Jurnal Keuangan dan Perbankan, 23(3): 361 – 375, 2019
http://jurnal.unmer.ac.id/index.php/jkdp

Jurnal Keuangan dan Perbankan
UNIVERSITY OF MERDEKA MALANG

Examining the day-of-the-week-effect and the-month-of-the-year-effect in cryptocurrency market

Robiyanto Robiyanto[1], Yosua Arif Susanto[1], Rihfenti Ernayani[2]

[1]Faculty of Economics and Business, Satya Wacana Christian University
Jl. Diponegoro No. 52-60, Salatiga, 50711, Indonesia.
[2]Faculty of Economics, University of Balikpapan
Jl. Pupuk Raya, Gunung Bahagia, Balikpapan, 76114, Indonesia

Article history:
Received: 2019-04-23
Revised: 2019-06-03
Accepted: 2019-07-04

Keywords:
Cryptocurrency; Bitcoin; Day-of-the-week-effect; Litecoin; Month-of-the-year-effect

JEL Classification: G14, G19

Kata Kunci:
Cryptocurrency; Bitcoin; Day-of-the-week-effect; Litecoin; Month-of-the-year-effect

Abstract

Cryptocurrency market is an attractive field for researchers in finance nowadays. One topic that can be studied is related to the existence of anomalies in the cryptocurrency market. This research was conducted to examine whether the cryptocurrency market, especially on Bitcoin and Litecoin, has day-of-the-week and month-of-the-year effects. The Bitcoin and Litecoin were used as objects because they were a cryptocurrency with a large market capitalization. The data used were monthly cryptocurrency returns for examining the month-of-the-year-effect and daily returns for examining the day-of-the-week-effect from 2014-2018. GARCH (1,1) analysis was done to see these effects on the cryptocurrency market. The results indicate that the phenomena of day-of-the-week and month-of-the-year effect existed in the cryptocurrency market. Therefore, the cryptocurrency market was not an efficient market. The pattern in the Bitcoin and Litecoin could later be utilized by investors. The investors should buy Bitcoin at the end of January and they should sell them at the end of February. While, for the investors who traded daily, can trade Bitcoin in Monday, Wednesday and Thursday because in these days, the Bitcoin have the potential to generate daily profits.

Abstrak

Cryptocurrency market *menjadi bidang yang menarik bagi peneliti di bidang keuangan. Salah satu topik yang dapat dikaji adalah terkait adanya anomali dalam* cryptocurrency market. *Penelitian ini dilakukan untuk menguji apakah pada cryptocurrency market khususnya pada* Bitcoin *dan* Litecoin *terdapat* day-of-the-week-effect *dan* month-of-the-year-effect. *Objek dalam penelitian ini adalah* Bitcoin *dan* Litecoin *yang merupakan cryptocurrency yang memiliki kapitalisasi pasar yang besar. Data pada penelitian ini menggunakan* return cryptocurrency *secara bulanan untuk pengujian* month-of-the-year-effect *dan* return *harian untuk pengujian* day-of-the-week-effect *dari tahun 2014-2018. Penelitian ini menggunakan analisis* GARCH (1,1) *untuk melihat adanya* day-of-the-week-effect *dan* month-of-the-year-effect *dari* cryptocurrency market. *Hasil dari penelitian ini menunjukkan bahwa pasar* cryptocurrency *tidak bergerak secara acak, melainkan terdapat* day-of-the-week-effect *dan* month-of-the-year-effect. *Sehingga pasar* cryptocurrency *bukanlah pasar yang efisien. Pola yang terjadi pada* Bitcoin *dan* Litecoin *dapat dimanfaatkan oleh investor. Investor dapat membeli* Bitcoin *pada akhir Januari karena* return *cenderung negatif dan dapat menjualnya pada akhir Februari. Sementara bagi investor yang melakukan perdagangan harian, hari Senin, Rabu dan Kamis merupakan hari potensial dimana* Bitcoin *dapat menghasilkan keuntungan.*

Corresponding Author:
Robiyanto Robiyanto:
Tel.+62 298 311 881
E-mail: robiyanto.robiyanto@uksw.edu

How to Cite: Robiyanto R., Susanto, Y. A., & Ernayani, R. (2019). Examining the day-of-the-week-effect and the-month-of-the-year-effect in cryptocurrency market. *Jurnal Keuangan dan Perbankan, 23*(3), 361-375. https://doi.org/10.26905/jkdp.v23i3.3005

ISSN: **2443-2687** (Online)
ISSN: **1410-8089** (Print)

1. Introduction

The development of technology has also reached the financial sector. One of these developments includes the emergence of virtual currencies that use cryptographic technology or often referred to as cryptocurrency. In cryptocurrency, each data transaction will be encoded using certain cryptographic algorithms (Nakamoto, 2008; Conway, 2014). One of the examples of cryptocurrency is Bitcoin. Bitcoin was first developed in 2010 as a financial instrument called virtual currency which was originally used for peer-to-peer payments among online video gamers (ICBA, 2015) and online gamblers through Satoshi Dice (Badev & Chen, 2014). This instrument was originally created by a programmer (Turpin, 2014) and was named Bitcoin by Satoshi Nakamoto, its inventor (Nakamoto, 2008; Richter, Kraus, & Bouncken, 2015; Seetharaman, Saravanan, Patwa, & Mehta, 2017). In 2010, Bitcoin was only valued at USD 0.04, and once reached the highest record of USD 19.345,49 in December 2017. The Bitcoin market even threatened other major currencies in the world. Bitcoin has been considered as a legal payment instrument in several countries such as the United States, Canada, Australia, and the European Union. However, there are still many countries rejecting the legality of Bitcoin payment instruments such as Iceland, Indonesia, etc. Nevertheless, with an online trading system, Bitcoin trading can be easily carried out, both on the real Bitcoin market and the Bitcoin futures market in any country (Robiyanto & Pangestuti, 2018).

Bitcoin is one type of cryptocurrency that is frequently used by people in several developed countries. Even in Indonesia, it has become an investment tool although it cannot be used as a means of payment because the virtual currency has not been recognized as a legal payment instrument in Indonesia. Although the cryptocurrency has not yet become a legal payment instrument in Indonesia, research discussing the cryptocurrency is considered interesting to do because there are limited studies that discuss the cryptocurrency in particular which examines seasonal patterns in the cryptocurrency market.

Bitcoin is one form of investment widely used in the world. There are also many types of cryptocurrency besides Bitcoin that can be used as one type of investment. For example, Ethereum, Ripple, Bitcoin Cash, and Stellar are five of the top ten cryptocurrencies that has the largest market capitalization according to Yahoo Finance. This can be seen in Table 1.

Table 1. Top ten cryptocurrency market capitalization 2018

Cryptocurrency Name	Market Capitalization (Billion USD)
Bitcoin	118.870
Ethereum	28.836
Ripple	13.431
Bitcoin Cash	9.393
Stellar	4.224
Lite Coin	3.498
EOS	3.488
Tether	2.809
Cardano	2.625
Tronix	2.518

Source: https://finance.yahoo.com/cryptocurrencies (2019), accessed on April 30, 2019, 14:35.

There is also a cryptocurrency named Litecoin which is the result of the development of Bitcoin, especially in terms of increasing speed of volume and transactions. Litecoin is a developed version of Bitcoin launched in 2011. It is now included in the top ten cryptocurrencies that have the largest market capitalization. The concept of Litecoin is basically the same as Bitcoin which is a virtual currency on a peer-to-peer basis that allows instant payments to anyone in the world whose sources are open and has a global payment network that is fully decentralized without any third parties (http://zioncoins.co.uk, 2015).

Based on the data in Table 1, it appears that the amount of cryptocurrency market capitalization is so large that this cryptocurrency has been highly developed in the world. However, studies on the cryptocurrency market are still relatively limited, especially whether it has random walk feature or there is a certain pattern (for example seasonal patterns). Seasonal studies of the stock and commodity markets have been widely applied. A previous study by Robiyanto (2015) examined the month-of-the-year effect on stock and commodity markets in Southeast Asia. He concluded that there was a month-of-the-year effect on the capital markets in Indonesia, Malaysia, Thailand, and the Philippines and the gold, silver, platinum and palladium products also had seasonal patterns. While a study by Olowe (2010) which examined the commodity market found that there was a month-of-the-year effect on the Brent North Sea crude oil product in a certain period. Swami (2012) examined the day-to-the-week effect in five countries in South Asia (India, Sri Lanka, Pakistan, Bangladesh, and Nepal) and found that there was a day-to-the-week effect in Sri Lanka and Bangladesh. Meanwhile, Abdalla (2012) conducted research on a day-to-the-week effect in the Indian capital market and concluded that there was no day-to-the-week effect. Another research on the commodity market, named the Crude Palm Oil (CPO) market, was conducted by Pulungan, Wahyudi, & Suharnomo (2018).

Previous researches on the month-of-the-year and day-to-the-week effect on the capital and commodity markets have widely done and they obtained different results. While researches on the cryptocurrency market are still limited. Moreover, researches on the cryptocurrency market which runs for seven days a week are certainly interesting to do. The results of this study are expected to be useful for the participants of the cryptocurrency market in designing their short-term trading strategies. In relation to the hypotheses development of this study, a market will be considered running well if the market runs randomly or has a feature of random walk and the return movement does not have a certain seasonal pattern (Robiyanto, 2017; Suganda, Sumargo, & Robiyanto, 2018). In previous studies (Rita, 2009; Marrett & Worthington, 2011; Caporale & Zakirova, 2017; Caporale & Plastun, 2018), studies of seasonal patterns usually had seasonal patterns on a monthly and daily basis.

The month-of-the-year effect occurs if the return in a certain period is significantly different from other months, both higher and lower. The usual pattern includes the after-new-year effect (in the first month) where the return is usually higher than the following month because investors rearrange their portfolio positions and purchase shares at the beginning of the year (Olowe, 2010; Swami, 2012; Robiyanto, 2017). Based on previous researches examining the month-of-the-year-effect on the commodity market and the stock market, the first hypothesis that can be proposed is:

H_1: there is a month-of-the-year-effect on the cryptocurrency market

The day-of-the-week-effect is a seasonal pattern that occurs on a daily basis, where the returns obtained differ greatly compared to other days (Marrett & Worthington, 2011; Þilicã & Oprea, 2014; Zhang, Lai, & Lin, 2017; Caporale & Plastun, 2018). Based on previous researches examining seasonal patterns on a daily basis or day-to-the-week effect that might also occur in the cryptocurrency market, the second hypothesis that can be proposed is:

H_2: there is a day-of-the-week effect on the cryptocurrency market

2. Method, Data, and Analysis

The type of data used to see the return of cryptocurrency was obtained through a website (investing.com) which meant that this research used secondary data. The cryptocurrency market data used as the return was daily closing data for examining the day-of-the-week-effect (the number of observations was 1826 days) and monthly closing data for examining the month-of-the-year-effect (the number of observations was 60 months) starting from 2014 to 2018.

This study used two variables as the samples including Bitcoin and Litecoin. From various cryptocurrency markets in the world, the researchers chose these two variables using the purposive sampling method where they should meet the following criteria: were considered in the top ten cryptocurrencies with the largest market capitalization in the world, and published and circulated globally in early 2014. Based on the first criteria, the data obtained can be seen in the following Table 2.

Table 2. Cryptocurrency market capitalization in 2018 and publication year

Cryptocurrency Name	Market Capitalization (Billion USD)	Publication Year
Bitcoin	118.870	2009
Ethereum	28.836	2015
Ripple	13.431	2012
Bitcoin Cash	9.393	2017
Stellar	4.224	2014
Litecoin	3.498	2011
EOS	3.488	2018
Tether	2.809	2014
Cardano	2.625	2017
Tronix	2.518	2017

Furthermore, based on the second criteria where it should be published at the beginning of 2014 and had been circulating globally, the samples that met the criteria were Bitcoin and Litecoin.

This study used the price of the return of the cryptocurrency market as a dependent variable. The returns used were daily and monthly returns calculated by using the following equation:

$$RC_t = \frac{P_t - P_{t-1}}{P_t} \quad (1)$$

Where: RC_t = Return cryptocurrency in period t; P_t = Cryptocurrency price in period t; P_{t-1} = Cryptocurrency price in period t-1

In this study, the data were analysed by using Generalized Autoregressive Conditional Heteroscedasticity (GARCH), especially GARCH (1,1). The GARCH model developed by Bollerslev (1986) was a refinement of the ARCH model. This GARCH model was created to avoid a too high level on the ARCH model based on the parsimony principle or to choose a simple model so that it would guarantee a positive variance.

Equations used for month-of-the-year-effect testing

$$RC_t = \beta_1 JAN + \beta_2 FEB + \beta_3 MAR + \beta_4 APR + \beta_5 MAY + \beta_6 JUN + \beta_7 JUL + \beta_8 AUG + \beta_9 SEP + \beta_{10} OCT + \beta_{11} NOV + \beta_{12} DEC + \varepsilon_t \quad (2)$$

With:

$$\varepsilon_t = \Phi_t \varepsilon_{t-1} + \cdots + \Phi_t \varepsilon_t + \eta_t \quad (3)$$
$$\eta_t = \sigma_t \varepsilon_t \quad (4)$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 \eta_{t-1}^2 + \cdots + \alpha_p \eta_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \beta_q \sigma_{t-q}^2 \quad (5)$$

Where: ε_t is independent and identically distributed N (0.1) and independent of the past state of η_{t-p}; RC_t = Return cryptocurrency in period month t; Jan, Feb, Mar, Apr, May, Jun, Jul, Aug, Sept, Oct, Nov, Dec = dummy variable of the trading month, and 1 if it refers to the month and 0 if it does not.

Equations used for day-of-the-week-effect testing

The cryptocurrency market lasts 7 days a week and 24 hours per day, so the day variable used included those seven days: Monday, Tuesday, Wednesday, Thursday, Friday, Saturday and Sunday.

$$RC_t = \beta_1 MON + \beta_2 TUE + \beta_3 WED + \beta_4 THU + \beta_5 FRI + \beta_6 SAT + \beta_7 SUN + \varepsilon_t \quad (6)$$

With:

$$\varepsilon_t = \Phi_t \varepsilon_{t-1} + \cdots + \Phi_t \varepsilon_t + \eta_t \quad (7)$$

$$\eta_t = \sigma_t \varepsilon_t \quad (8)$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 \eta_{t-1}^2 + \cdots + \alpha_p \eta_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \beta_q \sigma_{t-q}^2 \quad (9)$$

Where: ε_t is independent and identically distributed N (0.1) and independent of the past state of η_{t-p}; RC_t = Return Cryptocurrency in period day t; Mon, Tue, Wed, Thu, Fri, Sat, Sn = dummy variable of the trading day, and 1 if it refers to the day and 0 if it does not.

Before the GARCH analysis was performed, a data stationarity test was performed using the Augmented Dickey-Fuller (ADF) test to see whether the data was flat or did not have a trend component (Greene, 2003).

3. Results

This study aims to determine the seasonal patterns in the cryptocurrency market, especially in the Bitcoin and Litecoin markets using the GARCH test. Before conducting the GARCH test, the data stationarity test was performed by using the Augmented Dickey-Fuller (ADF) to see whether the data was stationary or not. Then, a correlogram test was performed to see whether the cryptocurrency market was efficient or not. After performing the correlogram test, it was followed with the GARCH test which used returns from Bitcoin and Litecoin, both daily and monthly, for the last 5 years from 2014-2018.

Descriptive statistics

The following Table 3 presents detail descriptive statistics of each trading day of Bitcoin and Litecoin.

During the study period, the average daily return value of Bitcoin (0.00321) is higher than Litecoin (0.00248), but the risk measured from the standard deviation value of Bitcoin (0.09541) is also higher than Litecoin (0.07261). Based on the trading days, the highest average of Bitcoin daily return is found on Wednesday with a value of 0.01504, while the lowest is found on Tuesday (-0.00330). The greatest risk measured from the standard deviation of Bitcoin is found on Saturday (0.08714), and the lowest was on Friday (0.03632). Different things are also found in Litecoin. The highest average of Litecoin daily return is found on Tuesday with a value of 0.00494, while the lowest is on Thursday (-0.00026). The greatest risk measured from the Litecoin standard deviation is found on Tuesday (0.07465), and the lowest is on Sunday (0.01827). The Bitcoin daily returns can be seen in Figure 1, while the Litecoin daily returns can be seen in Figure 2.

Table 3. Descriptive statistics of Bitcoin and Litecoin daily return

	Daily Return							
	All-Day	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
Bitcoin								
Mean	0.00321	0.00213	-0.00330	0.01504	-0.00108	0.00156	0.00448	0.00363
Maximum	3.36839	0.21599	0.13901	3.36839	0.27201	0.13351	1.29105	0.21355
Minimum	-0.57205	-0.43901	-0.21965	-0.25473	-0.57205	-0.16072	-0.13236	-0.19207
Std. Dev.	0.09541	0.04858	0.04102	0.21414	0.05743	0.03632	0.08714	0.03988
Litecoin								
Mean	0.00248	0.00494	0.00116	-0.00007	-0.00026	0.000538	0.000295	0.000111
Maximum	1.436	0.45116	1.43600	0.73611	0.244898	0.342321	0.300699	0.236842
Minimum	-0.60722	-0.60723	-0.20712	-0.27273	-0.43947	-0.1482	-0.18045	-0.13827
Std. Dev.	0.07261	0.07465	0.04280	0.02935	0.024032	0.019624	0.022125	0.01827

Meanwhile, the descriptive statistics of the Bitcoin and Litecoin monthly returns based on the trading month can be seen in Table 4. From Table 4, it can be seen that the monthly average value of Litecoin (0.06224) is higher than the Bitcoin's (0.055419). The risks measured on the standard deviation of Litecoin (0.41588) is greater than the Bitcoin's (0.23686). Based on the trading month, the highest average of Bitcoin monthly return is found in May (0.21561), while the lowest is in March (-0.14642). The same is also found in the risk level, the highest standard of monthly return deviation is

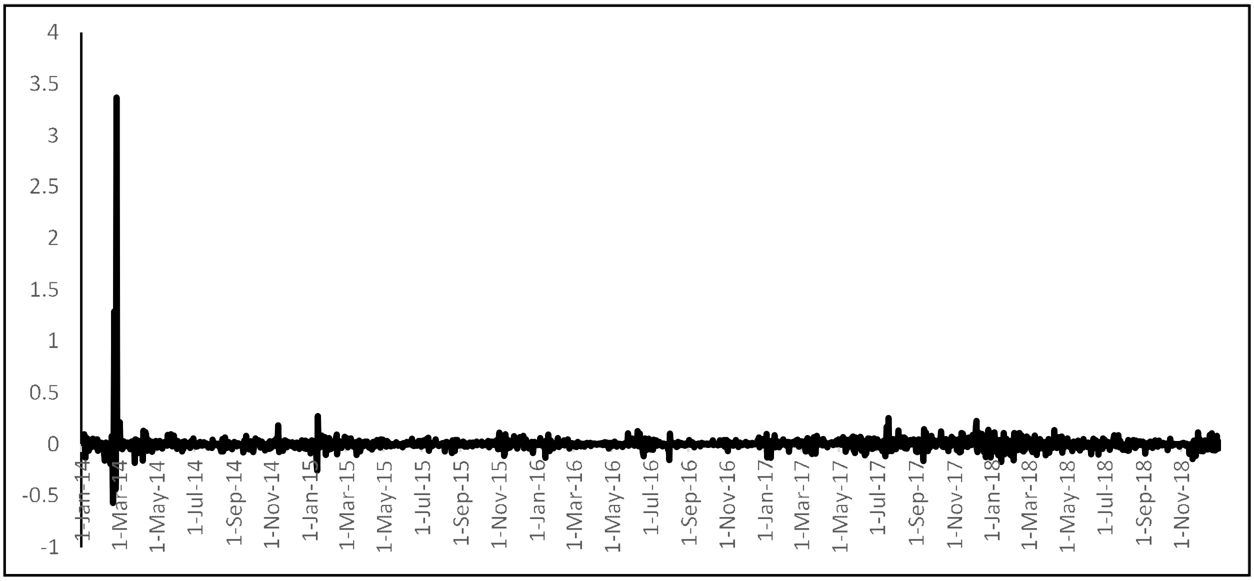

Figure 1. Bitcoin daily return in 2014-2018

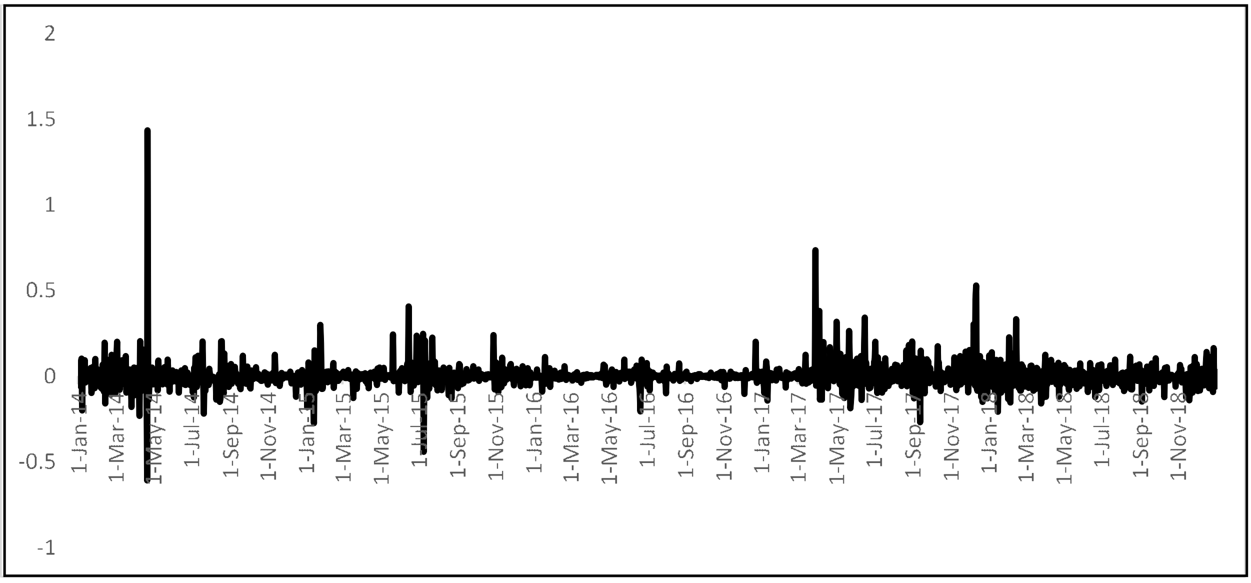

Figure 2. Litecoin daily return in 2014-2018

found in May (0.35305), and the lowest is in March (0.12601). Meanwhile, the highest Litecoin monthly return is found in June (0.02433), while the lowest is in January -0.01430). The highest Litecoin risk is found in December with a standard deviation of 0.21463, while the lowest risk is in July with a standard deviation of 0.02880. The Bitcoin monthly return can be seen in Figure 3, while the Litecoin monthly return can be seen in Figure 4.

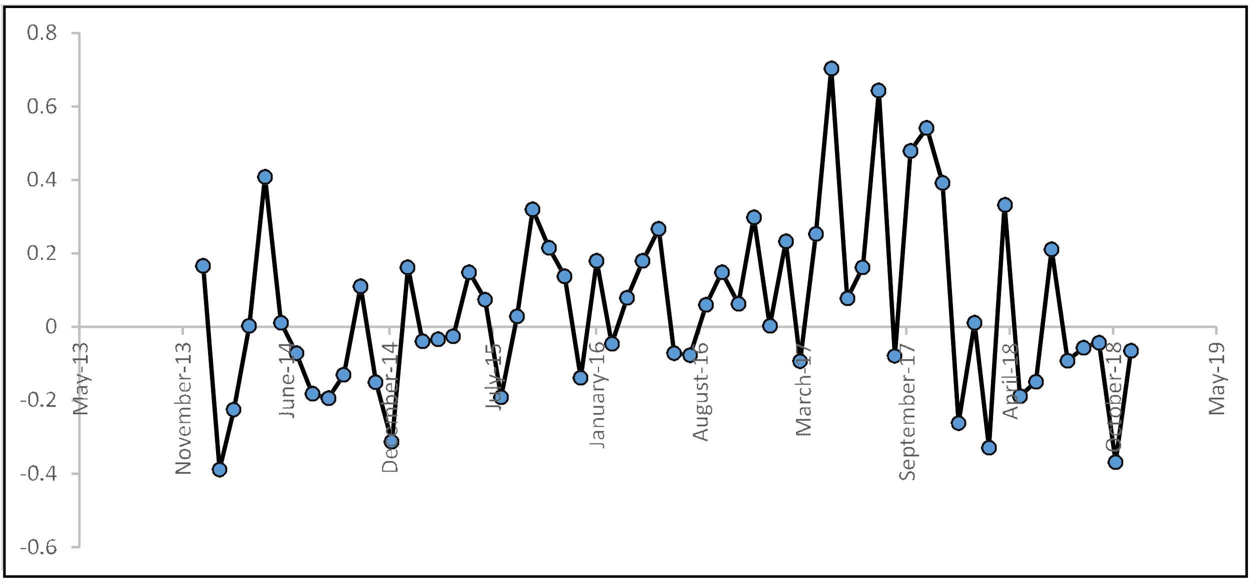

Figure 3. Bitcoin monthly return in 2014-2018

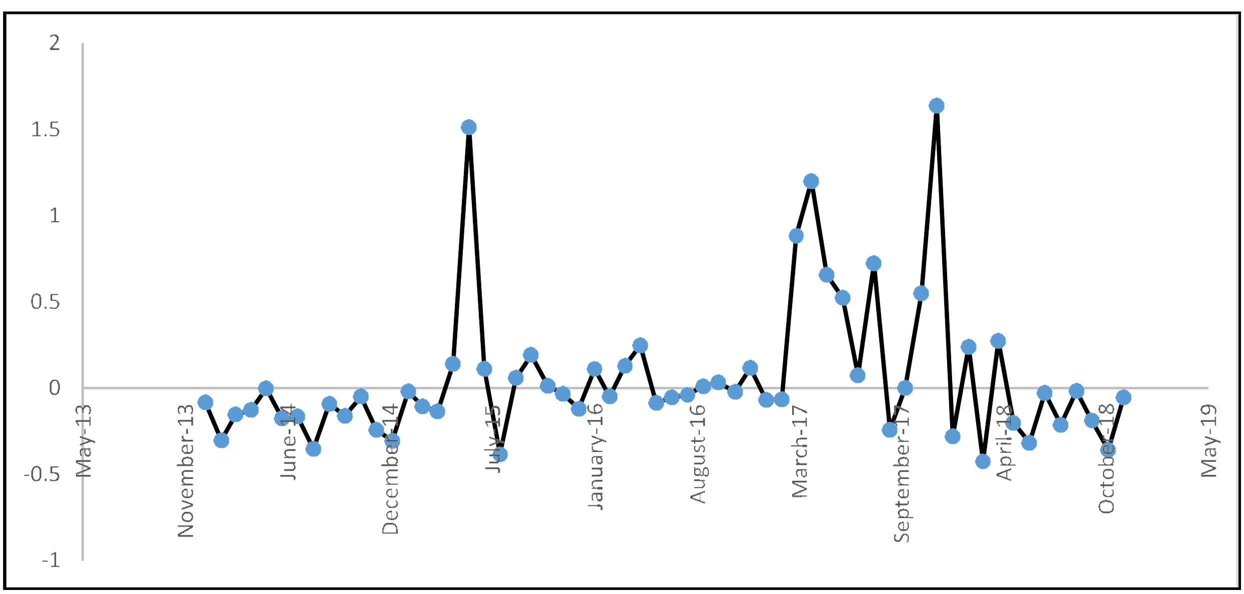

Figure 4. Litecoin monthly return in 2014-2018

Table 3. Descriptive statistic of Bitcoin and Litecoin monthly return

	Monthly Return												
	All-Month	January	February	March	April	May	June	July	August	September	October	November	December
Bitcoin													
Mean	0.05149	-0.10954	0.03915	-0.14642	0.12633	0.21561	0.07111	0.06086	0.01991	-0.04858	0.15510	0.11216	0.12217
Maximum	0.70377	0.16491	0.23178	-0.03901	0.33191	0.70377	0.26677	0.21141	0.64227	0.05970	0.47943	0.54184	0.39245
Minimum	-0.38868	-0.31338	-0.38868	-0.32809	-0.03432	-0.18882	-0.14886	-0.07186	-0.19124	-0.19430	-0.12958	-0.36782	-0.15120
Std. Dev.	0.23686	0.19583	0.25294	0.12601	0.15946	0.35305	0.15520	0.13073	0.35173	0.09982	0.25111	0.32707	0.23127
Litecoin													
Mean	0.06224	-0.01430	-0.00058	0.00253	0.02241	0.01404	0.02433	-0.00102	-0.00436	-0.00467	-0.00201	0.00217	0.02368
Maximum	1.63579	0.00000	0.24066	0.88329	1.20141	0.65771	1.51534	0.11220	0.72322	0.05674	0.19128	0.54847	1.63579
Minimum	-0.42456	-0.30627	-0.30292	-0.42456	-0.13333	-0.20159	-0.31475	-0.16557	-0.38158	-0.24127	-0.18691	-0.35890	-0.24090
Std. Dev.	0.41588	0.05616	0.05309	0.12998	0.16155	0.09594	0.21285	0.02880	0.11924	0.03408	0.04081	0.08563	0.21463

Unit Root Test

In this study, the data stationarity test was performed by using Augmented Dickey-Fuller (ADF) with a significance level of 5 percent and the results can be seen in the following Table 4.

In Table 4, it can be seen that at a significance level of 5 percent, Prob. ADF Bitcoin and Litecoin, both daily and monthly, is smaller than alpha of 0.05. As the probability of ADF is smaller than the alpha, the data is then considered stationary. After the Bitcoin and Litecoin return data are stationary, a correlogram test is then performed to see whether there is an autocorrelation on the return. After the correlogram test is done, a GARCH test is performed to see the seasonal patterns in the return of Bitcoin and Litecoin.

Correlogram Test

In addition to using the ADF to see the data stationarity, this study also used a correlogram test to see whether there is autocorrelation. The data returns used were the daily and monthly returns from Bitcoin and Litecoin. Determination of lag was done by using the natural logarithm of the number of observations. $\ln(1836) = 7.509 \approx 8$ was used for daily return, while $\ln(60) = 4.09 \approx 5$ was used for monthly return.

Table 5 presents the result of the correlogram test of the Bitcoin daily return. It shows that the second to eighth Q-statistic lag probability has a probability value smaller than 0.05. This indicates the existence of autocorrelation in the Bitcoin daily return data. This result is also reinforced by the presence of stand out autocorrelation (AC) and partial autocorrelation (PAC) (the second, fourth, and sixth lag for AC and the second, fourth, fifth and eighth lag for PAC). The AC shows the correlation value of an observation with the value at certain lag, whereas the PAC shows the correlation value of an observation with the value at a certain lag which calculates the value of the interval in it, as well as showing the residual correlation with the next lag after issuing a correlation with the lag in between. Overall, this finding supports Sifat, Mohamad, and Mohamed Shariff (2019)

Table 4. Result of the Augmented Dickey-Fuller (ADF) Test

	Daily Return Data		Monthly Return Data	
	Prob. Bitcoin	Prob. Litecoin	Prob. Bitcoin	Prob. Litecoin
Level	0.0000	0.0001	0.0000	0.0000

Table 5. Correlogram test on Bitcoin daily return

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>| |</td><td>| |</td><td>1</td><td>-0.022</td><td>-0.022</td><td>0.8741</td><td>0.350</td></tr>
<tr><td>*| |</td><td>*| |</td><td>2</td><td>-0.183</td><td>-0.184</td><td>62.427</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>3</td><td>0.021</td><td>0.012</td><td>63.204</td><td>0.000</td></tr>
<tr><td>|** |</td><td>|** |</td><td>4</td><td>0.282</td><td>0.257</td><td>208.39</td><td>0.000</td></tr>
<tr><td>| |</td><td>|* |</td><td>5</td><td>0.059</td><td>0.086</td><td>214.68</td><td>0.000</td></tr>
<tr><td>*| |</td><td>| |</td><td>6</td><td>-0.125</td><td>-0.039</td><td>243.49</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>7</td><td>-0.037</td><td>-0.039</td><td>246.01</td><td>0.000</td></tr>
<tr><td>| |</td><td>*| |</td><td>8</td><td>0.019</td><td>-0.092</td><td>246.69</td><td>0.000</td></tr>
</table>

Table 6. Correlogram test on Litecoin daily return

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>*| |</td><td>*| |</td><td>1</td><td>-0.090</td><td>-0.090</td><td>14.724</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>2</td><td>-0.051</td><td>-0.059</td><td>19.399</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>3</td><td>0.044</td><td>0.034</td><td>22.920</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>4</td><td>0.006</td><td>0.011</td><td>22.995</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>5</td><td>0.009</td><td>0.015</td><td>23.131</td><td>0.000</td></tr>
<tr><td>|* |</td><td>|* |</td><td>6</td><td>0.086</td><td>0.089</td><td>36.648</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>7</td><td>-0.009</td><td>0.008</td><td>36.794</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>8</td><td>-0.022</td><td>-0.015</td><td>37.698</td><td>0.000</td></tr>
</table>

Table 7. Correlogram test on Bitcoin monthly return

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>1</td><td>0.138</td><td>0.138</td><td>1.2082</td><td>0.272</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>2</td><td>0.074</td><td>0.056</td><td>1.5642</td><td>0.457</td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>3</td><td>0.145</td><td>0.130</td><td>2.9367</td><td>0.401</td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>4</td><td>0.142</td><td>0.108</td><td>4.2836</td><td>0.369</td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>5</td><td>0.122</td><td>0.082</td><td>5.2985</td><td>0.381</td></tr>
</table>

Table 8. Correlogram test on Litecoin monthly return

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>. |** |</td><td>. |** |</td><td>1</td><td>0.267</td><td>0.267</td><td>4.4951</td><td>0.034</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>2</td><td>0.103</td><td>0.034</td><td>5.1748</td><td>0.075</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>3</td><td>0.024</td><td>-0.013</td><td>5.2120</td><td>0.157</td></tr>
<tr><td>. |** |</td><td>. |** |</td><td>4</td><td>0.252</td><td>0.264</td><td>9.4220</td><td>0.051</td></tr>
<tr><td>. | . |</td><td>.*| . |</td><td>5</td><td>0.026</td><td>-0.119</td><td>9.4682</td><td>0.092</td></tr>
</table>

Meanwhile, Table 6 presents the results of the correlogram test for daily Litecoin daily return. It shows that the probability of the first to eighth lag has a Q-statistical probability value of less than 0.05. This indicates the existence of autocorrelation in the Litecoin daily return data. Similar to the Bitcoin, the Litecoin's significant Q-statistic value also reinforces this finding. The first and sixth AC and PAC lags on Litecoin stand out more than any other lag.

Table 7presents the result of correlogram for Bitcoin monthly return. It shows that the Q-statistic has a probability value greater than 0.05. This indicates the absence of autocorrelation in the Bitcoin monthly return data, although all AC and PAC values are relatively prominent. Meanwhile, Table 8 presents the result of the correlogram test for Litecoin monthly return. It shows that the Q-statistic has a probability value smaller than 0.05 for the first lag only, reinforced by the AC and PAC values that stand out in the first lag, and the AC and PAC values for the next lag start to decline.

In general, the results of correlogram analysis on the Bitcoin and Litecoin markets indicate that there is an autocorrelation which means that the Bitcoin and Litecoin markets tend to be inefficient.

Result of GARCH Analysis

After performing the stationarity and correlogram tests on Bitcoin and Litecoin returns, the GARCH test was performed. The type of GARCH test used in this study was GARCH (1,1) which would be performed on Bitcoin and Litecoin return, both daily and monthly.

Based on Table 9, the average Bitcoin return on Monday is positive. The average return on other days is not significantly different from Monday except on Wednesday and Thursday whose average return is different from Monday (marginally significant at 10 percent).

Table 9. GARCH (1,1) test for examining the day-of-the-week-effect on Bitcoin

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Monday	0.003830	0.001504	2.546492	0.0109
Tuesday	-0.002883	0.001781	-1.619324	0.1054
Wednesday	0.002311	0.001342	1.722107	0.0851
Thursday	0.003277	0.001678	1.953428	0.0508
Friday	0.001644	0.001630	1.008272	0.3133
Saturday	-0.000128	0.001611	-0.079156	0.9369
Sunday	0.001411	0.001556	0.906660	0.3646
		Variance Equation		
C	4.79E-05	3.58E-06	13.38509	0.0000
RESID(-1)^2	0.226515	0.009449	23.97117	0.0000
GARCH(-1)	0.789415	0.006512	121.2241	0.0000
R-squared	-0.000062	Mean dependent var		0.003213
Adjusted R-squared	-0.003360	S.D. dependent var		0.095416
S.E. of regression	0.095576	Akaike info criterion		-3.763447
Sum squared resid	16.61614	Schwarz criterion		-3.733272
Log-likelihood	3446.027	Hannan-Quinn criteria.		-3.752316
Durbin-Watson stat	2.041630			

Table 10. GARCH (1,1) test for examining the day-of-the-week-effect on Litecoin

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Monday	0.003442	0.001509	2.280539	0.0226
Tuesday	-0.000427	0.001630	-0.261690	0.7936
Wednesday	-0.002537	0.001147	-2.211971	0.0270
Thursday	0.001586	0.001033	1.535525	0.1247
Friday	0.003840	0.000914	4.201091	0.0000
Saturday	0.000252	0.001529	0.164544	0.8693
Sunday	-0.000278	0.001254	-0.221545	0.8247
Variance Equation				
C	7.30E-05	7.86E-06	9.291123	0.0000
RESID(-1)^2	0.892241	0.023546	37.89374	0.0000
GARCH(-1)	0.558620	0.008783	63.60022	0.0000
R-squared	-0.000695	Mean dependent var		0.002481
Adjusted R-squared	-0.003996	S.D. dependent var		0.072613
S.E. of regression	0.072758	Akaike info criterion		-3.030756
Sum squared resid	9.629191	Schwarz criterion		-3.000581
Log-likelihood	2777.080	Hannan-Quinn criteria.		-3.019625
Durbin-Watson stat	2.177162			

Table 11. GARCH (1,1) test for examining the month-of-the-year-effect on Bitcoin

Variable	Coefficient	Std. Error	z-Statistic	Prob.
January	-0.139807	0.027361	-5.109676	0.0000
February	0.179456	0.006415	27.97639	0.0000
March	-0.047114	4.49E-06	-10497.33	0.0000
April	0.079092	1.20E-06	66131.13	0.0000
May	0.179178	1.73E-05	10343.07	0.0000
June	0.266545	0.000135	1969.134	0.0000
July	-0.070792	0.000445	-158.9553	0.0000
August	-0.082765	0.001620	-51.09788	0.0000
September	0.028592	0.005766	4.959002	0.0000
October	0.319141	0.003972	80.35163	0.0000
November	0.214404	0.003062	70.01466	0.0000
December	0.137524	0.105559	1.302816	0.1926
Variance Equation				
C	6.17E-12	3.28E-11	0.187842	0.8510
RESID(-1)^2	4.795348	0.263413	18.20468	0.0000
GARCH(-1)	0.004486	0.001440	3.115678	0.0018
R-squared	-0.022600	Mean dependent var		0.051488
Adjusted R-squared	-0.256946	S.D. dependent var		0.236858
S.E. of regression	0.265550	Akaike info criterion		-1.166619
Sum squared resid	3.384818	Schwarz criterion		-0.643033
Log-likelihood	49.99856	Hannan-Quinn criteria.		-0.961815
Durbin-Watson stat	1.622535			

Based on Table 10, the average Litecoin return on Monday is positive. The average return on other days is not significantly different from Monday except on Wednesday and Friday whose average return is different from Monday.

Based on Table 11, the average monthly return of Bitcoin in January, March July and August is negative, and the other months are positive. The average return for each month is significantly different except for December whose average return is relatively no different from January.

Based on Table 12, the average monthly return of Litecoin in February is positive. The average return for each month is not significantly different except for May. It was found that there are several months that have a significant effect on cryptocurrency returns. Therefore, H1 which states that there is a month-of-the-year effect on the cryptocurrency market is empirically supported. Furthermore, this study also found that there are days that have a significant effect on cryptocurrency returns. Therefore, H2 stating that there is a day-of-the-week effect on the cryptocurrency market is empirically supported. The results of this study also show that in the cryptocurrency market, there are also exists anomalies. This finding supports Caporale and Plastun (2018), also consistent with other financial markets as documented by Olowe (2010), Abdalla (2012), Robiyanto (2015), and Swami (2012).

The coefficient of determination (R^{2}) on all models used in this study has a negative sign. This was a common condition because R^2 was not necessarily the number of squares of a figure (Alexander, Tropsha, & Winkler, 2015). This finding indicated that the model used did not follow the trends in the data, making the results of the model calculation to not follow a horizontal line (Motulsky & Christopoulos, 2003). This condition was possible

Table 12. GARCH (1,1) test for examining the month-of-the-year-effect on Litecoin

Variable	Coefficient	Std. Error	z-Statistic	Prob.
January	-0.161896	0.322404	-0.502152	0.6156
February	0.241065	0.104290	2.311486	0.0208
March	-0.100034	0.152193	-0.657283	0.5110
April	-0.009007	0.162172	-0.055542	0.9557
May	-0.257506	0.087999	-2.926225	0.0034
June	-0.013149	0.155417	-0.084603	0.9326
July	-0.212614	0.144792	-1.468416	0.1420
August	-0.152806	0.176572	-0.865404	0.3868
September	-0.065143	0.336270	-0.193723	0.8464
October	-0.054923	0.174246	-0.315201	0.7526
November	-0.057052	0.126134	-0.452313	0.6510
December	0.014744	0.180117	0.081861	0.9348
Variance Equation				
C	0.061808	0.032851	1.881470	0.0599
RESID(-1)^2	0.903487	0.463227	1.950419	0.0511
GARCH(-1)	-0.030762	0.063473	-0.484646	0.6279
R-squared	-0.148615	Mean dependent var		0.062243
Adjusted R-squared	-0.411839	S.D. dependent var		0.415883
S.E. of regression	0.494156	Akaike info criterion		1.079296
Sum squared resid	11.72111	Schwarz criterion		1.602882
Log-likelihood	-17.37889	Hannan-Quinn criteria.		1.284099
Durbin-Watson stat	1.237733			

because the independent variables used were the return cryptocurrency which can also be seen in Figure 1., 2., 3., and 4.

The study also found that only December which has no significant effect on the Bitcoin return. This showed that towards the end of the year, the cryptocurrency market participants tend to reduce their trading activities to enjoy the end of year holidays. The cryptocurrency market is always known as a market that is always active and never stops so. Therefore, the market participants must be wise in responding to the time of the non-stop trading. A relatively similar thing was also found in the stock and commodity markets (Lucey & Zhao, 2008; Lean & Tan, 2010; Lean, 2011).

4. Conclusion, Limitations, and Suggestions

Conclusion

This study aims to understand whether there are patterns on the cryptocurrency market, especially on Bitcoin and Litecoin, or whether the market moves randomly. The results of GARCH (1,1) and correlogram test show that the cryptocurrency market does not move randomly, but there are phenomena of day-of-the-week and month-of-the-year effect. Therefore, the cryptocurrency market was not an efficient market because it had a certain pattern in the movement of the returns which made it followed a certain pattern and was not moving randomly because of the many requests and offers that occurred in the market. The pattern in the Bitcoin and Litecoin pattern could later be utilized by investors by buying the cryptocurrency before there was an increase in the return and selling them when the returns increased. For example, the investors should buy Bitcoin at the end of January because the return tended to be significantly negative and they should sell them at the end of February because the return tended to be significantly positive. Meanwhile, to conduct Litecoin trading, the investors could make a purchase before the end of January and then sell them at the end of February because it was found that there is a significant positive return in February which shows the potential for generating profits for investors. Meanwhile, for the investors who traded daily, Monday, Wednesday and Thursday were found to be the days where the Bitcoin have the potential to generate daily profits. While on the Litecoin, Friday was found to have the potential to generate daily profits.

Limitations and suggestions

This study has several shortcomings and limitations. It is expected that future studies may examine another potential cryptocurrency. Furthermore, due to limited researches discussing the cryptocurrency market, it is expected that there will be more future studies discussing in-depth cryptocurrency markets. For example, there can be studies examining the feasibility of cryptocurrency as an investment tool. Further, other research may examine the Rogalski effect to see the anomaly of the level of cryptocurrency returns on certain days with a certain month.

References

Abdalla, S. Z. S. (2012). Day-of-the-week effect on returns and conditional volatility/ : Empirical Evidence from Sudanese Stock Market. *Middle Eastern Finance Economics*, (16), 167-180.

Alexander, D. L. J., Tropsha, A., & Winkler, D. A. (2015). Beware of R2: simple, unambiguous assessment of the prediction accuracy of QSAR and QSPR models. *Journal of Chemical Inference Model*, *55*(7), 1316-1322. https://dx.doi.org/10.1021%2Facs.jcim.5b00206

Anonimous. (2015). Lite coin white paper. Retrieved from http://zioncoins.co.uk/wp-content/uploads/2015/06/Lite-Coin-Whitepaper.pdf

Badev, A., & Chen, M. (2014). Bitcoin: technical background and data analysis. *Finance and Economics Discussion Series*. Retrieved from https://www.federalreserve.gov/econresdata/feds/2014/files/2014104pap.pdf

Bollerslev, T. (1986). Generalized autoregressive conditional heteroscedasticity. *Journal of Econometrics, 31*, 307-327. https://doi.org/10.1016/0304-4076(86)90063-1

Caporale, G. M., & Plastun, A. (2018). The day of the week effect in the cryptocurrency market. *Finance Research Letters*. https://doi.org/10.1016/j.frl.2018.11.012

Caporale, G. M., & Zakirova, V. (2017). Calendar anomalies in the Russian stock market. *Russian Journal of Economics, 3*(1), 101-108. https://doi.org/10.1016/j.ruje.2017.02.007

Conway, J. (2014). Beginners Guide to Cryptocurrencies. Retrieved from https://www.joeyconway.com/blog/wp-content/uploads/2014/10/Beginners-Guide-to-Cryptocurrencies-final.pdf

Greene, W. H. (2003). *Econometric Analysis 5th Edition*. New Jersey: Prentice-Hall.

ICBA. (2015). *Virtual Currency: Risks and Regulation*. Washington, DC: Independent Community Bankers of America Retrieved from https://www.icba.org

Lean, H. H. (2011). The halloween puzzle in selected Asian Stock Markets. *International Journal of Economics and Management, 5*(1), 216-225.

Lean, H. H., & Tan, V. K. M. (2010). Existence of the day of the week effect in FTSE Bursa Malaysia. *Jurnal Pengurusan, 31*, 3-11. https://doi.org/10.17576/pengurusan-2010-31-01

Lucey, B. M., & Zhao, S. (2008). Halloween or January? Yet another puzzle. *International Review of Financial Analysis, 17*, 1055-1069. https://doi.org/10.2139/ssrn.887861

Marrett, G., & Worthington, A. (2011). The month-of-the-year effect in the Australian Stock Market: A Short technical note on the market, industry and firm size impacts. *Australasian Accounting Business and Finance, 5*(1), 117-123. https://doi.org/10.2139/ssrn.1290886

Motulsky, H. J., & Christopoulos, A. (2003). *Fitting Models to Biological Data using Linear and Nonlinear Regression*. San Diego, CA.: GraphPad Software Inc.

Nakamoto, S. (2008). *Bitcoin: A peer-to-peer electronic cash system*.

Olowe, R. A. (2010). Oil price volatility, global financial crisis and the month-of-the-year effect. *International Journal of Business and Management, 5*(11), 156-170. https://doi.org/10.5539/ijbm.v5n11p156

Pulungan, D. P., Wahyudi, S., & Suharnomo, S. (2018). Does the crude palm oil market walk randomly. *Jurnal Keuangan dan Perbankan, 22*(2), 211–218 https://doi.org/10.26905/jkdp.v22i2.2023

Richter, C., Kraus, S., & Bouncken, R. B. (2015). Virtual currencies like Bitcoin as a paradigm shift in the field of transactions. *International Business & Economics Research Journal, 14*(4), 575-586. https://doi.org/10.19030/iber.v14i4.9350

Rita, M. R. (2009). Pengaruh hari perdagangan terhadap *return* saham: Pengujian *day of the week effect*, *week-four effect* dan *Rogalski Effect* di BEI. *Jurnal Ekonomi dan Bisnis, 15*(2), 121-134.

Robiyanto, R. (2015). *Month of the year effect* pada beberapa pasar modal di Asia Tenggara dan pasar komoditas. *Jurnal Ekonomi dan Bisnis, 18*(2), 53-64. https://doi.org/10.24914/jeb.v18i2.260

Robiyanto, R. (2017). Month of the year effect pada pasar obligasi di Indonesia. *Jurnal Ekonomi dan Bisnis, 20*(2), 291-302. https://doi.org/10.24914/jeb.v20i2.1093

Robiyanto, R., & Pangestuti, I. R. D. (2018). *Weak form market efficiency in the cryptocurrency market*. Paper presented at the 2nd International Conference on Management & Entrepreneurship (2nd i-CoME), Yogyakarta, Indonesia.

Seetharaman, A., Saravanan, A. S., Patwa, N., & Mehta, J. (2017). Impact of Bitcoin as a world currency. *Accounting and Finance Research, 6*(2), 230. https://doi.org/10.5430/afr.v6n2p230

Sifat, I. M., Mohamad, A., & Mohamed Shariff, M. S. B. (2019). Lead-lag relationship between Bitcoin and Ethereum: Evidence from hourly and daily data. *Research in International Business and Finance, 50*, 306-321. https://doi.org/10.1016/j.ribaf.2019.06.012

Suganda, T. R., Sumargo, I. K., & Robiyanto, R. (2018). Superstitious behavior and stock return: The case of Javanese traditional calendar. *Kasetsart Journal of Social Sciences*. https://doi.org/10.1016/j.kjss.2018.08.008

Swami, R. (2012). Calendar anomalies in the Bourses of South Asia. *Market Convergence, 2*(2), 64-74.

Þilicã, E. V., & Oprea, D. (2014). Seasonality in the Romanian Stock Market: The-day-of-the-week effect. *Procedia Economics and Finance, 15*, 704-710. https://doi.org/10.1016/s2212-5671(14)00543-7

Zhang, J., Lai, Y., & Lin, J. (2017). The day-of-the-week effects of stock markets in different countries. *Finance Research Letters, 20*, 47-62. https://doi.org/10.1016/j.frl.2016.09.006