strategy	Annualized Returns Generated
Buy Monday-Sell Tuesday	118.8%
Buy Tuesday-Sell Wednesday	117.3%
Buy Wednesday-Sell Thursday	99.5%
Buy Monday-Hold Tuesday-Sell Wednesday	60%
Buy-Hold	27%

Discussion and Implications

The findings of this study show the presence of calendar effects in terms of higher returns for certain days over others. The implication is that cryptocurrency markets are not even efficient in the weak form, highlighting their informational inefficiencies. Generally, an absence of weak form efficiency facilitates technical analysis-based trade strategies where past information about prices and events is relevant. To compare the profits from passive buy-and-hold cryptocurrency investing with active methods like buying on Sunday and selling on Monday or buying on Monday and selling on Tuesday, a trading strategy modeled after Sarma's (2004) approach is created. Table 7 shows the returns generated by these strategies and shows that active strategies would have earned a rate of return over the passive buy and hold. Even taking into account the trading costs (often nominal), these strategies would still have outperformed the markets during the period of study. While these results have emerged due to simplifications of actual trading with the benefit of hindsight, the abnormal returns over the buy-and-hold strategy warrant the attention of active investors.

Conclusion

The literature on the efficiency of crypto markets, often limited in its reasoning, methodology, and data, is inconclusive as to whether these markets are efficient in the context of EMH. The present study explores the efficiency of the global cryptocurrency markets by examining the existence of day-of-the-week effects on the returns of the top 25 cryptocurrencies. Starting with building arguments on why cryptocurrencies would be efficient, the study employs statistically robust methodologies, both parametric and bootstrapped, on multi-year daily returns data of both individual currencies and a composite market index to evaluate the conceptual framework. Accounting for financial time-series characteristics such as serial correlation and heteroskedasticity, significant day-of-the-week effects in both individual currencies and market index are found in both a static and dynamic context, leading to the conclusion that the global cryptocurrency market is not efficient, and it does not seem to evolve in terms of efficiency as is claimed in earlier literature.

Limitations of the Study and Scope for Future Research

While a simple inferential approach is adopted for the conceptual framework and methodology, advanced estimation procedures necessitating intensive data mining are employed in this study, which may often lead to all kinds of results (Sullivan et al., 2001). The study also limits itself to only the day-of-the-week and the weekend effect. Other calendar effects, such as the month-of-the-year effects and specific month effects, such as January effects, are not examined, presenting scope for future examination. The study also does not seek to explain these anomalies, limiting to what-is rather than why-it-is. Despite these considerations, the findings of the present study are of practical significance to investors, whose active search and trading strategies seem justified in the light of market anomalies, and other market participants, such as regulators seeking to understand the crypto market structure from an efficiency perspective and researchers seeking to explore the behavior and psychology of crypto markets in terms of efficiency.

Authors' Contribution

Prof. Kawal Gill conceived the idea and developed the research methodology to undertake the empirical study. Mr. Harish Kumar and Prof. Amit Kumar Singh did the literature review. Mr. Harish Kumar analyzed the data in EViews 11. Prof. Amit Kumar Singh verified the analytical methods and interpreted the results. Mr. Harish Kumar wrote the manuscript in consultation with the co-authors.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

Funding Acknowledgment

The authors received no financial support for the research, authorship, and/or for the publication of this article.

References

Al-Yahyaee, K. H., Mensi, W., & Yoon, S.-M. (2018). Efficiency, multifractality, and the long-memory property of the Bitcoin market: A comparative analysis with stock, currency, and gold markets. *Finance Research Letters*, *27*, 228–234. https://doi.org/10.1016/j.frl.2018.03.017

Apopo, N., & Phiri, A. (2021). On the (in)efficiency of cryptocurrencies: Have they taken daily or weekly random walks? *Heliyon*, *7*(4), E06685. https://doi.org/10.1016/j.heliyon.2021.e06685

Bartos, J. (2015). Does the Bitcoin follow the hypothesis of efficient market? *International Journal of Economic Sciences*, *IV*(2), 10–23. https://doi.org/10.20472/ES.2015.4.2.002

Bollerslev, T. (2008). Glossary to ARCH (GARCH). *SSRN Electronic Journal*. http://dx.doi.org/10.2139/ssrn.1263250

Borges, M. R. (2009). *Calendar effects in stock markets: Critique of previous methodologies and recent evidence in European Countries* (Working Paper WP 37/2009/DE/UECE). ISEG School of Economics and Management, Technical University of Lisbon, Department of Economics, Lisbon. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.469.2309&rep=rep1&type=pdf

Bundi, N., & Wildi, M. (2019). Bitcoin and market-(in)efficiency: A systematic time series approach. *Digital Finance, 1*(1), 47–65. https://doi.org/10.1007/s42521-019-00004-z

Caporale, G. M., & Plastun, A. (2019). Price overreactions in the cryptocurrency market. *Journal of Economic Studies*, *46*(5), 1137–1155. https://doi.org/10.1108/jes-09-2018-0310

Connolly, R. A. (1989). An examination of the robustness of the weekend effect. *The Journal of Financial and Quantitative Analysis*, *24*(2), 133–169. https://doi.org/10.2307/2330769

Connolly, R. A. (1991). A posterior odds analysis of the weekend effect. *Journal of Econometrics*, *49*(1–2), 51–104. https://doi.org/10.1016/0304-4076(91)90010-B

Cross, F. (1973). The behavior of stock prices on Fridays and Mondays. *Financial Analysts Journal*, *29*(6), 67–69. https://doi.org/10.2469/faj.v29.n6.67

Fama, E. F. (1965). The behavior of stock-market prices. *The Journal of Business*, *38*(1), 34–105. https://doi.org/10.1086/294743

Greene, W. H. (2012). *Econometric analysis.* Pearson.

Hannan, E. J., & Quinn, B. G. (1979). The determination of the order of an autoregression. *Journal of the Royal Statistical Society: Series B (Methodological)*, *41*(2), 190–195. https://doi.org/10.1111/j.2517-6161.1979.tb01072.x

Khuntia, S., & Pattanayak, J. K. (2017). Dynamics of Indian foreign exchange market efficiency: An adaptive market hypothesis approach. *Indian Journal of Finance*, *11*(9), 39–52. https://doi.org/10.17010/ijf/2017/v11i9/118088

Kumar, H., & Dawar, M. (2017). Seasonality in the Indian stock markets: A study of calendar effects. *MUDRA: Journal of Finance and Accounting*, *4*(1), 1–19. https://doi.org/10.17492/mudra.v4i01.9780

Kurihara, Y., & Fukushima, A. (2017). The market efficiency of Bitcoin: A weekly anomaly perspective. *Journal of Applied Finance & Banking*, *7*(3), 57–64. http://www.scienpress.com/Upload/JAFB%2fVol%207_3_4.pdf

López-Martín, C., Muela, S. B., & Arguedas, R. (2021). Efficiency in cryptocurrency markets: New evidence. *Eurasian Economic Review*, *11*(3), 403–431. https://doi.org/10.1007/s40822-021-00182-5

Malkiel, B. G., & Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, *25*(2), 383–417. https://doi.org/10.1111/j.1540-6261.1970.tb00518.x

Nadarajah, S., & Chu, J. (2017). On the inefficiency of Bitcoin. *Economic Letters*, *150*, 6–9. https://doi.org/10.1016/j.econlet.2016.10.033

Parthasarathy, S. (2019). Revisiting the weak form efficiency with structural breaks: Evidence from the Indian stock market. *Indian Journal of Finance*, *13*(10), 7–21. https://doi.org/10.17010/ijf/2019/v13i10/147744

Quiggin, J. (2013, April 16). The Bitcoin bubble and a bad hypothesis. *The National Interest*. https://nationalinterest.org/commentary/the-bitcoin-bubble-bad-hypothesis-8353

Ryaly, V. R., Subba Raju, G. V., & Urlankula, B. (2017). Testing the weak-form market efficiency in the Indian stock market: Evidence from the Bombay Stock Exchange Index (BSE) Sensex. *Indian Journal of Finance*, *11*(3), 26–40. https://doi.org/10.17010/ijf/2017/v11i3/111647

Sarma, S. N. (2004). Stock market seasonality in an emerging market. *Vikalpa: The Journal for Decision Makers*, *29*(3), 35–42. https://doi.org/10.1177/0256090920040303

Sensoy, A. (2019). The inefficiency of Bitcoin revisited: A high-frequency analysis with alternative currencies. *Finance Research Letters*, *28*, 68–73. https://doi.org/10.1016/j.frl.2018.04.002

Sullivan, R., Timmermann, A., & White, H. (2001). Dangers of data mining: The case of calendar effects in stock returns. *Journal of Econometrics*, *105*(1), 249–286. https://doi.org/10.1016/S0304-4076(01)00077-X

Tran, V. L., & Leirvik, T. (2019). A simple but powerful measure of market efficiency. *Finance Research Letters, 29*, 141–151. https://doi.org/10.1016/j.frl.2019.03.004

Tran, V. L., & Leirvik, T. (2020). Efficiency in the markets of crypto-currencies. *Finance Research Letters*, *35*, 101382. https://doi.org/10.1016/j.frl.2019.101382

Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters*, *148*, 80–82. https://doi.org/10.1016/j.econlet.2016.09.019

Vidal-Tomás, D., & Ibañez, A. (2018). Semi-strong efficiency of Bitcoin. *Finance Research Letters*, *27*, 259–265. https://doi.org/10.1016/j.frl.2018.03.013

Wei, W. C. (2018). Liquidity and market efficiency in cryptocurrencies. *Economic Letters*, *168*, 21–24. https://doi.org/10.1016/j.econlet.2018.04.003

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