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WHETHER THE CRYPTO MARKET IS EFFICIENT? EVIDENCE FROM TESTING THE VALIDITY OF THE EFFICIENT MARKET HYPOTHESIS

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ABSTRACT

This study examines the validity of the efficient market hypothesis for the cryptocurrency market. We use the Exponential Generalized Autoregressive Conditional Heteroscedastic approach to examine the presence of different calendar anomalies i.e., the Halloween effect, the day-of-the-week (DOW) effect, and the month-of-the-year effect in the case of Bitcoin, Ethereum, XRP, Tether, and USD Coin. The findings show that there is no strong evidence of the Halloween effect. We find only robust Thursday and Saturday effects in the mean equation. In the case of the month-of-the-year effect, there is only a reverse January effect. More specifically, we note that April and February are statistically significant in the case of Bitcoin and Ethereum, respectively. Results obtained from the variance equations imply that September and October are the least risky months for investors.

Keywords: Market efficiency; Cryptocurrencies; Volatility; Market anomalies.
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I. INTRODUCTION

The availability of all the information reflected by the prices is the criteria for the markets to be efficient and is necessary for the allocation of resources (Fama, 1970). An efficient mark*et al*lows innovative investment decisions by firms, and it also aids investors in choosing the securities by observing the prices in capital markets as the prices of securities reflect all available information on firms' activities. The Efficient Market Hypothesis (EMH) is one of the most crucial financial theories, which has been evaluated by many past studies. However, the presence of some irregular patterns of returns' behavior related to the calendar, also known as anomalies, made academicians and researchers question the existence of EMH in the real world. The concept of an efficient market is certainly not new in the literature. The EMH exists in three forms: weak, semi-strong, and strong. Fama (1970) and Fama *et al*. (1969) first identified these three forms of capital markets. A weak form of efficiency implies that current prices of stocks reflect all prior stock prices and volume, semi-strong efficiency presumes that current stock prices capture all publicly available information and strong efficiency presumes that present stock prices represent all publicly and privately available information. Many past studies oppose the idea of stock prices being inefficient, see for example, Malkiel (2003). According to Malkiel (2003), stock prices are unpredictable and the presence of anomalous behavior of stock prices cannot assist investors in any way to earn abnormal returns. On the other hand, innumerable literature exists against the random walk in the stock market, see for instance, Lee *et al*. (2010) and Lean and Smyth (2007).

Besides the conventional financial markets, the cryptocurrency markets are emerging rapidly, especially after the great fall of financial markets during the period 2007-2008 and the market capitalization of cryptocurrencies reached around $2.05 Trillion.[1] Since cryptocurrency has gained a lot of attention in the financial market in recent years, investors have become more intrigued to add it to their investment portfolios. Following the stock market's strategy, investors started to add them using various asset portfolio techniques to gain better-expected returns (see Sun *et al*., 2021).

There exist market patterns that might aid investors and investment portfolio managers in gaining abnormal profits against the random walk and this paper aims to find the existence of some of these patterns – which are also known as calendar anomalies in the literature. A calendar anomaly is any unusual behavior of returns associated with the calendar such as the time-of-the-day (TOD) effect, the day-of-the-week (DOW) effect, the month-of-the-year (MOY) effect, the January effect, and the Halloween effect.

Anomalies in the finance literature have been widely discussed. Numerous studies (see Kenourgios and Samios, 2021; Plastun *et al*., 2020 and Bouman and Jacobsen, 2002) conclude that returns are higher during the period November to April. This phenomenon is referred to as the "sell in May and go away" also known as the Halloween effect (Bouman and Jacobsen, 2002). According to the Halloween indicator, investors should sell the stocks in the month of May as returns on stock are lower in summer (between May and October) and buy in September to earn profit.

[1] https://coinmarketcap.com on September 14, 2021, at 23:00 hours

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Besides the Halloween effect, another important calendar anomaly is the DOW effect, and it has been also examined in the past literature, see Cross (1973), Thushara and Perera (2012), and Caporale and Plastun (2021). They confirmed the presence of the DOW effect in equity and commodity markets. Also, Zhang *et al*. (2017) conclude that the DOW effect causes each day of the week to have a different return and this difference in returns on each day of the week can affect investors' investment strategies and their portfolio selection. French (1980) and Gibbons and Hess (1981) for instance, concluded that the DOW effect in the returns of equity markets is higher on Friday than on Monday. Parallel to the DOW effect another widely tested calendar anomaly effect is the MOY effect. The MOY effect refers to the phenomena of higher stock returns in a specific month of the year as compared to the rest of the months in the year. The MOY effect was first evaluated by Rozeff and Kinney (1976). They find that returns in the month of January are higher than the other months. Additionally, some studies also report the presence of higher returns in different months of the year (see Giovanis, 2016; Marrett and Worthington 2011; Thushara and Perera, 2013).

There is enormous literature on cryptocurrency which examines and discusses different features of cryptocurrencies. These studies include but are not limited to speculative behavior in cryptocurrencies, their volatility, their limited supply, etc. However, there are very few studies discussing and assessing the efficiency of cryptocurrency markets. Urquhart (2016) assesses the efficiency of Bitcoin and conclude that Bitcoin is weakly efficient during the period 01 August 2010 to 31 July 2016. Bitcoin's efficiency is further evaluated by Urquhart (2016) by dividing data into two sub-sample periods to see if the degree of efficiency has changed over time. They document that Bitcoin has the potential to become efficient as the weak form of efficiency in Bitcoin increased in the latter period.

Over the past couple of years, cryptocurrencies, especially Bitcoin, grabbed a lot of attention. Past studies focused on different important and vital features of cryptocurrencies, such as speculative bubble behavior in Bitcoin's returns (Chaim and Laurini, 2019; Fendi *et al*., 2019), momentum effects after one-day abnormal return (Caporale and Plastun, 2020), opportunities and challenges of cryptocurrencies (Fauzi and Paiman, 2020), and speculative behavior of Bitcoin (Cheung *et al*., 2015). Additionally a most recent paper by Hattori and Ishida (2021) examines the arbitrage behaviors of the investors in the Bitcoin spot and futures markets and they report evidence in support of market efficiency. Baur *et al*. (2019) is the first study that examines the anomalies in prices and trading volumes of Bitcoin across seven different global cryptocurrency exchanges. Their findings show the absence of consistent seasonality in the returns of Bitcoin over the period December 2010 to October 2017. However, Baur *et al*. (2019) observed a considerable weekend effect to be present in the trade volume.

Surprisingly, enough attention has not been paid in examining the EMH for cryptocurrencies which is a very important feature for any financial market as concluded by Kinateder and Papavassiliou (2021). Numerous studies are available for the conventional financial markets discussing the EMH such as Kelikume *et al*. (2020), Loredana (2019), Santoso and Ikhsan, (2020), and Titan (2015). Kinateder and Papavassiliou (2021) analyzed the impact of seasonal anomalies on Bitcoin's return and conditional volatility using a GARCH model with a dummy variable.

They studied the Halloween effect, day-of-the-week effect, and month-of-the-year effect in the Bitcoin market for the period of six years, from 2013 to 2019. They document a stronger presence of calendar anomalies in conditional volatility than in returns. Overall, they show that the Bitcoin market is weakly efficient.

The EMH is a particularly important and vital feature of any financial market as these aids and helps investors in forming their investment strategies (Kalsie and Kalra, 2015). This is the main motivation behind our study to examine if EMH holds in the case of cryptocurrency market. An efficient crypto market will not allow any space for investors to earn any abnormal profit because of the existence of irregular calendar patterns related to returns. There is exiguous literature present that discusses the efficiency of digital currency. In particular, these studies concentrate on the efficiency of a single digital currency (see Bouri *et al*., 2019; Bouoiyour and Selmi, 2016; Nadarajah and Chu, 2017; Aggarwal, 2019; Urquhart, 2016). Multiple crypto market efficiency testing is also salient in the literature (Caporale *et al*., 2018: Brauneis and Mestel, 2018; Vidal-Tomás *et al*., 2019; Hu *et al*., 2019; Tran and Leirvik, 2019; Palamalai *et al*., 2021; Apopo and Phiri, 2021). Our study contributes to the multiple cryptocurrency market efficiency by evaluating the existence of random walk in the crypto market for three top cryptocurrencies (Bitcoin, Ethereum, and XRP) and two top stable coins (Tether and USD coin). The reason behind selecting these five currencies is because their share in the crypto market is almost 75% as of August 2021. The market capitalization of Bitcoin, Ethereum, and XRP are $532 billion, $214 billion, and $22 billion, respectively, while the market capitalization of the stablecoins used in this study, USD Coin, and Tether, is $33 billion and $79 billion, respectively.[2] We conclude that the crypto world follows a weak form of EMH, and investors can earn abnormal returns and reduce the risk by exploiting these anomalies. The purpose behind any investment made by the investor is to earn unexpected returns on their investment, and this study can aid the investors while making investment decisions and determining the best time to invest.

In this regard, the novelty of this study includes the following: to the best of our knowledge, this study is the first attempt to assess the three types of calendar anomalies, the Halloween effect, DOW effect, and MOY effect on the returns and volatility of the three top cryptocurrencies i.e., Bitcoin, Ethereum, and XRP, and in addition to that, the same anomalies are assessed for prices and volatility of the two top stablecoins i.e., USD Coin and Tether which adds new insight to the literature. And, to assess the anomalies, the Exponential Generalized Autoregressive Conditional Heteroscedastic (EGARCH) model with dummy variables representing the three anomalies has been utilized. This approach accounts for asymmetric volatility and return clusters which are common features of the crypto markets.

The rest of the paper is organized as follows: Section II describes the dataset and methodology, Section III provides a detail discussion on main findings, and Section IV concludes the paper.

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[2] https://coinmarketcap.com/

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II. DATA AND METHODOLOGY

This section describes the dataset followed by the discussion on the methodology used in this study.

A. Data

Our dataset includes daily closing prices of Bitcoin, Ethereum, XRP, Tether, and USD Coin. All data are collected from CoinDesk.[3] All variables have different starting dates depending on their availability, however, the ending date is same, i.e., 17 July 2021. We compute return series of each cryptocurrency (Bitcoin, Ethereum, and XRP) using the following formula:

$$R_t = [ln(P_t) - ln(P_{t-1})] \times 100 \quad (1)$$

where R_t refers to return, and P_t refers to prices of cryptocurrencies. We have used returns instead of prices because Bitcoin, Ethereum, and XRP follow a non-stationary process. However, since tether and USD Coin prices follow stationary process, we have taken price series rather returns for these two cryptocurrencies in our empirical model. Although we had less data on the available number of days for stablecoins compared to cryptocurrencies, we still had enough degree of freedom to not impact the analysis. Table 1 presents descriptive statistics of the cryptocurrencies.

Bitcoin has the highest mean value followed by Ethereum. Because Bitcoin is the most commonly used cryptocurrency, its price has risen from $108 to $63346 in less than eight years. Ethereum, the second most used cryptocurrency has had a similar price increase, increasing from $0.42 to $4132 in a period of five years. Another interesting observation from the reported decretive statistics is that Bitcoin has the highest mean value while XRP has the lowest. It is worth mentioning that XRP is used for inter-bank transfers and parallel to SWIFT transfers. Bitcoin being the costliest cryptocurrency also reports the highest volatility. While USD Coin is the least volatile one as it is a stable coin. The minimum and maximum value of stable coins i.e., Tether and USD Coin, are always hovering around $1.

3 https://www.coindesk.com/ on 18 July 2021 at 15:00 hours

Table 1.
Descriptive Statistics

This table reports descriptive statistics of all variables (cryptocurrencies) used in the study. The asterisk, ***, implies statistical significance at the 1% level.

	Bitcoin	Ethereum	XRP	Tether	USD
Mean	7142.445	390.994	0.392	0.999	1.000
Std. dev.	11560.78	610.837	0.258	0.006	0.001
Max	63346.79	4132.758	1.810	1.021	1.002
Min	108.585	0.428	0.139	0.952	0.992
Skewness	2.887	2.871	2.830	-3.437	-4.061
Kurtosis	11.530	12.050	12.217	19.125	38.268
Jarque-Bera	12581.82***	10381.31***	5566.073***	14838.80***	26250.6***
Starting date	01 Oct 2013	09 Aug 2015	01 June 2018	01 June 2018	24 Mar 2020
No. of days	2846	2169	1142	1142	481

B. Methodology

B.I. Stationarity Testing

It is important to test for the presence of unit root in all variables used in this study as many economic and financial time series show stochastic trending or non-stationarity pattern and econometric models based on such series would lead to spurious regression (Granger and Newbold, 1974). If a financial time series and in our case the prices show any sign of non-stationarity, then it can be converted into returns form to ensure stationarity. We use Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) (Kwiatkowski *et al*., 1992) and Elliot, Rothenberg, and Stock Point Optimal (ERSPO) (Elliott *et al*., 1996) unit root tests. The KPSS test assumes that the series follows a stationary process while the null hypothesis of ERSPO unit root test is that the series has a unit root. The two tests with opposite null hypotheses are used so that it can be confirmed that our results are robust.

B.II. The Econometric Model

To examine the impact of calendar anomalies, we use an EGARCH model (Nelson, 1991) with an exogenous dummy variable for calendar anomalies. EGARCH, in comparison to the other models, provides an analysis of the influence of the asymmetric effect of bad news. The "leverage effect" which refers to a negative association between shocks to variance and shocks to returns, is also a great advantage in the EGARCH model (Son-Turan, 2016). Furthermore, we choose EGARCH over other models because it offers to estimate the impact of returns along with the volatility of seasonal effects. To test if the EGARCH model is appropriately specified, we applied a variety of model diagnostics like the ARCH test and Normality test. The other heteroskedastic models like TGARCH or GARCH in mean are not suitable for our research purpose as the focus of this study is not to examine the threshold or mean effect, respectively. While assessing the calendar anomalies, to avoid a dummy variable trap, each day in the DOW effect and each month in the MOY effect have been studied separately. EGARCH model comprises two equations, the mean, and the variance equation.

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For the mean equation, an ARMA (p, q) model with a dummy variable representing the calendar anomaly is as follows:

$$R_t = c + \sum_{i=1}^{P} \theta i \, R_{t-i} + \sum_{i=1}^{q} \beta_i \, \epsilon_{t-j} + \delta D_{t,c} + \varepsilon_t \quad (2)$$

Where R_t represents the return series for Bitcoin, Ethereum, and XRP while it represents the price for Tether and USD Coin. ε_t is the random error component.

The variance equation with a dummy variable representing the calendar anomaly is as follows:

$$log(h_t) = \omega + \sum_{j=1}^{q} \beta_j log(h_{t-j}) + \sum_{i=1}^{p} \alpha_i \left| \frac{\epsilon_{t-i}}{\sqrt{h_{t-i}}} \right| + \sum_{k=1}^{r} \gamma_k \frac{\epsilon_{t-k}}{\sqrt{h_{t-k}}} + \rho_{2,c} D_{t,c} \quad (3)$$

where $\varepsilon t \sim F(0,h_t)$ assumed to take a stationary student *t*-distribution with mean zero and conditional variance h_t. The $D_{t,c}$ is the dummy variable that represents the calendar anomalies as explained in the following sections. $\alpha_i \frac{\epsilon_{t-i}}{\sigma_{t-i}^2}$ represents the asymmetric term and if this term is statistically significant, it means that negative news has a greater impact on volatility as compared to positive news.

C. Calendar Anomalies

Three types of calendar anomalies used in this study are the Halloween effect, DOW effect, and MOY effect.

C.I. Halloween Effect

The Halloween effect, which is also described as "sell in May and go away" in literature (see, Bouman and Jacobsen, 2002) refers to the good performance of stocks between the period 31 October to 01 MayThe dummy variable for Halloween effect takes the value one over the period 01 November to 30 April and zero otherwise.

C.II. DOW Effect

The DOW effect refers to the phenomena of abnormal positive or negative returns on a specific day of the week. In this study, each day has been analyzed separately. So, the day under consideration will take the value 1 and zero otherwise.

C.III. MOY Effect

The MOY refers to abnormal returns or volatility in a specific month of the year. MOY is also analyzed separately for each month. So, the dummy variable for a specific month of the year will take the value one and zero otherwise.

III. RESULTS

This section provides detail discussion on our main findings. The plots of cryptocurrency returns and stable coin values, as well as the findings of stationarity tests and the EGARCH model, are all included in this section.

Figure 1.
Bitcoin Return and Price

Figure 1 plots the return and closing price series of bitcoin over the period 2014-2018.

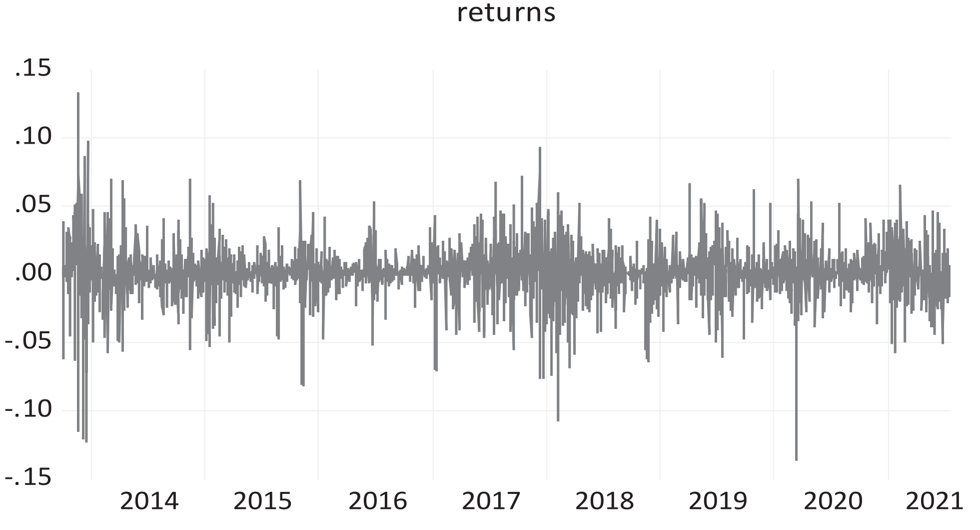

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Figure 2.
Ethereum Returns and Price

This figure plots the return and price series of Ethereum over the period 2015-2018.

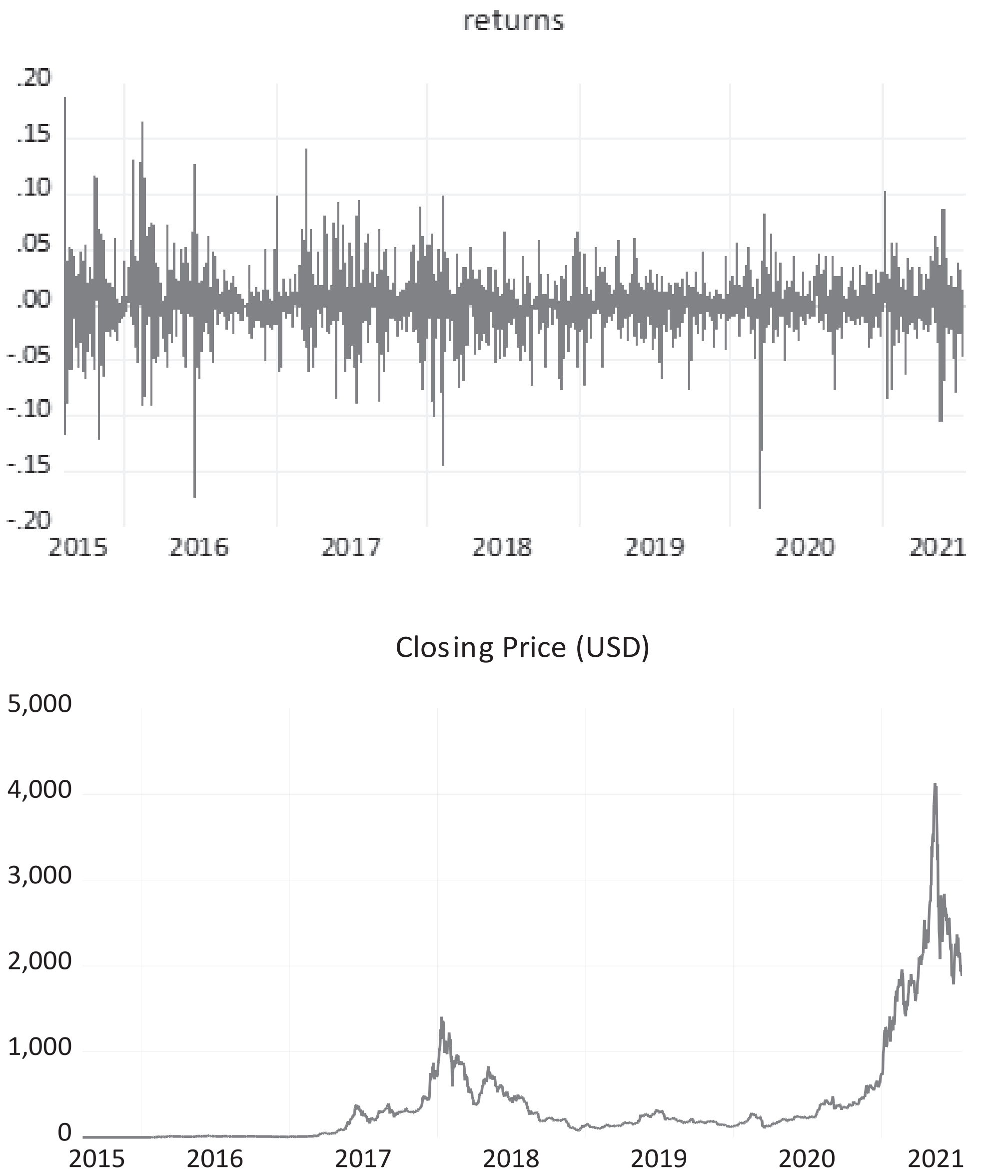
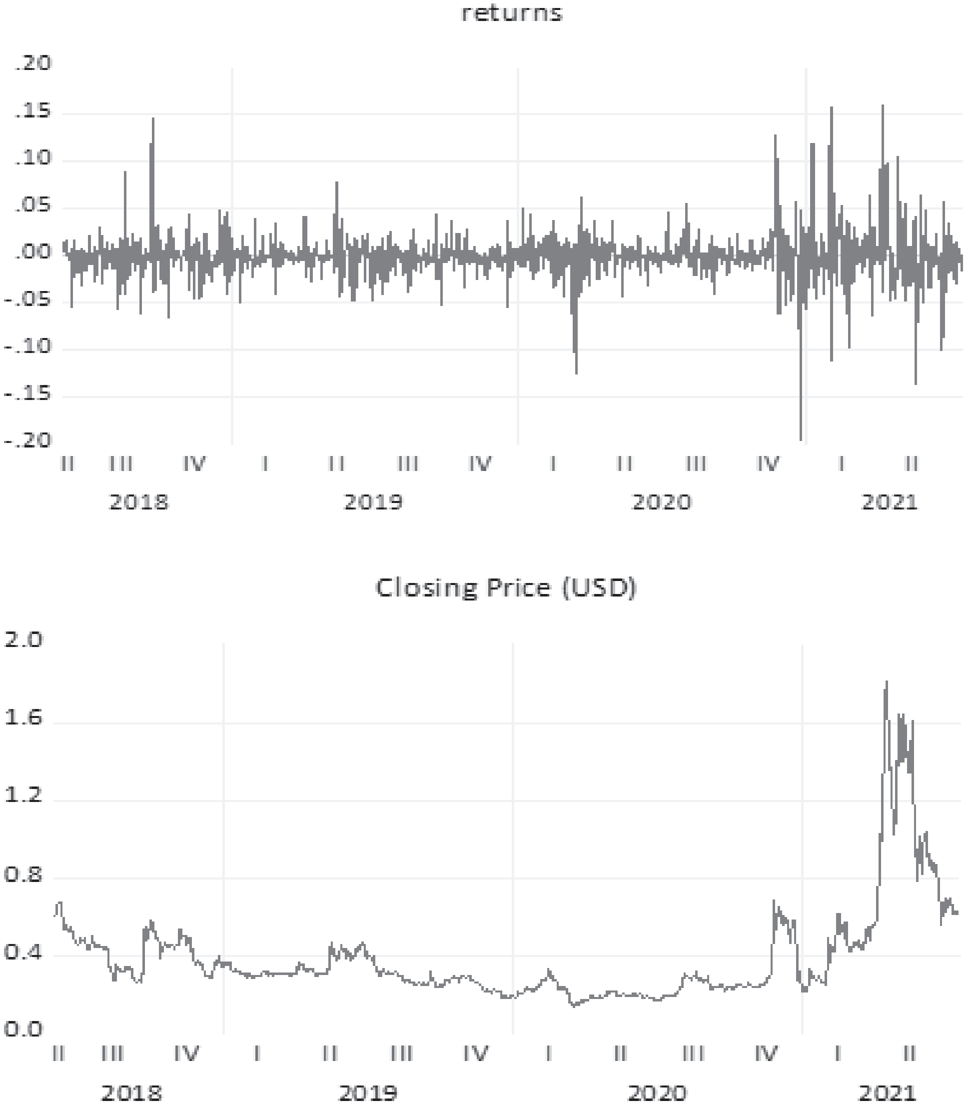


Figure 3.
XRP Returns and Price

This figure plots the return and price series of XRP over the period 2018-2021.



From Figures 1 - 3, it is evident that there was a great price surge by the end of 2016. However, the price of Bitcoin at the beginning of 2016 was just around $ 435 and then the Bitcoin price hit the three-year high of around $900. It is believed that this price surge was due to the long-term Yuan's depreciation. This high price also caused high volatility and the impact translated into the second most widely used cryptocurrency i.e., Ethereum[4] In 2018, there was a great cryptocurrency crash

[4] https://www.bbc.com/news/technology-38415066

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also known as the Bitcoin crash (this crash is explained because of the speculative nature of these cryptocurrencies and does not have very strong evidence of what caused it) and this impact can also be seen in Figure 1. The same impact is also observed in Figures 2 and 3. However, the impact was very intense in the case of Bitcoin compared to the rest of the currencies. It is also worth mentioning that the Bitcoin price never returned to its pre-bubble phase.

Figure 4.
Tether Prices

This figure plots the Tether price series over the period 2018-2021.

Figure 5.
USD Coin Price Behavior

This figure plots the USD Coin price series over the period 2020-2021.

Figure 4 depicts that the price of Tether declined drastically in 2018. Although stablecoins behave differently than the usual volatile cryptocurrencies, Tether is a token of Ethereum, which is a volatile cryptocurrency, and the impact of the crypto market shock of 2018 on Ethereum got translated into Tether as well. The literature offers no clear explanation for the drop in question, which in turn led to heightened volatility. This drop and increased volatility may have prompted investors to explore alternative stablecoins or less volatile cryptocurrencies, or both. It's worth noting that Tether's trading volume remained notably low throughout 2018 and most of 2019, only stabilizing and increasing in the final quarter of 2019 (according to coinmarketcap.com). Figure 5 illustrates that the USD Coin has remained relatively stable over the timeframe analyzed, with a single dip in early 2021.

The KPSS and ERSPO unit root test results are reported in Table 2. Our unit root test results indicate that return series of Bitcoin, Ethereum, and XRP follow stationary process. It is also evident from Table 2 that the two-price series i.e., Tether and USD Coin follow stationary process. This means that all these five series are converging to a constant mean and their variances are independent of time.

Table 2.
Stationarity Test Results

This table presents the stationarity unit root test results. The null hypothesis of the KPSS unit root test is that the variable follows a stationary process, while the null of the ERSPO is that the variable contains a unit root. ***, ** and * show the rejection of null hypothesis at 1%, 5% and 10% levels, respectively.

Cryptos	KPSS		ERSPO		Conclusion
	Intercept	Int+trend	Intercept	Int+trend	
Bitcoin Returns	0.074	0.074	0.019***	0.065***	I(0)
Ethereum Returns	0.271	0.141	0.486***	0.514***	I(0)
XRP Returns	0.116	0.024	0.004***	0.164***	I(0)
Tether Price	0.969***	0.132	0.409***	1.480***	I(0)
USD Coin Price	0.287	0.220	0.811***	2.658***	I(0)

Table 3.
Halloween Effect

This table reports results for Halloween effects. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively. The results in this table is obtained by estimating the following EGARCH model: $R_t = c + \sum_{i=1}^{p} \theta i\, R_{t-i} + \sum_{i=1}^{q} \beta_i\, \epsilon_{t-j} + \delta D_{t,c} + \varepsilon_t$ and $log(h_t) = \omega + \sum_{j=1}^{q} \beta_j log(h_{t-j}) + \sum_{i=1}^{p} \alpha_i \left|\frac{\epsilon_{t-i}}{\sqrt{h_{t-i}}}\right| + \sum_{k=1}^{r} \gamma_k \frac{\epsilon_{t-k}}{\sqrt{h_{t-k}}} + \rho_{2,c} D_{t,c}$.

	Bitcoin	Ethereum	XRP	Tether	USD Coin
Mean equation					
C	0.000	-0.000	-0.001*	1.000***	1.000***
R_{t-1}	-0.454***	-0.460***	0.836***	0.955271***	0.898***
R_{t-2}	-0.281***	-0.930***	-0.273*	-	-
MA(1)	0.396***	0.438***	-0.951***	-0.411***	-0.654***
MA(2)	0.263***	0.930***	0.326**	-0.110***	-0.082*
δ ($D_{t,c}$)	0.001	0.001*	0.001	0.000	0.000

Table 3.
Halloween Effect (Continued)

	Bitcoin	Ethereum	XRP	Tether	USD Coin
Variance equation					
Ω	-0.356***	-0.680***	-0.695***	-1.166***	-1.495*
ε_{t-12}	0.368***	0.403***	0.547***	0.470***	0.106
$\varepsilon_{t-12}\ I\{\varepsilon_{t-1}<0\}$	0.030	0.318	0.056	-0.080**	-0.091**
h_{t-1}	0.979***	0.943***	0.943***	0.937***	0.907***
$D_{t,c}$	0.015	0.010	0.017	0.062**	0.036

Table 3 presents the estimation results of the Halloween effect in Bitcoin, Ethereum, and XRP conditional returns (R_t) and conditional variance (h_t) using the EGARCH model. Additionally, Table 3 also presents results of the Halloween effect in Tether and USD Coin prices (R_t) and conditional variance (h_t) using the same EGARCH model. According to Table 3, a Halloween effect is observed only in the case of Ethereum for the mean equation (at a 10% significance level) and Tether for the variance equation (at a 5% significance level). Our findings suggest that investors who invest in cryptocurrencies or stablecoins do not earn any abnormal profit or face any abnormal risk during the Halloween period. These results are consistent with Kaiser's (2019) study. However, the returns of Ethereum are positive and significant during the Halloween period.

Table 4 summarizes the DOW effect results for all five cryptocurrencies. It is evident that the mean equation shows a weak Monday effect only in the case of the USD Coin. There is a statistically significant negative Thursday effect in the mean equation for all the cryptocurrencies, aiding investors with information to avoid trading on Thursdays as returns are negative. The Saturday effect is statistically significant in the mean equations for all the cryptocurrencies, which means investors earn abnormal profits on Saturday. The reason behind this could be that on weekends other transaction options such as bank transfers are not available. The reason behind higher returns and prices on Saturday might be because unlike the equity market which does not operate on weekends, cryptocurrencies are traded seven days a week. Tether shows a statistically significant Sunday effect as well. We do not report any statistically significant anomalies in the mean equation of Bitcoin, Ethereum, and XRP and prices of Tether and USD Coin for the remaining weekdays.

Table 4.
Day-of-the-Week Effect

This table reports results for the DOW effects. ***, ** and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

	Bitcoin	Ethereum	XRP	Tether	USD Coin
Mean equation					
Monday	0.000	0.000	0.000	0.000	0.000*
Tuesday	0.000	-0.001	-0.001	0.000	0.000
Wednesday	0.000	0.000	0.001	0.000	0.000
Thursday	-0.001**	-0.002**	-0.002**	-0.000***	-0.0001**
Friday	0.000	-0.000	-0.000	0.000	0.000***
Saturday	0.001**	0.002*	0.002**	0.000**	0.000**
Sunday	-0.000	0.001	-0.001	-0.000**	0.000
Variance equation					
Monday	0.362***	0.397***	0.671***	-0.164	-0.696**
Tuesday	0.301**	0.346***	0.172	-0.127	-0.187
Wednesday	0.288**	0.424***	0.170	-0.160	0.379
Thursday	-0.106	-0.077	-0.222	0.034	0.433
Friday	-0.222*	0.409***	-0.391**	0.250	0.307
Saturday	-0.517***	0.560***	-0.565*	0.116	0.196
Sunday	-0.155	-0.123	0.008	-0.071	-0.771***

However, when we consider volatility of cryptocurrencies, we document a strong DOW effect as compared to returns and prices. The variance equation shows that there is high volatility for all the cryptocurrencies except Tether on Monday. The reason behind this could be that Monday is the first working day and other options for transactions such as banks and Western unions are accessible to investors the same is the reason that Bitcoin and Ethereum show significant volatility even on Tuesday and Wednesday. On Friday and Saturday, the volatility is statistically significant for the top 3 volatile cryptocurrencies: Bitcoin, Ethereum, and XRP. The negative sign implies that the investors will be facing less risk while trading on Friday and Saturday as compared to the rest of the week. Sunday is statistically significant for the USD Coin and the negative sign represents safe trading for the USD Coin. The results back our argument of investors using cryptocurrency as a mode of transaction on weekends as other options are limited during the weekends.

Table 5 presents results for the MOY effects. When we consider the mean equation, we find that there is a statistically insignificant MOY effect except in the case of Bitcoin and Ethereum. Ethereum returns are reported positive and statistically significant in February, which means that investors earn positive profits in the month of February on average. The reason behind it could be that in January prices of stocks rise because of the tax loss hypothesis, investors intend to decrease their tax by realizing losses (Jones *et al.*, 1987), and the effect might get translated into Ethereum as it is the second most widely used cryptocurrency. The returns in the month of April for Bitcoin and Ethereum are statistically significant as April is usually considered the second strongest month of performance, and this could cause investors to earn abnormal profits in the month of April. Another phenomenon could be because of the Halloween effect, as investors sell in May which could cause April's monthly returns to be statistically significant. October and November are found to be weakly significant for Ethereum and USD Coin, respectively.

Table 5.
Month-of-the-Year Effect

This table reports results for the MOY effects. ***, ** and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

	Bitcoin	Ethereum	XRP	Tether	USD Coin
Mean equation					
January	0.000	0.002	0.000	0.000	0.000
February	0.001	0.003**	0.000	0.000	0.000
March	−0.00	0.000	0.001	0.000	0.000
April	0.002**	0.002*	0.001	0.000	0.000
May	0.000	0.002	0.001	0.000	0.000
June	0.000	0.000	-0.001	-0.000	-0.000
July	−0.001	-0.001	0.000	0.000	0.000
August	−0.001	0.610	-0.001	0.000	0.000
September	−0.001	-0.000	0.000	0.000	0.000
October	0.001	-0.001*	-0.000	0.000	-0.000
November	0.001	-0.000	0.001	0.000	-0.000*
December	−0.000	-0.002	-0.002	0.000	0.000
Variance equation					
January	0.004	-0.009	-0.002	-0.014	0.052
February	0.028	0.031	0.039	0.027	0.005
March	-0.023	0.013	-0.031	-0.051	0.014
April	−0.002	0.012	0.001	0.006	0.021
May	0.023	0.051*	-0.003	-0.022	0.034
June	0.006	0.004	-0.019	-0.032	-0.031
July	−0.012	0.009	0.011	0.027	-0.038
August	-0.023	-0.022	0.017	0.010	-0.000
September	−0.064***	-0.018	-0.047	-0.020	-0.075
October	0.027	-0.079**	-0.078	0.010	-0.041
November	0.024	0.005	0.081*	0.050	0.032
December	0.011	-0.003	0.033	0.010	0.025

The variance equations show strong volatility not only for volatile currencies like Bitcoin and Ethereum but also for stablecoins. The volatility for Bitcoin is negative and statistically significant in the month of September which means that investors will face negative risk in the Bitcoin market in September. It could be because September is the worst month for stock market performance and returns, according to Stock Trader's Almanac reports (Mistal, 2021), which turns out well for Bitcoin investors. For Ethereum, in October, returns are negatively volatile. Ethereum is the most popular cryptocurrency after Bitcoin so any activity in

Bitcoin can be also seen in Ethereum either at the same time or with some lag and this explains the negative volatility of returns of Ethereum in October.

IV. CONCLUSION

This study examines the validity of the efficient market theory in crypto markets by testing the impact of calendar anomalies on the daily returns of five different cryptocurrencies: Bitcoin, Ethereum, and XRP, and two stable coins- USD Coin and Tether. The EGARCH model with an exogenous dummy variable for calendar anomalies is employed to explore the effects of these events. According to the EMH, the stock market prices take in all the information and there is no abnormal pattern that can affect the efficiency of the market. In this study, we are assessing the EMH in the crypto world by testing the impact of anomalies. The Halloween effect is reported statistically insignificant in all return and volatility series except for Tether. Tether's volatility is found to be statistically significant over the Halloween period. This means that investors face high risk during the Halloween period while trading with Tether. The reason behind this could be that Tether is on top of the list of stable currencies and the Halloween period is highly profitable for equity markets which could be a risky time for investors to invest in Tether. We report a DOW anomaly in returns for all the cryptocurrencies analyzed. However, our findings show stronger calendar effects in conditional volatility representing the risk of all the cryptocurrencies used in this study. We find a statistically significant MOY anomaly for Bitcoin returns in the month of April while for Ethereum returns, February and April are found to be statistically significant. This means investors would earn positive abnormal returns in these months. However, for volatility, we find September and October to be statistically significant for Bitcoin and Ethereum, respectively. We find that September and October are the least risky months for investors. Our findings are in line with Kinateder and Papavassiliou (2021). Overall, we conclude that crypto markets do not comply with the EMH. The study demonstrates that investors can benefit from cryptocurrencies since returns exhibit volatility clustering. However, the year 2021 came to a challenging end for cryptocurrencies due to financial setbacks, a crisis in public opinion, and a fraud scandal. Nevertheless, the same vulnerabilities exist in other areas of financial services. It is apparent that this field still needs a lot of development which is why necessitating policymakers' intervention is advisable to make the crypto market effective for investors. The cryptocurrency market, unquestionably, requires additional research to see whether the random walk hypothesis holds for other cryptocurrencies.

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REFERENCES

Aggarwal, D. (2019). Do Bitcoins Follow a Random Walk Model? *Research in Economics*, 73, 15–22.

Apopo, N., & Phiri, A. (2021). On The (In)Efficiency of Cryptocurrencies: Have They Taken Daily or Weekly Random Walks? *Heliyon*, 7.

Baur, D. G., Cahill, D., Godfrey, K., & Liu, Z. F. (2019). Bitcoin Time-Of-Day, Day-Of-Week and Month-Of-Year Effects in Returns and Trading Volume. *Finance Research Letters*, 31, 78-92.

Bouman, S., & Jacobsen, B. (2002). The Halloween Indicator, "Sell in May and Go Away": Another puzzle. *American Economic Review,* 92, 1618-1635.

Bouoiyour, J., & Selmi, R. (2016). Bitcoin: A Beginning of a New Phase? *Economics Bulletin*, 36, 1430–1440.

Bouri, E., Gil-Alana, L. A., Gupta, R., & Roubaud, D. (2019). Modelling Long Memory Volatility in the Bitcoin Market: Evidence of Persistence and Structural Breaks. *International Journal of Finance & Economics*, 24, 412–426.

Brauneis, A., & Mestel, R. (2018). Price Discovery of Cryptocurrencies: Bitcoin and Beyond. *Economics Letters*, 165, 58–61.

Caporale, G. M., & Plastun, A. (2020). Momentum Effects in the Cryptocurrency Market after One-Day Abnormal Returns. *Financial Markets and Portfolio Management*, 34, 251–266.

Caporale, G. M., & Plastun, A. (2021). Gold And Oil Prices: Abnormal Returns, Momentum and Contrarian Effects. *Financial Markets and Portfolio Management*, 35, 353–368.

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

Chaim, P., & Laurini, M. P. (2019). Is Bitcoin A Bubble*? Physica A: Statistical Mechanics and its Applications*, 517, 222–232.

Cheung, A., Roca, E., & Su, J. J. (2015). Crypto-Currency Bubbles: An Application of The Phillips–Shi–Yu (2013) Methodology on Mt. Gox Bitcoin Prices. *Applied Economics*, 47, 2348-2358.

Cross, F. (1973). The Behavior of Stock Prices on Fridays and Mondays. *Financial Analysts Journal*, 29, 67–69.

Elliott, G., Rothenberg, T. J., & Stock, J. H. (1996). Efficient Tests for an Autoregressive Unit Root. *Econometrica*, 64, 813–836.

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 25, 383–417.

Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The Adjustment of Stock Prices to New Information. *International Economic Review*, 10, 1–21.

Fauzi, M., & Paiman, N. (2020). Bitcoin and Cryptocurrency: Challenges, Opportunities and Future Works. *Journal of Asian Finance Economics and Business*, 7, 695–704.

Fendi, U. A., Tahtamouni, A., Jalghoum, Y., & Mohammad, S. J. (2019). The Study of Bubbles in Bitcoin Behavior. *Banks and Bank Systems*, 14, 133–142.

French, K. (1980). Stock Returns and the Weekend Effect. *Journal of Financial Economics*, 8, 55–69.

Gibbons, M. R., & Hess, P. (1981). Day of the Week Effects and Asset Returns. *The Journal of Business*, 54, 579–596.

Giovanis, E. (2016). The Month-Of-The-Year Effect: Evidence from GARCH Models in Fifty-Five Stock Markets. *Aydın İktisat Fakültesi Dergisi*, 1, 20-49.

Granger, C. W. J., & Newbold, P. (1974). Spurious Regressions in Econometrics. *Journal of Econometrics*, 2, 111–120.

Hattori, T., & Ishida, R. (2021). The Relationship Between Arbitrage in Futures and Spot Markets and Bitcoin Price Movements: Evidence from the Bitcoin Markets. *Journal of Futures Markets*, 41, 105–114.

Hu, Y., Valera, H. G. A., & Oxley, L. (2019). Market Efficiency of the Top Market-Cap Cryptocurrencies: Further Evidence from a Panel Framework. *Finance Research Letters*, 31, 138–145.

Jones, C. P., Pearce, D. K., & Wilson, J. W. (1987). Can Tax-Loss Selling Explain the January Effect? A Note. *The Journal of Finance*, 42, 453–461.

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

Kalsie, A., & Kalra, J. K. (2015). An Empirical Study on Efficient Market Hypothesis of Indian Capital Markets. *Journal of Management Research and Analysis*, 2, 108-114.

Kelikume, I., Olaniyi, E., & Iyohab, F. A. (2020). Efficient Market Hypothesis in the Presence of Market Imperfections: Evidence from Selected Stock Markets in Africa. *International Journal of Management, Economics and Social Sciences*, 9, 37-57.

Kenourgios, D., & Samios, Y. (2021). Halloween Effect and Active Fund Management. *Quarterly Review of Economics and Finance*, 80, 534–544.

Kinateder, H., & Papavassiliou, V. G. (2021). Calendar Effects in Bitcoin Returns and Volatility. *Finance Research Letters*, 38, 101420.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing The Null Hypothesis of Stationarity Against the Alternative of a Unit Root. *Journal of Econometrics*, 54, 159–178.

Lean, H. H., & Smyth, R. (2007). Do Asian Stock Markets Follow a Random Walk? Evidence from LM Unit Root Tests with One and Two Structural Breaks. *Review of Pacific Basin Financial Markets and Policies*, 10, 15–31.

Lee, C. C., Lee, J. D., & Lee, C. C. (2010). Stock Prices and the Efficient Market Hypothesis: Evidence from a Panel Stationary Test with Structural Breaks. *Japan and the world economy*, 22, 49-58.

Loredana, M. E. (2019). A Critical Theoretical Analysis on The Implications of Efficient Market Hypothesis (EMH). *Annals of Constantin Brancusi University of Targu-Jiu. Economy Series*.

Malkiel, B. (2003). The Efficient Market Hypothesis and Its Critics. *Journal of Economic Perspectives*, 17, 59–82.

Marrett, G. J., & 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 Journal*, 5, 117-123.

DOI: 10.59091/2460-9196.2227

Mistal, C. (2021). *June 2021 Trading & Investment Strategy*: *Market at a Glance*. Stock Trader's Almanac. https://www.stocktradersalmanac.com/Newsletter/0621.aspx

Nadarajah, S., & Chu, J. (2017). On The Inefficiency of Bitcoin. *Economics Letters*, 150, 6–9.

Nelson, D. B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, 59, 347–370.

Palamalai, S., Kumar, K. K., & Maity, B. (2021). Testing The Random Walk Hypothesis for Leading Cryptocurrencies. *Borsa Istanbul Review*, 21, 256–268.

Plastun, A., Sibande, X., Gupta, R., & Wohar, M. (2020). Halloween Effect in Developed Stock Markets: A historical perspective. International Economics, 161, 130-138.

Rozeff, M. S., & Kinney, W. R. (1976). Capital Market Seasonality: The Case of Stock Returns. *Journal of Financial Economics*, 3, 379–402.

Santoso, E. B., & Ikhsan, M. (2020). Efficient Market Hypothesis in Indonesia Stock Exchange 2019. *In Annual International Conference on Accounting Research (AICAR 2019)*, 51-53.

Son-Turan, S. (2016). The Impact of Investor Sentiment on the 'Leverage Effect'. *International Econometric Review*, 8, 4–18.

Sun, W., Dedahanov, A. T., Shin, H. Y., & Li, W. P. (2021). Factors Affecting Institutional Investors to Add Crypto-Currency to Asset Portfolios. *The North American Journal of Economics and Finance*, 58, 101499.

Thushara, S. C., & Perera, P. (2012). Day of the Week Effect of Stock Returns: Empirical Evidence from Colombo Stock Exchange. *Kelaniya Journal of Management*, 1, 16–27.

Thushara, S. C., & Perera, P. (2013). The Month of the Year Effect: Empirical Evidence from Colombo Stock Exchange. *Proceedings of the 2nd International Conference on Management and Economics 2013*, Canada.

Ţiţan, A. G. (2015). The Efficient Market Hypothesis: Review of Specialized Literature and Empirical Research. *Procedia Economics and Finance*, 32, 442–449.

Tran, V. L., & Leirvik, T. (2019). A Simple but Powerful Measure of Market Efficiency. *Finance Research Letters*, 29, 141–151.

Urquhart, A. (2016). The Inefficiency of Bitcoin. *Economics Letters*, 148, 80–82.

Vidal-Tomás, D., Ibáñez, A. M., & Farinós, J. E. (2019). Weak Efficiency of The Cryptocurrency Market: A Market Portfolio Approach. *Applied Economics Letters*, 26, 1627–1633.

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.

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https://bulletin.bmeb-bi.org/bmeb
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