Southeast Asian Journal of Economics 9(1), April 2021: 1-26
Received: 19 October 2020
Revised: 15 November 2020
Accepted: 14 December 2020

Calendar Effects on Cryptocurrencies: Not so Straightforward

Konpanas Dumrongwong
Department of Finance, Thammasat Business School, Thammasat University, Bangkok 10200, Thailand
Corresponding author: konpanas@tbs.tu.ac.th

Abstract

This research investigates the existence of calendar anomalies on cryptocurrency markets with respect to calendar anomalies during 2010–2020. To account for potential clustering and non-normality in cryptocurrency returns, generalized autoregressive conditional heteroscedasticity (GARCH) regression with dummy variables is utilized. Two exploitable trading strategies are identified. First, it was found that Ethereum investors can generate abnormal returns in January. Second, abnormal profits can be generated from short-selling Litecoin on Mondays. Neither calendar anomaly is unique to the global COVID-19 pandemic. These results are robust after the considerations of volatility clustering, non-normality, and changes in methodologies to detect the anomalies, and are consistent with the literature in stock markets.

Keywords: cryptocurrency; calendar anomalies; seasonalities; market efficiency; GARCH

1. Introduction

The exponential growth of cryptocurrencies is a phenomenon that has attracted considerable attention from investors, central banks, and governments in recent years. Compared to traditional asset classes such as equity or debt, cryptocurrencies are relatively young (the first cryptocurrency, BitCoin, was invented in 2009, but active trading started in 2013), and therefore there is little literature documenting them. Among existing literature, many researchers have documented the existence of market anomalies in the cryptocurrency market. These market anomalies make it questionable whether aspects of traditional market theory, such as the efficient market hypothesis (EMH), can be used to correctly explain the abnormal behaviors of cryptocurrency markets. This theoretical background led to the key issue discussed in the present empirical research about calendar effects on cryptocurrencies, which would be inconsistent with the efficient market hypothesis (EMH), according to which prices and returns should be unpredictable (see Fama (1970) for the theoretical underpinnings).

Unlike most prior literature, which either focuses on Bitcoin or on a single calendar effect, this study carries out a more comprehensive analysis by considering five main cryptocurrencies and applying three different calendar effect tests over the period of 2010–2020. To the best of the author's knowledge, this study is the first to provide discussions about the COVID-19 pandemic in the context of calendar effects and is also the first to utilize generalized autoregressive conditional heteroscedasticity (GARCH) with quasi-maximum likelihood (QML) to investigate major cryptocurrencies other than Bitcoin. In particular, it was found that the calendar effects identified in the present research are not unique to the recent COVID-19 pandemic event and are consistent with results of cryptocurrency ranking research. In addition to academics, the contribution from this research is clear for market participants who could generate abnormal profits, as well as for market regulators to design the necessary regulations to prevent such arbitrage opportunities in the cryptocurrency markets.

The remainder of the paper is structured as follows. The following section presents a brief review of the literature regarding calendar anomalies. The next sections describe the research data, hypotheses, and methodology. The empirical results and robustness checks are then presented and discussed. Finally, the conclusions are given, along with suggestions for future research.

2. Literature Review

The present research on cryptocurrency is motivated by the number of stock market anomalies that have been identified in the stock market literature to have significant market-predictive ability, which is inconsistent with the EMH. One strand of these anomalies finds that stock returns are systematically lower or higher depending on the day of the week, the day of the month, or the month of the year. The anomalies are commonly known as calendar effects (also referred to as seasonalities or calendar anomalies). These include the well-known Monday effect, which scholars document as stock returns on Mondays being different from the other day days of the week (Connolly, 1989; Cross, 1973; French, 1980; Maberly, 1995; among others); the January effect, which refers to as an anomaly of stock returns in January being different compared to the returns during other months of the year (Gultekin & Gultekin, 1983; Keim, 1987; Rozeff & Kinney, 1976; Sun & Tong, 2010; among others); and the Halloween effect, which refers to an equity return anomaly in which the months of November through April provide higher returns than the remaining months of the year (see Andrade, Chhaochharia, & Fuerst., 2013; Bouman & Jacobsen, 2002; Haggard & Witte, 2010; Lucey & Zhao, 2008; among others). According to the EMH, these calendar effects should not exist because the security price should already reflect past information. These are the anomalies studied in this research.

Although the calendar effects are well-documented in stock markets, much less is documented about the calendar effects in cryptocurrency markets, especially among cryptocurrencies other than Bitcoin. Overall, prior literature suggests that Bitcoins are much more volatile than other securities (Carrick, 2016; Cheung, Roca, & Su., 2015; Dwyer, 2015), have persistence in their return and volatility series (there is a correlation between their past and future values) (Caporale, Gil-Alana, & Plastun, 2018; Urquhart, 2016), have correlations with other cryptocurrencies (Ji, Bouri, & Roubaud*,* 2019; Yi, Xu, & Wang, 2018), or have correlations with other asset classes (Dyhrberg, 2016; Okorie & Lin, 2020). These market anomalies make it questionable whether aspects of traditional market theory, such as the efficient market hypothesis (EMH), can be used to correctly explain the abnormal behaviors of cryptocurrency markets.

In particular, some researchers have found seasonalities in the cryptocurrency market, which potentially allow traders to earn abnormal profits and/or benefit from market timing. For example, Aharon and Qadan (2019) studied Bitcoin returns and volatility during 2010–2017 and found that Mondays are generally associated with higher returns and volatility compared to the other day of the week. Caporale and Plastun (2019), in their study of four cryptocurrencies during 2013–2017 using a different set of methods, document positive abnormal returns on Mondays in Bitcoin. Finally, Kaiser (2019) studied 10 cryptocurrencies during 2013–2018 and documented that trading volume, volatility, and spreads are on average lower in January, on weekends, and during the summer months. These findings are consistent with prior stock market literature, which documents the existent of the January effect, Monday effect, and Halloween effect in many stock markets.

Other scholars argue against the existence of such anomalies in cryptocurrency. For example, Nadarajah and Chu (2017) argue that the Bitcoin market is at least weakly efficient after a simple power transformation of the Bitcoin return (and thus no calendar anomalies are possible). Baur et al. (2019), in their study of Bitcoin prices and volume during 2011–2017, argue that higher returns observed on Mondays are due to returns in particular years rather than being consistently high relative to the other days of the week. However, they also document evidence for persistent variations in trading volume over each day and each week with lower trading volumes at non-peak hours and on weekends. Caporale, Plastun, and Oliinyk (2019) document that no seasonal patterns are detected in their study of daily Bitcoin returns during 2013–2018. Finally, Kinateder and Papavassiliou (2019) document that no Halloween effect, day-of-the-week effect, or month-of-the-year effects were found in their study of Bitcoin returns and volatility during 2013–2019.

To summarize, prior literature about calendar effects in cryptocurrencies exists, but there seems to be disagreement among scholars about the existence of such effects. Some researchers have documented that seasonality is not present in cryptocurrency (Baur et al., 2019; Caporale et al., 2019; Kinateder & Papavassiliou, 2019), noting that cryptocurrency markets are indeed efficient (Bartos, 2015; Nadarajah & Chu, 2017; Tiwari et al., 2018). Others argue that Bitcoin shows calendar effects (Aharon & Qadan, 2019; Caporale & Plastun, 2019; Kaiser, 2019), noting the lack of government regulations and the potentially inefficient cryptocurrency market (Kristoufek & Vosvrda, 2019; Urquhart, 2016; Urquhart & McGroarty, 2014). Hence, the existence of seasonality in cryptocurrencies warrants an empirical investigation, as well as some theoretical background addressing whether such market anomalies are found.[1] These prior contributions lay a solid foundation for this present research.

To the extent that calendar anomaly studies are theoretically related to efficiency in the cryptocurrency markets, it is worth noting the contributions from prior research in the field. Several studies examine the cryptocurrency market by considering efficiency. For example, Urquhart (2016) investigates the efficiency of the Bitcoin market between 2010 and 2016 and found that the market is mostly inefficient but reports that it can be seen as efficient in the later periods. Nadarajah and Chu (2017) oppose these ideas, using different methodologies, and argue that the market is in fact efficient. Alvarez-Ramirez,

[1] Since EMH cannot be used to explain market anomalies such as calendar effects, some researchers rely on alternative market hypotheses to explain unusual market behaviors. Notable among the literature is a study by Lo (2004), who proposed the Adaptive Market Hypothesis (AMH). A few studies support AMH in the cryptocurrency market (for example, Chu, Zhang, & Chan, 2019; Khuntia & Pattanayak, 2018) and hence connect it to cryptocurrency.

Rodriguez, and Ibarra-Valdez (2018) examine the cryptocurrency trading data at high frequencies and find that the market can be characterized by switching periods of efficiency and inefficiency. Recent literature documents that the efficiency of each cryptocurrency is different (for example, Kristoufek & Vosvrda, 2019; Tran & Leirvik, 2020).

Notable among the literature is the study by Kristoufek and Vosvrda (2019), who document that the efficiency of each cryptocurrency is different and Ethereum and Litecoin are the least efficient among the top cryptocurrencies.[2] Based on this prior research, it is hypothesized that these two cryptocurrencies will be less efficient compared to other cryptocurrencies. Thus, seasonal anomalies should be present in their return series. Accordingly, the null hypotheses addressed in this study are stated as,

H1: There is a seasonal effect in Ethereum returns

and

H2: There is a seasonal effect in Litecoin returns.

A recent study by Kinateder and Papavassiliou (2019) documents that the returns of Bitcoin are severely leptokurtic. They proposed the use of GARCH with a QML estimator to account for serial correlation and high kurtosis associated with cryptocurrency data. However, only Bitcoin was analyzed in their study. This present research extends Kinateder and Papavassiliou (2019) and contributes to the knowledge in the field in three ways. First, to the best knowledge of the author, no other cryptocurrencies other than Bitcoin have been investigated using a robust method for cryptocurrency data (for example, Kaiser (2019) utilizes t-tests, which is a questionable approach for severely leptokurtic and potentially serially correlated cryptocurrency data, while Kinateder and Papavassiliou (2019) examine only Bitcoin). Second, it

[2] Kristoufek and Vosvrda (2019) arrive with their conclusion based on efficiency index, factual dimension, long-range dependence and entropy, which are a statistical approach. The true reason behind the phenomena is a matter of ongoing debates which lies outside the scope of this empirical study.

was found that after skewness is accounted for, the empirical results presented are consistent with recent evidence from cryptocurrency efficiency ranking research, which posits that Ethereum and Litecoin are the least efficient among the top cryptocurrencies. Thus, the results presented in this present research provide starting contexts for possible future research about the reconciliation of the two research areas. Third, this study is among the first to include observations during the COVID-19 pandemic, and it is found that calendar anomalies in cryptocurrencies are not unique to the recent global event. Unlike most prior literature, which either focuses on Bitcoin (Baur et al., 2019; Kurihara & Fukushima, 2017; Urquhart, 2016) or on a single calendar effect (Aharon & Qadan, 2019; Caporale & Plastun, 2019; Ma & Tanizaki, 2019), this study carries out a more comprehensive analysis by considering five main cryptocurrencies and applying three different calendar effect tests over the period 2010–2020.

3. Data

As noted by Kaiser (2019), sufficient market capitalization and liquidity are important criteria to be considered by investors and to qualify for the construction of a crypto fund under the regulation of the alternative investment fund managers (AIFM) directive by market regulators. The analysis, therefore, focusses on the five largest cryptocurrencies by market capitalization as of December 2019 (Bitcoin, Ethereum, Ripple, Tether, and Litecoin) with a sufficiently long historical price series to estimate seasonality patterns. The data source is Coinmarketcap.com. The application of daily returns, the data source, and the focus on the largest cryptocurrencies is in line with prior research (Kaiser, 2019; Nadarajah & Chu, 2017; Urquhart, 2016) and therefore provides a solid basis for comparison. Table 1 reports descriptive statistics of the data.

Table 1. Descriptive statistics.

	Mean	SD	Skew	Kurt	ADF	Market Capitalization ($billion)	Obs. Start	#Obs
Bitcoin (BTC)	0.03	6.00	0.22	23.87	−22.18 ***	130.45	Jul 2010	3536
Ethereum (ETH)	0.23	7.19	−3.45	71.11	−44.09 ***	14.14	Aug 2015	1690
Ripple (XRP)	0.14	7.24	1.97	32.71	−49.55 ***	8.36	Aug 2013	2423
Tether (USDT)	0.01	2.07	−12.37	19.90	−36.68 ***	4.11	Feb 2015	1845
Litecoin (LTC)	0.01	6.49	1.51	27.98	−49.55 ***	2.64	Apr 2013	2520

Note: This table presents the descriptive statistics for the five cryptocurrencies considered in this study. The coins considered are Bitcoin (BTC), Ethereum (ETC), Ripple (XRP), Tether (USDT) and Litecoin (LTC) during July 2010–March 2020. *** represent statistical significance at the 1% level. The coins were selected on the basis of being the largest by market capitalization as of December 2019, excluding recent Bitcoin spinoffs (Bitcoin cash and Bitcoin SV), and collected from www.coinmarketcap.com.

Source: Authors' calculations.

Table 1 shows that the returns from the five major cryptocurrencies exhibit severe kurtosis (kurtosis of considered coins range from 23.87 to 71.11). Therefore, this research utilizes generalized autoregressive conditional heteroscedasticity (GARCH) with a quasi-maximum likelihood (QML) estimator to account for the high kurtosis present in the data (discussion in the next section). The results from the Augmented Dickey–Fuller (ADF) suggest that all considered cryptocurrencies do not contain a unit root. Finally, the observation period spans from 2010 to 2020; however, the cryptocurrency's market capitalization is ranked based on the market data at the end of 2019 instead of the most recent observations from 2020 in order to avoid potential market bias from the global COVID-19 pandemic.

4. Methodology and Hypotheses

Urquhart and McGroarty (2014) and Kinateder and Papavassiliou (2019) argue that the method used to investigate calendar effects in cryptocurrency returns and volatilities should be the generalized autoregressive conditional heteroscedasticity (GARCH) model with dummy variables because the model is capable of capturing volatility clustering and non-normality in cryptocurrency price series. This is particularly important when dealing with calendar effects, as these effects are sensitive to model specification. Ignoring the stylized facts can produce bias (see, for example, Auer & Rottman, 2014; Bollerslev, 1986; Connolly, 1989; for discussion). In addition, it is a consistent method for investigating not only how seasonality affects returns, but also how they impact volatility.

Since Engle (2001) shows that GARCH(1,1) is the simplest and most robust of the family of volatility models and is the most widely used in the literature, this research utilizes GARCH(1,1) dummy regression following prior research. In this regard, Auer and Rottman (2014) recommend using Bollerslev and Wooldridge's (1992) quasi-maximum likelihood (QML) procedure for high-kurtosis data in order to correct the standard errors. As shown in Table 1, Bitcoin returns (and those of all other coins under consideration) are characterized by excess kurtosis ($k = 23.87$) being far away from normal kurtosis ($k = 3$); therefore, the QML estimation is used in the analysis throughout.

Since the EMH predicts that returns should be unpredictable, the null hypotheses for all tests conducted (except Ethereum and Litecoin) are that there will be no excess returns on any particular day or in any particular month. The null hypothesis is tested against an alternative hypothesis that there are excess returns on Mondays (the Monday effect), in January (the January effect) or in the summer months (the Halloween effect). Statistically, this involves testing whether the coefficient of the dummy variable representing the calendar effect is zero against an alternative hypothesis that the coefficient of the dummy variable representing the calendar effect in question is statistically different from zero in Equation (1).

Following Caporale and Plastun's (2019) methodology, the general form of the regression equation used in this study is stated as,

$$Y_t = a_0 + a_1 D_{1t} + a_2 D_{2t} + \ldots + a_n D_{nt} + \varepsilon_t \tag{1}$$

where:

Y_t = return in period t;

a_n= mean return (on the nth day of the week or on the nth month of the year;

ε_t = error term for period *t*; and

D_{nt} = a dummy variable.

The dummy variable varies according to the calendar effect being tested (January effect, Monday effect, and Halloween effect). They take the values as follows.

Monday dummy: The dummy variable D_{nt} takes on the value of 1 on Mondays and 0 otherwise.

January dummy: The dummy variable D_{nt} takes on the value of 1 in January and 0 otherwise.

Halloween dummy: The dummy variable D_{nt} takes on the value of 1 in the months within the Halloween period from November to April and 0 otherwise.

The Halloween period used in this study is in line with prior literature, corresponding to the financial-world adage "sell in May and go away." The cryptocurrency returns are computed as:

$$R_i = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{2}$$

where $P_{i,t}$ is the close price of coin *i* on the *t*th day.

As trading volume indicates the level of activity on the markets, as well as being a proxy for market liquidity, it is included in the analysis. This variable is expressed in natural logarithm. For robustness, this study also considers Amihud's (2002) illiquidity measure (ILLIQ) instead of trading volume. The results show no material differences from the main analysis.

Since an investor chooses to invest in cryptocurrency *i* based on their ex-ante expectation of risks rather than their ex-post realization of risk at time *t*, a volatility estimator is utilized. The daily volatility estimator ($Vol_{i,t}$) is estimated following Rogers and Satchell's (1991) methodology on the basis of high, low, and closing prices at time *t*. Accordingly, the volatility is estimated as follows:

$$Vol_{i,t} = \sqrt{\ln\left(\frac{H_{i,t}}{L_{i,t}}\right) * \ln\left(\frac{H_{i,t}}{O_{i,t}}\right) + \ln\left(\frac{L_{i,t}}{C_{i,t}}\right) * \ln\left(\frac{L_{i,t}}{O_{i,t}}\right)} \qquad (3)$$

where $H_{i,t}$ is the highest price, $L_{i,t}$ the lowest price, $O_{i,t}$ the opening price, and $C_{i,t}$ the closing price of coin *i* at day *t*. For robustness, this study also considers the squared daily return as an estimator for volatility. The results show no material differences from the main analysis.

5. Results and Discussion

5.1. January Effect

Since the 1970s, when Rozeff and Kinney (1976) documented higher average stock returns in January than the rest of the year, scholars have been proposing potential reasons behind the phenomenon. The literature generally links the stock market anomaly with tax-loss selling, window-dressing, omitted risk-factors, bid-ask bounce, information-release, or a combination of all (see, for example, Ritter, 1988). Although many of the aforementioned reasons appear to be unlikely in the case of cryptocurrency, tax-loss selling (Chang & Pinegar, 1986; Starks, Yong, & Zheng, 2006; among others) appears to be reasonable because the United States' Internal Revenue Service (IRS) and similar authorities in many countries treat cryptocurrency as a property for tax purposes. In addition, the wash sale regulations do not apply to cryptocurrency because it is classified as property.[3] This makes tax-loss selling even more likely to be present in cryptocurrency and is also consistent with the observed empirical results of higher trading volume in January. Table 2 reports the results for the January effect.

Table 2. January effect.

	Return		Volume		Volatility	
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
BTC	−0.14	−0.32	0.13	2.31 **	−0.13	0.47
ETH	1.12	2.20 **	0.15	3.57 ***	0.30	0.65
XRP	−0.28	−0.66	0.74	9.34 ***	1.37	3.31 ***
USDT	−0.02	−0.33	0.16	5.59 ***	−0.08	−0.01
LTC	−0.01	−0.03	0.41	5.89 ***	0.92	1.57

Note: This table reports the results for the January effect across the returns of each coin (Return), the trading volume of each coin (Volume) and the volatility estimator of each coin (Volatility). t-statistics reported are based on Bollerslev and Wooldridge's (1992) robust estimator. ***,** represent statistical significance at the 1% and 5% levels, respectively.

Source: Authors' calculations.

Two main points are observed from Table 2. First, the returns of Ethereum in January are on average positive, implying a January effect is present in Ethereum returns. The result confirms *H1*, and is also consistent with Kristoufek and Vosvrda's (2019) research in cryptocurrency ranking, which documents that Ethereum (as well as Litecoin) is the least efficient among the top cryptocurrencies. Second, the trading volume of all coins under consideration is found to be higher in January. This result is consistent with the tax-loss selling hypothesis documented in prior literature, which predicts that trading volume should be higher in January because investors buy back assets at the beginning of the year after a tax-loss selling at the previous year's end (see, for example, Chang & Pinegar, 1986; Chen, Estes, & Ngo, 2011; Starks et al., 2006). Finally, no consistent inference can be drawn from the

[3] A wash sale is a sale of a security (stocks, bonds, options) at a loss and repurchase of the same or substantially identical security shortly before or after. Losses from such sales are not tax-deductible in most cases under the Internal Revenue Code in the United States. (See Section 1091 of the US Internal Revenue Code, "Loss from wash sales of stock or Securities" for more details.)

volatility series since only one out of five coins under consideration shows a significant relationship.

5.2. Monday Effect

The Monday effect refers to the tendency of returns on Monday to be lower compared to the rest of the week. The weekend effect, often used interchangeably with the Monday effect in the stock market literature, is observed separately in this study on the basis of continuous trading over the weekends in cryptocurrency markets. This allows the present study to investigate if trading patterns on Saturday and Sunday deviate from working days and thereby deviate from the classical specification of the weekend effect. Table 3 reports the results.

Table 3. Monday effect.

	Return		Volume		Volatility	
Panel A: Monday Effect	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
BTC	0.30	1.15	0.19	3.84 ***	0.28	1.52
ETH	−0.28	−0.57	0.09	2.16 **	−0.17	−0.43
XRP	−0.12	−0.28	0.33	4.86 ***	0.46	1.33
USDT	−0.00	0.87	0.14	5.10 **	−0.75	−0.01
LTC	−0.82	−2.21 **	0.12	1.87 *	0.28	0.45
Panel B: Weekend Effect						
BTC	0.18	0.64	−0.26	−6.26 ***	−0.20	−1.03
ETH	0.45	1.12	−0.14	−4.64 ***	0.00	0.01
XRP	0.49	1.19	−0.49	−7.92 ***	−0.01	−0.22
USDT	−0.01	−0.36	−0.12	−3.94 ***	−0.00	−0.11
LTC	0.71	1.59	−0.20	−3.62 ***	−0.28	−0.80

Note: This table reports the results for the Monday effect across the returns of each coin (Return), the trading volume of each coin (Volume) and the volatility estimator of each coin (Volatility). t-statistics reported are based on Bollerslev and Wooldridge's (1992) robust estimator. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.
Source: Authors' calculations.

The null hypothesis of no Monday effect cannot be rejected for 4 out of 5 considered cryptocurrency returns. However, the coefficient of the Monday dummy was found to be negative and statistically significant at 5%

for Litecoin. This suggests the existence of the Monday effect in Litecoin and is consistent with the stock market literature (Abraham & Ikenberry, 1994; French, 1980; Ülkü & Rogers, 2018; among others). The result confirms *H2* and once again confirms Kristoufek and Vosvrda's (2019) posit that Ethereum and Litecoin are the least efficient among the top cryptocurrencies. All coins under consideration show higher trading volume on Mondays, which is also in line with the stock market literature.

No evidence with respect to a difference in returns and volatility between weekend and non-weekend days were found. However, all considered coins have significantly lower trading volume during weekends. (Panel B: all considered coefficients are negative and statistically significant at 1%.) The result suggests that trading activities, although possible seven days per week, take place primarily during working days and are in line with Buar et al. (2019) using a different approach.

5.3 Halloween Effect

The Halloween effect (also known as the "Sell in May" effect) refers to the market anomaly in which returns from November to April are higher than for the other half of the year. The first empirical evidence was documented by Bouman and Jacobsen (2002), who detected the Halloween effect in 36 out of 37 considered equity markets. Most literature in the field posits that the Halloween effect is present in stock markets, and the results are robust even after outlier observations, transaction costs, compensation for risks, or seasonality in news are taken into account (for example, Andrade et al., 2013; Bouman & Jacobsen, 2002; Haggard & Witte, 2010; Lucey & Zhao, 2008). Since Haggard and Witte (2010) argue that the Halloween effect is not driven by the January effect, it is therefore preferable to include the anomaly in the analysis. Table 4 reports the results for the Halloween effect.

Table 4. Halloween effect.

	Return		Volume		Volatility	
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
BTC	0.04	0.31	0.29	15.38 ***	0.13	1.21
ETH	0.32	1.36	0.45	29.33 ***	−0.24	−1.15
XRP	0.00	0.03	0.61	21.07 ***	0.09	0.49
USDT	−0.02	−0.68	2.90	68.81 ***	−0.01	−0.09
LTC	0.10	−0.59	0.07	0.30	−0.34	−1.09

Note: This table reports the results for the Halloween effect across the returns of each coin (Return), the trading volume of each coin (Volume) and the volatility estimator of each coin (Volatility). t-statistics reported are based on Bollerslev and Wooldridge's (1992) robust estimator. *** represent statistical significance at the 1% level.

Source: Authors' calculations.

Contrary to the results from the equity market, it was found that the return and volatility of cryptocurrency in non-summer months are not statistically different from the return from the other half of the year, for all considered cryptocurrencies. Most considered coins show higher trading volume in non-summer months, in line with the stock market literature (Bouman & Jacobsen, 2002; Hong & Yu, 2009). The results reject the existence of the Halloween effect in cryptocurrency. No evidence of exploitable trading strategies, based on the Halloween effect, was found in all considered coins.

6. Robustness Checks

6.1 COVID-19 Pandemic

The recent COVID-19 global pandemic offers a unique opportunity to investigate if the calendar anomalies are unique to the recent global event. In 2020, the global spread of the COVID-19 virus has affected the prices of financial assets worldwide. One of the first public reports about the spread of the virus is found in a *Wall Street Journal* publication on 8 January 2019 that reported the outbreak of the COVID-19 virus in China (named "mysterious illness" at the time). Since then, the outbreak became a global pandemic, and securities prices have been significantly affected. Considering the timing of the media report on the matter, this research assumes that the information regarding the spread of the COVID-19 virus became public information sometime at the beginning of 2020 and considers the year of 2020 to be the year under the influence of the COVID-19 pandemic.

To the extent that the recent pandemic may bias the cryptocurrency market data in the year 2020, this paper reinvestigates the subsample of pre-COVID-19 years (2010–2019) and examines if the trend differs from the full sample. Table 5 reports the results from the pre-COVID-19 period (2010–2019).

Overall, it was found that the calendar anomalies during the pre-COVID-19 period are not materially different from the trend observed from the full sample, including observations from the COVID-19 year (2020). The results confirm the initial findings from the full sample that Ethereum generates abnormal returns in January and that abnormal profits can be generated from short-selling Litecoin on Mondays. This suggests that the calendar effects identified in the present research are not unique to the recent COVID-19 pandemic event. In short, the results suggest no evidence that calendar effects are biased by the COVID-19 pandemic.

Table 5. January effect, Monday effect, and Halloween effect (Pre-COVID-19: 2010–2019).

	Return		Volume		Volatility	
Panel A: January Effect	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
BTC	0.00	0.04	0.13	2.31 **	−0.2	−0.75
ETH	0.10	1.83 *	0.20	3.97 ***	0.22	0.45
XRP	−0.43	−0.91	0.71	8.83 ***	1.12	2.65 ***
USDT	−0.03	−0.36	0.15	5.15 ***	−0.04	−1.78 *
LTC	−0.48	−0.76	0.38	5.39 ***	0.28	0.45
Panel B: Monday effect						
BTC	0.25	1.02	0.19	3.84 ***	0.29	1.51
ETH	−0.20	−0.47	0.09	2.08 **	−0.14	−0.33
XRP	−0.10	−0.24	0.33	4.89 ***	0.56	1.55
USDT	−0.01	−1.10	0.06	1.27	−0.72	−0.01
LTC	−0.80	−2.18 **	0.12	1.86 *	0.26	0.79
Panel C: Weekend effect						
BTC	−0.02	−0.11	−0.26	−6.22 ***	−0.41	−1.531
ETH	0.57	1.14	−0.11	−3.65 ***	0.14	0.36
XRP	0.41	1.08	−0.49	−7.97 ***	−0.26	−0.77
USDT	−0.01	−0.34	−0.12	−4.00 ***	−0.00	−0.08
LTC	0.61	1.44	−0.20	−3.59 ***	−0.38	−1.16
Panel D: Halloween effect						
BTC	0.02	0.31	0.25	13.38 ***	0.13	1.21
ETH	−0.04	−0.36	0.52	30.00 ***	0.18	0.77
XRP	−0.32	0.03	0.66	22.90 ***	0.09	0.49
USDT	−0.01	1.43	0.22	13.69 ***	−0.01	−0.09
LTC	−0.12	1.18	0.05	1.99 **	−0.28	0.61

Note: This table reports the results for the calendar effect across the returns of each coin (Return), the trading volume of each coin (Volume) and the volatility estimator of each coin (Volatility) in the years 2010–2019. t-statistics reported are based on Bollerslev and Wooldridge's (1992) robust estimator. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Authors' calculations.

6.2 Other Robusness Checks

For robustness, this study also utilized the non-parametric Kruskal–Wallis test (Kruskal & Wallis, 1952) with respect to calendar effects on cryptocurrency returns in order to account for non-normality, but found no material differences. In addition, to account for potential asymmetries, tests with respect to calendar effects on cryptocurrency returns based on a Glosten, Jagannathan, and Runkle's (1993) generalized least squares approach (GLS-GARCH(1,1)) were also conducted, but no material differences were detected. Consistently, traditional OLS regression yields directionally identical results with lower significance.

This research also tests the Monday effect using a 5-days-a-week system (excluding the weekend) to be consistent with the literature on stock markets, but observes no material differences. The test for the turn-of-the-month effect (Ariel, 1987; Atanasova & Hudson, 2010; Lakonishok & Smidt, 1988; McConnell & Xu, 2008; among others) was also conducted, but no statistically significant evidence was found across the set of the considered cryptocurrencies. In addition, this study also tests the Mark twain effect (the phenomenon of returns in October being lower than in other months), the Santa clause effect (the tendency for the returns to rally over the last weeks of December into the New Year), and the Lunar effect (the tendency for the returns to follow lunar cycles), but observes no evidence of such effects in all considered coins. Finally, this research investigates the January barometer (the phenomenon of returns in January can predict those of the rest of the year) as a robustness check. No evidence of the phenomenon was found. However, since there is less available cryptocurrency data than stock market data, it is arguable that the data may not be sufficient to provide reliable statistical inference. Accordingly, it is recognized as one of the limitations of this paper and identified as a promising area for future research, should the data become available.

7. Conclusions

This study examines calendar anomalies in daily cryptocurrency returns, trading volume, and volatility in multiple cryptocurrencies. As calendar effects are sensitive to model specifications, the present research uses a robust method and estimator that accounts for the stylized facts of cryptocurrency returns. Overall, the results differ from those documented in the stock market. In general, no consistent evidence of a Monday effect, January effect, or Halloween effect in cryptocurrency returns was found (i.e., investors cannot earn abnormal profits on Mondays, in January, or in non-summer months)

As the existence of calendar anomalies is not consistent with the efficient market hypothesis (EMH), the findings from this research validate the view that cryptocurrency returns are mostly weak-form efficient with respect to calendar anomalies, which is in line with the findings of prior literature (Baur et al., 2019; Kinateder & Papavassiliou, 2019; Nadarajah & Chu, 2017). The absence of significant calendar effects in most cryptocurrencies under consideration indicates that there are generally no seasonal return patterns that could be exploited by arbitragers to generate abnormal profits.

However, two major exceptions were found in this study. First, it was found that Ethereum investors can generate abnormal returns in January. Second, abnormal profits can be generated from short-selling Litecoin on Mondays. These results are robust after the considerations of volatility-clustering, non-normality, and changes in methodologies to detect the anomalies. Although the anomalies are at odds with the rest of the conducted tests, it is consistent with the hypothesis that each cryptocurrency has a different level of efficiency. In particular, the results are consistent with Kristoufek and Vosvrda's (2019) who posit that Ethereum and Litecoin are the least efficient cryptocurrencies. Thus, future research about cryptocurrency efficiency ranking as well as the potential reasons behind the phenomena is highly encouraged. Finally, it was found that the results from the full sample (including observations during the COVID-19 pandemic) are not materially different from results obtained from pre-COVID-19, suggesting that the identified calendar anomalies are not unique to the recent COVID-19 global pandemic.

In summary, this study contributes to the literature on cryptocurrency market efficiency and seasonality. It was found that most considered coin returns are in line with EMH's prediction. However, two major exceptions were found, both of which are not unique to COVID-19 pandemic event. The results are supportive of the existence of calendar anomalies in the cryptocurrency market (Aharon & Qadan, 2019; Caporale & Plastun, 2019; among others), as well as consistent with recent evidence from cryptocurrency ranking research (Kristoufek & Vosvrda, 2019). Besides academics, the implications of this study may be beneficial for Ethereum/Litecoin investors to improve their portfolio performance. Ultimately, the practical implications also extend to market regulators in order to design necessary regulations to promote fair trade and prevent arbitrage in the fast-growing cryptocurrency markets.

References

Abraham, A., & Ikenberry, D. (1994). The individual investor and the weekend effect. *Journal of Financial and Quantitative Analysis, 29*, 263-277.

Aharon, D. Y., & Qadan, M. (2019). Bitcoin and the day-of-the-week effect. *Finance Research Letters, 31,* 415-424.

Alvarez-Ramirez, J., Rodriguez, E., & Ibarra-Valdez, C. (2018). Long-range correlations and asymmetry in the Bitcoin market. *Physica A: Statistical Mechanics and its Applications, 492*, 948-955.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Market*s, *5*, 31-56.

Andrade, S. C., Chhaochharia, V., & Fuerst, M. E. (2013). Sell in May and go away. Just will not go away. *Financial Analysts Journal, 69*, 94-105.

Ariel, R. A. (1987). A monthly effect in stock returns. *Journal of Financial Economics, 18*, 116-174.

Atanasova, C. V., & Hudson, R. S. (2010). Technical trading rules and calendar anomalies—Are they the same phenomena? *Economics Letters, 106*, 128-130.

Auer, B. R., & Rottman, H. (2014). Is there a Friday the 13th effect in emerging Asian stock markets? *Journal of Behavioural and Experimental Finance, 1*, 17-26.

Bartos, J. (2015). Does Bitcoin follow the hypothesis of efficient market? *International Journal of Economic Sciences, 4*, 10-23.

Baur, D. G., Cahill, D., Godfrey, K., & Liu, Z. (2019). Bitcoin time-of-day, day-of-week and month-of-year effects in returns and trading volume. *Finance Research Letters, 31*, 78-92.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31,* 307-327.

Bollerslev, T., & Wooldridge, J. (1992). Quasi maximum likelihood estimation and inference in dynamic models with time varying covariances. *Econometric Reviews*, *11*, 143-172.

Bouman, S., & Jacobsen, B. (2002). The Halloween indicator: Sell in May and go away. *The American Economic Review, 92,* 1618-1635.

Caporale, G. M., & Plastun, A. (2019). The day of the week effect in the cryptocurrency market. *Finance Research Letters, 31*, 258-269.

Caporale, G. M., Gil-Alana, L., & Plastun, A. (2018). Persistence in the cryptocurrency market. *Research in International Business and Finance, 46*, 141-148.

Caporale, G. M., Plastun, A., & Oliinyk, V. (2019). Bitcoin fluctuations and the frequency of price overreactions. *Financial Markets and Portfolio Management*, *33,* 109-131.

Carrick, J. (2016). Bitcoin as a complement to emerging market currencies. *Emerging Markets Finance and Trade*, *52*, 2321-2334.

Chang, E. C., & Pinegar, J. M. (1986). Return seasonality and tax-loss selling in the market for long-term government and corporate bonds. *Journal of Financial Economics*, *17*, 391-415.

Chen, H., Estes, J., & Ngo, T. (2011). Tax calendar effects in the municipal bond market: Tax-loss selling and cherry picking by investors and market timing by fund managers. *Financial Review*, *46*, 703-721.

Cheung, A., Roca, E., & Su, J. (2015). Crypto-currency bubbles: An application of the Phillips–Shi–Yu (2013) methodology on Mt. Gox bitcoin prices. *Applied Economics*, *47*, 2348-2358.

Chu, J., Zhang, Y., & Chan, S. (2019). The adaptive market hypothesis in the high frequency cryptocurrency market. *International Review of Financial Analysis*, *64*, 221-231.

Connolly, R. A. (1989). An examination of the robustness of the weekend effect. *Journal of Financial and Quantitative Analysis, 24*, 133-169.

Cross, F. (1973). The behaviour of stock prices on Friday and Monday. *Financial Analysts Journal*, *29,* 67-69.

Dwyer, G. P. (2015). The economics of Bitcoin and similar private digital currencies. *Journal of Financial Stability*, *17*, 81-91.

Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar—A GARTH volatility analysis. *Finance Research Letters*, *16*, 85-92.

Engle, R. (2001). GARCH 101: The use of ARCH/GARCH models in applied econometrics. *Journal of Economic Perspectives*, *15*, 157-168.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance, 25,* 383-417.

French, K. R. (1980). Stock returns and the weekend effect. *Journal of Financial Economics, 8,* 55-69.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance, 48,* 1779-1801.

Gultekin, M. N., & Gultekin, N. B. (1983). Stock market seasonality: International evidence. *Journal of Financial Economics, 12,* 469-481.

Haggard, K. S., & Witte, H. D. (2010). The Halloween effect: Trick or treat? *International Review of Financial Analysis, 19,* 379-387.

Hong, H., & Yu, J. (2009). Gone fishin: Seasonality in trading activity and asset prices. *Journal of Financial Markets, 12,* 672-702.

Ji, Q., Bouri, E., Lau, C. K., & Roubaud, D. (2019). Dynamic connectedness and integration in cryptocurrency markets. *International Review of Financial Analysis, 63,* 257-272.

Kaiser, L. (2019). Seasonality in cryptocurrencies. *Finance Research Letters*, *31*, 232-238.

Keim, D. B. (1987). Daily returns and size- related premiums: One more time. *Journal of Portfolio Management*, *13*, 41-47.

Khuntia, S., & Pattanayak, J. K. (2018). Adaptive market hypothesis and evolving predictability of bitcoin. *Economic Letters*, *167*, 26-28.

Kinateder, H., & Papavassiliou, V. G. (2019). Calendar effects in Bitcoin returns and volatility. *Finance Research Letters*. doi:10.1016/j.frl.2019.101420

Kristoufek, L., & Vosvrda, M. (2019). Cryptocurrencies market efficiency ranking: Not so straightforward. *Physica A: Statistical Mechanics and its Applications*. doi:10.1016/j.physa.2019.04.089

Kruskal, W. H., & Wallis, A. (1952). Use of ranks in one-criterion variance analysis. *Journal of the American Statistical Association, 47*, 583-621.

Kurihara, Y., & Fukushima, A. (2017). The market efficiency of bitcoin:

A weekly anomaly perspective. *Journal of Applied Finance & Banking, 7*, 57-64.

Lakonishok, J., & Smidt, S. (1988). Are seasonal anomalies real? A ninety-year perspective. *Review of Financial Studies, 1*, 403-425.

Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. *Journal of Portfolio Management, 5*, 15-29.

Lucey, B. M., & Zhao, S. (2008). Halloween or January? Yet another puzzle. *International, Review of Financial Analysis, 17*, 1055-1069.

Ma, D., & Tanizaki, H. (2019). The day-of-the-week effect on Bitcoin return and volatility. *Research in International Business and Finance, 49*, 127-136.

Maberly, E. D. (1995). Eureka! Eureka! Discovery of the Monday effect belongs to the ancient scribes. *Financial Analysts Journal, 51*, 10-11.

McConnell, J., & Xu, W. (2008). Equity returns at the turn of the month. *Financial Analysts Journal, 64*, 49-64.

Nadarajah, S., & Chu, J. (2017). On the efficiency of Bitcoin. *Economic Letters, 150*, 6-9.

Okorie, D. I., & Lin, B. (2020). Crude oil price and cryptocurrencies: Evidence of volatility connectedness and hedging strategy. *Energy Economics.* doi:10.1016/j.eneco.2020.104703

Ritter, J. R. (1988). The buying and selling behavior of individual investors at the turn of the year. *Journal of Finance, 43,* 701-717.

Rogers, L. C. G., & Satchell, S. (1991). Estimating variance from high, low and closing prices. *Annals of Applied Probability, 1,* 504-512.

Rozeff, M. S., & Kinney, W. R. (1976). Capital market seasonality: The case of stock returns. *Journal of Financial Economics, 3,* 379-402.

Starks, L. T., Yong, L., & Zheng, L. (2006). Tax-loss selling and the January effect: Evidence from municipal bond closed-end funds. *Journal of Finance, 61,* 3049-3067.

Sun, Q., & Tong, W. H. S. (2010). Risk and the January effect. *Journal of Banking & Finance, 34,* 965-974.

Tiwari, A. K., Jana, R. K., Das, D., & Roubaud, D. (2018). Informational efficiency of Bitcoin-An extension. *Economics Letters, 163,* 106-109.

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

Ülkü, N., & Rogers, M. (2018). Who drives the Monday effect? *Journal of Economic Behavior & Organization, 148,* 46-65.

Urquhart, A. (2016). The inefficiently of Bitcoin. *Economic Letters, 148,* 80-82.

Urquhart, A., & McGroarty, F. (2014). Calendar effects, market conditions and the adaptive market hypothesis: Evidence from long-run U.S. data. *International Review of Financial Analysis, 35,* 154-166.

Yi, S., Xu, Z., & Wang, G. (2018). Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency? *International Review of Financial Analysis, 60*, 98-114.