Paper Title:

Exploring Calendar Effects in Bitcoin Returns: An Analysis of Market Efficiency

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Abstract

This study delves into the exploration of calendar effects within Bitcoin returns to examine the validity of the Efficient Market Hypothesis (EMH) in the context of the cryptocurrency market. Leveraging data spanning from October 2015 to November 2021, this research employs regression analysis and power ratio analysis to investigate the presence of day-of-the-week and intraday effects on Bitcoin prices. The findings reveal statistically significant anomalies for Fridays and specific intraday periods, suggesting the potential for abnormal returns. However, these calendar effects are not pervasive enough to conclusively impact overall market efficiency. The study's results indicate that while Bitcoin's market may exhibit short-term inefficiencies, it largely conforms to the principles of market efficiency over extended periods. This research contributes to the ongoing discourse on the efficiency of cryptocurrency markets and highlights the necessity for further investigation using diverse methodologies to fully understand the dynamics at play.

Keywords: Calendar Effect, Bitcoin Price, Regression Analysis, Power Ratio

Introduction

The foundation of this study is the Efficient Market Hypothesis (EMH), initially posited by Fama [1] in 1970. EMH argues that historical data cannot predict future asset returns, suggesting that market prices integrate all available information. Numerous studies have examined calendar effects, investigating anomalies in asset pricing related to specific time periods, such as days, weeks, months, holidays, and other seasonal factors. These calendar effects, characterized by deviations in asset prices from their average during specific periods, are seen as anomalies that could represent investment opportunities, thereby challenging the notion of market efficiency.

Among various calendar effects, the weekend effect is extensively studied in traditional assets. This is due to the potential impact of information released or acquired over weekends, when most markets are closed, on asset prices, particularly on Mondays. Introduced in 2009, cryptocurrency, with its cost-efficiency, initial independence from government regulation, peer-to-peer payment system, and speculative nature, rapidly gained investor attention. This leads to the hypothesis that Bitcoin, and similar cryptocurrencies, may exhibit different seasonal performance patterns compared to conventional assets like stocks, bonds, and commodities. Furthermore, the 24/7 operation of cryptocurrency markets introduces a new dimension to calendar effects, transcending traditional temporal measures.

This research aims to explore potential calendar effects in Bitcoin, the foremost cryptocurrency, which operates without the temporal constraints of traditional financial markets. Investigating Bitcoin's pricing behavior in the context of specific time periods offers a unique opportunity to test EMH and contributes to our understanding of market efficiency in the rapidly evolving digital asset landscape.

Literature Review

With its status as the world’s leading cryptocurrency by market capitalization, there has been a significant interest in the study of Bitcoin and calendar anomalies in its returns and volatility. Recent studies analyzing calendar anomalies in Bitcoin include Aharon and Qadan [2], Baur et al. [3], Kaiser [4], Ma and Tanizaki [5], and Kinateder and Papavassiliou [6], among others. The main benefit of researching Bitcoin's seasonality is that it helps further determine the validity of the efficiency market hypothesis. Shanaev and Ghimire [7] found that cryptocurrency markets are less efficient than national stock markets, with predominantly irregular seasonality periodicity that cannot be reduced to conventional weekly, monthly, or annual cycles. Kim et al. [8] and Yi et al. [9] focused on the market capitalization and information discovery speed in the Bitcoin market. It highlighted the fast information circulation in the Bitcoin market, suggesting its efficiency and robustness against the predictability of future prices based on past performance. Another benefit is to allow investors to improve their investment portfolio performance. The most comprehensive research method is to use a generalized autoregressive conditional heteroskedastic (GARCH) model with dummy variables. For example, Kinateder and Papavassiliou [6] used the GJR-GARCH(1,1) model proposed by Glosten et al. [10]. The most extensively investigated form of seasonality in these papers is the day-of-the-week effect.

Caporale and Plastun [11] examined the day-of-the-week effect by using statistical methods such as average analysis, Student's t-test, ANOVA, and regression analysis with dummy variables. They found a Monday anomaly for Bitcoin, by which returns are considerably greater than on the other days of the week. They offered no conclusive evidence against market efficiency for Bitcoin. Décourt et al. [12] examined the Monday effect in Bitcoin by using the average daily returns on Monday, compared to other days of the week. They noted that Bitcoin tends to have higher returns on Mondays. Aharon and Qadan [2] investigated the day-of-the-week effect with daily data for 2010-2017. Their study explained that the day-of-the-week effect is present in both the returns and volatility of Bitcoin, and that Mondays are associated with higher returns and higher volatility in Bitcoin prices compared with other days of the week. Durai and Paul [13] presented evidence for a day-of-the-week calendar anomaly in Bitcoin returns. Decourt et al. [12] found a statistically significant difference in the average daily returns of each day, and that Tuesdays and Wednesdays have higher returns as compared to other days. Qadan et al. [14] collected ten years of daily data and concluded that the Monday effect on Bitcoin occurs primarily in the first three weeks of a month. Susana et al. [15] studied a three-year daily dataset of Bitcoin prices and confirmed the existence of anomalies during Thursdays, the months March and April, and at the turn of the year. In conclusion, the existence of calendar anomalies is not consistent with the Efficient Market Hypothesis (EMH).

Yaya and Ogbonna [16] and Kinateder and Papavassiliou [6] conversely found no significant proof of the day-of-the-week effect in Bitcoin returns that support market efficiency. This validates the view that Bitcoin returns exhibit mostly weak-form efficiency with respect to calendar anomalies, which is in line with the findings of Nadarajah and Chu [17] and Baur et al. [3]. The absence of significant calendar anomalies indicates that there are no seasonal patterns in returns that could be used by investors to generate abnormal returns, based on past Bitcoin price information. Kurihara and Fukushima [18] examined the day effect in Bitcoin trading. They concluded that Bitcoin shows anomalies on weekends during the earlier period when Bitcoin was not as widely known nor traded, but Bitcoin trading has now become more efficient, and its returns should be random in the future. Erdogan et al. [19] explored the impact of lunar cycles on Bitcoin prices and concluded that lunar cycles have no statistically significant impact on Bitcoin price changes

Understanding calendar anomalies is helpful in developing models that forecast Bitcoin's price movement. This literature review indicates a wide array of conclusions and questions. First, some recent research results about calendar anomalies in Bitcoin returns contradict one another. The validation of the market efficiency of Bitcoin is still not clear. Second, the Bitcoin market is open 24/7, and few studies examine the calendar effect intraday. The purpose of this research is to examine if EMH holds true for Bitcoin trading by answering the following issue: How the temporal anomalies vary over time and frequencies, affects Bitcoin price. The main objective of this study is to examine the calendar effect through using regression analysis with dummy variables and the power ratio method. Since Bitcoin trading is 24 hours a day and 7 days a week, the calendar effect from Monday through Sunday as well as during every hour within each day is examined.

Data Description and Methodology

Traditional calendar effect analysis has been performed for investigating Monday through Friday effects. However, unlike traditional stocks and commodities, the Bitcoin market is not traded at a regulated time period. The Bitcoin market is open to trade 24/7. Therefore, the calendar effect analysis is modified. Bitcoin data (including time, high, low, close price, volume information) were downloaded from https://www.CryptoDataDownload.com. Two sets of data were gathered: dataset_1, daily data (2241 entries in total) between 2015/10/08 and 2021/11/25; and dataset_2, hourly data (53769 entries in total) between 2015/10/08/13:00 and 2021/11/26/00:00. The dataset_1 is used for examining the day-of-the-week (Monday through Sunday) effect, while dataset_2 is used to examine if there are abnormal returns intraday.

Figure 1 presents the time series of Bitcoin prices between 2015/10/9 and 2021/10/9 (period of dataset_1 and dataset _2). The time series exhibit substantial variation, covering both a distinct boom and bust cycle. This figure illustrates the price fluctuation of Bitcoin (BTC) in USD over a six-year period from October 9, 2015, to October 9, 2021. The time series chart showcases a noteworthy upward trend in the value of Bitcoin throughout the observed period. The early phase, spanning from 2015 to late 2017, depicts a gradual increase in price, with occasional spikes and corrections. Notably, the period of late 2017 and early 2018 marks the first substantial surge in Bitcoin's price, reaching an unprecedented peak before experiencing a sharp decline, a phenomenon often associated with speculative bubbles. Following this period, the chart shows a relative stabilization with smaller fluctuations until late 2020, where another dramatic increase signals the onset of a bull market, leading to new all-time highs. This surge, characterized by steep climbs and swift drops, reflects heightened investor interest and the maturation of cryptocurrency as an asset class. This period is long enough to cover the time from when Bitcoin began to receive public attention, to its drastic price rise, and then to its sharp up and down cycles.

It also covers the COVID-19 pandemic. Therefore, it is reasonable to use this dataset to determine the calendar effect.

This description aims to convey the information presented in the chart while also providing context and insight into the nature of Bitcoin's price movements over the specified period.

The returns are calculated as the logarithmic value of the closing price of time t divided by the closing price of time t-1. For example, for dataset_1, the return for day (R_d) is calculated as the logarithmic value of the closing price of day t ($P_{d,t}$) divided by the closing price of the day prior to it ($P_{d,t-1}$).

$$R_{d,t} = \ln (P_{d,t}/P_{d,t-1}) \tag{1}$$

Figure 2 present the daily returns of Bitcoin price for each weekday and for different year.

Dataset_2 aims to check if any abnormal returns exist intraday. The returns for each interval (R_h) are calculated as the logarithmic value of the closing price of hour t ($P_{h,t}$) divided by the closing price two-hour prior to it ($P_{h,t--1}$):

$$R_{h,t} = \ln (P_{h,t}/P_{h,t-1}) \tag{2}$$

Figure 3 present the returns of Bitcoin price for different times of day for different year.

Dataset_1 is used for examining the day-of-the-week effect by using the Fama-MacBeth regression format with dummy variables, as follows:

$$R_{d,t} = c_1 D_{1,t} + c_2 D_{2,t} + c_3 D_{3,t} + c_4 D_{4,t} + c_5 D_{5,t} + c_6 D_{6,t} + c_7 D_{7,t} + \varepsilon_d \tag{3}$$

Here, dummy variables $D_{i,t}$ (i=1 to 7) are 1 corresponding to Sunday, Monday, …Saturday, respectively, and otherwise 0. The random process ε_d is the normal deviate, distributed normally with mean value of 0 and variance of 1. The coefficients $c_1 \ldots c_7$ are best estimated based on ordinary least square (OLS), which provides information on the day-of-the-week anomaly of Bitcoin returns.

Dataset_2 is used for examining the intraday effect. Similarly, the regression equation with dummy variables is:

$$R_{h,t} = d_1 H_{1,t} + d_2 H_{2,t} + d_3 H_{3,t} + \ldots + d_{10} H_{10,t} + d_{11} H_{11,t} + d_{12} H_{12,t} + \varepsilon_h \tag{4}$$

Here, dummy variables $H_{i,t}$ (i=1 to 12) are 1 corresponding to 0:00, 2:00, 4.00,…20:00, 22:00, respectively, and otherwise 0. The random process ε_h is the normal deviation distributed normally with a mean value of 0 and variance of 1. The coefficients $d_1 \ldots d_{12}$ are best estimated based on ordinary least square (OLS), which provides information on the intraday anomaly of Bitcoin returns.

This research also applies the power ratio model, used in Gu [20], to look into the calendar effect of Bitcoin. The power ratio model was originally designed to study day-of-the-week effects of the stock market. For examining the day-of-the-week effect:

$$\text{power ratio}_{D,i} = (R_{D,i}/R_W),\ i=1 \text{ to } 7 \tag{5}$$

$$R_{D,i} = (1+ \text{mean return of weekday } i)^7 \tag{6}$$

$$R_W = (1+ \text{mean return of week}) \tag{7}$$

For example, the average value of all Monday returns for a certain year (say, 2020) is calculated and inserted into Equation (6) for $R_{D,Monday}$, while the average value of weekly returns is calculated and inserted into Equation (7) for R_W in that year. The power ratio for Monday in 2020 can then be calculated according to Equation (5). After making similar calculations, the power ratio for each day of the week in 2020 can be calculated. When the power ratio is greater than 1, the return of that day is higher than the average of the returns of the other days within the same week, and vice versa. The ratio indicates no anomaly in the return of the day if the power ratio is equal to 1. The power ratio analysis is conducted for each weekday and for different year.

The Bitcoin market, instead of trading over a regulated time, it is open for trading 24/7. Therefore, the power ratio model is modified as follows to examine the intraday effect:

$$\text{power ratio}_{H,i} = (R_{H,i}/R_D),\ i=1 \text{ to } 12 \tag{8}$$

$$R_{H,i} = (1+ \text{mean return of hour } i)^{12} \tag{9}$$

$$R_D = (1+ \text{mean return of day}) \tag{10}$$

The examination of the intraday effect using power ratio analysis is similar to that for weekday effect. For example, the average value of all returns at 0:00 for a certain year (say, 2020) is calculated and inserted into Equation (9) for $R_{D,0:00}$, while the average value of daily returns is calculated and inserted into Equation (10) for R_D in that year. The power ratio for 0:00 in 2020 can then be calculated according to Equation (8). After making similar calculations, the power ratio for each two o'clock intraday in 2020 can be calculated. When the power ratio is greater than 1, the return of that time is higher than the average of the returns of the other time within the same day, and vice versa. The ratio indicates no anomaly in the return of the time if the power ratio is equal to 1.

Analysis Results

Tables 1 presents the key descriptive statistics (mean, standard deviation, skewness, and kurtosis) of Bitcoin price returns and trade volumes for different days (Monday through Sunday). The returns of Bitcoin's price were calculated using Equations (1). From the provided data, it is evident that there are variations in Bitcoin's market behavior across different days of the week. For instance, Fridays on average show the highest mean return, suggesting a potential trend or pattern that investors may consider. Meanwhile, Thursdays exhibit the highest kurtosis and skewness in trade volume, indicating a larger number of outlier events and a more pronounced asymmetry in volume distribution on that day of the week. This table provides valuable insights into the daily patterns of Bitcoin's trading dynamics.

Tables 2 present the key descriptive statistics of Bitcoin price returns and trade volumes for different intraday times (1:00 through 24:00). The returns of Bitcoin's price were calculated using Equation (2). From the data, notable patterns emerge, such as particular hours where the returns are consistently positive or negative on average, or times where trading volume is particularly high or prone to extreme values. For instance, at around 2 o'clock, a significant positive skewness and extremely high kurtosis in price returns, suggesting infrequent yet extreme positive returns. Similarly, the trade volume at around noon shows very high kurtosis, indicating a higher occurrence of unusual trading volume. The table offers a comprehensive overview of

Bitcoin's intraday trading behavior, which could be crucial for investors and traders who focus on short-term price movements.

Furthermore, it is of interest to investigate the calendar effect for different years. Therefore, the daily Bitcoin price returns for 2015-2021 are separated into Table 3 and also illustrated in Figure 2. The data suggests there may be identifiable patterns or anomalies in Bitcoin returns based on the day of the week. For instance, Mondays in 2015 and Fridays in 2019 show particularly high average returns compared to other days in the same years. Conversely, there are also days with negative average returns, such as Mondays in 2018 and 2021. ANOVA is conducted to examine the significance of weekdays and years on returns. For the factor of different weekday, the revised F-statistic is approximately 1.29 with a p-value of 0.284. This indicates that the differences among the average returns for different weekdays are not statistically significant at the common 0.05 significance level, suggesting that the day of the week does not significantly impact returns. For the factor of different year, the F-statistic remains approximately 1.95 with a p-value of 0.095. The analysis confirms that there is no statistically significant difference in returns across different years at the 0.05 significance level.

The intraday Bitcoin price returns for various two-hour intervals starting from midnight (0:00) and ending at 22:00 throughout the day spanning from the year 2015 to 2021 are shown on Table 4 and Figure 3. This intraday return figure illustrates the behavior of Bitcoin's price within specific time blocks. For example, in the year 2015, the 14:00 interval shows notably higher returns compared to the early morning intervals. Conversely, the 16:00 interval in 2018 registered negative returns, indicating a period of price decline on average during those hours. ANOVA is conducted to examine the significance of time and years on returns. The corrected p-value for the time-based ANOVA is 0.4477, which is greater than the commonly used significance level of 0.05. This suggests that the differences in returns at different times of the day are not statistically significant. The p-value for the year-based ANOVA is 0.0229, indicating that the year significantly affects the returns. This result implies that there are statistically significant differences in returns across different year.

The findings reinforce the idea that, according to this dataset, both the specific day of the week and the year do not have a statistically significant impact on returns. However, the varying values of Bitcoin return across multiple years highlight the dynamic nature of Bitcoin's intraday and weekday price movement and suggest that it may consistently exhibit distinctive return patterns. Such information could be particularly insightful for traders who specialize in strategies and for those studying the market behavior of Bitcoin. Rigorous analyses including regression analysis and power ratio analysis using the organized data are conducted for examining the calendar effect on Bitcoin returns.

Regression Analysis Results for the Calendar Effect

The regression analysis with dummy variables as shown in Equation (3) is applied for day-of-the-week effect examination. The coefficients $c_1 \ldots c_7$, which corresponding to Monday through Sunday as shown in Table 5, are best estimated based on ordinary least square (OLS). The coefficients provide insights into the daily effects on Bitcoin returns. For instance, c_5 (Friday) are significantly higher than average. The significance of these results is evaluated through the p-values, with c_5 low p-value (0.009) suggesting its effect is statistically significant. The analysis results indicate that only Fridays' returns show the presence of day-of-the-week effect. The dummy's positive coefficient implies that investors earn abnormal returns on Friday. No anomaly is detected on the remaining weekdays.

To study the intraday effect, dataset_2 for regression analysis with dummy variables as shown in Equation (4) is applied. Table 6 details the coefficients from the Fama-MacBeth regression analysis aimed at identifying the intraday time anomaly in Bitcoin returns. Dummy variables d_1-d_{12} represent different two-hour intervals throughout a 24-hour day, with each coefficient indicating the average effect of the specific time interval on Bitcoin returns. The coefficients are estimated based on ordinary least squares (OLS). The coefficients provide insights into how specific two-hour intervals throughout the day influence Bitcoin returns. For example, it indicates that 10:00-12:00 (d_6), 14:00-16:00 (d_8), and 20:00-22:00 (d_{11}) possess the calendar effect on intraday returns and are statistically significant at the 5%, 10%, and 1% levels, respectively. The dummy variable's positive coefficients of these parameters imply that investors may earn abnormal returns more easily if they trade within this timeframe. No other anomalies are detected in other time periods. The lack of statistically significant p-values for most time intervals suggests that, based on this analysis, there is limited evidence of a strong intraday timing anomaly in Bitcoin returns.

Power Ratio Analysis Results for the Time Effect

Power ratio analysis of the day-of-the-week effect on Bitcoin returns for different years between 2015 and 2021 is performed using Equations (5)-(7). It is noted that the data in 2015 and in 2021 are not complete yearly data. The analysis results are tabulated in Table 7 and plotted in Figure 4. They provide the power ratios for each day of the week from Monday to Sunday, across different years (2015-2019). The power ratios reflect how the average return of each weekday compares to the overall weekly average. The analysis reveals fluctuations in the power ratio across weekdays for different years, indicating varying daily returns compared to the weekly average. For instance, in 2015, Mondays and Fridays exhibited significantly higher returns than the weekly average with power ratios above 1. Conversely, other days, like Tuesdays and Saturdays, showed lower returns with power ratios below 1. This model provides insight into the day-of-the-week anomaly in Bitcoin returns, suggesting that certain days consistently outperform or underperform against the weekly average. Notably, Fridays in 2015 and 2019 show a strong positive anomaly, with the highest power ratios among all days, indicating a higher return than the average of other days within the same week. By examining the average power ratio for each day (Figure 4), it is observed that Friday has the highest power ratio. This is consistent with the finding of the previous described regression analysis results.

ANOVA analysis of the data is also performed. The p-value is 0.119, which is not strong enough to support the hypothesis that there is an anomaly between different days within the same week. The lack of significant differences in power ratios across weekdays suggests that, on average, no specific time of day consistently offers higher or lower returns than others. This could imply that market efficiency is relatively high, with information quickly reflected in prices throughout the day. The ANOVA which examines the day-of-the-week effect results with a p-value of 1.00 suggest that the power ratio is stable across different years. This implies that any identified day-of-the-week patterns in Bitcoin returns do not significantly change year over year, according to the power ratio model used. Since the year does not significantly influence the power ratios, this stability might suggest that any observed day-of-the-week effects are inherent to market behavior rather than temporal anomalies specific to certain years.

The power ratio analysis of the intraday effect on Bitcoin returns for different years between 2015 and 2021 is performed using Equations (8)-(10). The results are tabulated in Table 8 and plotted in Figure 5. It is observed that in a certain time, the power ratios across different years vary and could be greater or less than 1.0. In the early morning, 0-4 am, the power ratios are greater than 1.0 across 2015 to 2021. The analysis' results are not consistent with the findings of the previous described regression analysis results, in that 0:00-2:00 (d_1) and 2:00-4:00 (d_2) possess a negative effect on intraday returns. The ANOVA identifies significant differences in power ratios across various intraday times did not yield statistically significant results (p-value = 0.538). This suggests that there is no substantial evidence to support the existence of a consistent intraday timing effect where certain periods of the day are associated with higher or lower Bitcoin returns compared to others. The absence of a significant intraday effect according to the power ratio analysis suggests that Bitcoin's market efficiency may be high throughout the day, with information quickly reflected in prices. This could be due to the global nature of the cryptocurrency market, which operates 24/7, unlike traditional stock markets with fixed trading hours.

Conclusions and Discussions

Investors aim to profit from their decisions over investment assets, and Bitcoin is one of the most popular assets that have emerged in the last decade. This research examines if Bitcoin's price satisfies the efficient market hypothesis (EMH) and specifically examines if the calendar effect is significant for it. The calendar effect can be used to obtain abnormal profits which can be integrated into profit models.

The day-of-the-week and intraday effects are studied herein on daily and hourly Bitcoin price data spanning between October 2015 and November 2021. Regression analysis with dummy variables and power ratio analysis are then conducted. One limitation of this research is that the calendar effects are based on the data of the selected time period, and the results may not be appropriate for extrapolating to other durations. Another limitation of this research is most that the p-values are not significant as examined in analysis. Even though, some conclusions are drawn.

Regression analysis results reveal that, except for Friday, no anomaly is detected on the other days of the week. This research goes a step further by analyzing intraday effects on Bitcoin prices. This is particularly novel as most studies generally focus on longer-term anomalies. For the intraday effect, some positive intraday anomalies are found at 10:00-12:00, 14:00-16:00, and 20:00-22:00. The findings on specific time intervals exhibiting calendar effects add a new dimension to the understanding of Bitcoin pricing behavior. These analysis results give credence that Bitcoin returns do not conform to the efficient market with respect to day-of-the-week and intraday anomalies. The analysis results might indicate that while some calendar effects exist, they are not strong or consistent enough to significantly impact overall market efficiency. This suggests that Bitcoin's market may be efficient in a broader sense, but subject to short-term inefficiencies or anomalies.

Based on the inferred statistics of power ratio analysis, consistent with the finding of the previous described regression analysis results, Friday has the highest power ratio across research duration. However, the anomaly between day-of-the-week and intraday is not significant. More contradictory, power ratio analysis shows positive returns in the early morning, while regression analysis gives the opposite results. The discrepancy could be attributed to some factors. First, the divergence in findings from regression analysis and power ratio analysis can be attributed to the inherent differences in these methods' focus and sensitivity. The nature of regression analysis allows it to detect subtle, day-specific or time-specific patterns in financial data, such as daily returns or price movements. Power ratio analysis, while not as commonly discussed in general financial literature, tends to focus on broader trends and overall market dynamics. It is more suited to analyzing long-term trends and market efficiency over extended periods. Regression might be capturing subtle patterns that the power ratio analysis, which looks at broader market trends, might miss. The discrepancy could also suggest that Bitcoin's market is generally efficient over longer periods, but it may still exhibit short-term inefficiencies or anomalies, as indicated by the significant findings on Fridays and specific intraday periods in regression analysis. This nuanced view acknowledges the existence of calendar effects, albeit not strong enough to dominate the market's efficiency

This research uses of both regression analysis with dummy variables and power ratio analysis offers a more comprehensive approach to examine calendar effect on Bitcoin price. This dual approach allows for a more understanding of the market dynamics and provides a cross-validation of findings. It is interesting to find that varied conclusions arise based on the same dataset, but different research methods. It explains why recent research results about calendar anomalies in Bitcoin returns refute each other. It also implies that Bitcoin's market efficiency and predictability are complex and potentially influenced by a multitude of factors beyond traditional market theories and highlights the need for further research using diverse methodologies to fully understand cryptocurrency market dynamics. The study's contribution to the discourse on cryptocurrency market efficiency is twofold. First, it provides empirical evidence of temporal anomalies within Bitcoin returns, enriching our understanding of market behavior in this emerging asset class. Second, it challenges and refines our comprehension of market efficiency in the context of cryptocurrencies, indicating that while Bitcoin exhibits traits of market efficiency, it also presents unique anomalies shaped by its trading characteristics and investor behaviors. In conclusion, while this research marks a significant step towards deciphering the calendar effects in Bitcoin returns and their implications for market efficiency, it also opens the door to a myriad of research opportunities. As the cryptocurrency market continues to mature and evolve, so too will our understanding of its complexities and the strategies investors might employ to navigate its unique challenges and opportunities.

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Table 1 Descriptive statistics of weekday data (Dataset_1) of Bitcoin price return and trade volume

Weekday	Daily Return				Daily Volume			
	mean	sdv	skewness	kurtosis	mean	sdv	skewness	kurtosis
Monday	0.00299	0.0440	-0.33	4.73	3662.86	3850.82	2.63	8.15
Tuesday	0.00160	0.0432	-0.13	3.59	3898.58	4222.86	3.07	11.79
Wednsday	0.00355	0.0420	-0.36	2.98	4017.87	3829.77	2.13	4.97
Thursday	0.00001	0.0511	-1.40	10.15	4294.12	5272.35	4.25	28.60
Friday	0.00677	0.0408	0.25	5.76	3757.34	4301.03	3.25	15.07
Saturday	-0.00019	0.0362	-0.87	4.50	1934.63	2376.26	2.79	9.47
Sunday	0.00264	0.0358	0.38	6.55	2111.55	2628.10	3.05	13.80

Table 2 Descriptive statistics of intraday data (Dataset_2) of Bitcoin price return and trade volume

O'clock	Return				Volume			
	mean	sdv	skewness	kurtosis	mean	sdv	skewness	kurtosis
0	0.00010	0.00947	-0.58	10.35	136.54	243.35	7.00	83.31
1	0.00019	0.00871	-0.80	29.62	126.64	212.81	4.54	29.71
2	-0.00033	0.00881	3.19	92.84	122.75	198.12	4.16	28.39
3	-0.00028	0.00746	-0.11	14.49	116.36	229.90	7.23	86.19
4	-0.00011	0.00826	0.22	31.14	108.83	186.98	4.85	36.83
5	-0.00012	0.00758	-0.97	14.88	99.00	181.40	5.86	54.08
6	0.00019	0.00751	-0.96	17.10	93.12	171.01	6.13	58.15
7	0.00035	0.00793	0.98	17.37	91.63	158.44	6.58	75.84
8	-0.00005	0.00868	0.55	23.31	92.53	159.95	5.38	45.16
9	0.00002	0.00840	0.52	16.60	93.54	158.23	4.01	22.85
10	-0.00006	0.00933	-4.56	81.93	99.38	182.65	4.44	26.53
11	0.00024	0.00836	0.90	19.49	141.26	284.95	5.01	42.68
12	0.00036	0.00977	0.01	26.90	140.03	336.70	11.68	203.27
13	0.00018	0.01004	-1.26	20.89	167.37	338.06	10.20	191.18
14	-0.00021	0.00973	0.10	16.93	195.92	395.72	9.16	130.48
15	0.00042	0.00908	0.83	11.73	190.76	302.93	5.59	48.50
16	0.00015	0.00997	-0.17	14.27	193.20	278.41	4.48	34.55
17	0.00002	0.00842	-0.48	14.07	178.15	337.71	10.08	160.90
18	-0.00001	0.00768	-1.19	17.46	162.74	262.50	6.39	71.35
19	0.00025	0.00828	0.41	20.40	168.63	280.82	5.90	54.23
20	-0.00006	0.00927	-0.31	15.03	258.94	442.33	3.73	18.60
21	0.00070	0.00958	-1.26	56.97	187.99	322.95	4.60	39.41
22	0.00044	0.00992	-4.31	94.40	127.60	188.39	4.04	24.64
23	0.00006	0.01015	-1.77	79.79	133.95	249.62	8.91	154.69

Table 3 Daily returns of Bitcoin price (Dataset_1)

Weekday	2015	2016	2017	2018	2019	2020	2021
Monday	0.02077	0.00048	0.01469	-0.01382	0.00559	0.01066	-0.00415
Tuesday	-0.00154	-0.00235	0.00881	0.00010	-0.00275	0.00539	0.00116
Wednesday	0.01501	0.00504	0.00729	-0.00807	0.00124	0.00606	0.00692
Thursday	0.00160	0.00392	0.00992	-0.00617	-0.00807	0.00001	-0.00030
Friday	0.02057	0.00414	-0.00534	0.00848	0.01705	0.00388	0.00501
Saturday	-0.00605	0.00113	0.00395	-0.00762	-0.00043	0.00271	-0.00073
Sunday	-0.00250	0.00303	0.01097	0.00257	0.00031	-0.00179	0.00260

Table 4 Intraday returns of Bitcoin price (Dataset_2)

O'clock	2015	2016	2017	2018	2019	2020	2021
0	0.00014	0.00008	0.00264	0.00053	0.00086	-0.00001	0.00006
2	0.00034	0.00028	0.00089	-0.00038	0.00071	0.00070	0.00006
4	0.00082	0.00057	-0.00001	-0.00096	-0.00008	-0.00034	-0.00009
6	0.00034	-0.00029	0.00084	-0.00124	-0.00034	-0.00018	-0.00003
8	0.00003	-0.00048	-0.00014	0.00068	-0.00090	0.00012	-0.00003
10	0.00132	0.00035	0.00178	-0.00082	-0.00023	-0.00047	-0.00002
12	0.00213	0.00055	0.00001	-0.00131	0.00022	-0.00108	0.00005
14	0.00320	0.00024	0.00005	0.00169	0.00012	-0.00051	-0.00006
16	-0.00177	0.00032	-0.00016	-0.00068	0.00005	-0.00007	0.00001
18	0.00044	-0.00027	0.00163	-0.00010	0.00103	-0.00144	0.00001
20	0.00016	0.00092	-0.00036	-0.00072	0.00013	-0.00149	-0.00010
22	-0.00051	0.00004	-0.00001	-0.00028	0.00020	0.00096	-0.00005

Table 5 Regression analysis results of weekday effect on Bitcoin price return

parameter	value	sdv	t-statistic	p- value
c1	0.00296	0.00234	1.26623	0.206
c2	0.0016	0.00234	0.68272	0.495
c3	0.00349	0.00234	1.49011	0.136
c4	-5E-05	0.00234	-0.02	0.984
c5	0.00609	0.00234	2.60383	0.009***
c6	-0.0004	0.00234	-0.1652	0.869
c7	0.00277	0.00234	1.18775	0.235

Note:

1 The average daily return is 0.002357.

2. *, **, and *** shown in p-value column denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6 Regression analysis results of intraday effect on Bitcoin price return

parameter	value	sdv	t-statistic	p- value
d_1	-0.00005	0.00032	-0.166	0.868
d_2	-0.00024	0.00032	-0.743	0.458
d_3	-0.00017	0.00032	-0.531	0.595
d_4	0.00031	0.00032	0.978	0.328
d_5	-0.00010	0.00032	-0.311	0.756
d_6	0.00074	0.00032	2.318	0.020**
d_7	-0.00017	0.00032	-0.543	0.587
d_8	0.00056	0.00032	1.750	0.080*
d_9	0.00005	0.00032	0.151	0.880
d_{10}	-0.00008	0.00032	-0.246	0.806
d_{11}	0.00105	0.00032	3.290	0.001***
d_{12}	0.00035	0.00032	1.099	0.272

Note:

1 The average two=hour return is 0.000182.

2. *, **, and *** shown in p-value column denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7 Power ratio analysis results of weekday effect on Bitcoin price return

Weekday	2015	2016	2017	2018	2019	2020	2021
Monday	1.103	0.989	1.054	0.930	1.027	1.051	0.960
Tuesday	0.945	0.970	1.012	1.026	0.969	1.013	0.996
Wednesday	1.060	1.021	1.001	0.968	0.996	1.018	1.037
Thursday	0.966	1.013	1.020	0.981	0.933	0.975	0.986
Friday	1.101	1.015	0.917	1.087	1.111	1.002	1.023
Saturday	0.915	0.994	0.978	0.971	0.984	0.994	0.983
Sunday	0.938	1.007	1.027	1.043	0.990	0.963	1.006

Table 8 Power ratio analysis results of intraday effect on Bitcoin price return

O'clock	2015	2016	2017	2018	2019	2020	2021
0-2	1.002	1.001	1.032	1.006	1.010	1.000	1.001
2-4	1.004	1.003	1.011	0.995	1.009	1.008	1.001
4-6	1.010	1.007	1.000	0.989	0.999	0.996	0.999
6-8	1.004	0.997	1.010	0.985	0.996	0.998	1.000
8-10	1.000	0.994	0.998	1.008	0.989	1.001	1.000
10-12	1.016	1.004	1.022	0.990	0.997	0.994	1.000
12-14	1.026	1.007	1.000	0.984	1.003	0.987	1.001
14-16	1.039	1.003	1.001	1.020	1.001	0.994	0.999
16-18	0.979	1.004	0.998	0.992	1.001	0.999	1.000
18-20	1.005	0.997	1.020	0.999	1.012	0.983	1.000
20-22	1.002	1.011	0.996	0.991	1.002	0.982	0.999
22-24	0.994	1.001	1.000	0.997	1.002	1.012	0.999

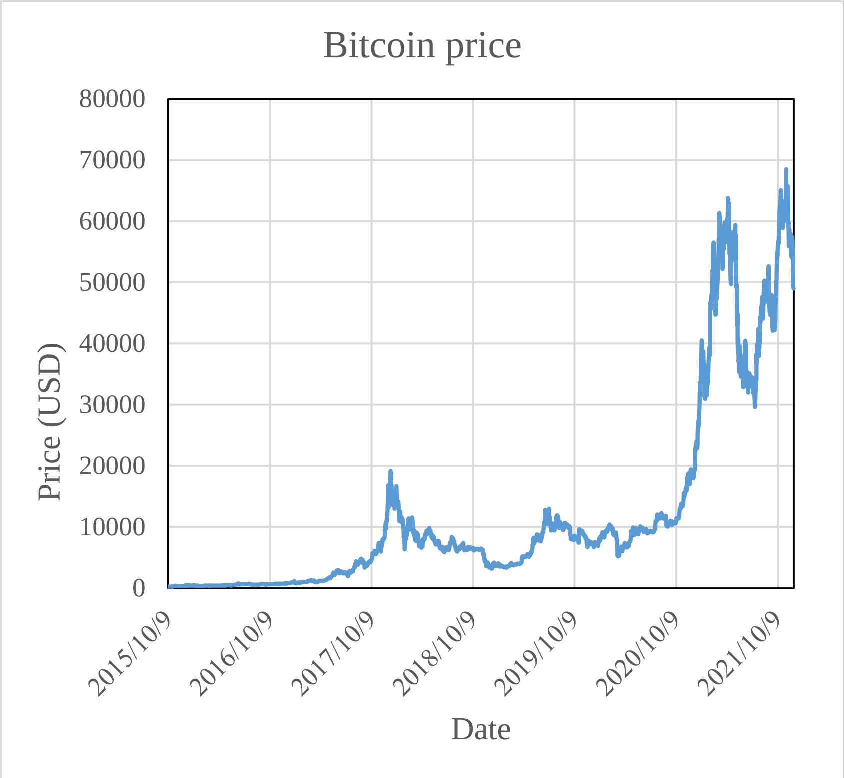

Figure 1 Time series of Bitcoin price between 2015/10/9 and 2021/10/9

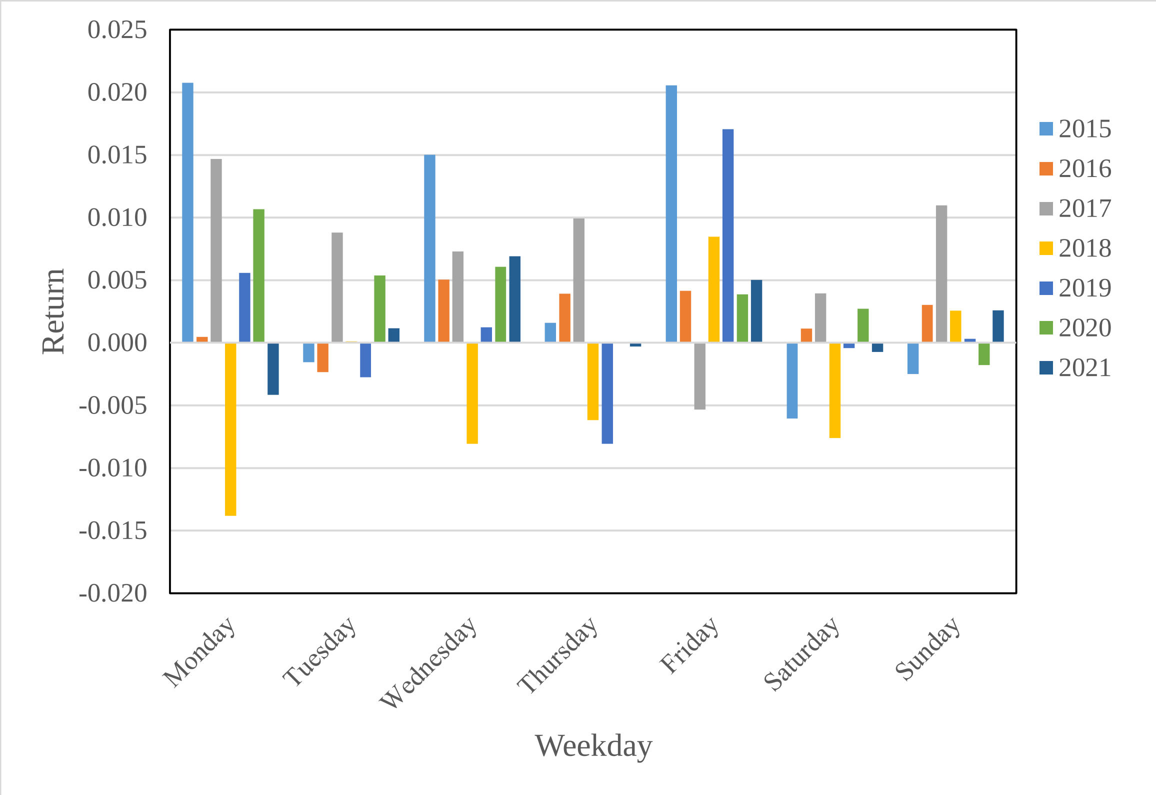

Figure 2 Daily returns of Bitcoin price (Dataset_1)

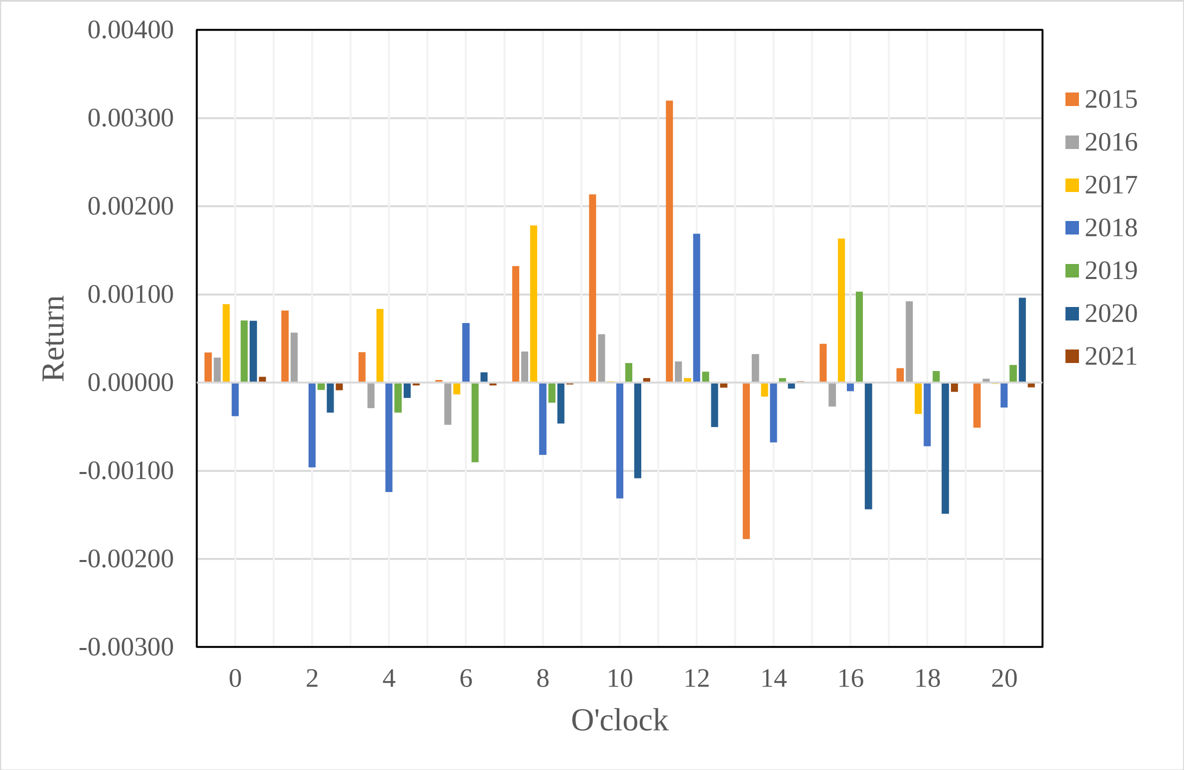

Figure 3 Intraday returns of Bitcoin price (Dataset_2)

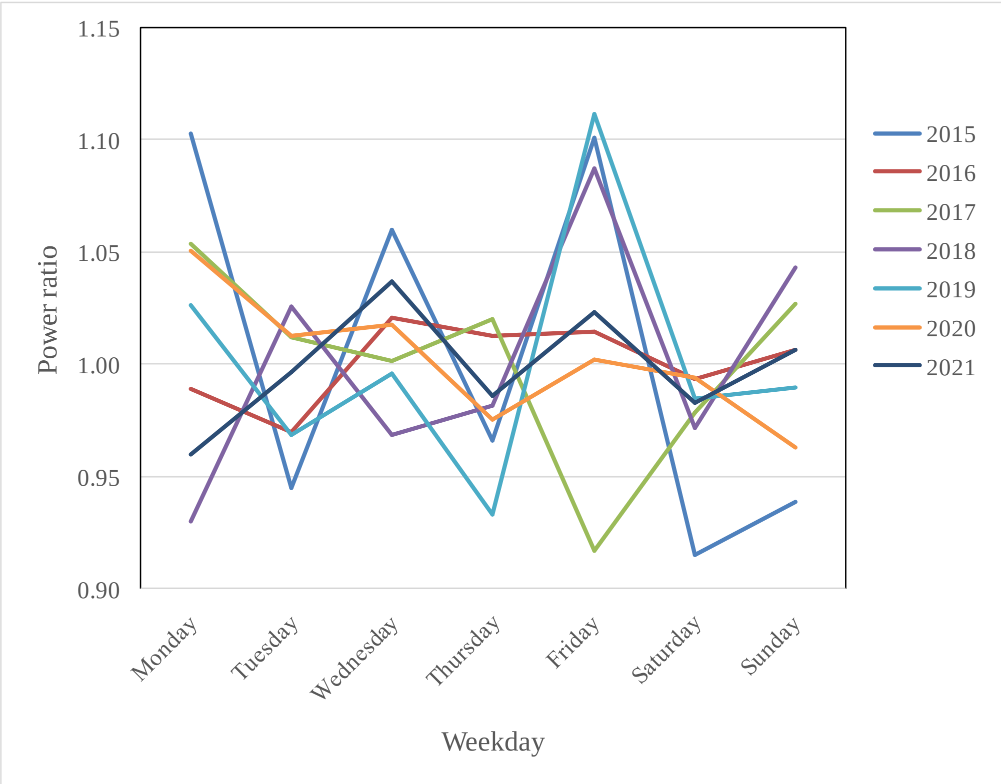

Figure 4 Weekday power ratios of Bitcoin price return over 2015 to 2021

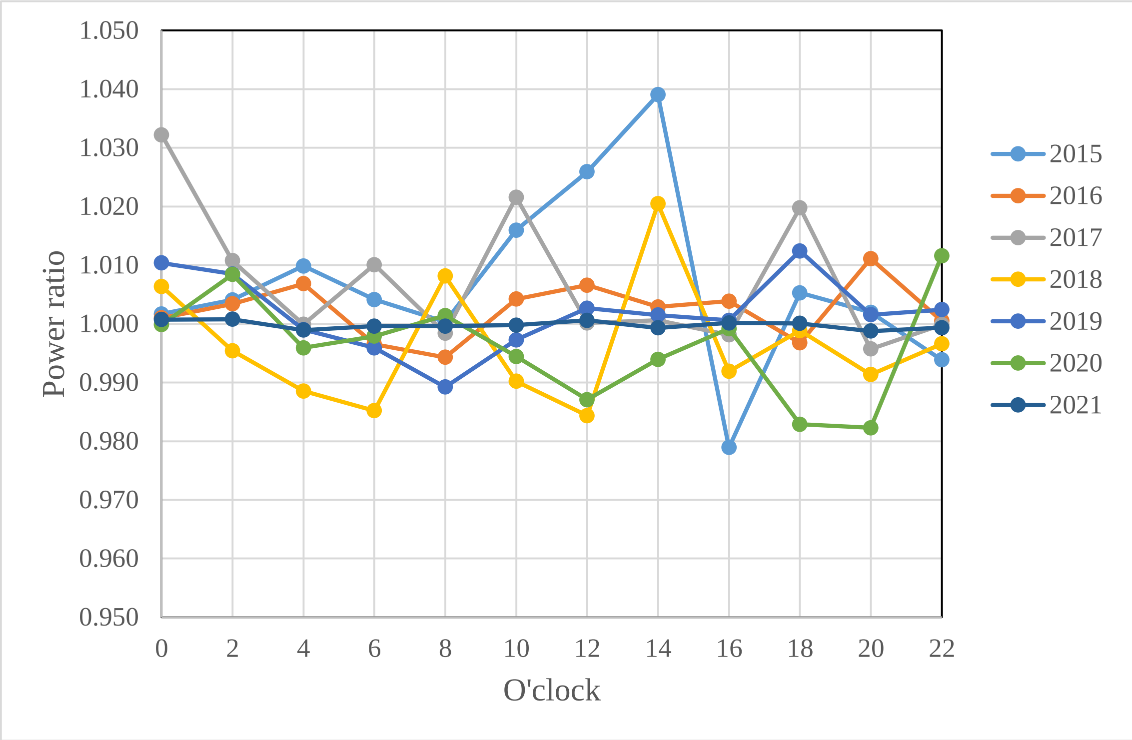

Figure 5 Intraday power ratios of Bitcoin price return over 2015 to 2021