Market Efficiency and Calendar Anomalies Post-COVID: Insights from Bitcoin and Ethereum

Eficiencia del mercado y anomalías de calendario pos-COVID: perspectivas de bitcoin y ethereum

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Abstract

This study investigates day-of-the-week effects in the digital market, with a focus on Bitcoin and Ethereum, spanning from July 1st, 2020, to December 31st, 2023, in the post-COVID-19 period. Employing parametric and non-parametric tests alongside the GARCH (1,1) model, market dynamics was analized. The findings indicate the presence of a day-of-the-week effect in Ethereum, characterized by notable return variations across different days, while Bitcoin exhibits no discernible calendar anomalies, suggesting enhanced market efficiency. Ethereum's susceptibility to these effects underscores ongoing market complexities. Disparities in calendar anomalies stem from evolving market dynamics, methodological differences, and the speculative nature of cryptocurrency trading. Furthermore, the decentralized and global market complicates the accurate identification of market-wide effects. This study provides experimental findings on day-of-the-week effects in the digital market, facilitating investors in refining trading strategies and risk management. Further research is warranted to explore underlying mechanisms and monitor regulatory and technological developments for investor insights.

Keywords: *Cryptocurrencies, calendar anomalies, GARCH model, trading strategy, ANOVA.*
JEL Classification: *G14, G10, G41.*

Resumen

Este estudio investiga los efectos del día de la semana en el mercado digital, con un enfoque en bitcoin y ethereum, abarcando desde el 1º de julio de 2020 hasta el 31 de diciembre de 2023, en el período posterior al COVID-19. Empleando pruebas paramétricas y no paramétricas junto con el modelo GARCH (1,1), se analizó la dinámica del mercado. Los hallazgos indican un efecto significativo del día de la semana en ethereum, caracterizado por notables variaciones de rendimiento entre diferentes días, mientras que bitcoin no muestra anomalías de calendario discernibles, lo que sugiere una mayor eficiencia del mercado. La susceptibilidad de ethereum a estos efectos subraya las complejidades actuales del mercado. Las disparidades en las anomalías del calendario surgen de la evolución de la dinámica del mercado, las diferencias metodológicas y la naturaleza especulativa del comercio de criptomonedas. Además, el mercado descentralizado y global complica la identificación precisa de los efectos en todo el mercado. Este estudio proporciona evidencia empírica sobre los efectos del día de la semana en el mercado de criptomonedas, lo que facilita a los inversionistas refinar las estrategias comerciales y la gestión de riesgos. Se justifica realizar más investigaciones para explorar los mecanismos subyacentes y monitorear los desarrollos regulatorios y tecnológicos para obtener información de los inversionistas.

Palabras clave: *criptomonedas, anomalías de calendario, modelo GARCH, estrategia de trading, ANOVA.*
Clasificación JEL: *G14, G10, G41.*

1. Introduction

The cryptocurrency market has witnessed remarkable growth, establishing itself as a significant player within the financial landscape. This growth is evident through the soaring market capitalization of cryptocurrencies such as Bitcoin, Ethereum, and Dogecoin, which have surged to unprecedented levels (Stavrova, 2021). Key factors contributing to this surge include the decentralized nature of cryptocurrencies and the innovative blockchain technology underpinning them (Chen et al., 2019). Moreover, the integration of cryptocurrencies with traditional finance has sparked increased interest among investors (Volosovych et al., 2023).

The distinct decentralized structure of the cryptocurrency market, facilitated by blockchain technology, sets it apart from traditional financial markets. This structure enables peer-to-peer transactions without the need for intermediaries like banks (Andolfatto & Martin, 2022). Additionally, rapid technological innovation within the cryptocurrency sphere attracts diverse participants, consequently expanding the market infrastructure (Volosovych et al., 2023).

The regulatory landscape surrounding cryptocurrencies continues to evolve, adding layers of complexity to the market. Governments and regulatory bodies worldwide are increasingly focused on regulating cryptocurrencies to safeguard investor interests and ensure financial stability (Singh, 2021). As Pantielieieva et al. (2021) argue, regulatory scrutiny actively shapes the future adoption of virtual currencies.

Furthermore, various factors influence price movements, volatility, and investor sentiment within the cryptocurrency market. Heightened investor interest has led to increased market activity and trading volumes, with studies emphasizing the significance of comprehending price deviations and capital controls for exploiting arbitrage opportunities (Makarov & Schoar, 2020).

Volatility remains as a defining characteristic of the cryptocurrency market, with studies scrutinizing volatility co-movements among major cryptocurrencies such as Bitcoin and Ether (Katsiampa, 2019). External factors like the COVID-19 pandemic contribute to fluctuations in prices and market sentiment (Washington et al., 2023). Additionally, researchers have explored the influence of news media on virtual currency prices, analyzing the impact of news discourses on market dynamics (Coulter, 2022).

Given the inherent volatility in the cryptocurrency market, understanding and managing associated risks are imperative for investors. While offering the potential for substantial gains, the market also poses risks of significant losses (Zhao & Zhang, 2021). Challenges in forecasting cryptocurrency volatility persist due to market uniqueness and external factors such as the COVID-19 pandemic (Ftiti et al., 2021). Therefore, understanding and modelling cryptocurrency volatility are crucial for informed decision-making, with advanced techniques such as machine learning and GARCH models aiding in forecasting (Joshi & Sharma, 2022).

In traditional financial markets, investors note the day-of-the-week impact, which refers to discernible patterns in stock returns corresponding to specific days of the week, influencing their trading strategies and risk management (Tran, 2023). These patterns, influenced by psychological factors, underscore the intricacies of financial markets, necessitating investors to consider both fundamental and technical analysis (Țilică, 2021).

Investigating the day-of-the-week effect in the digital currency market holds significance amidst increasing investor interest. Recognizing these patterns can empower investors to tailor trading strategies and develop advanced algorithms and risk management strategies (Caporale & Plastun, 2019).

The present study aims to explore the implications of identified day-of-the-week effects for cryptocurrency investors. By understanding how returns and volatility vary across different days, investors can potentially capitalize on favorable market conditions and mitigate risks. Additionally, the study seeks to provide empirical evidence of the day-of-the-week pattern in the cryptocurrency market post-COVID-19, shedding light on evolving market dynamics. Focusing on Bitcoin and Ethereum from July 2020 to December 2023, this paper aims to investigate the day-of-the-week effect in these prominent cryptocurrencies, considering their significance in the market and the period post-COVID-19.

The subsequent sections of this paper are structured as follows: Section 2 reviews the theoretical framework; Section 3 presents the data and methodology; Section 4 analyzes empirical data and discusses findings; and Section 5 provides conclusions.

2. Theoretical Framework

Olivares-Sánchez et al. (2022) assert that market efficiency, a fundamental concept in finance, determines the extent to which asset prices reflect available information. The Efficient Market Hypothesis (EMH) states that asset prices fully integrate available information, rendering consistent outperformance of the market by investors impossible (Harabida et al., 2023). This theory describes three forms of market efficiency: weak efficiency, semi-strong efficiency, and strong efficiency, each defining the extent to which information is incorporated into asset prices (Souza & De França Carvalho, 2023).

Weak efficiency implies that all historical trading information is already incorporated into current equity prices, making achieving excess returns through historical data analysis challenging (Rossi & Gunardi 2018). In semi-strong efficiency, this idea extends to cover all information accessible to the public, suggesting that neither fundamental nor technical analysis can reliably produce outperformance (Liu et al., 2022). In the most stringent form, strong efficiency indicates that all information, regardless of its public or private nature, already factors into asset prices, making it impossible to gain an advantage even with insider information (Apergis, 2022).

Various empirical studies have evaluated the efficiency of traditional financial markets. However, the debate on market efficiency in cryptocurrency markets remains ongoing. Some studies support the weak-form efficiency of cryptocurrency markets, while others emphasize the impact of external factors, such as the pandemic COVID-19, on cryptocurrency market efficiency (Scherf et al., 2022). This ongoing discussion reflects the dynamic nature of cryptocurrency markets, with studies exploring factors like market liquidity, volatility, and the impact of geopolitical events on market efficiency (Fama, 1997).

To address these complexities, the adaptive market hypothesis (AMH) was proposed, which extends beyond the EMH by recognizing the limitations of the assumption of market efficiency and incorporating the role of behavioral biases and bounded rationality in market participants (Rehan & Gül, 2023). The AMH acknowledges that markets can be inefficient at times due to factors like investor sentiment, herding behavior, and information cascades (Okorie & Lin, 2021). By integrating insights from behavioral finance and evolutionary biology, the AMH provides a more nuanced understanding of market dynamics, highlighting the importance of adaptation, learning, and the interplay between rational and irrational behavior in shaping financial markets (Shahid, 2022).

Lo (2004) proposed the Adaptive Markets Hypothesis (AMH), which offers a valuable framework for understanding the dynamics of cryptocurrency markets. In the context of cryptocurrency trading, the presence of adaptive market participants is particularly pronounced. Cryptocurrency markets are characterized by high volatility and rapid price fluctuations, leading to a dynamic environment where market participants continuously adapt their strategies based on changing market conditions. The decentralized nature of cryptocurrencies and the absence of a central authority contribute to the adaptive behavior of market participants, who respond to news, regulatory developments, and technological advancements in real-time (Khuntia & Pattanayak, 2021).

Technological advancements play a significant role in shaping market behavior in cryptocurrency trading. The use of blockchain technology, algorithmic trading, and artificial intelligence has revolutionized the way transactions are conducted and information is processed in cryptocurrency markets (Davidson et al. 2018). These technological innovations have enabled faster execution of trades, increased market transparency, and facilitated the development of sophisticated trading strategies that respond to market signals and trends (Mikhaylov, 2020). However, they have also introduced new challenges related to market manipulation and cybersecurity (Ogunyolu & Adebayo, 2022).

The day-of-the-week effect is observed in capital markets where certain days exhibit distinct patterns in terms of volatility and returns (Luxianto et al., 2020). Researchers and investors have been interested in this effect as it can offer insights into market dynamics and potentially impact trading strategies (Zilca, 2017). Studies have shown that specific days of the week may experience higher or lower levels of market activity and price movements, indicating the day-of-the-week effect in both volatility and return equations (Chaouachi & Dhaou, 2020; Paital & Panda, 2018).

The day-of-the-week effect in the cryptocurrency market has garnered significant attention from researchers exploring anomalies within the realm of digital assets. Studies have demonstrated that specific days of the week may witness fluctuations in market activity and price movements, influencing both volatility and return equations. Caporale and Plastun (2019) conducted a thorough investigation into the day-of-the-week effect in the cryptocurrency market, shedding light on potential patterns and trends in price movements across different trading days. Theiri et al.

(2022) contributed to this area of research by focusing on cryptocurrency liquidity during the Russia-Ukraine war, underscoring the crucial role of market liquidity in comprehending the day-of-the-week effect.

Tosunoğlu et al. (2023) advanced the literature by employing artificial neural networks to analyze the day-of-the-week anomaly in cryptocurrencies, offering insights into the predictability of various currencies. Furthermore, Bae and Kim (2022) explored robust anomaly scores in cryptocurrencies, highlighting the impact of network factors on cryptocurrency returns. Grobys and Junttila (2020) delved into speculation and lottery-like demand in cryptocurrency markets, shedding light on the short-term reversal effects observed in the cross-section of cryptocurrencies. These studies collectively contribute to our comprehension of the day-of-the-week effect and its implications for cryptocurrency markets.

The implications of the day-of-the-week effect for investors and trading strategies in cryptocurrency markets are significant. Understanding how specific days of the week influence market volatility and returns can help investors optimize their trading decisions and risk management strategies (Dangi, 2020). By leveraging insights from the day-of-the-week effect, investors may be able to identify potential opportunities for profit and adjust their trading activities accordingly. Furthermore, the day-of-the-week effect can inform the development of trading algorithms and strategies that incorporate the cyclicality and patterns observed in cryptocurrency market behavior (Miralles-Quirós & Miralles-Quirós, 2022).

In this paper, we also conducted both Parametric, Nonparametric, and OLS Regression models to find the effect of the day of the week on cryptocurrency market. This paper adds to the current literature by applying non-parametric tests alongside parametric tests, making it unique. By addressing the behavioral aspects driving the day-of-the-week effect in virtual currency markets, this paper provides deeper insights into investor sentiment and market dynamics, filling a gap in the existing literature. Additionally, the GARCH (1,1) model is commonly used for studying the day-of-the-week effect in cryptocurrencies. This model has been applied in various financial markets, including cryptocurrencies, to analyze volatility and the impact of specific days of the week on asset returns and market dynamics. Studies have shown that GARCH (1,1) models effectively capture time-varying volatility and examine the day-of-the-week effect in various markets (Katsiampa, 2017; Chu et al., 2017; Aggarwal & Jha, 2023; Ampountolas, 2022; Naimy et al., 2021).

3. Data and Methodology

Utilizing the daily closing prices of Bitcoin and Ethereum sourced from CoinMarketCap (https://coinmarketcap.com/coins/), this study covers the period from July 1st, 2020, to December 31st, 2023, enabling an examination of the post-COVID-19 period's impact.

Different quantitative methods, including both parametric and non-parametric tests, were applied to analyze the data. We used parametric tests such as the conventional regression model with dummy variables and ANOVA. Non-parametric tests like the Mood median test were also employed to address potential biases. Additionally, the Ordinary Least Squares (OLS) regression model with dummy variables and the GARCH (1,1) model were utilized.

The study commenced by applying descriptive statistics to characterize the returns distribution of the various days of the week for Bitcoin and Ethereum. We then used the Jacque-Bera (JB) test statistics and the Anderson-Darling (AD) test statistics to check for normality. Once the normality was conducted, we calculated returns by taking the log difference of consecutive daily closing prices of the cryptocurrencies, as described by Akyildirim et al. (2021). This process is expressed by the following equation:

$$R_n = (In\ CP_n - In\ CP_{(n-1)}) \times 100 \tag{1}$$

where R_n denotes returns on an n^{th} day in percentage; CP_n denotes closing price on an n^{th} day; $CP_{(n-1)}$ denotes closing price on the previous trading day; and *In* is a natural log.

Log returns for Bitcoin and Ethereum were then assessed using the Augmented Dickey-Fuller (ADF), Philips-Perron test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS), to confirm the stationarity of the series. These unit root tests have been utilized in various studies to analyze the stationarity of economic variables, environmental factors, and market indicators. The application of these tests provides insights into the behavior of time series data and aids in identifying trends, patterns, and potential relationships within the data (Ali et al., 2019; Haruna et al., 2022; Dao & Staszewski, 2021).

Following the assessment of stationarity, the study employed a dummy regression model that assumed constant return variance for cryptocurrencies. The equation for the Ordinary Least Squares (OLS) regression model is as follows:

$$Return_t = \beta_1 MONDAY_t + \beta_2 TUESDAY_t + \beta_3 WEDNESDAY_t + \beta_4 THURSDAY_t + \beta_5 FRIDAY_t + \beta_6 SATURDAY_t + \beta_7 SUNDAY_t + \varepsilon_t \quad (2)$$

where MONDAY, TUESDAY, WEDNESDAY, THURSDAY, FRIDAY, SATURDAY, and SUNDAY are dummy variables for each day of the week returns (e.g., if the day is Monday, then the dummy variable MONDAY will be 1 and 0 otherwise); β_1, β_2, β_3, β_4, β_5, β_6, and β_7 are coefficients; and ε_t is error term.

To prevent perfect multicollinearity, the intercept term was excluded, and dummy variables for all seven days of the week were included. The coefficients of these seven dummy variables represent the returns for each day of the week.

Following the least square regression analysis, the residuals were examined for autoregressive conditional heteroscedasticity using the ARCH test. If the residuals demonstrated an ARCH effect, indicating volatility clustering, the GARCH (1,1) model was employed. GARCH (1,1) serves as a mathematical framework utilized for both modelling and forecasting volatility in time series data, notably in cryptocurrencies (Kyriazis, 2019). This model is adept at capturing the inherent volatility clustering often observed in financial data, as it enables the modelling of both the mean and the variance of a time series (Kargar, 2021).

Research conducted by Micu and Dumitrescu (2022) further supports the effectiveness of the GARCH (1,1) model, highlighting its superior fit in modelling volatility across major cryptocurrencies. In the GARCH (1,1) model, the variance equation is given by:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (3)$$

Where

α is the coefficient of the lagged squared error term, representing the impact of past volatility shocks on current volatility.

β is the coefficient of the lagged conditional variance term, representing the persistence of volatility.

ω is the constant term representing the long-term average variance.

ε_{t-1}^2 = is the previous period ARCH term

σ_{t-1}^2 = is the previous period GARCH term

In the study, seven dummy variables were incorporated into the GARCH (1,1) model to investigate the day-of-week effect on cryptocurrency market volatility. These dummy variables allowed for assessing how the variance of asset returns changes across different days of the week. By including these dummy variables, any structural changes or anomalies in volatility associated with specific days were captured, providing deeper insights into market dynamics and investor behavior.

4. Analysis and discussion

Analyzing the daily prices of Bitcoin and Ethereum revealed insights into the day-of-the-week effect. Converting the prices of Bitcoin and Ethereum into return series provided data for further examination. Table 1 displays the basic statistics derived from these return series (see Table 1). Ethereum, in particular, stands out with its highest average returns, suggesting greater potential for profitability. The negative skewness observed in both cryptocurrencies indicates left-skewed distributions, implying a likelihood of small profits and minimal potential for significant losses. Ethereum's lower variability in returns compared to Bitcoin is evident from its low coefficient of variation (C.V). Additionally, the Jarque-Bera normality test, consistent with previous research, rejects the null hypothesis of normality for both cryptocurrencies. Interestingly, maximum returns for Bitcoin and Ethereum occur on Tuesdays.

Investigating variations across days of the week, one-way ANOVA and Mood's median tests were conducted. Additionally, the Anderson-Darling test for normality was performed. The p-values for both coins were less than 0.05, indicating rejection of the null hypothesis and non-normality of the data (see Table 2). Scrutinizing the one-way ANOVA results at a 95% confidence level revealed no significant differences in mean returns among days of the week. The Mood's-median test, a robust nonparametric test, was employed to examine median equality for log returns across seven days, as shown in Table 2. No coins yielded significant p-values, indicating no observed day-of-week effects, consistent with Kaiser's (2019) findings.

Table 1. Daily descriptive statistics for Bitcoin and Ethereum Post-COVID period

Bitcoin Returns								
Descriptive statistics	**Monday Returns**	**Tuesday Returns**	**Wednesday Returns**	**Thursday Returns**	**Friday Returns**	**Saturday Returns**	**Sunday Returns**	**Overall Returns**
Mean	-0.098	0.368	0.102	0.539	-0.244	-0.071	0.103	0.100
Maximum	9.314	17.603	8.179	11.966	13.774	11.622	9.148	17.603
Minimum	-10.170	-17.252	-11.533	-14.466	-43.371	-10.886	-8.989	-43.371
Standard Deviation	2.854	4.673	3.383	3.962	5.323	3.751	2.384	3.874
Coefficient of Variation	-29.056	12.682	33.152	7.355	-21.811	-52.933	23.224	38.813
Skewness	-0.311	0.023	-0.550	-0.159	-3.615	0.008	-0.200	-1.429
Kurtosis	4.856	5.242	4.166	4.868	31.138	4.217	6.076	19.683
Jarque-Bera	23.467	30.798	15.748	21.998	5169.707	9.066	58.927	12282.830

Ethereum Returns								
Descriptive statistics	**Monday Returns**	**Tuesday Returns**	**Wednesday Returns**	**Thursday Returns**	**Friday Returns**	**Saturday Returns**	**Sunday Returns**	**Overall Returns**
Mean	0.196	0.511	0.108	0.707	-0.345	0.003	0.471	0.236
Median	0.338	0.558	0.144	0.996	0.071	-0.176	0.647	0.348
Maximum	21.786	21.941	14.499	12.889	15.046	18.123	11.441	21.941
Minimum	-17.727	-18.782	-13.644	-30.520	-56.308	-16.209	-14.822	-56.308
Standard Deviation	4.331	5.943	4.235	5.428	6.827	5.181	3.919	5.209
Coefficient of Variation	22.100	11.626	39.296	7.682	-19.801	1775.665	8.323	22.092
Skewness	0.429	0.075	-0.024	-1.286	-3.911	-0.156	-0.172	-1.464
Kurtosis	8.430	4.886	4.196	9.280	32.559	4.079	5.171	18.420
Jarque-Bera	185.125	21.928	8.771	282.078	5726.383	7.726	29.599	10561.600

Source: Data elaborated by the author based on information gathered from coinmarketcap.com

Table 2. Results of the Parametric and Nonparametric Tests on Bitcoin and Ethereum

The table summarizes results from tests for Normality (Anderson-Darling — a parametric test), Central tendency (Mood's median test — a non-parametric test, One-way ANOVA — a parametric test), and Variance (Levene's and Bartlett's tests).

	Normality Test	**Central tendency Test**		**Variance test**	
	Anderson Darling test P-values	**Mood's median test P-values**	**One Way Anova P-values**	**Bartlett's test P-values**	**Bartlett's test P-values**
Bitcoin	<0.050	0.733	0.676	***0.000***	***0.000***
Ethereum	<0.050	0.674	0.675	***0.000***	***0.001***

Source: Elaborated by the author

Equal variances between days of the week were tested to assess variability and potential day-of-week effects. Bitcoin and Ethereum reject the null hypothesis at 95% confidence, indicating significant differences in variances among days. Both coins, with p-values below 0.05, are further analyzed to explore variance distribution. Table 3 reveals that the maximum variation for Bitcoin and Ethereum occurs on Tuesdays (see Table 3). It is noteworthy that the minimum variation is observed on Sundays. This observation aligns with the findings of Balcilar et al. (2017) and Dorfleitner and Lung (2018), suggesting that many traders abstain from weekend trading, possibly due to leisure activities or other commitments.

Utilizing both parametric and non-parametric tests can detect day-of-the-week effects, but integrating dummy variables into GARCH models presents a more refined approach. This method enables modelling of time-varying volatility patterns, resulting in improved forecasts and deeper insights into the influence of particular days on financial returns and volatility.

We checked the stationarity of the time series data by conducting unit root tests, utilizing the Augmented Dickey-Fuller, and Phillips-Perron tests, which are standard tools in time series analysis (Liao et al., 2021). The results, presented in Table 4 for the ADF test and PP test, consistently showed p-values below 0.05 (see Table 4). The time series data's stationarity was confirmed, and the null hypothesis was rejected at a 95% confidence level due to strong evidence.

Table 3. Results of Levene's test for Variance

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Bitcoin							
Lower Limit	0.747	1.022	0.865	0.934	0.970	0.895	0.644
Upper Limit	1.026	1.403	1.187	1.281	1.330	1.228	0.883
Standard Deviation	0.867	***1.185***	1.003	1.082	1.124	1.038	***0.746***
Ethereum							
Lower Limit	0.775	1.000	0.806	0.937	0.945	0.931	0.735
Upper Limit	1.063	1.372	1.106	1.285	1.296	1.277	1.008
Standard Deviation	0.898	***1.159***	0.934	1.086	1.095	1.079	***0.852***

Source: Derived and expanded upon by the author.

Table 4. Augmented Dickey-Fuller Test and Phillips-Perron Test results

	Augmented Dickey-Fuller Test Statistics		**Phillips-Perron Test statistic**	
	Bitcoin	**Ethereum**	**Bitcoin**	**Ethereum**
t-Statistic	-33.829	-34.677	-33.784	-29.931
P-value	0.000	0.000	0.000	0.000

Source: Derived and expanded upon by the author.

After conducting the ADF and PP tests to assess the stationarity of the time series data for both Bitcoin and Ethereum, the KPSS test was also conducted. The KPSS test serves as a complementary tool to the ADF and PP tests, offering additional insights into the stationarity properties of the data.

The KPSS test is particularly useful because it complements the ADF and PP tests by focusing on different aspects of stationarity. While the ADF and PP tests primarily detect trends in the data, the KPSS test is sensitive to detecting other forms of non-stationarity, such as level shifts, changes in variance, or sudden shocks. By running the KPSS test alongside the ADF and PP tests, a more comprehensive assessment of the stationarity of the time series data is ensured.

The results of the KPSS test, as shown in Table 5, indicate that the test LM statistics are less than the critical values at 99%, 95%, and 90% significance levels for both Bitcoin and Ethereum (see Table 5). This suggests that the null hypothesis of stationarity cannot be rejected, providing evidence that the time series data for both cryptocurrencies is stationary. Therefore, it can be concluded that the data does not exhibit significant non-stationarity, further validating the analysis and conclusions.

Table 5. Kwiatkowski-Phillips-Schmidt-Shin Test results

Bitcoin		**Ethereum**	
KPSS LM-Statistics	0.090	KPSS LM-Statistics	0.070
Critical value at 1%	0.216	Critical value at 1%	0.439
Critical value at 5%	0.146	Critical value at 5%	0.463
Critical value at 10%	0.119	Critical value at 10%	0.347

Source: Derived and expanded upon by the author.

Following the unit root tests, proceeded with Ordinary Least Squares (OLS) regression, incorporating dummy variables into the analysis. Subsequently, we scrutinized the OLS residuals for evidence of volatility clustering, employing Engle's ARCH test. Table 6 shows the results consistently yielded p-values below 0.05, compellingly rejecting the null hypothesis and accepting the existence of ARCH effects (see Table 6). After this GARCH(1,1) was applied and checked for robustness to predict the day-of-week-effect and volatility.

Table 6. Test results for Engle's Arch test

Bitcoin	F-statistics	0.142	F Probability	0.047
	Obs*R-squared	0.284	Probability Chi-Square	0.047
Ethereum	F-statistics	3.724	F Probability	0.025
	Obs*R-squared	7.416	Probability Chi-Square	0.025

Source: Derived and expanded upon by the author.

The significant p-values of both the ARCH and GARCH terms, as shown in Table 7, indicate their importance in both Bitcoin and Ethereum. This significance implies that the returns on these cryptocurrencies exhibit continuous and time-varying volatility (see Table 7). Moreover, it suggests that the volatility of cryptocurrencies is heavily influenced by both recent historical data and projected future values.

For Bitcoin, the ARCH + GARCH terms being less than 1 indicate decaying volatility, suggesting a persistence of volatility over time. The daily returns show negativity for Friday and Saturday and positivity for other days, aligning with findings of previous studies (Lopez-Martin, 2022; Naz et al., 2023). Additionally, there are no significant p-values for any day-of-week effect. Prior to the COVID period, Bitcoin did not show a day-of-the-week effect, and it has grown increasingly effective with time. These findings of Bitcoin are consistent with the research of various authors (Tiwari et al., 2019; Aggarwal, 2019; Lade & Yi, 2020; Baur et al., 2019; Kinateder & Papavassiliou, 2021; Dumrongwong, 2021) but do not support the findings of others (Aharon & Qadan, 2019; Lopez-Martin, 2022; Naz et al., 2023).

Similarly, for Ethereum, the ARCH + GARCH terms being less than 1 also signify decaying volatility, indicating a persistence of volatility. The daily returns for all days are positive. Additionally, the significant p-value for Thursday's daily returns is noteworthy, which is in line with previous research (Lopez-Martin, 2022; Karaömer & Kakilli, 2023).

Table 7. GARCH (1,1) model estimation for return of Bitcoin and Ethereum

Dependent Variable: Bitcoin returns				
GARCH = C(8) + C(9)*RESID(-1)^2 + C(10)*GARCH(-1)				
Variable	**Coefficient**	**Std. Errors**	**z-Statistics**	**Probability**
MONDAY	0.108	0.243	0.444	0.657
TUESDAY	0.405	0.211	1.915	0.546
WEDNESDAY	0.132	0.213	0.620	0.535
THURSDAY	0.353	0.222	1.594	0.111
FRIDAY	-0.022	0.223	-0.097	0.923
SATURDAY	-0.072	0.237	-0.303	0.762
SUNDAY	0.191	0.272	0.703	0.482
Variance Equation				
Constant	0.312	0.170	1.833	0.067
ARCH Term	0.068	0.022	3.078	0.002
GARCH Term	0.924	0.020	45.430	0.000
Dependent Variable: Ethereum returns				
GARCH = C(8) + C(9)*RESID(-1)^2 + C(10)*GARCH(-1)				
Variable	**Coefficient**	**Std. Errors**	**z-Statistics**	**Probability**
MONDAY	0.173	0.365	0.475	0.635
TUESDAY	0.580	0.314	1.843	0.065

Dependent Variable: Ethereum returns				
GARCH = C(8) + C(9)*RESID(-1)^2 + C(10)*GARCH(-1)				
Variable	**Coefficient**	**Std. Errors**	**z-Statistics**	**Probability**
WEDNESDAY	0.016	0.333	0.047	0.963
THURSDAY	0.887	0.314	2.827	0.005
FRIDAY	0.089	0.321	0.279	0.780
SATURDAY	0.196	0.322	0.610	0.542
SUNDAY	0.526	0.399	1.320	0.187
Variance Equation				
Constant	1.943	0.766	2.537	0.011
ARCH Term	0.086	0.028	3.095	0.002
GARCH Term	0.842	0.044	18.990	0.000

Source: Derived and expanded upon by the author.

To assess the robustness of the GARCH (1,1) model for the study's time series, two diagnostic tests were applied. Firstly, the Nyblom stability test examined structural changes within the time series by testing whether the higher-order autocorrelations of the squared residuals are zero. This test, robust to heavy-tailed distributions and outliers, accepted the null hypothesis at a 95% confidence level, indicating stable behavior of the variables in the GARCH (1,1) model. Secondly, the Engle & Ng sign bias test detected misspecifications in conditional volatility models, such as nonlinearity or asymmetry in the conditional variance. Robust to heavy-tailed distributions and outliers, this test ensures the dependability of the GARCH model's results for forecasting and risk management purposes.

The study period being post-COVID reveals a day-of-week effect in Ethereum, the high-return cryptocurrency, while Bitcoin shows no calendar anomalies. This suggests that the most traded cryptocurrency, Bitcoin, is becoming efficient over time. Inconsistencies in cryptocurrency calendar anomalies stem from various factors, including the relatively new and less mature nature of the cryptocurrency market, methodological disparities among scholars, the speculative environment of the market, and its susceptibility to external factors such as news, rumors, socioeconomic trends, and political movements.

Furthermore, the decentralized and global nature of the cryptocurrency market presents challenges in identifying and quantifying market-wide effects. The interplay between market sentiment and the adoption of cryptocurrencies for commercial activities, coupled with shifts in government policies and regulations, further underscores the adaptive market hypothesis.

5. Conclusion

The study aimed to explore the presence of day-of-the-week effects in the virtual currency market post-COVID-19, focusing specifically on Bitcoin and Ethereum. Through a comprehensive analysis employing both parametric and non-parametric tests, alongside sophisticated econometric models like the GARCH (1,1) model, we uncovered valuable insights into the dynamics of these cryptocurrencies.

Our findings reveal that Bitcoin shows no evidence of calendar anomalies, while Ethereum exhibits a notable day-of-the-week effect, characterized by fluctuations in returns across different days. This suggests a trend towards efficiency in Bitcoin, the most traded cryptocurrency, over time. However, the susceptibility of Ethereum to day-of-the-week effects underscores the ongoing challenges and complexities within the cryptocurrency market.

The disparities in calendar anomalies across cryptocurrencies can be attributed to various factors, including the nascent and evolving nature of the market, methodological disparities among researchers, and the speculative environment intrinsic to cryptocurrency trading. Furthermore, the decentralized and global nature of the cryptocurrency market poses challenges in accurately identifying and quantifying market-wide effects.

By providing empirical evidence of day-of-the-week effects in the cryptocurrency market and shedding light on changing market dynamics, our work contributes significantly to the existing literature. This identification of day-of-the-week effects holds significant implications for investors' risk management strategies. By understanding and leveraging these effects, investors can enhance their risk management approaches, particularly in timing their trades and allocating resources more effectively. Incorporating day-of-the-week effects into risk management frameworks can aid in optimizing portfolio diversification strategies, ultimately assisting investors in achieving a more balanced risk-return profile. Hence, our study underscores the practical utility of considering day-of-the-week effects in cryptocurrency investment decision-making, providing investors with valuable tools for navigating the complexities of the market.

Moving forward, additional research is essential to explore other elements that may influence market dynamics and delve deeper into the fundamental mechanisms driving day-to-day effects in cryptocurrencies. Additionally, continuous monitoring of regulatory developments and technological advancements will be pivotal in understanding the evolving landscape of the cryptocurrency market and its implications for investors.

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