Examining The Existence Of Day-Of-Week And Month-Of-Year Anomalies In Bitcoin

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Abstract

The main purpose of this study is to reveal whether seasonal/time-oriented/calendar anomalies affect the price and transaction volume of Bitcoin. Day of the week and month of the year anomalies are examined in this context. The data for the years 2013-2021 are handled in 3 different sampling periods, consisting of the whole of this time period and each of its divided parts. The existence of these anomalies is analyzed with EGARCH models created separately. The most important conclusion reached in this study is that the analyzed anomalies differ according to the sampling periods. The common findings reached as a result of the analyzes for all three time intervals are as follows: It has been determined that Monday has positive effects in terms of both Bitcoin return and transaction volume, while Saturday has negative effects only regarding transaction volume. Mondays, Tuesdays, and Wednesdays create volatility-increasing effects concerning returns, Friday, Saturday and Sunday reduce volatility. In terms of trading volume, Monday and Tuesday reduce volatility, while Thursday and Friday increase volatility. Whereas March has a positive effect on return volatility, it has a negative effect on trading volume volatility, and September has only a negative effect on return volatility.

Key words: behavioral finance, bitcoin, calendar anomalies, EGARCH.

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Bitcoin'de Haftanın Günü Ve Yılın Ayı Anomalilerinin Varlığının İncelenmesi

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Öz

Bu çalışmanın temel amacı, mevsimsel/zaman odaklı/takvim anomalilerin Bitcoin fiyatını ve işlem hacmini etkileyip etkilemediğini ortaya çıkarmaktır. Haftanın günü ve yılın ayı anomalileri bu kapsamda incelenmiştir. 2013-2021 yıllarına ait veriler, bu sürenin tamamından ve bölünmüş bölümlerinden oluşan 3 farklı örnekleme döneminde ele alınmıştır. Bu anomalilerin varlığı ayrı ayrı oluşturulan EGARCH modelleri ile analiz edilmiştir. Bu çalışmada ulaşılan en önemli sonuç, analiz edilen anomalilerin örnekleme periyotlarına göre farklılık gösterdiğidir. Her üç zaman aralığı için yapılan analizler sonucunda ulaşılan ortak bulgular şu şekidedir: Pazartesi gününün hem Bitcoin getirisi hem de işlem hacmi açısından olumlu etkilerinin olduğu, Cumartesi gününün ise sadece işlem hacmi açısından olumsuz etkileri olduğu belirlenmiştir. Pazartesi, Salı ve Çarşamba günleri getiriler üzerinde oynaklığı artırıcı etkiler yaratmakta, Cuma, Cumartesi ve Pazar günleri oynaklığı azaltmaktadır. İşlem hacmi açısından Pazartesi ve Salı oynaklığı azaltırken, Perşembe ve Cuma oynaklığı artırmaktadır. Mart ayı getiri oynaklığı üzerinde olumlu bir etki yaratırken, işlem hacmi oynaklığı üzerinde olumsuz bir etki yaratmaktadır ve ayrıca Eylül ayı ise yalnızca getiri oynaklığı üzerinde olumsuz bir etki oluşturmaktadır.

Anahtar sözcükler: davranışsal finans, bitcoin, takvim anomalileri, EGARCH.

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Introduction

Behavioral finance research, which examines irrational people and their financial behaviors, examines cognitive and emotional tendencies as well as seasonal anomalies.

The primary goal of this research is to see if seasonal anomalies have an impact on Bitcoin's price and transaction volume. Anomalies related to the day of the week and month of the year are investigated in this context.

In the studies on seasonal anomalies, it is seen that there are studies on the stock markets. Lakonishok and Smidt (1988) investigated seasonal anomalies using daily statistics over the past 90 years on the Dow Jones Industrial Average. In the study, they obtained the results of abnormal returns at the beginning of the week, at the beginning of the month, at the beginning of the year, and on holidays.

Chan, Khanthavit, and Thomas (1996) researched at calendar anomalies on the stock exchanges in Kuala Lumpur, Mumbai, Singapore, and Thailand. The findings reveal that there are anomalies on the day of the week for all stock markets, that other anomalies vary by stock market, that cultural holidays have a bigger influence than public holidays, and that cultural effects are significant in stock price.

Within the context of the effect of cultural and structural factors, Ong (2006) investigated the presence of seasonal anomalies in the stock pricing of Chinese stock markets. The study's findings suggest that in the Chinese stock market, both cultural and structural variables have a role in stock price.

Guidi, Gupta, and Maheshwari explored the day of the week anomaly in the equity markets of Poland, Hungary, Czech Republic, Slovakia, Romania, Bulgaria, and Slovenia (2011). While the results of the ordinary least squares method suggest differing daily irregularity patterns between the stock markets of Central and Eastern Europe, the full sample GARCH-M model results show that the day of the week impact is evident in both volatility and returns, and that four of the seven indices analyzed have a substantial influence on the volatility equation, particularly on Monday and Tuesday.

Calendar anomalies for Romania, Bulgaria, Croatia, Turkey, and Greece from 2000 to 2008 were investigated by Georgantopoulos, Kenourgios, and Tsamis (2011). While calendar anomalies in both the mean and volatility equations have been discovered for Greece and Turkey, the findings for other countries show that these impacts are limited and can only be observed in volatility.

Seasonal anomalies in emerging stock markets were investigated by Seif, Docherty, and Shamsuddin (2017). According to the findings shared in the study, while the existence of month of the year, day of the week, holiday and week of the year anomalies was supported, no evidence was found to support the existence of the January effect. They found that stock returns tend to be higher on Fridays and in December when both pre-holiday and post-holiday returns are significantly higher, positive abnormal returns are common in the 44th week of the year.

In their study, Yardımcı and Erdem (2020) analyzed the day of the week effect for stock markets in 19 countries with a Muslim majority in the world, using the GARCH (1,1) model during the 2005-2015 period. When compared to earlier research in the literature, the findings of the study suggest that there are distinct patterns of anomalies in some nations, and that most Islamic stock markets have a day of the week anomaly. Additional aspects affecting the stock markets of Islamic nations, such as geographical proximity, trading days, market valuation, and ethnicity, should be considered in the analysis, according to this study.

There are also studies investigating seasonal anomalies in cryptocurrencies.

Kaiser (2019) stated that in his study of seasonality effects in the top 10 cryptocurrencies, no seasonal anomalies that can be described as consistent and robust were observed. Besides, he shared the finding that In January, on weekends, and throughout the summer months, trade volume, volatility, and spreads are all on average lower.

The effect of the day of the week on the return and volatility of Bitcoin (BTC) was investigated by Ma and Tanizaki (2019). It is stated that the effect of the day of the week varies according to the sample periods, and significantly high volatility is observed on Mondays and Thursdays.

The effects of an intraday hour, day of the week, and month of the year for Bitcoin returns and trading volume were examined by Baur, Cahill, Godfrey, and Liu (2019). According to the results, it is stated that there are time-specific anomalies in the returns and they do not have permanent effects over time.

Using statistical techniques and a trade simulation approach, the day-of-week effect in the cryptocurrency market was examined by Caporale, and Plastun (2019). The results showed that this anomaly is not seen in LiteCoin, Ripple, Dash currencies; Besides, the returns of BitCoin on Mondays are significantly higher than other days of the week.

In their study, Aharon and Qadan (2019) presented evidence for the existence of Bitcoin's return and volatility day-of-the-week effect anomaly, using OLS and GARCH models with daily data between 2010-2017.

Kinateder and Papavassiliou (2019) examined the effects of calendar anomalies on Bitcoin's daily conditional returns and volatility in the 2013-2019 period with the GARCH model. According to the results, only a weak day-of-week effect was found on Wednesday's returns. In addition, it is found that Bitcoin has seen weak form volatility significantly higher on Monday and Tuesday than the rest of the week and lower on Friday, Saturday, and Sunday. Moreover, according to the average equation obtained, Bitcoin returns were negative in January and March, and according to the variance equation, stronger negative anomalies were detected in September and weak in April and July.

Researching the day-of-week price cluster structure in Bitcoin, Mbanga (2019) found that Bitcoin prices clustered around integers on Fridays and at least on Mondays.

Long, Zaremba, Demir, Szczygielski, and Vasenin (2020) conducted a study in which they investigated the cross-sectional seasonality anomaly on the daily returns of 151 cryptocurrencies for the years 2016-2019. In this study, an important seasonal structure, which is expressed as past average returns on the same week, positively predicts future performance in the horizontal section, has been determined. It has been shared Cryptocurrencies with high same-day returns have outperformed those with low same-day returns in the past.

Qadan, Aharon, and Eichel (2021) used several seasonal and calendar anomalies to investigate the pricing of eight cryptocurrencies, including Bitcoin, Ethereum, Litecoin, Ripple, Dash, Monero, Nem, and Ethereum Classic. The findings show that there is little similarity between the examined cryptocurrencies in terms of the anomalies investigated, that the Monday anomaly discovered for Bitcoin is not valid for other cryptocurrencies, and that the within-the-month effect is the only effect that is common to all cryptocurrencies.

Apart from these research, Abraham, Sutiksno, Kurniasih, and Warokka (2019) investigated the influence of psychological distance and country culture on Bitcoin acceptance and penetration. The first part of the study, which looked at the predictive relationship between national cultural orientation and Bitcoin adoption in 60 countries, and the second part, which looked at the predictive power of psychological distances against Bitcoin acceptance in 565 Indonesians, found that individualism, uncertainty avoidance, and long-term orientation are all determinants of Bitcoin adoption. Considering that the differences in the factors affecting the social acceptance of bitcoin may also affect the market dynamics, it comes to mind that market findings may vary on the basis of cultural and social differences.

In this study, the periodic anomalies on bitcoin, the most important cryptocurrency, are tried to be examined with the analyzes made on the data until the end of May 2021. It is aimed to investigate the current validity of the findings of previous studies and to reveal the differences if any.

Material and Methods

The daily price and transaction volume data for bitcoin are taken from coinmarketcap.com, the price monitoring website for crypto assets. Since the data used for bitcoin could be obtained as of 28.03.2013 for the price and 27.12.2013 for the transaction volume, the analyzes are made on the data between these dates and 31.05.2021. Unit root tests are applied to the original version of the series and it is determined that they became stationary when the first-order differences were taken. Analyzes are made by taking logarithmic differences of bitcoin price and trading volume variables.

By investigating suitable models for both return and volume, it has been understood that ARMA(0,0) models are suitable for both variables if Schwartz is chosen as the criterion while determining ARMA.

As a result of the analyzes made, it is decided that the most suitable model on the variables examined is the EGARCH model. EGARCH models are established to evaluate the relationships between variables in terms of increase or decrease and volatility. In the models established separately to examine the effect of each day of the week and month of the year for both the price and the transaction volume of Bitcoin, a dummy variable is defined with the name of the day of the week and the month of the year respectively. This dummy variable is defined as 1 for the days of the week and month of the year on which the anomaly is examined, and 0 for the other days and months.

The mean and variance equations for EGARCH models are given in the formulas of (1) and (2), a dummy variable is added to both of the equations.

Mean equation (M.E.): $r_t = \mu + \varepsilon_r$ + DM1(DayofTheWeek or Month Of The Year) (1)

r_t is the return at time t

μ is the average return

ε_r is a residual return

D_{M1} is an indicator of the day of the week and month of the year dummy variable effect of the mean equation.

Variance equation (V.E.): $\text{Log}(\sigma_t^2) = \alpha_0 + \alpha_1 |\varepsilon_{t-1} / \sigma_{t-1}| + \gamma_1 (\varepsilon_{t-1} / \sigma_{t-1}) + \beta_1 \log(\sigma_{t-1}^2) +$ D_{V1}(DayofTheWeek or Month Of The Year) (2)

In this equation:

ε_t is the prediction error

σ_t^2 is the conditional variance of ε_t given information at time t

α_1 is an indicator of volatility size effect

γ_1 is an indicator of asymmetry in volatility structure

β_1 is an indicator of the volatility persistence

D_{V1} is an indicator of the day of the week or month of the year dummy variable effect on volatility

The studied main time frame is separated into two sections, and the preceding analyses were applied independently for these time frames in order to determine whether the conclusions obtained are valid in different time periods.

Results

Table 1 shows the analysis results of the EGARCH models for the main time frame, in which the effect of each day of the week on the bitcoin price and transaction volume are examined separately. When the results of the mean equations for the price given in the upper section of Table 1 are examined, it is seen that statistically significant results are obtained for Monday, Tuesday, and Saturday. Another finding for the price is that all three of the coefficients in these mean equations (D_{M1}), which have the property of $p<0.1$, are positive. No significant results are obtained in the mean equations of the other days for price. The results show that Monday, Tuesday, and Saturday have a positive effect on the returns and there is no such effect for the other days.

Probability values of the obtain ed variance equations are found to be significant for all days. The coefficients (D_{V1}) showing the effect of all days of the week on the volatility in prices are determined as positive for Monday, Tuesday, Wednesday, and Thursday, and negative for Friday, Saturday, and Sunday. In addition, all days are effective on the volatility of bitcoin returns; it has been determined that Monday, Tuesday, Wednesday, and Thursday increase volatility, and Friday, Saturday, and Sunday decrease volatility.

The analysis results of the EGARCH models, in which the effect of each day of the week on the transaction volume of bitcoin are examined separately, are given in the lower part of Table 1. It is understood that the probability values of the mean equations in the models in which the transaction volume is examined are significant for Monday, Tuesday, Thursday and Saturday, but not significant for Wednesday, Friday, and Sunday.

The transaction volume section of Table 1 shows that the coefficients (D_{M1}) in the mean equations for Monday, Tuesday, and Thursday are positive and negative for Saturday. When the probability values of the dummy variables, which show the effect of the days of the week on the volatility in the trading volumes in the variance equations, are examined, it is understood that these values are significant except for Wednesday. It is revealed that Monday, Tuesday, and Thursday increase the transaction volumes, Saturday decrease, and the other days do not have any effect. When the coefficients (D_{V1}) are examined, it is seen that Thursday, Friday, and Saturday are positive, and Monday, Tuesday, and Sunday are negative. When the effects of the days of the week on the volatility in the trading volumes are analyzed; it is observed that Monday, Tuesday, and Sunday decrease, Thursday, Friday, and Saturday increase, and Wednesday do not have any effect on it.

Table 1. EGARCH analyzes of Bitcoin price and transaction volume for all the days of the week (for the main timeframe)

Price	Monday		Tuesday		Wednesday		Thursday		Friday		Saturday		Sunday	
	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p
M.E.														
D_{M1}	0.005	0.000*	0.002	0.030**	-0.001	0.226	-0.002	0.195	0.000	0.899	0.002	0.087***	-0.001	0.464
V.E.														
α_0	-0.580	0.000*	-0.573	0.000*	-0.589	0.000*	-0.564	0.000*	-0.459	0.000*	-0.457	0.000*	-0.448	0.000*
α_1	0.319	0.000*	0.313	0.000*	0.310	0.000*	0.304	0.000*	0.317	0.000*	0.317	0.000*	0.308	0.000*
γ_1	-0.081	0.000*	-0.079	0.000*	-0.083	0.000*	-0.078	0.000*	-0.085	0.000*	-0.082	0.000*	-0.075	0.000*
β_1	0.950	0.000*	0.951	0.000*	0.948	0.000*	0.949	0.000*	0.948	0.000*	0.949	0.000*	0.949	0.000*
D_{V1}	0.383	0.000*	0.395	0.000*	0.417	0.000*	0.316	0.000*	-0.526	0.000*	-0.526	0.000*	-0.551	0.000*
Volume	**Monday**		**Tuesday**		**Wednesday**		**Thursday**		**Friday**		**Saturday**		**Sunday**	
	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p
M.E.														
D_{M1}	0.102	0.000*	0.019	0.083***	0.015	0.293	0.028	0.059***	-0.009	0.529	-0.119	0.000*	-0.003	0.831
V.E.														
α_0	-0.199	0.000*	-0.135	0.000*	-0.188	0.000*	-0.210	0.000*	-0.219	0.000*	-0.191	0.000*	-0.098	0.000*
α_1	0.222	0.000*	0.185	0.000*	0.187	0.000*	0.175	0.000*	0.167	0.000*	0.176	0.000*	0.163	0.000*
γ_1	0.005	0.536	-0.011	0.161	-0.019	0.008*	-0.019	0.007*	-0.022	0.005*	-0.040	0.000*	-0.029	0.000*
β_1	0.974	0.000*	0.978	0.000*	0.980	0.000*	0.981	0.000*	0.982	0.000*	0.979	0.000*	0.984	0.000*
D_{V1}	-0.196	0.003*	-0.381	0.000*	0.012	0.874	0.252	0.000*	0.367	0.000*	0.102	0.047**	-0.425	0.000*

*note: Coef = coefficient M.E. = mean equation. V.E. = variance equation. p = probability. * Significant at the %1 level. ** Significant at the %5 level. *** Significant at the %10 level.*

Table 2. EGARCH analyzes of Bitcoin price for the months of the year
(for the main time frame)

Price	January		February		March		April		May		June	
	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p
M.E.												
D_{M1}	0.002	0.199	**0.002**	**0.001***	**0.006**	**0.001***	0.001	0.562	0.001	0.671	-0.002	0.340
V.E.												
α_0	-0.529	0.000*	-0.509	0.000*	-0.536	0.000*	-0.515	0.000*	-0.522	0.000*	-0.553	0.000*
α_1	0.310	0.000*	0.307	0.000*	0.326	0.000*	0.307	0.000*	0.309	0.000*	0.316	0.000*
γ_1	-0.080	0.000*	-0.075	0.000*	-0.070	0.000*	-0.079	0.000*	-0.081	0.000*	-0.083	0.000*
β_1	0.948	0.000*	0.951	0.000*	0.950	0.000*	0.950	0.000*	0.949	0.000*	0.945	0.000*
D_{V1}	**0.022**	**0.021****	-0.005	0.207	**0.078**	**0.000***	**-0.036**	**0.000***	**-0.016**	**0.046****	**0.037**	**0.000***
Price	**July**		**August**		**September**		**October**		**November**		**December**	
	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p
M.E.												
D_{M1}	-0.001	0.615	0.002	0.350	-0.001	0.391	**0.004**	**0.002***	0.002	0.443	-0.001	0.763
V.E.												
α_0	-0.528	0.000*	-0.515	0.000*	-0.538	0.000*	-0.521	0.000*	-0.522	0.000*	-0.522	0.000*
α_1	0.312	0.000*	0.305	0.000*	0.309	0.000*	0.310	0.000*	0.305	0.000*	0.307	0.000*
γ_1	-0.082	0.000*	-0.083	0.000*	-0.091	0.000*	-0.079	0.000*	-0.085	0.000*	-0.083	0.000*
β_1	0.948	0.000*	0.949	0.000*	0.945	0.000*	0.949	0.000*	0.949	0.000*	0.949	0.000*
D_{V1}	**-0.047**	**0.000***	**-0.048**	**0.001***	**-0.090**	**0.000***	**-0.024**	**0.032****	**0.031**	**0.000***	0.011	0.295

*note: Coef = coefficient M.E. = mean equation. V.E. = variance equation. p = probability. * Significant at the %1 level. ** Significant at the %5 level. *** Significant at the %10 level.*

The month of the year anomalies is included in this part of the analysis. When the mean equations of the results of the analyzes of the EGARCH models of Bitcoin prices are examined, it is understood that February, March, and October move in the same direction as the prices, but this effect does not exist in the other months (see coefficients of D_{M1} in Table 2). When the impacts of the months of the year on bitcoin prices are analyzed, it is observed that bitcoin returns grow in February, March, and October, but this effect does not exist in other months. On looking at the variance equations that indicate the impact of the months of the year on volatility, it is concluded that anomalies are affecting the volatility except for February and December. Coefficients (D_{V1}) are obtained as positive for January, March, June, and November, and negative for April, May, July, August, and October. It is determined that the volatility in Bitcoin returns increase in January, March, June, and November, and decrease in April, May, July, August, September, and October.

Table 3. EGARCH analyzes of Bitcoin price and transaction volume for all the days of the week (for the main timeframe)

Volume	January		February		March		April		May		June	
	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p
M.E.												
D_{M1}	0.001	0.963	0.004	0.383	0.003	0.832	0.009	0.554	-0.001	0.949	**-0.031**	**0.005***
V.E.												
α_0	-0.200	0.000*	-0.208	0.000*	-0.177	0.000*	-0.185	0.000*	-0.175	0.000*	-0.209	0.000*
α_1	0.196	0.000*	0.216	0.000*	0.179	0.000*	0.185	0.000*	0.176	0.000*	0.205	0.000*
γ_1	-0.022	0.002*	-0.004	0.629	-0.019	0.006*	-0.018	0.007*	-0.017	0.011**	-0.013	0.179
β_1	0.977	0.000*	0.961	0.000*	0.980	0.000*	0.979	0.000*	0.982	0.000*	0.977	0.000*
D_{V1}	**0.022**	**0.000***	**-0.053**	**0.000***	**-0.019**	**0.004***	-0.012	0.224	**0.020**	**0.002***	**0.032**	**0.000***
Volume	July		August		September		October		November		December	
	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p
M.E.												
D_{M1}	-0.001	0.970	0.011	0.532	0.005	0.771	0.009	0.596	0.001	0.958	0.000	0.983
V.E.												
α_0	-0.181	0.000*	-0.184	0.000*	-0.190	0.000*	-0.183	0.000*	-0.183	0.000*	-0.187	0.000*
α_1	0.182	0.000*	0.185	0.000*	0.190	0.000*	0.182	0.000*	0.184	0.000*	0.187	0.000*
γ_1	-0.020	0.003*	-0.019	0.006*	-0.020	0.005*	-0.020	0.003*	-0.019	0.006*	-0.019	0.006*
β_1	0.980	0.000*	0.980	0.000*	0.978	0.000*	0.980	0.000*	0.980	0.000*	0.979	0.000*
D_{V1}	-0.014	0.199	-0.012	0.219	**-0.020**	**0.049****	0.010	0.308	-0.007	0.476	-0.012	0.177

*note: Coef = coefficient M.E. = mean equation. V.E. = variance equation. p = probability. * Significant at the %1 level. ** Significant at the %5 level. *** Significant at the %10 level.*

When the mean equations of the model results revealing the interaction of the transaction volume and the month of the year are examined, a negative relationship is detected only for

June (see coefficients of D_{M1} in Table 3). It is concluded that Bitcoin transaction volume decreases only in June, and there is no such effect in other months. When the variance equations are examined, it is understood that the other months except for April in the first half of the year affect volatility (see coefficients of D_{V1} in Table 3). This effect is negative in February and March and positive in January, May, and June. In the second half of the year, only in September, an anomaly that negatively affected volatility is detected. It is determined that the volatility in the transaction volume increases in January, May, and June, and decreases in February, March, and September.

Tables 1, 2, and 3 show that in all established EGARCH models, α_0 coefficients are negative, α_1 coefficients are positive and β_1 coefficients are positive on all days of the week and all months of the year. When γ_1 coefficients in the tables are examined, it is seen that all the coefficients are significant and negative except transaction volumes of Monday, Tuesday, February, and June which are insignificant.

In order to understand whether the findings obtained are valid in different time periods, the analyzed time interval is divided into two parts, as the first time interval (03.2013-05.2017) and the last time interval (06.2017-05.2021), and analyses performed for the whole period are repeated for each part. Table 4-6 and 7-9 contains the results of the analysis for the first and the last time intervals respectively.

When the upper part of Table 4, which deals with the bitcoin returns in the first-time interval, is examined, it is understood that the coefficients of Monday and Tuesday are positive and significant in the mean equations and that there are significant volatility coefficients with positive signs for Monday, Tuesday and Wednesday, and negative for Friday, Saturday and Sunday in the variance equations.

The analysis results of the day of the week anomaly of the trading volume in the same time period are given in the lower part of Table 4. When the D_{M1} coefficients, which show the relationship of anomalies on the trading volume, are considered, it is seen that Monday and Tuesday have plus and Saturday has minus signs. When the D_{V1} coefficients showing the effect of day-of-week anomalies on trading volume volatility are analyzed, it is understood that Monday, Tuesday, and Wednesday are negative, Thursday and Friday are positive.

Table 4. EGARCH analyzes of Bitcoin price and transaction volume for all the days of the week (the first part of the main timeframe)

Price	Monday		Tuesday		Wednesday		Thursday		Friday		Saturday		Sunday	
	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p
M.E.														
D_{M1}	**0.003**	**0.083*** **	**0.005**	**0.002***	0.000	0.751	0.000	0.833	0.002	0.262	0.001	0.218	0.002	0.182
V.E.														
α_0	-0.575	0.000*	-0.600	0.000*	-0.542	0.000*	-0.513	0.000*	-0.467	0.000*	-0.448	0.000*	-0.478	0.000*
α_1	0.302	0.000*	0.317	0.000*	0.297	0.000*	0.299	0.000*	0.303	0.000*	0.309	0.000*	0.305	0.000*
γ_1	-0.012	0.199	-0.005	0.630	-0.015	0.083***	-0.015	0.102	-0.013	0.130	-0.010	0.264	-0.012	0.167
β_1	0.953	0.000*	0.956	0.000*	0.953	0.000*	0.953	0.000*	0.952	0.000*	0.951	0.000*	0.953	0.000*
D_{V1}	**0.422**	**0.000***	**0.652**	**0.000***	**0.192**	**0.000***	0.003	0.956	**-0.386**	**0.000***	**-0.613**	**0.000***	**-0.299**	**0.000***
Volume	Monday		Tuesday		Wednesday		Thursday		Friday		Saturday		Sunday	
	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p
M.E.														
D_{M1}	**0.253**	**0.000***	**0.086**	**0.001***	0.009	0.768	0.031	0.402	-0.014	0.713	**-0.256**	**0.000***	0.003	0.911
V.E.														
α_0	-0.096	0.002*	-0.032	0.336	-0.066	0.042**	-0.177	0.000*	-0.214	0.000*	-0.152	0.000*	-0.114	0.000*
α_1	0.143	0.000*	0.138	0.000*	0.133	0.000*	0.132	0.000*	0.139	0.000*	0.124	0.000*	0.130	0.000*
γ_1	0.056	0.040**	0.039	0.177	0.011	0.674	-0.018	0.495	-0.021	0.414	-0.046	0.085***	-0.019	0.501
β_1	0.979	0.000*	0.982	0.000*	0.983	0.000*	0.983	0.000*	0.981	0.000*	0.979	0.000*	0.983	0.000*
D_{V1}	**-0.344**	**0.001***	**-0.743**	**0.000***	**-0.463**	**0.001***	**0.322**	**0.024*** **	**0.517**	**0.000***	0.173	0.140	-0.112	0.346

*note: Coef = coefficient M.E. = mean equation. V.E. = variance equation. p = probability. * Significant at the %1 level. ** Significant at the %5 level. *** Significant at the %10 level.*

Table 5. EGARCH analyzes of Bitcoin price for the months of the year (the first part of the main timeframe)

Price	January		February		March		April		May		June	
	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p
M.E.												
D_{M1}	-0.001	0.797	**0.002**	**0.001***	0.002	0.474	0.001	0.402	**0.003**	**0.057*****	0.000	0.993
V.E.												
α_0	-0.604	0.000*	-0.590	0.000*	-0.530	0.000*	-0.497	0.000*	-0.519	0.000*	-0.512	0.000*
α_1	0.316	0.000*	0.310	0.000*	0.306	0.000*	0.293	0.000*	0.300	0.000*	0.300	0.000*
γ_1	-0.013	0.145	0.000	0.968	-0.012	0.152	-0.014	0.117	-0.014	0.126	-0.015	0.080***
β_1	0.942	0.000*	0.938	0.000*	0.951	0.000*	0.954	0.000*	0.952	0.000*	0.953	0.000*
D_{V1}	**0.086**	**0.000***	**-0.052**	**0.000***	**0.028**	**0.014****	**-0.054**	**0.000***	-0.011	0.325	-0.005	0.751
Price	July		August		September		October		November		December	
	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p
M.E.												
D_{M1}	-0.001	0.708	0.001	0.664	0.000	0.847	**0.005**	**0.002***	0.001	0.725	0.002	0.579
V.E.												
α_0	-0.533	0.000*	-0.517	0.000*	-0.572	0.000*	-0.513	0.000*	-0.521	0.000*	-0.494	0.000*
α_1	0.306	0.000*	0.307	0.000*	0.313	0.000*	0.305	0.000*	0.299	0.000*	0.286	0.000*
γ_1	-0.021	0.012**	-0.009	0.345	-0.023	0.012**	-0.012	0.158	-0.017	0.079***	-0.015	0.060***
β_1	0.950	0.000*	0.954	0.000*	0.945	0.000*	0.953	0.000*	0.952	0.000*	0.955	0.000*
D_{V1}	**-0.065**	**0.000***	**0.030**	**0.021****	**-0.086**	**0.000***	-0.007	0.739	0.015	0.297	**0.042**	**0.004***

*note: Coef = coefficient M.E. = mean equation. V.E. = variance equation. p = probability. * Significant at the %1 level. ** Significant at the %5 level. *** Significant at the %10 level.*

When the D_{M1} coefficients in Table 5, which shows the analysis results of the month-of-year anomalies in the returns in the first part of the study time interval, are examined, it is understood that the months of February, March, and October are positive and the D_{V1} coefficients are positive for January and March and negative for February and April.

Table 6. EGARCH analyzes of Bitcoin volume for the months of the year (the first part of the main timeframe)

Volume	January		February		March		April		May		June	
	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p
M.E.												
D_{M1}	0.005	0.890	0.014	0.304	0.006	0.872	0.006	0.877	0.018	0.607	0.030	0.520
V.E.												
α_0	-1.621	0.571	-0.143	0.000*	-0.111	0.000*	-0.126	0.000*	-0.126	0.000*	-0.127	0.000*
α_1	0.010	0.783	0.132	0.000*	0.120	0.000*	0.127	0.000*	0.128	0.000*	0.128	0.000*
γ_1	0.010	0.649	0.017	0.537	-0.006	0.807	-0.010	0.686	-0.008	0.763	-0.008	0.745
β_1	0.010	0.996	0.965	0.000*	0.988	0.000*	0.983	0.000*	0.984	0.000*	0.984	0.000*
D_{V1}	0.000	1.000	**-0.028**	**0.021****	**-0.023**	**0.044****	-0.013	0.281	0.004	0.719	0.004	0.744
Volume	July		August		September		October		November		December	
	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p
M.E.												
D_{M1}	-0.006	0.893	0.040	0.335	-0.007	0.846	0.010	0.807	0.002	0.964	-0.002	0.967
V.E.												
α_0	-0.127	0.000*	-0.130	0.000*	-0.140	0.000*	-0.118	0.000*	-0.127	0.000*	-0.126	0.000*
α_1	0.128	0.000*	0.132	0.000*	0.131	0.000*	0.122	0.000*	0.128	0.000*	0.127	0.000*
γ_1	-0.010	0.680	-0.007	0.791	-0.018	0.496	-0.009	0.708	-0.010	0.693	-0.011	0.667
β_1	0.984	0.000*	0.983	0.000*	0.976	0.000*	0.987	0.000*	0.984	0.000*	0.984	0.000*
D_{V1}	0.002	0.875	-0.002	0.844	**-0.041**	**0.019****	0.016	0.263	0.002	0.889	0.013	0.258

*note: Coef = coefficient M.E. = mean equation. V.E. = variance equation. p = probability. * Significant at the %1 level. ** Significant at the %5 level. *** Significant at the %10 level.*

The analysis results of the presence of month-of-year anomalies in the transaction volume in the second part of the time interval are given in Table 6. While the results could not reveal a significant effect in the mean equation, the results indicate that February, March, and October in the variance equation have a negative effect on volatility.

Table 7. EGARCH analyzes of Bitcoin price and transaction volume for all the days of the week (the second part of the main timeframe)

Price	Monday		Tuesday		Wednesday		Thursday		Friday		Saturday		Sunday	
	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p
M.E.														
D_{M1}	**0.005**	**0.022****	0.000	0.924	**0.008**	**0.004***	**-0.005**	**0.086*****	0.004	0.235	**0.004**	**0.089*****	-0.002	0.179
V.E.														
α_0	-0.568	0.000*	-0.548	0.000*	-0.597	0.000*	-0.574	0.000*	-11.054	0.000*	-0.445	0.000*	-0.406	0.000*
α_1	0.283	0.000*	0.267	0.000*	0.269	0.000*	0.256	0.000*	0.168	0.000*	0.267	0.000*	0.260	0.000*
γ_1	-0.133	0.000*	-0.135	0.000*	-0.132	0.000*	-0.122	0.000*	-0.041	0.000*	-0.135	0.000*	-0.124	0.000*
β_1	0.945	0.000*	0.944	0.000*	0.944	0.000*	0.945	0.000*	-0.882	0.000*	0.943	0.000*	0.943	0.000*
D_{V1}	**0.362**	**0.000***	**0.261**	**0.000***	**0.572**	**0.000***	**0.551**	**0.000***	**-0.343**	**0.000***	**-0.518**	**0.000***	**-0.753**	**0.000***
Volume	Monday		Tuesday		Wednesday		Thursday		Friday		Saturday		Sunday	
	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p
M.E.														
D_{M1}	**0.078**	**0.000***	-0.003	0.736	0.022	0.183	**0.028**	**0.090*****	0,009	0,549	**-0,056**	**0,001***	-0,002	0,872
V.E.														
α_0	-1.563	0.000*	-1.722	0.000*	-1.569	0.000*	-1.595	0.000*	-1,621	0,000*	-1,743	0,000*	-1,393	0,000*
α_1	0.482	0.000*	0.485	0.000*	0.475	0.000*	0.457	0.000*	0,450	0,000*	0,485	0,000*	0,439	0,000*
γ_1	0.074	0.000*	0.043	0.038**	0.035	0.113	0.051	0.024**	0,048	0,053***	0,005	0,790	0,028	0,138
β_1	0.590	0.000*	0.530	0.000*	0.607	0.000*	0.587	0.000*	0,578	0,000*	0,544	0,000*	0,620	0,000*
D_{V1}	**-0.200**	**0.047*****	**-0.329**	**0.000***	**0.278**	**0.000***	**0.131**	**0.039****	**0,164**	**0,019***	**0,121**	**0,054*****	**-0,527**	**0,000***

*note: Coef = coefficient M.E. = mean equation. V.E. = variance equation. p = probability. * Significant at the %1 level. ** Significant at the %5 level. *** Significant at the %10 level.*

When looking at the upper part of Table 7, which shows the second-time interval returns, it's clear that Monday, Wednesday, and Saturday are positive, Tuesday is negative, and Thursday is significant in the mean equations, and there are significant volatility coefficients in the variance equations with positive signs for Monday, Tuesday, Wednesday, and Thursday, and negative signs for Friday, Saturday, and Sunday.

The lower part of Table 7 shows the results of the examination of the trading volume by day of the week anomaly for the same time period. When looking at the D_{M1} coefficients, which illustrate the association between anomalies and trade volume, Monday and Tuesday have plus signs whereas Saturday has minus values. When looking at the D_{V1} coefficients that illustrate how day-of-week anomalies affect trade volume volatility, it's clear that Monday, Tuesday, and Sunday are negative, while Wednesday, Thursday, Friday, and Saturday are positive.

Table 8. EGARCH analyzes of Bitcoin price for the months of the year (the second part of the main timeframe)

Price	January		February		March		April		May		June	
	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p
M.E.												
D_{M1}	0.002	0.598	0.002	0.502	**0.011**	**0.000***	0.003	0.352	-0.001	0.814	**-0.007**	**0.079*****
V.E.												
α_0	-0.513	0.000*	-0.511	0.000*	-0.507	0.000*	-0.510	0.000*	-0.512	0.000*	-0.623	0.000*
α_1	0.270	0.000*	0.267	0.000*	0.301	0.000*	0.266	0.000*	0.269	0.000*	0.293	0.000*
γ_1	-0.135	0.000*	-0.133	0.000*	-0.112	0.000*	-0.132	0.000*	-0.133	0.000*	-0.144	0.000*
β_1	0.943	0.000*	0.944	0.000*	0.950	0.000*	0.944	0.000*	0.944	0.000*	0.929	0.000*
D_{V1}	**-0.029**	**0.087*****	-0.016	0.378	**0.071**	**0.000***	-0.011	0.449	-0.013	0.429	**0.081**	**0.000***
Price	July		August		September		October		November		December	
	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p
M.E.												
D_{M1}	0.004	0.164	0.000	0.936	-0.003	0.135	0.001	0.720	0.002	0.591	-0.004	0.292
V.E.												
α_0	-0.500	0.000*	-0.494	0.000*	-0.500	0.000*	-0.528	0.000*	-0.502	0.000*	-0.515	0.000*
α_1	0.262	0.000*	0.263	0.000*	0.255	0.000*	0.267	0.000*	0.263	0.000*	0.269	0.000*
γ_1	-0.133	0.000*	-0.129	0.000*	-0.139	0.000*	-0.134	0.000*	-0.134	0.000*	-0.136	0.000*
β_1	0.945	0.000*	0.945	0.000*	0.943	0.000*	0.940	0.000*	0.945	0.000*	0.943	0.000*
D_{V1}	-0.036	0.143	**-0.093**	**0.000***	**-0.086**	**0.000***	**-0.053**	**0.000***	0.019	0.277	0.007	0.659

*note: Coef = coefficient M.E. = mean equation. V.E. = variance equation. p = probability. * Significant at the %1 level. ** Significant at the %5 level. *** Significant at the %10 level.*

Glancing at the D_{M1} coefficients in Table 8, which displays the findings of the monthly anomalies in the returns in the second half of the time frame examined, it is evident that March and June are both positive. Moreover, positive D_{V1} coefficients are found between March and June, whereas negative D_{V1} coefficients are seen in January, August, September, and October.

Table 9. EGARCH analyzes of Bitcoin volume for the months of the year (the second part of the main timeframe)

Volume	January		February		March		April		May		June	
	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p
M.E.												
D_{M1}	0.001	0.969	0.019	0.325	0.000	0.986	0.017	0.295	-0.002	0.900	-0.014	0.438
V.E.												
α_0	-1.654	0.000*	-1.621	0.000*	-1.634	0.000*	-1.569	0.000*	-1.625	0.000*	-1.303	0.000*
α_1	0.478	0.000*	0.467	0.000*	0.462	0.000*	0.461	0.000*	0.471	0.000*	0.450	0.000*
γ_1	0.030	0.180	0.045	0.042**	0.042	0.030**	0.043	0.020**	0.034	0.076***	0.052	0.008**
β_1	0.569	0.000*	0.575	0.000*	0.563	0.000*	0.588	0.000*	0.568	0.000*	0.689	0.000*
D_{V1}	**0.126**	**0.001***	0.020	0.689	**-0.233**	**0.000***	-0.062	0.324	**-0.245**	**0.001***	**0.340**	**0.000***
Volume	July		August		September		October		November		December	
	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p	Coef	p
M.E.												
D_{M1}	0.005	0.772	0.005	0.768	0.023	0.195	0.017	0.375	0.015	0.477	0.006	0.694
V.E.												
α_0	-1.580	0.000*	-1.550	0.000*	-1.582	0.000*	-1.592	0.000*	-1.610	0.000*	-1.582	0.000*
α_1	0.467	0.000*	0.458	0.000*	0.465	0.000*	0.459	0.000*	0.465	0.000*	0.466	0.000*
γ_1	0.038	0.040**	0.040	0.030**	0.045	0.016**	0.043	0.025**	0.040	0.029**	0.046	0.016**
β_1	0.584	0.000*	0.593	0.000*	0.587	0.000*	0.584	0.000*	0.578	0.000*	0.581	0.000*
D_{V1}	**-0.128**	**0.098*** **	-0.103	0.240	0.014	0.843	0.074	0.248	0.038	0.594	**-0.225**	**0.002***

*note: Coef = coefficient M.E. = mean equation. V.E. = variance equation. p = probability. * Significant at the %1 level. ** Significant at the %5 level. *** Significant at the %10 level.*

The analysis results regarding the presence of monthly anomalies in the trading volume in the second part of the time interval are given in Table 9. Although the results cannot reveal a significant effect in the mean equation, it shows that March, May, July, and December have negative effects on volatility in the variance equation, while January and June have positive effects.

Discussion and Conclusion

In this section, the common findings reached as a result of the analyzes in all three time intervals are evaluated.

It is found that Monday has positive effects both in terms of bitcoin return and transaction volume, and Saturday has negative effects in terms of the trading volume. The finding of high returns in bitcoin on Monday revealed in Caporale and Plastun's (2019) research is consistent with the Monday finding obtained in this study. On the other hand, Kinateder and Papavassiliou (2019) found a weak day-of-the-week effect on Wednesday returns only.

Other findings in this study are that while Mondays, Tuesdays, and Wednesdays create volatility-increasing effects in terms of returns, Friday, Saturday and Sunday reduce volatility. The high volatility finding was also reached by Ma and Tanizaki (2019) for Mondays and Thursdays. High volatility on Mondays is the common findings of this study and ours. Kinateder and Papavassiliou (2019) also found that weak form volatility was significantly higher on Monday and Tuesday than the rest of the week, and lower on Friday, Saturday, and Sunday. Except for Wednesday, the findings in this research are consistent with our study.

In addition, in terms of transaction volume, we come across as common results for all time periods in which Monday and Tuesday decrease volatility and Thursday and Friday increase volatility.

When the results for the month of year anomaly are examined for all time intervals, it is understood that March has a positive effect on the volatility of return and negative effect on the volatility of the transaction volume and September has a negative effect of the volatility of return. Kinateder and Papavassiliou (2019), who examined the changes in Bitcoin returns according to the months of the year, found that there were negative returns in January and March. These findings are not compatible with our study. A strong decrease in volatility in September and a weak decrease in April and July are shared in the studies of Kinateder and Papavassiliou (2019). The decrease in volatility in September is interpreted as consistent with our study.

All these results mentioned above reveal that the anomalies of the day of the week and the month of the year differ according to the sampling periods. From this point of view, this finding supports the conclusion expressed by Ma and Tanizaki (2019) that the anomalies differ according to the stated sampling periods.

On the basis of the results revealed in the study, it is thought that the herding behavior effect on investors. Herding behavior is a behavioral finance tendency that occurs when rational individuals make decisions based on the assessments of others and then act irrationally (Kumar and Goyal, 2015).

It is important to understand the herd behavior tendency and especially why some days show different behavior for investors in order to understand the dynamics of the event.

In the study of Brahmana et al. (2012), which examined the Monday anomaly in the Malaysian stock market, it was found that herding behavior was the determinant of this anomaly. In particular, it is expressed in the study of Szyszka (2013) that individual stock exchange investors slow down their transactions on Fridays only to speed up on Mondays in anticipation of the weekend. It is stated in the study of Lakonishok and Maberly (1990) on NYSE that the lowest transaction volume is realized on Mondays, there is a relative increase in the buying and selling activity of individuals, and that the selling transactions of individuals are more than their buying transactions. It is also stated in this study that during the weekend, individual investors have more time to process information, therefore the probability of trading on Monday is rather high.

According to Osbour's research (1962), individual investors who invest little sums of money make more purchases on Mondays than on Fridays, and they do so in a methodical manner. The explanation for this is that individual investors' thoughts, which are preoccupied with other matters during the week, recuperate over the weekend and take action on Monday.

In the article on the Korean stock market by Park (2011), it is pointed out that there is evidence that strongly supports the intuition that herd behavior causes excessive volatility.

The relationship of bitcoin with other currencies in the cryptocurrency market is important in terms of being able to project the findings of the study.

The conditional volatility and correlation of two cryptocurrencies (Bitcoin and Ether) were demonstrated to be sensitive to important news by Katsiampa et al. (2019). Gkillas et al. (2018) discovered similarities of considerably high bivariate dependency in the distribution tails of some of the most fundamental and widely used cryptocurrencies, mostly due to numerous downward limitations. Osterrieder et al. (2016) found that cryptocurrencies have substantial non-normal features, large tail dependencies owing to individual cryptocurrencies, and heavy tails, as well as statistical commonalities amongst cryptocurrencies that share the same technology. These mentioned studies revealing that there are connections between cryptocurrencies constitute the idea that the findings obtained in our study should be especially emphasized in terms of the effects that these interconnected relations can create on market dynamics.

It is thought that the findings obtained in the study are important since bitcoin, which is among the most important cryptocurrencies, is handled in terms of seasonal anomalies from the behavioral finance perspective. The study's findings, which demonstrate the occurrence of seasonal anomalies on bitcoin, are deemed to be useful in terms of literature and market actors in comprehending bitcoin.

It's essential to mention that the identified anomalies could have systematic reasons.

Considering only bitcoin and excluding other possible factors that may affect anomalies are seen as limitations of the study. For future studies, it is recommended to design a study to eliminate the mentioned limits.

Ethical Statement Information of the Article Titled As "Examining The Existence Of Day-Of-Week And Month-Of-Year Anomalies In Bitcoin"

	This study has been prepared in accordance with the values of "Research and Publication Ethics"
Acknowledgement	The study is not a re-production of a paper or thesis-like work.
Conflict of Interest Statement	I assure as the author that there is no conflict or interest with third parties.
Author Contributions	I declare that I prepared the study myself as Çağrı HAMURCU.
Support	There is no situation that requires thanks in the study.
Ethics Committee Certificate Of Approval	Ethics committee approval is not required for the study.
Scale Permission	Not used.

References

Abraham, J., Sutiksno, D. U., Kurniasih, N., & Warokka, A. (2019). Acceptance and Penetration of Bitcoin: The Role of Psychological Distance and National Culture. *SAGE Open*, *9*(3). https://doi.org/10.1177/2158244019865813

Aharon, D. Y., & Qadan, M. (2019). Bitcoin and the Day-of-the-week Effect. *Finance Research Letters, 31*, 415-424. https://doi.org/10.1016/j.frl.2018.12.004

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

Brahmana, R., Hooy, C. W., & Ahmad, Z. (2012). The Role Of Herd Behaviour In Determining The Investor's Monday Irrationality. *Asian Academy of Management Journal of*

Accounting & Finance, *8*(2), 1-20. http://web.usm.my/journal/aamjaf/vol%208-2-2012/AAMJAF8-2-2012(1-20).pdf

Caporale, G. M., & Plastun, A. (2019). The Day of the Week Effect in the Cryptocurrency Market. *Finance Research Letters*, *31*, 258-269. https://doi.org/10.1016/j.frl.2018.11.012

Chan, M.W.L., Khanthavit, A. & Thomas, H. Seasonality and Cultural Influences on Four Asian Stock Markets. *Asia Pacific Journal of Management*, *13*(2), 1-24. https://doi.org/10.1007/BF01733814

Georgantopoulos, A. G., Kenourgios, D., & Tsamis, A. (2011). Calendar Anomalies in Emerging Balkan Equity Markets. *International Economics and Finance Journal*, *6*(1), 67-82. https://ssrn.com/abstract=1856983

Gkillas, K., Bekiros, S., & Siriopoulos, C. (2018). Extreme Correlation in Cryptocurrency Markets. https://dx.doi.org/10.2139/ssrn.3180934

Guidi, F., Gupta, R., & Maheshwari, S. (2011). Weak-form Market Efficiency and Calendar Anomalies for Eastern Europe Equity Markets. *Journal of Emerging Market Finance*, *10*(3), 337-389. https://doi.org/10.1177/097265271101000304

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

Katsiampa, P., Corbet, S., & Lucey, B. (2019). Volatility Spillover Effects in Leading Cryptocurrencies: A BEKK-MGARCH Analysis. *Finance Research Letters*, *29*, 68-74. https://doi.org/10.1016/j.frl.2019.03.009

Kinateder, H., & Papavassiliou, V. G. (2019). Calendar Effects in Bitcoin Returns and Volatility. *Finance Research Letters*, 101420. https://doi.org/10.1016/j.frl.2019.101420

Kumar, S., & Goyal, N. (2015). Behavioural Biases in Investment Decision Making–a Systematic Literature Review. *Qualitative Research in Financial Markets*, *7*(1), 88-108. https://doi.org/10.1108/QRFM-07-2014-0022

Lakonishok, J., & Maberly, E. (1990). The Weekend Effect: Trading Patterns of Individual and Institutional Investors. *The Journal of Finance*, *45*(1), 231-243. https://doi.org/10.1111/j.1540-6261.1990.tb05089.x

Lakonishok, J., & Smidt, S. (1988). Are Seasonal Anomalies Real? A Ninety-year Perspective. *The Review of Financial Studies*, *1*(4), 403-425. https://doi.org/10.1093/rfs/1.4.403

Long, H., Zaremba, A., Demir, E., Szczygielski, J. J., & Vasenin, M. (2020). Seasonality in the Cross-section of Cryptocurrency Returns. *Finance Research Letters*, *35*, 101566. https://doi.org/10.1016/j.frl.2020.101566

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

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

Ong, L. (2006). Seasonalities in China's Stock Markets: Cultural or Structural?. *IMF Working Paper No. 06/4*, Available at SSRN: https://ssrn.com/abstract=888149 or http://dx.doi.org/10.2139/ssrn.888149 http://dx.doi.org/10.2139/ssrn.888149

Osterrieder, J., Lorenz, J., & Strika, M. (2016). Bitcoin and Cryptocurrencies-not for the Faint-Hearted. Available at SSRN 2867671. https://dx.doi.org/10.2139/ssrn.2867671

Park, B. J. (2011). Herd Behavior and Volatility in Financial Markets. *Journal of the Korean Data and Information Science Society, 22*(6), 1199-1215. https://www.koreascience.or.kr/article/JAKO201109649112606.page

Qadan, M., Aharon, D. Y., & Eichel, R. (2021). Seasonal and Calendar Effects and the Price Efficiency of Cryptocurrencies. *Finance Research Letters*, 102354. https://doi.org/10.1016/j.frl.2021.102354

Seif, M., Docherty, P., & Shamsuddin, A. (2017). Seasonal Anomalies in Advanced Emerging Stock Markets. *The Quarterly Review of Economics and Finance, 66*, 169-181. https://doi.org/10.1016/j.qref.2017.02.009

Szyszka A. (2013). *Asset-Pricing Anomalies and Investment Strategies*. In: Behavioral Finance and Capital Markets. Palgrave Macmillan, New York. https://doi.org/10.1057/9781137366290_5

Yardımcı, B. and Erdem, S. (2020), The Day of the Week Effects in Stock Markets of Countries with Predominantly Muslim Populations, *International Journal of Islamic and Middle Eastern Finance and Management*, *13*(2), 195-218. https://doi.org/10.1108/IMEFM-06-2018-0199