MAKÜ | Journal of Mehmet Akif Ersoy University
Economics and Administrative Sciences Faculty

e-ISSN: 2149-1658
Volume: 11 / Issue: 1
March, 2024
pp.: 346-365

Day-of-the-Week and Month-of-the-Year Effects in the Cryptocurrency Market *

İbrahim Korkmaz KAHRAMAN[1], Dündar KÖK[2]

1. Dr., Pamukkale University,
ikahraman@pau.edu.tr,
https://orcid.org/0000-0001-5083-3586

2. Prof. Dr., Pamukkale University,
dkok@pau.edu.tr,
https://orcid.org/0000-0002-5250-3369

* This article is derived from İbrahim Korkmaz Kahraman's PhD thesis prepared under the supervision of Dündar Kök.

https://doi.org/10.30798/makuiibf.1387108

Abstract

This study examines the day-of-the-week (DoW) and month-of-the-year (MoY) effects in the cryptocurrency market, with a focus on Bitcoin (BTC) and Ethereum (ETH). Due to the absence of a specific closing time in the cryptocurrency market, the closing time of the daily data is taken as 23:59 UTC. Initially, an appropriate volatility model for the cryptocurrency market is established using the GARCH, EGARCH, and TGARCH models. The most appropriate model for BTC is ARMA(1,0)-EGARCH(1,1) and ARMA(1,0)-GARCH(1,1) for ETH. The results of the analysis indicate a leverage effect in the cryptocurrency market, where negative shocks cause a more significant increase in volatility than positive shocks. Based on this volatility structure, the DoW and MoY are analyzed. For BTC, returns on other days are lower compared to Mondays. However, for ETH, returns on Thursdays are lower than those on Mondays. In terms of volatility, both BTC and ETH show that the highest volatility occurs on Mondays. For the MoY effect, neither BTC nor ETH don't exhibit a significant effect in the mean equation. Nevertheless, the variance equation indicates that January has higher volatility compared to other months, indicating the presence of a MoY effect in terms of volatility.

Keywords: Bitcoin, Ethereum, Cryptocurrency, Day-of-the-week effect, Month-of-the-year effect.

Article Type	Application Date	Acceptance Date
Research Article	November 6, 2023	March 9, 2024

To cite this article: Kahraman, İ. K. & Kök, D. (2024). Day-of-the-week and month-of-the-year effects in the cryptocurrency market. *Journal of Mehmet Akif Ersoy University Economics and Administrative Sciences Faculty, 11*(1), 346-365. https://doi.org/10.30798/makuiibf.1387108

1. INTRODUCTION

The literature analyzing calendar effects in stock markets identifies various effects. Among these, DoW effects, MoY effects, January effects, holiday effects, and Halloween effects have received the most attention (Mills and Coutts, 1995). The DoW effect is a well-known phenomenon detected in financial markets, where assets such as stocks, bonds, currencies, and commodities have different returns on some days of the week compared to other days (Aharon and Qadan, 2019; Ma and Tanizaki, 2019a). Notably, this calendar effect is often observed in stock market returns and stock market volatility. It is reported in the literature that the market generally has negative returns on Mondays and positive returns on Fridays (Berument and Dogan, 2012). For example, French (1980) observed that stock markets have above-average returns on the last trading day (Friday) and below-average returns on the first trading day (Monday).

The MoY effect, on the other hand, denotes significantly different returns during specific months compared to others. The different returns and characteristics of any month compared to other months constitute a month-specific effect. In financial markets, the January effect is considered to be the most striking compared to other months. Studies in the stock market show that stocks generate higher returns in January compared to other months. This was first demonstrated by Rozeff and Kinney (1976), who found that stock returns are higher on average in January than in other months. Keim (1983) states that the January effect is mostly due to small-scale firms.

The main motivation for this study is to investigate whether the cryptocurrency market exhibits calendar effects, as it operates continuously 24/7, including holidays and weekends. It is expected that any published information will be immediately reflected in prices and that the distribution of returns will be the same. Notably, investing in cryptocurrencies differs from other asset classes as the days and months with potentially favorable returns can vary throughout the twelve months of the year and the seven days of the week. The DoW effect and the MoY effect are worth investigating in the cryptocurrency market as well as in financial markets.

This study contributes to the literature by analyzing the DoW and MoY effects on both BTC and ETH returns. While most of the studies in the literature focus only on BTC, this study considers both leading cryptocurrencies. In particular, it is examined whether cryptocurrency investors apply different investment strategies when stock markets are closed. These questions were answered by analyzing the DoW and MoY patterns in BTC and ETH returns. In addition, the fact that cryptocurrencies are traded continuously and globally every second of the day is very important for analyzing the DoW and MoY effects. The non-stop operation of cryptocurrency markets is a critical factor in this study. It is possible to buy and sell any cryptocurrency, such as BTC, ETH, LTC, or XRP, at any time, every day, every night, even on Sundays or holidays. Due to these characteristics, the study of calendar effects in the cryptocurrency market is of particular interest.

The rest of this paper is organized as follows: Section two presents a literature review on the DoW and MoY effects in the cryptocurrency market. Section three introduces the dataset and explains the methodology used in the analysis. The fourth section discusses the empirical findings. Finally, the fifth section presents the conclusions.

2. LITERATURE REVIEW

Research on the cryptocurrency market has revealed significant findings regarding the DoW effect. Décourt et al. (2017) conducted the initial research on this topic. Their research indicated that BTC does not have an efficient market and provides the prospect of producing notably higher abnormal returns; specifically, Tuesdays and Wednesdays have higher returns compared to other days. Mbanga (2018) reported that BTC prices tend to cluster around whole numbers, with prices ending in 0.99 decimals every DoW and showing stronger clustering on Fridays and weaker clustering on Mondays. According to Yaya and Ogbonna's (2019) findings, the effect of the DoW on returns is not significant. However, there is potentially significant evidence for the existence of Monday and Friday effects exclusively in the volatility of BTC.

Ma and Tanizaki (2019b) conducted a study on the DoW effect on BTC and found that the Monday effect is significant. Additionally, Wednesdays exhibit low average return levels. Ma and Tanizaki (2019a) also found that Mondays and Thursdays exhibited significantly higher volatility, and the highest and lowest returns, respectively, were seen on Mondays and Wednesdays. Aharon and Qadan (2019) found in their study that the DoW effect has an impact on both BTC's return and volatility, with Mondays associated with higher returns and volatility compared to other weekdays.

Baur et al. (2019) observed low activity during local evening hours and weekends across all trading venues, indicating differences in activity. Most trading venues experienced lower trading activity during midnight and early morning (local time), even though BTC trading increased when trading venues in Europe were open. Therefore, it can be concluded that there is no persistent effect on returns by DoW or MoY. The findings provide support for the view that the cryptocurrency markets are, at the very least, weakly efficient. Kinateder and Papavassiliou's (2019) study does not find any evidence of a Halloween or DoW effect. On weekends, the risks are significantly lower. BTC is less volatile in September and on weekends but more intense at the beginning of the week. Plastun et al. (2019) discovered that BTC returns are abnormally low in July and August in comparison to other months. However, they found that returns are 3-4 times higher in March and October in comparison to other months.

In addition to studies on BTC, there is research that examines altcoins. For example, Dorfleitner and Lung (2018) analyzed the returns of eight cryptocurrencies, finding that returns on Sundays are markedly lower compared to other days, while Tuesdays and Fridays typically offer the highest returns. As a result, the authors suggest purchasing cryptocurrencies before Tuesday's or Friday's end to avoid potential losses, even though Sunday returns are the lowest. In addition, the study suggests that trading on Sundays may have a lower return since cryptocurrencies tend to have substantially lower volatility in most cases.

Caporale and Plastun (2019) examined BTC, XRP, LTC, and DASH and found that only BTC had higher returns on Mondays compared to other days of the week. By using an investment strategy based on this effect, higher returns were achieved than by making random investments over the sample period (2013-2017). Robiyanto et al. (2019), on the other hand, argued that investing in BTC at the end of January and selling towards the end of February is advisable, while Mondays, Wednesdays, and Thursdays hold the potential for higher returns in the case of day investors. Regarding LTC, there is significant positive return potential for investors in February. Additionally, Friday holds the highest return potential on a daily basis. Kaiser (2019) notes that, although there is no significant calendar effect in the cryptocurrency market, the trading volume and volatility of ten cryptocurrencies (BTC, BCH, ADA, DASH, ETH, MIOTA, LTC, NEO, XRP, and XLM) are lower on average during January, weekends, and summer.

3. DATA AND METHODOLOGY

3.1. Data

As of November 4, 2023, more than 27,000 cryptocurrencies were available in the cryptocurrency market, with BTC and ETH comprising around 69% of the total market capitalization (CoinMarketCap, 2023). Due to the absence of a definitive closing time for cryptocurrency trading, 23:59 UTC was considered the end of the day for the purpose of daily data. In this study, all data was obtained from the Bitstamp cryptocurrency trading platform and valued in US dollars. The analysis covers daily data starting on January 1, 2015, for BTC and August 18, 2017, for ETH, and ending on December 31, 2022.

According to Le Tran and Leirvik (2020), caution is necessary when interpreting the findings due to the high volatility of financial asset returns. Differences exist between simple returns and logarithmic returns. For example, a 5% simple return would yield a logarithmic return of approximately 4.88%, while a 10% simple return would result in a logarithmic return of about 9.53%. Additionally, logarithmic returns for negative simple returns exhibit greater absolute value. In cases of significant negative deviations, logarithmic returns may drop below -100%, which is economically nonsensical. As an example, if the price of a cryptocurrency drops from \$50 to \$10, the simple return would be -80%, whereas the logarithmic return would be approximately -160%. Given the highly volatile nature of the cryptocurrency market, in this study, we calculated the simple return as follows:

$$R_{i,t} = \left[\frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}\right] \tag{1}$$

Return series are constructed using the formula in Equation 1, where $R_{i,t}$ is the return and $P_{i,t}$ is the price. Descriptive statistics and unit root test results of BTC and ETH daily return data are shown in Table 1.

Table 1. Descriptive statistics and unit root test

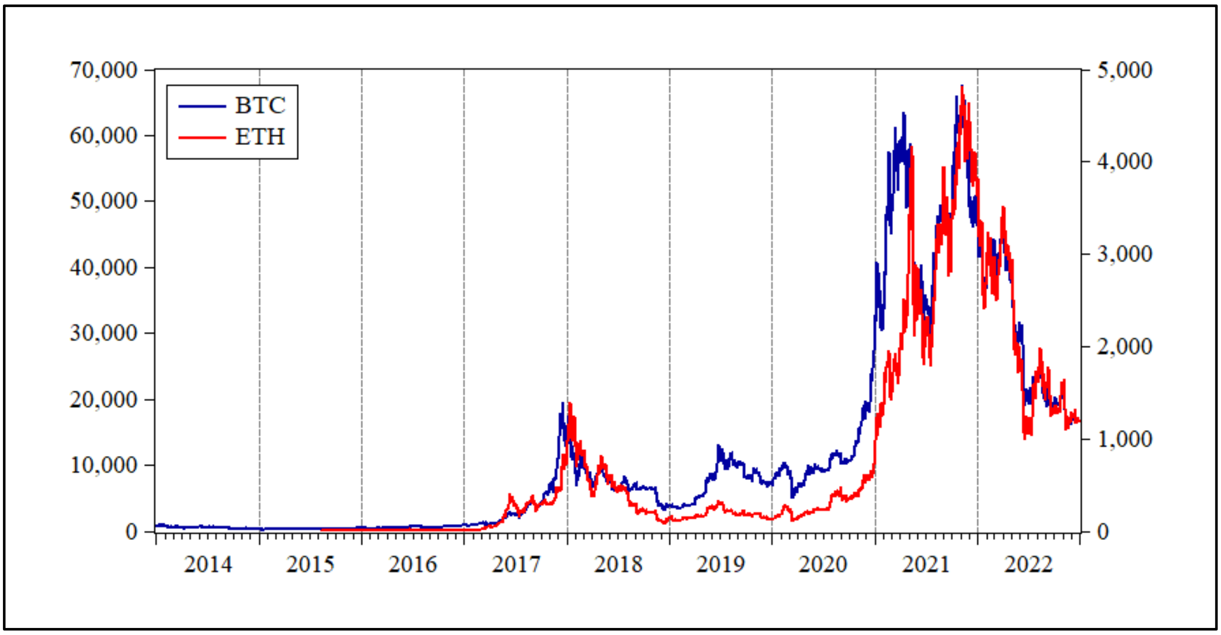
	BTC	ETH
	Panel A: Descriptive statistics	
N	2,921	1,961
Mean	0.0021	0.0021
Standard Deviation	0.0391	0.0519
Minimum	-0.3898	-0.4376
Maximum	0.2692	0.2637
Skewness	-0.1796	-0.2043
Kurtosis	10.5809	8.0574
	Panel B: Unit root test	
ADF	-56.8265^{***}	-47.4625^{***}
PP	-56.7665^{***}	-47.3698^{***}

***, indicate significance at the 1% level.

Notes: N stands for the number of observations; ADF stands for Augmented Dickey-Fuller; and PP stands for Phillips-Perron unit root test. For ADF and PP unit root tests, a constant model is used.

Table 1 presents the descriptive statistics and unit root test for the daily return series of BTC and ETH. As shown in Panel A, the average daily return of both cryptocurrencies was positive during the sample period. However, ETH has a higher standard deviation than BTC, indicating that it is riskier. Daily returns have a negatively skewed and leptokurtic distribution, indicating a higher likelihood of loss than gain and the presence of more outliers. In Panel B, the results of both ADF (Dickey and Fuller, 1979) and PP (Phillips and Perron, 1988) unit root tests indicate that both series are stationary.

Figure 1. BTC and ETH daily price series



Notes: The left axis shows the BTC price level, and the right axis shows the ETH price level.

In the cryptocurrency market, while prices increased steadily until the first quarter of 2017, there was rapid and significant growth in the prices of cryptocurrencies until the end of 2017, and prices started to fall again in 2018. Notably, by 2021, cryptocurrencies had experienced a price increase again. Figure 1 shows the daily price series of BTC and ETH. The all-time high for BTC was $68,789.63 on November 10, 2021, while the all-time high for ETH was $4,891.70 on November 16, 2021.

3.2. Methodology

Most studies investigating the calendar effect analyze returns using standard OLS methodology with dummy variables. However, Kiymaz and Berument (2003) mention two drawbacks of this methodology. First, autocorrelated errors in the model may lead to misleading inferences. Secondly, error variances may not remain constant over time. Therefore, in this study, we choose the appropriate volatility model from the calendar effect GARCH, EGARCH, and TGARCH models and also include DoW dummy variables in both the mean and variance equations of the model, as suggested by Berument and Kiymaz (2001) and Kiymaz and Berument (2003). A similar model also applies to the MoY effect. Therefore, the study first determines the appropriate volatility structure for the cryptocurrency market, and then this model is used to analyze the DoW effect and the MoY effect.

The ARCH model assumes that the error term is time-varying. This model uses a variance term combined with the squares of past errors to explain the variability defined as an error term. The mathematical representation of the conditional variance equation of the ARCH(1) model is as in Equation 2:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 \tag{2}$$

Since σ_t^2 is the conditional variance, its value must always be positive; a negative variance at any point in time would be meaningless (Brooks, 2014). ω and α are unknown parameters of the model, and the conditional variance is positive if $\omega > 0$ and $\alpha \geq 0$. In the ARCH(1) model, the conditional variance is explained only by the shock, which is a function of the square of the one-period lagged value of the error term, implying that a shock at time t-1 will lead to a larger variance at time t. Moreover, in the ARCH(p) model, old news reaching the market before period p has no effect on current volatility.

Although it is widely acknowledged that volatility is predictable, there are various approaches to modeling this predictability. A particularly intriguing approach is the “asymmetric” or “leverage” volatility model, in which good news and bad news have different predictability for future volatility. This phenomenon arises when an unexpected decrease in price (i.e., bad news) affects predictable volatility more than an unexpected increase in price (i.e., good news) of a similar magnitude (Engle and Ng, 1993). One of the methods proposed to model such asymmetric effects is the EGARCH model, developed by Nelson (1991), and another is the TGARCH model, developed by Zakoian (1994). Table

2 presents the conditional variance equations of various GARCH models, including GARCH, EGARCH, and TGARCH, which were used in this study.

Table 2. Conditional variance equation

Model	Conditional variance equation	Authors
GARCH	$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$	Bollerslev (1986)
EGARCH	$log(\sigma_t^2) = \omega + \alpha\left[\left\|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\| - \sqrt{\frac{2}{\pi}}\right] + \beta\, log(\sigma_{t-1}^2) + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$	Nelson (1991)
TGARCH	$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta\varepsilon_{t-1}^2 I_{t-1}$ $I_{t-1} = \begin{cases} 1, & \varepsilon_{t-1} < 0 \\ 0, & \varepsilon_{t-1} \geq 0 \end{cases}$	Zakoian (1994)

As discussed under the volatility structure of the cryptocurrency market, ARMA(1,0)-EGARCH(1,1) for BTC and ARMA(1,0)-GARCH(1,1) for ETH are the most appropriate models. In addition, DoW dummy variables suggested by Berument and Kiymaz (2001) and Kiymaz and Berument (2003) are added to both the mean equation and the variance equation of the model. The conditional mean equation of the model is given in Equation 3:

$$R_t = \phi_0 + \sum_{i=1}^{6} D_i\phi_{i,t} + \phi_7 R_{t-1} + \varepsilon_t \quad (3)$$

In Equation 3, R_t denotes daily returns, and D_i denotes dummy variables for Tuesday, Wednesday, Thursday, Friday, Saturday, and Sunday for $i = 1, 2, 3,..., 6$. ε_t denotes the error term. Mondays are excluded from the conditional mean equation to avoid the trap of perfect multicollinearity. Therefore, Mondays form the basis for comparison.

The conditional variance equation of the EGARCH model, including the days of the week effect:

$$log(\sigma_t^2) = \omega + \alpha\left[\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\pi}}\right] + \beta\, log(\sigma_{t-1}^2) + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \sum_{i=1}^{6} D_i V_{i,t} \quad (4)$$

Conditional variance equation of the GARCH model, including the days of the week effect:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \sum_{i=1}^{6} D_i V_{i,t} \quad (5)$$

For $i = 1, 2, 3,..., 6$ in these models, D_i denotes the dummy variables for Tuesday, Wednesday, Thursday, Friday, Saturday, and Sunday, respectively. At the same time, statistically significant coefficients of $V_{i,t}$ indicate that there is a DoW effect on volatility on the relevant days.

In the section where the MoY effect is investigated, dummy variables are utilized in accordance with the methodology mentioned for the DoW effect. Similarly, ARMA(1,0)-EGARCH(1,1) for BTC and ARMA(1,0)-GARCH(1,1) for ETH were determined to be the most appropriate models. In the model, the months of the year are included as dummy variables in both the mean equation and the variance equation. The mean equation of the model is given in Equation 6:

$$R_t = \phi_0 + \sum_{i=1}^{11} D_i\phi_{i,t} + \phi_{12} R_{t-1} + \varepsilon_t \quad (6)$$

In Equation 6, R_t denotes daily returns, and D_i denotes dummy variables for February, March, April, May, June, July, August, September, October, November, and December for $i = 1, 2, 3,..., 11$. ε_t denotes the error term. To avoid the multicollinearity trap, January is omitted from the conditional mean equation and used as a basis for comparison.

Conditional variance equation of the EGARCH model, including the MoY effect:

$$log(\sigma_t^2) = \omega + \alpha\left[\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\pi}}\right] + \beta\, log(\sigma_{t-1}^2) + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \sum_{i=1}^{11} D_i V_{i,t} \tag{7}$$

Conditional variance equation of the GARCH model, including the MoY effect:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \sum_{i=1}^{11} D_i V_{i,t} \tag{8}$$

For $i = 1, 2, 3,..., 11$ in these models, D_i denotes dummy variables for February, March, April, May, June, July, August, September, October, November, and December, respectively. At the same time, statistically significant coefficients of $V_{i,t}$ indicate that there is a MoY effect on volatility in the respective month.

4. EMPIRICAL RESULTS

In this section of the study, we begin by examining the volatility structure of the cryptocurrency market. Subsequently, we conduct a calendar effect analysis, accounting for the volatility structure. In this section, we employ the GARCH, EGARCH, and TGARCH models to analyze the volatility structure of the cryptocurrency market, deriving the conditional mean and variance equations for BTC and ETH. Following appropriate model selection, these models are utilized to investigate MoY and DoW variables.

4.1. Volatility structure of the cryptocurrency market

Constructing a volatility model for an asset return series involves four steps (Tsay, 2010). Initially, we test for autocorrelation in the data, determine the mean equation, and, if necessary, construct an econometric model such as an ARMA model. Subsequently, we test for the ARCH effect using the error term of the mean equation. If the ARCH effect is statistically significant, we select a volatility model and estimate the mean and variance equations together. Finally, we check the appropriateness of the model and revise it if deemed necessary.

4.1.1. Mean Equation

To determine the mean equation, we first estimate the ARMA(p,q) model. In this model, p represents the lags of the autoregressive (AR) component, and q represents the lags of the moving average (MA) component. Equation 9 specifies the ARMA(p,q) model.

$$R_t = \phi_0 + \phi_1 R_{t-1} + \phi_2 R_{t-2} + \cdots + \phi_p R_{t-p} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q} \tag{9}$$

$$\varepsilon_t \sim N(0,\sigma^2)$$

The first step in model selection involves checking the stationarity of the series. After analyzing the unit root test results in Table 1, both ADF and PP indicate that the data exhibit stationarity. For BTC and ETH returns, all combinations for p,q ≤ 2 are tested. Table 3 displays the LL, AIC, BIC, HQ, Q(5), and ARCH(5) values for alternative models. The BIC criterion is used for model selection.

Table 3. Mean equation selection

	ARMA(1,0)	ARMA(2,0)	ARMA(1,1)	ARMA(2,1)	ARMA(1,2)	ARMA(2,2)
			Panel A: BTC			
LL	5,324.85	5,325.03	5,324.96	5,327.33	5,327.28	5,327.34
AIC	-3.6445	-3.6440	-3.6439	-3.6449	-3.6448	-3.6442
BIC	-3.6404	-3.6378	-3.6378	-3.6367	-3.6366	-3.6340
HQ	-3.6431	-3.6418	-3.6417	-3.6419	-3.6419	-3.6405
Q(5)	1.93	1.53	1.71	0.39	0.47	0.39
ARCH(5)	114.72***	115.29***	114.91***	115.28***	115.34***	115.37***
			Panel B: ETH			
LL	3,024.96	3,027.92	3,026.91	3,028.76	3,028.40	3,029.15
AIC	-3.0831	-3.0851	-3.0840	-3.0849	-3.0845	-3.0843
BIC	-3.0774	-3.0765	-3.0755	-3.0735	-3.0732	-3.0701
HQ	-3.0810	-3.0819	-3.0809	-3.0807	-3.0804	-3.0791
Q(5)	7.57	1.23	3.88	0.74	1.38	0.19
ARCH(5)	70.55***	72.02***	69.23***	72.56***	73.27***	71.33***

***, indicate significance at the 1% level.

Notes: LL is the log-likelihood; AIC is Akaike; BIC is Schwarz-Bayesian; HQ is Hannan-Quinn information criteria. Q is the Ljung-Box Q statistic. ARCH is the ARCH LM test. The values in parentheses indicate the number of lags.

Panel A in Table 3 shows that the best-fitting model for BTC's daily return series is ARMA(1,0). In the model, the Q(5) statistic indicates that there is no autocorrelation in the series. The 5th-lag ARCH-LM test indicates that there is an ARCH effect in the series. Panel B shows the results for the daily return series of ETH. As with BTC, ARMA(1,0) is the minimum BIC value for ETH. The Q(5) statistic indicates that there is no autocorrelation in the series, while the ARCH-LM test indicates that there is an ARCH effect in the series.

4.1.2. Conditional Variance Equation

In the previous section, having constructed an appropriate ARMA model for the return series and determined the mean equation, we detected the ARCH effect. In this section, we discuss the process of selecting the appropriate volatility model, comparing the GARCH, EGARCH, and TGARCH models to determine the most suitable one for the variables.

Selecting the appropriate models for forecasting cryptocurrency volatility is of critical importance. There are many GARCH models in the literature, making it difficult to identify a single GARCH model as a forecasting tool (Köchling et al., 2020). Asymmetric GARCH models have been noted to outperform others for all cryptocurrencies (Ngunyi et al., 2019). Moreover, Gyamerah (2019) and Franke et al. (2019) observed that the TGARCH model outperforms the other models, while Qi et al. (2020) found the EGARCH model to outperform others.

In line with these discussions, the ARMA(1,0) model is chosen as the mean equation for the daily return data for both BTC and ETH. Therefore, Table 4 shows the results of the ARMA(1,0)-GARCH(1,1), ARMA(1,0)-EGARCH(1,1), and ARMA(1,0)-TGARCH(1,1) models.

Table 4. GARCH model estimates

	BTC			ETH		
	GARCH	EGARCH	TGARCH	GARCH	EGARCH	TGARCH
Constant (ϕ_0)	0.0021*** (0.0006)	0.0018*** (0.0006)	0.0019*** (0.0006)	0.0020* (0.0011)	0.0021** (0.0010)	0.0017 (0.0011)
AR(1) (ϕ_1)	-0.0347* (0.0195)	-0.0566*** (0.0183)	-0.0286 (0.0199)	-0.0493* (0.0257)	-0.04530 (0.0244)	-0.0409 (0.0261)
Constant (ω)	0.0001*** (0.0000)	-0.6159*** (0.0409)	0.0001*** (0.0000)	0.0002*** (0.0000)	-0.6315*** (0.0802)	0.0002*** (0.0000)
ARCH (α)	0.1219*** (0.0076)	0.2557*** (0.0142)	0.1028*** (0.0101)	0.0876*** (0.0086)	0.2001*** (0.0184)	0.0723*** (0.0118)
GARCH (β)	0.8462*** (0.0092)	0.9336*** (0.0049)	0.8402*** (0.0096)	0.8429*** (0.0159)	0.9186*** (0.0121)	0.8220*** (0.0183)
EGARCH (γ)		-0.0318*** (0.0062)			-0.0336*** (0.0086)	
TGARCH (δ)			0.04467*** (0.0090)			0.0443*** (0.0127)
LL	5,571.97	5,587.52	5,575.35	3,098.54	3,100.13	3,100.62
AIC	-3.8130	-3.8230	-3.8146	-3.1567	-3.1573	-3.1578
BIC	-3.8028	-3.8107	-3.8023	-3.1424	-3.1402	-3.1407
HQ	-3.8093	-3.8185	-3.8102	-3.1514	-3.1510	-3.1515
ARCH(5)	3.5563	3.6044	3.6441	5.0078	5.2244	4.9815

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Notes: LL is the log-likelihood; AIC is Akaike; BIC is Schwarz-Bayesian; HQ is Hannan-Quinn information criteria. ARCH is the ARCH LM test. The values in parentheses are standard errors.

The ARMA(1,0)-EGARCH(1,1) model shows the highest LL value (5,587.52) for BTC returns. It also has the lowest value for the three information criteria (AIC: -3.8230; BIC: -3.8107; HQ: -3.8185). In the model, all parameters in the mean and variance equations are statistically significant, and the ARCH(5) test results demonstrate that the ARCH effect is no longer present. Therefore, the ARMA(1,0)-EGARCH(1,1) model is the most appropriate model for BTC data. The ARMA(1,0)-TGARCH(1,1) model has the highest LL value (3,100.62) for ETH returns. Among the considered models, ARMA(1,0)-TGARCH(1,1) has the lowest values for AIC (-3.1578) and HQ (-3.1515), while ARMA(1,0)-GARCH(1,1) has the lowest BIC value (-3.1424). Although the parameters for the mean equation are not statistically significant in the ARMA(1,0)-TGARCH(1,1) model, those in the variance equation are. The ARCH(5) test results reveal the absence of an ARCH effect in both models. Thus, as previously noted (taking into account the BIC in model selection), the optimal model for ETH daily return data is ARMA(1,0)-GARCH(1,1).

The findings in this section indicate that the most suitable mean equation for both BTC and ETH daily data is ARMA(1,0), which represents the volatility structure of the cryptocurrency market. Specifically for the BTC daily data, the most appropriate volatility model is the ARMA(1,0)-EGARCH(1,1) model. Analysis of the model parameters reveals a statistically significant negative value for γ (-0.0318), indicating the presence of a leverage effect. Consequently, negative news seems to have a stronger impact on volatility than positive news. For the ETH daily data, the most appropriate volatility model is the ARMA(1,0)-GARCH(1,1) model.

These findings align with those of Bouiyour and Selmi (2016), Zargar and Kumar (2019), and Zhou (2021), indicating that negative news has a stronger effect on volatility than positive news. On the other hand, studies by Baur and Dimpfl (2018), Ahmed (2020), Farkhfekh and Jeribi (2020), Wajdi et al. (2020), and Wang et al. (2021) suggest that the impact of positive news is more significant than negative news. Baur and Dimpfl (2018) attribute the subdued volatility response to negative shocks to the cautious approach adopted by informed investors. Fakhfekh and Jeribi (2020) argue that the augmented volatility in response to positive shocks may stem from the herd behavior of uninformed investors. Similarly, Wang et al. (2021) posit that uninformed investors continue to play an important role in the market and point out their participation in the market out of concern for possible price increases.

4.2. Day-of-the-week effect analysis

Table 5 shows the descriptive statistics of the BTC and ETH return series for each DoW.

Table 5. Descriptive statistics for days of the week

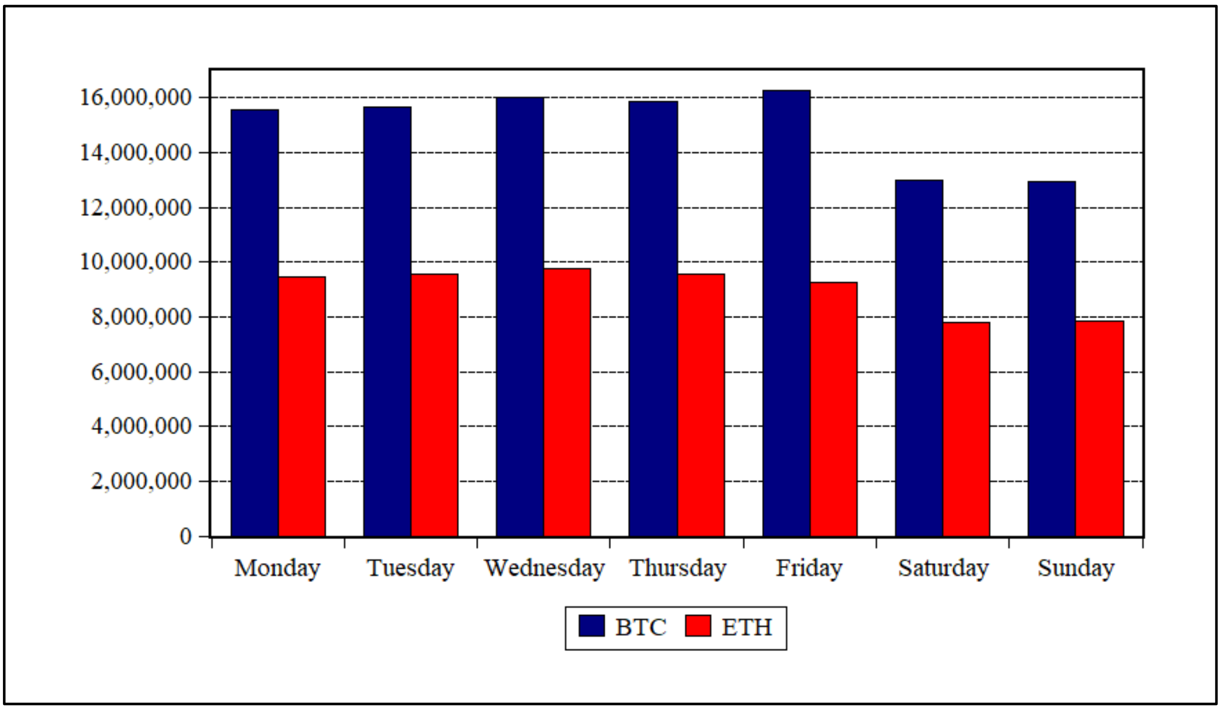
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Panel A: BTC Descriptive Statistics (02.01.2015-31.12.2022)							
N	417	417	417	417	418	418	417
Mean	0.0054	0.0008	0.0015	0.0021	0.0026	0.0024	-0.0001
SD	0.0421	0.0389	0.0417	0.0481	0.0383	0.0314	0.0306
Min	-0.1607	-0.1632	-0.2449	-0.3898	-0.1619	-0.1185	-0.1122
Max	0.1945	0.1845	0.1667	0.2692	0.1651	0.1431	0.1295
Skew	0.2874	-0.2619	-0.5036	-0.5168	0.1975	-0.0129	-0.1228
Kurt	5.8658	6.2348	7.5699	17.5209	5.9824	6.9623	5.6336
Panel B: ETH Descriptive Statistics (18.08.2017-31.12.2022)							
N	280	280	280	280	280	281	280
Mean	0.0031	0.0007	0.0028	-0.0037	0.0045	0.0056	0.0014
SD	0.0581	0.0509	0.0547	0.0598	0.0528	0.0382	0.0455
Min	-0.1743	-0.1714	-0.2771	-0.4376	-0.1460	-0.1322	-0.1625
Mak	0.2637	0.2326	0.1439	0.1775	0.2379	0.1238	0.2627
Skew	0.4128	0.3185	-0.6461	-1.3587	0.4442	0.0802	0.2709
Kurt	5.4077	5.5896	5.6939	13.2281	5.0611	4.6082	8.2072

Return statistics for the entire sample period were previously presented in Table 1. Accordingly, the average return for BTC was 0.0021 with a standard deviation of 0.0391, while the average return for

ETH was 0.0021 with a standard deviation of 0.0519. Analyzing each day's return, it was found that the highest average return for BTC was 0.0054 on Monday, while the lowest return was -0.0001 on Sunday. In contrast, these findings are different for ETH. For ETH, the highest average return was 0.0056 on Saturday, while the lowest was -0.0037 on Thursday. Table 5 presents the standard deviations, minimum and maximum returns, skewness, and kurtosis values for each day. Regarding BTC, the highest standard deviation occurred on Thursday, with a value of 0.0481, while the lowest was 0.0306 on Sunday. As for ETH, the day with the highest standard deviation, 0.0598, was also Thursday, the same day as BTC, while the smallest standard deviation was 0.0382 and was observed on Saturday.

BTC returns on Sundays were significantly lower and negative than on other days during the sample period. Similarly, the standard deviation was lower than on other days. Dorfleitner and Lung (2018) explain this observation by the low trading volume observed on Sundays, assuming a causal relationship between trading volume and asset returns and risk. This phenomenon, however, does not occur in the case of ETH. This information is supported by the trading volume graph presented in Figure 2. Specifically, on weekdays, BTC and ETH experience notably higher trading volumes, with trading volumes dropping during weekends.

Figure 2. Day-of-the-week BTC and ETH trading volume (USD 1,000)



Notes: The average daily trading volume for BTC is from January 1, 2014, to December 31, 2022, and for ETH, from August 7, 2015, to December 31, 2022. Trading volume is reported in US dollars. Data obtained from https://coinmarketcap.com/

Table 6 shows the results of the DoW analysis for BTC and ETH. Since the coefficients for Mondays are removed, this day serves as the basis for comparison.

Table 6. Day-of-the-week effect analysis results

	BTC	ETH
Constant (ϕ_0)	0.0042*** (0.0015)	0.0018 (0.0030)
Tuesday (ϕ_1)	-0.0004 (0.0020)	-0.0014 (0.0041)
Wednesday (ϕ_2)	-0.0052*** (0.0019)	0.0001 (0.0043)
Thursday (ϕ_3)	-0.0022 (0.0022)	-0.0078* (0.0043)
Friday (ϕ_4)	-0.0028 (0.0021)	0.0015 (0.0041)
Saturday (ϕ_5)	-0.0011 (0.0019)	0.0040 (0.0036)
Sunday (ϕ_6)	-0.0045** (0.0019)	0.0001 (0.0039)
AR(1) (ϕ_7)	-0.0604*** (0.0192)	-0.0567** (0.0260)
Constant (ω)	0.0157 (0.0769)	0.0010*** (0.0002)
ARCH (α)	0.2749*** (0.0160)	0.1012*** (0.0124)
GARCH (β)	0.9347*** (0.0055)	0.8089*** (0.0255)
EGARCH (γ)	-0.0191*** (0.0074)	
Tuesday (V_1)	-0.4952*** (0.1024)	-0.0009*** (0.0003)
Wednesday (V_2)	-0.7646*** (0.0759)	-0.0005** (0.0003)
Thursday (V_3)	-0.4609*** (0.0823)	-0.0007*** (0.0003)
Friday (V_4)	-0.8662*** (0.0755)	-0.0010*** (0.0003)
Saturday (V_5)	-1.1301*** (0.0841)	-0.0019*** (0.0002)
Sunday (V_6)	-0.7879*** (0.0964)	-0.0005** (0.0002)
LL	5,664.57	3,137.39
AIC	-3.8675	-3.1841
BIC	-3.8307	-3.1357
HQ	-3.8542	-3.1663
ARCH(5)	6.6313	7.8320

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Notes: LL is the log-likelihood; AIC is Akaike; BIC is Schwarz-Bayesian; HQ is Hannan-Quinn information criteria. ARCH is the ARCH LM test. The values in parentheses are standard errors.

The estimated coefficients for the dummy variables in the conditional mean equation indicate that BTC returns are higher on Mondays than on other days of the week. All the coefficients corresponding to the dummy variables from Tuesday to Sunday (ϕ_1 to ϕ_6) are negative. Notably, the coefficient for Wednesday is significantly different from zero at the 1% significance level, while the coefficient for Sunday is also significantly different from zero at the 5% level of significance. In the conditional variance equation, all coefficients except the constant term (ω) are statistically significant at the 1% level of significance. For BTC, all coefficients of the dummy variables from Tuesday to Sunday in the conditional variance equation are consistently negative and statistically significant.

For ETH, the estimated coefficients for the dummy variables in the conditional mean equation indicate that the return on Thursday is lower than on Monday. The coefficient for Thursday (ϕ_3) is statistically significant at the 10% level and is negative. Furthermore, while the coefficient for Tuesday in the conditional mean equation is negative, it is not statistically significant. The estimated coefficients for the other days are all positive. In the equation for conditional variance, the coefficients of the constant term (ω), the ARCH term (α), and the GARCH term (β) are positive and statistically significant. As expected, the model coefficients satisfy the constraints $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, and $\alpha + \beta < 1$. For ETH, similar to BTC, the coefficients of all dummy variables in the conditional variance equation from Tuesday to Sunday are negative and statistically significant.

These findings align with the research of Ma and Tanizaki (2019a) and Ma and Tanizaki (2019b), which indicates that BTC shows higher returns and volatility on Mondays compared to other days. Similarly, Aharon and Qadan's (2019) research indicates the DoW effect on both the return and volatility of BTC. According to the mean equation results, our research demonstrates that there is no DoW effect for ETH, which aligns with the findings of Yaya and Ogbanna's (2019) study. Furthermore, our findings indicate that the highest volatility for ETH occurs on Mondays. Dorfleitner and Lung (2018) observe considerably lower returns on Sundays compared to other days, whereas Caporale and Plastun (2019) note higher returns on Mondays. Our research supports these findings, indicating lower returns, specifically on weekends, and reducing trading volume. While in the stock market, negative returns are generally observed on Mondays in the DoW effect, with positive returns on other days (Cross, 1973; French, 1980), the cryptocurrency market exhibits different behavior, revealing a disparity from the stock market in terms of the DoW effect.

4.3. Month-of-the-year effect analysis

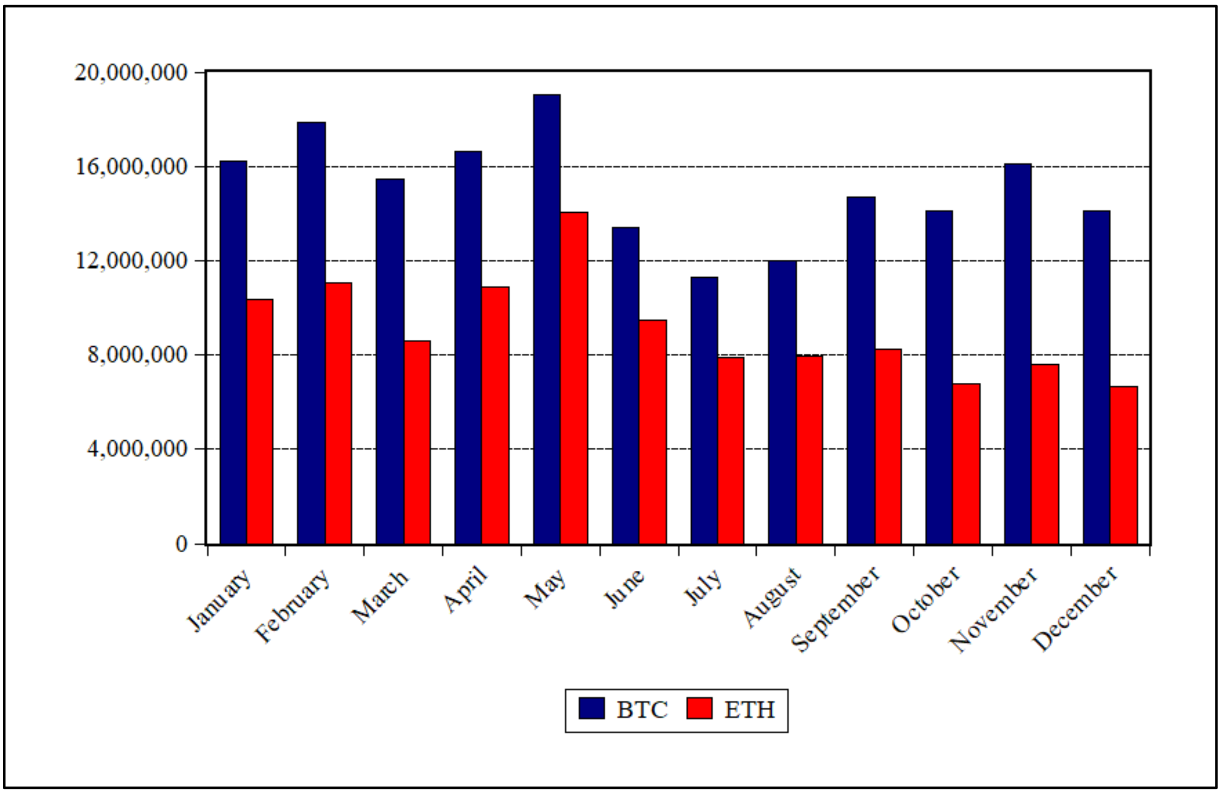
Table 7 shows the descriptive statistics of the BTC and ETH return series for each MoY.

Table 7. Descriptive statistics for the months of the year

	N	Mean	SD	Min	Max	Skew	Kurt
Panel A: BTC descriptive statistics (02.01.2015-31.12.2022)							
January	247	-0.0016	0.0502	-0.2449	0.2309	-0.4801	7.4250
February	226	0.0053	0.0417	-0.1608	0.1945	0.3308	6.3969
March	248	-0.0008	0.0458	-0.3898	0.1613	-2.3043	23.8301
April	240	0.0043	0.0321	-0.0831	0.1845	1.2930	8.9247
May	248	0.0025	0.0401	-0.1422	0.1379	-0.0190	4.9310
June	240	0.0006	0.0419	-0.1555	0.1194	-0.3813	4.3855
July	248	0.0041	0.0393	-0.1325	0.2692	1.3750	12.2002
August	248	0.0007	0.0313	-0.1235	0.1431	-0.1435	5.9015
September	240	-0.0011	0.0335	-0.1649	0.1463	-0.4853	8.5473
October	248	0.0064	0.0265	-0.0692	0.1651	1.4646	9.9704
November	240	0.0014	0.0404	-0.1482	0.1191	-0.2828	5.1825
December	248	0.0038	0.0406	-0.1186	0.2185	1.0569	7.4180
Panel B: ETH descriptive statistics (18.08.2017-31.12.2022)							
January	155	0.0070	0.0620	-0.1941	0.2627	0.2066	5.2074
February	141	0.0038	0.0554	-0.1625	0.1441	-0.1890	3.6618
March	155	-0.0031	0.0600	-0.4376	0.2379	-2.0661	21.0931
April	150	0.0097	0.0482	-0.1232	0.2001	0.6848	4.8317
May	155	0.0028	0.0648	-0.2771	0.2637	0.0758	5.9083
June	150	-0.0051	0.0486	-0.1583	0.1315	-0.4955	3.9104
July	155	0.0052	0.0447	-0.1604	0.1811	0.0434	5.4089
August	168	0.0013	0.0423	-0.1289	0.1173	-0.0616	3.8102
September	180	-0.0032	0.0571	-0.2007	0.1591	-0.3935	4.5368
October	186	0.0029	0.0327	-0.1565	0.1298	0.3958	7.2119
November	180	0.0010	0.0499	-0.1758	0.1775	-0.3318	5.3806
December	186	0.0034	0.0514	-0.1460	0.2326	0.9378	6.4727

Table 7 shows that both BTC and ETH generated positive returns overall, based on their monthly average returns. Nonetheless, there were some months in which both assets recorded negative returns. Upon examining each month's return, BTC registered an average monthly return of 0.0064 in October, which is the highest, and -0.0016 in January, which is the lowest. Similarly, for March and September, there were negative returns of -0.0008 and -0.0011, respectively. ETH had its highest average return of 0.0097 in April and its lowest of -0.0051 in June. Negative returns were also observed in March (-0.0031) and September (-0.0051). Table 7 presents the standard deviations, minimum and maximum returns, skewness, and kurtosis values for each month. BTC exhibited the highest standard deviation of 0.0502 in January and the lowest of 0.0265 in October. In regard to ETH, the standard deviation reached its highest point in January at 0.0620 and its lowest point of 0.0327 in October. ETH exhibited higher standard deviations than BTC in all months across the sample period, indicating that it is a relatively more volatile asset. Both BTC and ETH experienced a significant decrease in trading volume throughout the year, especially in the second half, as demonstrated in Figure 3, depicting the average trading volume by month. Lower trading volumes in the second half of the year followed high trading volumes in the first half.

Figure 3. BTC and ETH trading volume for the month-of-the-year (USD 1,000)



Notes: The average monthly trading volume for BTC is from January 1, 2014, to December 31, 2022, and for ETH, from August 7, 2015, to December 31, 2022. Trading volume is reported in US dollars. Data obtained from https://coinmarketcap.com/

Table 8 shows the results of the MoY analysis for BTC and ETH. Since the coefficients for January are removed, this month provides the basis for comparison.

Table 8. Month-of-the-year effect analysis results

	BTC	ETH
Constant (ϕ_0)	0.0016 (0.0022)	0.0051 (0.0048)
February (ϕ_1)	0.0042 (0.0029)	0.0003 (0.0063)
March (ϕ_2)	0.0013 (0.0028)	-0.0055 (0.0072)
April (ϕ_3)	0.0010 (0.0029)	0.0038 (0.0063)
May (ϕ_4)	-0.0011 (0.0032)	-0.0008 (0.0067)
June (ϕ_5)	-0.0016 (0.0032)	-0.0099 (0.0062)
July (ϕ_6)	0.0018 (0.0031)	0.0001 (0.0059)
August (ϕ_7)	-0.0020 (0.0032)	-0.0033 (0.0060)
September (ϕ_8)	-0.0022 (0.0025)	-0.0068 (0.0063)
October (ϕ_9)	0.0022 (0.0025)	-0.0018 (0.0053)
November (ϕ_{10})	0.0006 (0.0031)	-0.0025 (0.0060)
December (ϕ_{11})	-0.0007 (0.0031)	-0.0056 (0.0056)
AR(1) (ϕ_{12})	-0.0537*** (0.0200)	-0.0559** (0.0265)
Constant (ω)	-0.6152*** (0.0491)	0.0007*** (0.0001)
ARCH (α)	0.2596*** (0.0161)	0.0965*** (0.0147)
GARCH (β)	0.9282*** (0.0083)	0.7452*** (0.0377)
EGARCH (γ)	-0.0255*** (0.0066)	
February (V_1)	-0.0455*** (0.0175)	-0.0002** (0.0001)
March (V_2)	0.0173 (0.0127)	-0.0002** (0.0001)
April (V_3)	-0.0674*** (0.0149)	-0.0003*** (0.0001)
May (V_4)	-0.0363** (0.0169)	-0.0001 (0.0001)
June (V_5)	-0.0405** (0.0164)	-0.0003*** (0.0001)
July (V_6)	-0.0469*** (0.0164)	-0.0004*** (0.0001)
August (V_7)	-0.0643*** (0.0146)	-0.0003*** (0.0001)
September (V_8)	-0.0923*** (0.0158)	-0.0002* (0.0001)
October (V_9)	-0.0754*** (0.0167)	-0.0005*** (0.0001)
November (V_{10})	-0.0200 (0.0160)	-0.0003*** (0.0001)
December (V_{11})	-0.0425** (0.0175)	-0.0004*** (0.0001)
LL	5,617.68	3,121.83
AIC	-3.8285	-3.1580
BIC	-3.7712	-3.0811
HQ	-3.8079	-3.1297
ARCH(5)	3.9125	5.1568

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Notes: LL is the log-likelihood; AIC is Akaike; BIC is Schwarz-Bayesian; HQ is Hannan-Quinn information criteria. ARCH is the ARCH LM test. The values in parentheses are standard errors.

The findings of the MoY effect are presented in Table 8. The results of the mean equation do not indicate a significant MoY effect for both BTC and ETH. In these equations, the coefficients corresponding to the year are not statistically significant. A noteworthy finding is that the coefficients for ETH are negative in the mean equation. This inference implies that other months have lower returns than January. Nevertheless, this discovery lacks statistical significance and remains unconfirmed in the BTC return series. Consequently, the mean equation results for both BTC and ETH do not support the existence of a January effect. Regarding the variance equation, BTC demonstrates a significant MoY effect, particularly notable in March and November. Despite a positive coefficient in March, it lacks statistical significance, similar to the negative coefficient for November. However, coefficients for the other months are all negative and statistically significant, indicating higher volatility in January compared to other months for BTC, with a subsequent decrease in volatility. The findings from ETH's variance equation mirror those of BTC, with all months except May exhibiting negative and statistically significant results. This suggests that both BTC and ETH experience their highest volatility in January, followed by significant decreases in volatility in the subsequent months.

These findings are consistent with the studies by Baur et al. (2019) and Kaiser (2019), which find no significant MoY effect in the cryptocurrency market. However, our research shows that volatility is higher in January when compared to other months of the year. These results differ from those of Kinater and Papavassiliou (2019), who report lower volatility in September, and Plastun et al. (2019), who observe lower returns in July and August compared to other months. Additionally, our results differ from Robiyanto et al.'s (2019) suggestion to buy BTC in late January and sell in February. Another significant aspect of our study regarding the MoY effect is the substantial decline in trading volume during the second half of the year. While January typically yields higher returns in the stock market, our research underscores differences between the stock market and the cryptocurrency market concerning the MoY effect, suggesting distinct behaviors.

5. CONCLUSION

In this study, we initially analyze the volatility structure of the cryptocurrency market using various ARCH models. To account for asymmetrical effects, we utilize the GARCH, EGARCH, and TGARCH models. Our analysis reveals that ARMA(1,0)-EGARCH(1,1) model is optimal for BTC, while ARMA(1,0)-GARCH(1,1) is optimal for ETH.

Following the determination of the volatility structure, we investigate calendar effects based on this structure. Firstly, we explore the existence of the DoW effect. Descriptive statistics highlight that BTC demonstrates the highest average return on Mondays and the lowest on Sundays. Conversely, ETH exhibits its highest average return on Saturdays and the lowest on Thursdays. Additionally, BTC returns are notably lower and negative on Sundays compared to other days, accompanied by a lower standard deviation. Notably, it is worth noting that both BTC and ETH exhibit higher trading volumes on weekdays and lower trading volumes on weekends, resulting in higher returns on weekdays than on weekends.

Subsequently, we analyzed the DoW effect by incorporating it as a dummy variable in the ARMA(1,0)-EGARCH(1,1) model for BTC and the ARMA(1,0)-GARCH(1,1) model for ETH. The results indicate that BTC returns are lower on all days except Mondays, with statistically significant negative coefficients from Tuesday to Sunday. For ETH, Thursdays exhibit lower returns compared to

Mondays, with other days showing higher returns. However, volatility remains higher for both BTC and ETH on Mondays.

Furthermore, we explore whether BTC and ETH returns outperform in specific months. Descriptive statistics reveal varying average returns throughout the year for both cryptocurrencies. While the mean equation does not show significant MoY effects, the variance equation indicates higher volatility in January compared to other months for both BTC and ETH. In other words, for both cryptocurrencies, the highest volatility occurs in January, with a significant decrease in the following months. Another notable finding is the significant drop in trading volumes for both BTC and ETH, especially in the second half of the year. High trading volumes in the first half of the year are offset by lower volumes later in the year. Furthermore, May is the month with the highest trading volumes for both cryptocurrencies.

The study does not necessitate Ethics Committee permission.

The study has been crafted in adherence to the principles of research and publication ethics.

The authors declare that there exists no financial conflict of interest involving any institution, organization, or individual(s) associated with the article. Furthermore, there are no conflicts of interest among the authors themselves.

The authors contributed equally to the entire process of the research.

REFERENCES

Aharon, D. Y., & Qadan, M. (2019). Bitcoin and the day-of-the-week effect. *Finance Research Letters*, *31*. https://doi.org/10.1016/j.frl.2018.12.004

Ahmed, W. M. (2020). Is there a risk-return trade-off in cryptocurrency markets? The case of Bitcoin. *Journal of Economics and Business*, *108*, 105886. https://doi.org/10.1016/j.jeconbus.2019.105886

Baur, D. G., & Dimpfl, T. (2018). Asymmetric volatility in cryptocurrencies. *Economics Letters*, *173*, 148-151. https://doi.org/10.1016/j.econlet.2018.10.008

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. https://doi.org/10.1016/j.frl.2019.04.023

Berument, H., & Kiymaz, H. (2001). The day-of-the-week effect on stock market volatility. *Journal of Economics and Finance*, *25*(2), 181-193. https://doi.org/10.1007/BF02744521

Berument, M. H., & Dogan, N. (2012). Stock market return and volatility: day-of-the-week effect. *Journal of Economics and Finance*, *36*, 282-302. https://doi.org/10.1007/s12197-009-9118-y

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307-327. https://doi.org/10.1016/0304-4076(86)90063-1

Bouoiyour, J., & Selmi, R. (2016). Bitcoin: A beginning of a new phase. *Economics Bulletin*, *36*(3), 1430-1440.

Brooks, C. (2014). *Introductory Econometrics for Finance*. Cambridge University Press.

Caporale, G. M., & Plastun, A. (2019). The day-of-the-week effect in the cryptocurrency market. *Finance Research Letters*, *31*. https://doi.org/10.1016/j.frl.2018.11.012

CoinMarketCap. (2023). https://coinmarketcap.com/

Cross, F. (1973). The behavior of stock prices on Fridays and Mondays. *Financial Analysts Journal*, *29*(6), 67-69. https://doi.org/10.2469/faj.v29.n6.67

Décourt, R. F., Chohan, U. W., & Perugini, M. L. (2017). Bitcoin returns and the Monday effect. *Horizontes Empresariales*, *16*(2).

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366a), 427-431. https://doi.org/10.1080/01621459.1979.10482531

Dorfleitner, G., & Lung, C. (2018). Cryptocurrencies from the perspective of euro investors: a re-examination of diversification benefits and a new day-of-the-week effect. *Journal of Asset Management*, *19*, 472-494. https://doi.org/10.1057/s41260-018-0093-8

Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. *The Journal of Finance*, *48*(5), 1749-1778. https://doi.org/10.1111/j.1540-6261.1993.tb05127.x

Fakhfekh, M., & Jeribi, A. (2020). Volatility dynamics of crypto-currencies' returns: Evidence from asymmetric and long memory GARCH models. *Research in International Business and Finance*, *51*, 101075. https://doi.org/10.1016/j.ribaf.2019.101075

Franke, J., Härdle, W. K., & Hafner, C. M. (2019). Financial Econometrics of Cryptocurrencies. *Statistics of Financial Markets: An Introduction*, 545-568.

French, K. R. (1980). Stock returns and the weekend effect. *Journal of Financial Economics*, *8*(1), 55-69. https://doi.org/10.1016/0304-405X(80)90021-5

Gyamerah, S. A. (2019). Modelling the volatility of Bitcoin returns using GARCH models. *Quantitative Finance and Economics*, *3*(4), 739-753. https://doi.org/10.3934/QFE.2019.4.739

Kaiser, L. (2019). Seasonality in cryptocurrencies. *Finance Research Letters*, *31*, 232-238. https://doi.org/10.1016/j.frl.2018.11.007

Keim, D. B. (1983). Size-related anomalies and stock return seasonality: Further empirical evidence. *Journal of Financial Economics*, *12*(1), 13-32. https://doi.org/10.1016/0304-405X(83)90025-9

Kinateder, H., & Papavassiliou, V. G. (2021). Calendar effects in bitcoin returns and volatility. *Finance Research Letters*, *38*, 101420. https://doi.org/10.1016/j.frl.2019.101420

Kiymaz, H., & Berument, H. (2003). The day-of-the-week effect on stock market volatility and volume: International Evidence. *Review of Financial Economics*, *12*(4), 363-380. https://doi.org/10.1016/S1058-3300(03)00038-7

Köchling, G., Schmidtke, P., & Posch, P. N. (2020). Volatility forecasting accuracy for Bitcoin. *Economics Letters*, *191*, 108836. https://doi.org/10.1016/j.econlet.2019.108836

Le Tran, V., & Leirvik, T. (2020). Efficiency in the markets of crypto-currencies. *Finance Research Letters*, *35*, 101382. https://doi.org/10.1016/j.frl.2019.101382

Ma, D., & Tanizaki, H. (2019a). The day-of-the-week effect on Bitcoin return and volatility. *Research in International Business and Finance*, *49*, 127-136. https://doi.org/10.1016/j.ribaf.2019.02.003

Ma, D., & Tanizaki, H. (2019b). On the day-of-the-week effects of Bitcoin markets: international evidence. *China Finance Review International*, *9*(4), 455-478. https://doi.org/10.1108/CFRI-12-2018-0158

Mbanga, C. L. (2019). The day-of-the-week pattern of price clustering in Bitcoin. *Applied Economics Letters*, *26*(10), 807-811. https://doi.org/10.1080/13504851.2018.1497844

Mills, T. C., & Andrew Coutts, J. (1995). Calendar effects in the London Stock Exchange FTSE indices. *The European Journal of Finance*, *1*(1), 79-93. https://doi.org/10.1080/13518479500000010

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the Econometric Society*, *59*(2), 347-370. https://doi.org/10.2307/2938260

Ngunyi, A., Mundia, S., & Omari, C. (2019). Modelling volatility dynamics of cryptocurrencies using GARCH models. *Journal of Mathematical Finance*, *9*, 591-615. https://doi.org/10.4236/jmf.2019.94030

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*(2), 335-346. https://doi.org/10.1093/biomet/75.2.335

Plastun, A., Drofa, A. O., & Klyushnik, T. V. (2019). Month-of-the-year effect in the cryptocurrency market and portfolio management. *European Journal of Management Issues*, *27*(1-2), 29-35. https://doi.org/10.15421/191904

Qi, T., Wang, T., Zhu, J., & Bai, R. (2020). The correlation and volatility between bitcoin and the blockchain index. *International Journal of Crowd Science*, *4*(2), 103-115. https://doi.org/10.1108/IJCS-11-2019-0036

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

Rozeff, M. S., & Kinney Jr, W. R. (1976). Capital market seasonality: The case of stock returns. *Journal of Financial Economics*, *3*(4), 379-402. https://doi.org/10.1016/0304-405X(76)90028-3

Tsay, R. S. (2010). *Analysis of Financial Time Series*. John Wiley & Sons.

Wajdi, M., Nadia, B., & Ines, G. (2020). Asymmetric effect and dynamic relationships over the cryptocurrencies market. *Computers & Security*, *96*, 101860. https://doi.org/10.1016/j.cose.2020.101860

Wang, J. N., Liu, H. C., Zhang, S., & Hsu, Y. T. (2021). How does the informed trading impact Bitcoin returns and volatility?. *Applied Economics*, *53*(28), 3223-3233. https://doi.org/10.1080/00036846.2020.1814944

Yaya, O. S., & Ogbonna, E. A. (2019). *Do we experience day-of-the-week effects in returns and volatility of cryptocurrency?*. MPRA Paper No. 91429

Zakoian, J. M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and control*, *18*(5), 931-955. https://doi.org/10.1016/0165-1889(94)90039-6

Zargar, F. N., & Kumar, D. (2019). Long range dependence in the Bitcoin market: A study based on high-frequency data. *Physica A: Statistical Mechanics and its Applications*, *515*, 625-640. https://doi.org/10.1016/j.physa.2018.09.188

Zhou, S. (2021). Exploring the driving forces of the Bitcoin currency exchange rate dynamics: an EGARCH approach. *Empirical Economics*, *60*(2), 557-606. https://doi.org/10.1007/s00181-019-01776-4