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CALENDAR ANOMALIES IN NFT COINS

NFT Paralarında Takvim Anomalileri

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Keywords:
Calendar Anomalies,
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JEL Codes:
G14, G19,
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Abstract

This study examines the effect of day-of-the-week, month-of-the-year, and turn-of-the-month anomalies on NFT coins (Stacks, Tezos, and Decentraland) and Bitcoin. To this end, the generalized autoregressive conditional heteroscedasticity (GARCH) model was employed over the period 2019–2023. Based on the day-of-the-week anomaly results, Bitcoin has lower returns on Thursdays and Fridays, and Stacks has lower returns on Wednesdays. The remaining coins do not exhibit that anomaly. According to the month-of-the-year effect results, all evaluated coins generate abnormal returns in January. Moreover, positive returns are also reported in February for Tezos, Decentraland, and Bitcoin. Additionally, Bitcoin has positive returns in March as well. Furthermore, besides January, Stacks has significantly positive returns in April and May. Finally, the results of the turn-of-the-month anomaly suggest that only Stacks has statistically significant and positive returns on the last day of the month and the next three days. The remaining cryptocurrencies do not have such an anomaly. Overall, the findings of this study suggest the existence of calendar anomalies in the cryptocurrency market that contradict the assumptions of market efficiency. By using these outcomes, investors may develop trading strategies for their portfolio selection; hence, by taking advantage of the market, they could earn unusual profits.

Anahtar Kelimeler:
Takvim Anomalileri,
Etkin Piyasalar,
Kripto Paralar.

JEL Kodları:
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G40, G41

Öz

Bu çalışma, haftanın günü, yılın ayı ve ayın dönüşü anomalilerinin NFT coinleri (Stacks, Tezos ve Decentraland) ve Bitcoin üzerindeki etkisini incelemektedir. Bu amaçla, 2019-2023 dönemi için genelleştirilmiş otoregresif koşullu değişen varyans (GARCH) modeli kullanılmıştır. Haftanın günü anomalisi sonuçlarına göre, Bitcoin perşembe ve cuma günleri, Stacks ise çarşamba günleri daha düşük getiri sağlamaktadır. Diğer kripto paralarda bu anomali görülmemektedir. Yılın ayı etkisi sonuçlarına göre, değerlendirilen tüm kripto paralar ocak ayında anormal getiri sağlamaktadır. Ayrıca, Tezos, Decentraland ve Bitcoin için şubat ayında da pozitif getiriler rapor edilmiştir. Ek olarak, Bitcoin mart ayında da pozitif getiriye sahiptir. Ayrıca, ocak ayının yanı sıra, Stacks Nisan ve Mayıs aylarında önemli ölçüde pozitif getiriye sahiptir. Son olarak, ay dönümü anomalisinin sonuçları, yalnızca Stacks'ın ayın son gününde ve sonraki üç günde istatistiksel olarak anlamlı ve pozitif getirilere sahip olduğunu göstermektedir. Geri kalan kripto para birimlerinde böyle bir anomali bulunmamaktadır. Genel olarak, bu çalışmanın bulguları kripto para piyasasında piyasa etkinliği varsayımlarını ihlal eden takvim anomalilerinin varlığına işaret etmektedir. Yatırımcılar bu sonuçları kullanarak portföy seçimleri için alım satım stratejileri geliştirebilir; dolayısıyla piyasadan faydalanarak olağandışı kârlar elde edebilirler.

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1. Introduction

Since the beginning of the 2000s, the rapid growth of cryptocurrencies has attracted the interest of numerous investors, scholars, media, and policymakers. Satoshi Nakamoto, an unidentified person, or entity founded Bitcoin (BTC) in 2009. After the development of BTC, around 4000 alternative cryptocurrencies evolved (Pintelas et al., 2020). Initially regarded only as a way to exchange money, cryptocurrencies are now considered enticing investment opportunities (Jay et al., 2020). Therefore, investors and academics have spent a great deal of time and attention figuring out whether cryptocurrency pricing and movements are predictable (Ergun and Karabiyik, 2021). Specifically, to better understand market efficiency, many academics studied whether calendar anomalies exist on cryptocurrency marketplaces.

Calendar anomalies contradict the findings of Fama’s (1970) Efficient Market Hypothesis (EMH) which states that all available information is reflected in the asset prices, hence it is not possible to earn abnormal profits by following the trend. Many studies, however, demonstrate that anomalies exist in most financial markets, and as a result, stock values tend to be systematically different at specific times, and investors may earn abnormal profits during these periods. The day-of-the-week (DoW), month-of-the-year (MoY), and the turn-of-the-month (ToM) are among the most popular calendar anomalies, which are also the focus of this study. According to the DoW anomaly, the returns varied substantially on certain days. For example, early studies indicated that returns are lower on Mondays than on other days (Cross, 1973), but more recent investigations found that this impact has vanished from the markets and that Mondays now have higher returns than other days (Qadan and Aharon, 2022). MoY anomaly reflects the abnormal returns in any month of the year compared to other months. For example, returns in January are typically higher than in other months, as Wachtel (1942) noted. The ToM anomaly, on the other hand, implies that there is an upward trend in average stock returns on the final trading day of the month and the following three trading days (Lakonishok and Smidt, 1988).

Although calendar anomalies have been thoroughly investigated in the literature for a variety of cryptocurrencies, the findings appear to be contradictory in terms of their presence, despite the fact that many results suggest that the market is not efficient. Furthermore, prior studies have primarily focused on BTC and other popular altcoins, but to the best of the author's knowledge, calendar anomalies have not before been examined for non-fungible tokens (NFTs). NFTs are cryptographic assets with unique properties that cannot be substituted by another token, and each NFT has only one owner (Ante, 2022). In addition to the digital assets they sell, NFTs also have linked cryptocurrencies that are traded in the cryptocurrency market. They are exchanged in crypto marketplaces (such as Binance) like regular cryptocurrencies, and they influence determining the market value of their associated NFT projects (Gunay and Muhammed, 2022). Understanding the market efficiency of NFT coins is particularly important because they are a unique, relatively new, and growing market in comparison to traditional cryptocurrencies, so individual investors probably constitute the majority of the market who may lack the ability to prevent these calendar anomalies.

The purpose of this study is to investigate the impact of three selected anomalies on NFT coins, including DoW, MoY, and ToM effects. Stacks (STX), Tezos (XTZ), and Decentraland (MANA) are chosen to represent the NFT coin market based on market capitalization and available price history. BTC is included in the analysis to compare findings to the traditional cryptocurrency market. To this end, the generalized autoregressive conditional heteroscedasticity

(GARCH) model is applied as an econometric method, and the daily data spans the period 2019-2023. The contribution of this study is threefold. First, while prior studies examined several anomalies in traditional cryptocurrencies, none of them considered NFT coins, hence the current study will fill this gap. Second, because anomalies might disappear or reappear over time, the data may provide insight into whether the anomalies are still persistent for BTC returns in the recent timeframe. Third, the findings may provide useful information concerning cryptocurrency hedging strategies and portfolio selections.

In the following parts, first, the literature will be summarized; second, the data and methodology will be explained; third, the empirical results will be discussed; and finally, the paper will be concluded with discussion, suggestions for future research, and policy implications.

2. Literature Review

Although seasonal/calendar anomalies are widely researched for stock markets (i.e., Cross, 1973; Barone, 1990; Ariss et al., 2011; Cilingirturk et al., 2020; Ozic, 2023), the studies that focused on the cryptocurrency market are relatively brand new and still need more examination. Table 1 summarizes the studies chronologically that investigated the effect of several anomalies on the cryptocurrency market. While the DoW effect is the most studied anomaly in the analysis, BTC, which has the biggest market capitalization, is the most examined cryptocurrency. The earliest study that analyzed the DoW effect on BTC returns was conducted by Kurihara and Fukushima (2017) for the time frame 2010-2016. They divided the period into two subperiods and found that while the anomaly occurs on weekends in the first subperiod, it tends to disappear in the second. Aharon and Qadan (2019) and Ma and Tanizaki (2019) examined the DoW effect on BTC return and volatility for the period 2010-2017 and 2013-2018, respectively. Aharon and Qadan (2019) found that on Mondays BTC returns and volatility tend to be higher. Additionally, Ma and Tanizaki (2019) concluded that BTC volatility is higher not only on Mondays but also on Thursdays. Mbanga (2019), on the other hand, studied whether the BTC price clustering resulted from the DoW effect, and found that prices cluster mostly on Fridays.

Some studies included other altcoins besides BTC in their analyses to measure the DoW effect. Dorfleitner and Lung (2018) investigated eight cryptocurrencies and found significantly negative returns on Sundays. On the other hand, Caporale and Plastun (2019) stated that among the four cryptocurrencies they analyzed, only BTC showed the DoW anomaly on Mondays. Yaya and Ogbonna (2019) examined thirteen cryptocurrencies and concluded that none of their returns are affected by the DoW anomaly, but the volatility of BTC is different on Mondays and Fridays. Tosunoglu et al. (2023) employed an artificial neural networks (ANN) algorithm to explore the DoW impacts on BTC, Ethereum, and Cardano and observed that only BTC exhibited it. Lastly, Verma et al. (2023) investigated the effect of DoW on six cryptocurrencies and did not find any statistically significant results. Although the results between the studies differ according to the econometric model used and the period considered, it is generally found that BTC shows a DoW effect, especially on Mondays.

Table 1. Literature Summary

Author(s)	Anomalies	Cryptocurrencies	Methodology	Period
Kurihara and Fukushima (2017)	DoW	BTC	OLS & RLS	2010-2016
Eyuboglu (2018)	DoW, MoY	BTC, Litecoin	GARCH	2013-2017
Dorfleitner and Lung (2018)	DoW	BTC, Litecoin, Dash, Ether, Ripple, Monero, Stellar Lumens, Nem	EGARCH	2015-2018
Aharon and Qadan (2019)	DoW	BTC	OLS & GARCH	2010-2017
Baur et al. (2019)	DoW, Time-of-the-day, MoY	BTC	Heatmaps	2011-2017
Caporale and Plastun (2019)	DoW	BTC, Litecoin, Ripple, Dash	t-test, ANOVA, Kruskal-Wallis, OLS	2013-2017
Cimen (2019)	Day-of-the-month, ToM	BTC, Litecoin, CCI30	GARCH	2015-2019
Fraz et al. (2019)	DoW, MoY	BTC	OLS	2013-2017
Kaiser (2019)	Monday and weekend, January, Halloween	BTC, Bitcoin Cash, Cardano, DASH, Ethereum, IOTA, Litecoin, NEO, Ripple, Stellar	OLS & GARCH	2013-2018
Ma and Tanizaki (2019)	DoW	BTC	Stochastic Volatility & OLS	2013-2018
Mbanga (2019)	DoW	BTC	M-Values	2011-2018
Yaya and Ogbonna (2019)	DoW	BTC, Dash, Digibyte, Doge, Ethereum, Litecoin, Maidsafecoin, Monero, Nem, Ripple, Stellar, Verge, Vertcoin	Fractional Integration Regression	2015-2019
Susana et al. (2020)	Day-of-the-month, ToM, End-of-the-year	BTC, Ethereum, Tether, XRP, Bitcoin Cash	GARCH	2017-2020
Dumrongwong (2021)	Monday, January, Halloween	BTC, Ethereum, Ripple, Tether, Litecoin	GARCH with quasi-maximum likelihood (QML)	2010-2020
Kinateder and Papavassiliou (2021)	DoW, MoY, Halloween	BTC	GJR-GARCH	2013-2019
Khuntia and Pattanayak (2021)	ToM, Monday, January, Weekend	BTC, Ripple, Litecoin, Monero, Dash, Dogecoin, Bitshares, Verge, Bytecoin	GARCH & Kruskal–Wallis	2014-2019
Kumar (2022)	ToM	BTC, Ethereum, Litecoin	OLS & GARCH	2015-2021
Lopez-Martin (2022a)	Ramadan	BTC, Ethereum, Ripple, Stellar, Litecoin, Binance Coin	EGARCH & GJR-GARCH	2012/8-2021

Table 1. Continued

Lopez-Martin (2022b)	DoW, MoY	BTC, Ethereum, Ripple, Monero, EOS, Bitcoin Cash, BinanceCoin, Litecoin, Stellar, Dash, Zcash	OLS, ANOVA & Friedman Tests	2012/7-2020
Ossola (2022)	Weekend, Weekly, MoY, Halloween	Cardano, Binance Coin, BTC, Pancake Swap Coin, Dogecoin, Polkadot, Ethereum, Litecoin, Terra Classic, Polygon, Shiba Inu, Solana, Uniswap, Monero, Ripple	OLS	2013/7-2022
Qadan et al. (2022)	DoW, Fourth and fifth Monday of the month, Friday the 13th, Halloween, October, ToM, Week-of-the-year, Within the month, intra-quarter, SAD, Lunar cycle, Holiday	BTC, Ethereum, Litecoin, Ripple, Dash, Monero, Nem, Ethereum Classic	OLS	2011/6-2020
Almosfi (2023)	January, Halloween, Second quarter, Monday	CCI30, BTC, Ethereum, XRP, Litecoin, Stellar	OLS, CAPM, Fama-French's three factors & Carhart's Four factors	2015-2020
Ergun (2023)	SAD	Cardano, Tron, Stellar	OLS	2018-2023
İmre Bıyıklı and Özaydın (2023)	DoW, MoY, ToM, New Year, End-of-the-year	BTC_Cash, Binance Coin, BTC, Cardano, Ethereum, ChainLink, Litecoin, Theta, XRP	GARCH	2018-2021
Kahraman (2023)	DoW, MoY, Time-of-the-day	BTC, Ethereum	GARCH, EGARCH, TGARCH	2015/7-2022
Naz et al. (2023)	DoW, January	BTC, Dash, Ethereum, Litecoin, Ripple	MGARCH	2015-2020
Tosunoğlu et al. (2023)	DoW	BTC, Ethereum, Cardano	ANN	2018-2022
Vasileiou (2023)	ToM	BTC, Ethereum	EGARCH	2017-2021
Verma et al. (2023)	DoW	BTC, Ethereum, Ripple, Litecoin, Stellar, Tether	Bar Graph, Heat map, Student's t-test, ANOVA, OLS & Kruskal-Wallis	2015-2019

The second most examined calendar anomaly is the MoY effect, and studies commonly investigated this anomaly together with the DoW effect. Eyuboglu (2018) analyzed the effects of DoW and MoY on BTC and Litecoin returns. The results indicate that BTC returns are higher on Mondays, Tuesdays, and Fridays; and Litecoin returns are lower on Saturdays. Among the months, in February, October, and November BTC returns tend to be positive; and in August Litecoin returns tend to be negative. Fraz et al. (2019) examined only BTC and similar to the prior studies they found that on Mondays and in November the returns are significantly different. Moreover, Lopez-Martin (2022b) investigated eleven cryptocurrencies and concluded that DoW and MoY effects are present especially on Thursdays and in November, respectively. In addition to the DoW and MoY effects on BTC returns, Baur et al. (2019) incorporated the time-of-day effect in their research and concluded that these anomalies are not long-lasting. Similarly, Kahraman (2023) examined the DoW, MoY, and time-of-the-day effects on BTC and Ethereum and found the existence of calendar anomalies in the cryptocurrency market.

Furthermore, several studies focused on specific days (Mondays, weekends), months (January), and holidays (Halloween, Ramadan) in their research. Kaiser (2019) examined Monday, weekend, January, and Halloween effects on returns, trading volume, volatility, and spreads of ten cryptocurrencies. Trading volume, volatility, and spreads are found to be lower in January, on weekends, and throughout the summer. Similarly, Dumrongwong (2021) analyzed the effects of Monday, January, and Halloween on five cryptocurrencies. Abnormal returns are observed in January for Ethereum, and on Mondays for Litecoin. Kinateder and Papavassiliou (2021) considered the Halloween effect together with the DoW and MoY effects for BTC returns and volatility. The results indicate that the volatility is lower on weekends and in September, and there is also a reverse January effect. Ossola (2022), on the other hand, investigated weekend, weekly, monthly, and Halloween effects for fifteen cryptocurrencies. While significant Monday, Thursday, and Friday impacts are found, the Monday effect appears to be more prevalent in the last week of the month, while the Friday effect appears to be more prevalent in the second week of the month. Furthermore, there are February, April, and May impacts, which are congruent with the holiday and Halloween effects (Ossola, 2022). Almosfi (2023) analyzed the January, Halloween, Monday, and additionally, second-quarter effects for five cryptocurrencies and cryptocurrency index (CCI30), and the findings show the January effect only for Ethereum. Naz et al. (2023) also investigated the DoW and January effects for five cryptocurrencies and found that positive abnormal returns are present on Mondays and in December. Moreover, İmre Bıyıklı and Özaydın (2023) investigated the DoW, MoY, ToM, New Year and end-of-the-year effects on nine cryptocurrencies and concluded that calendar anomalies are present in the cryptocurrency market.

Moreover, the ToM and day-of-the-month impacts are among the most commonly studied calendar anomalies. Cimen (2019) examined these anomalies for BTC, Litecoin, and CCI30, and found a statistically significant ToM effect for CCI30 and Litecoin. Similarly, Susana et al. (2020) analyzed the ToM effect together with DoW and year-end effects for five cryptocurrencies. According to the results, on Thursdays, in March and April, and at the turn of the year abnormal returns are observed. Khuntia and Pattanayak (2021) studied ToM, Monday, January, and weekend effects for nine cryptocurrencies, and stated that these calendar anomalies vary across time. Moreover, İmre Bıyıklı and Özaydın (2023) investigated the DoW, MoY, ToM, New Year and end-of-the-year effects on nine cryptocurrencies and concluded that calendar anomalies are present in the cryptocurrency market. Kumar (2022) investigated the impact of ToM on BTC, Ethereum, and Litecoin, and found positive returns during the ToM. Also, Vasileiou (2023) investigated and proved the existence of ToM anomaly for BTC and Ethereum. Additionally, apart from prior research, Ergun (2023) analyzed the seasonal affective disorder (SAD) effect on three selected green cryptocurrencies but found no impact. Finally, Qadan et al. (2022) conducted a comprehensive study including several anomalies and investigated the effects of these selected anomalies on eight cryptocurrencies. They concluded that anomalies detected in BTC do not apply to other cryptocurrencies, and vice versa. However, the results suggest that the within-the-month effect is present in all analyzed cryptocurrencies.

3. Data and Methodology

In addition to the digital assets they offer, NFTs have associated coins and tokens that are traded on the cryptocurrency market. Based on their market capitalization as of 17 October 2023, Table 2 presents the top ten listed NFT coins, and their date of establishment[1]. Three cryptocurrencies are chosen for examination based on their trading history and market capitalization: STX, XTZ, and MANA. Additionally, BTC is used to represent the overall market and to revisit each anomaly for the current period.

The data period, which is roughly 4 years, spans the period from October 30, 2019, to October 19, 2023. The longest period that is available has been considered to generate more satisfying results, and the cryptocurrencies that have less than four years of trading history are excluded from the analysis. The daily closing USD prices of the selected cryptocurrencies are obtained from https://finance.yahoo.com/. Since the cryptocurrency market is operating 24/7, the coinmarketcap website identifies the opening and closing times as 12:00 AM (00:00) and 11:59 PM (23:59) UTC, respectively.

Table 2. Top Listed NFT Coins

Rank	Name	Start Date
1	Internet Computer (ICP)	10.05.2021
2	Render (RNDR)	11.06.2020
3	**Stacks (STX)**	**29.10.2019**
4	Immutable (IMX)	06.11.2021
5	Axie Infinity (AXS)	04.11.2020
6	The Sandbox (SAND)	14.08.2020
7	**Tezos (XTZ)**	**09.11.2017**
8	**Decentraland (MANA)**	**09.11.2017**
9	Theta Network (THETA)	17.01.2018
10	Flow (FLOW)	29.01.2021

The following Equation (1) calculates the natural logarithmic returns of each cryptocurrency I on trading day t (ri,t) where pi,t, and pi,t-1 indicate the closing prices of cryptocurrency I on trading day t and t-1, respectively:

$$r_{I,t} = \ln\left(\frac{p_{I,t}}{p_{I,t-1}}\right) \tag{1}$$

[1] Retrieved from Coinmarket (2023) (accessed on 17.10.2023).

Since most financial time series include a heteroscedasticity problem, the GARCH model is recommended for the examination of the effects of calendar anomalies. The GARCH model was developed by Bollerslev (1986) and Taylor (1986) as an extension of Engle’s (1982) autoregressive conditional heteroscedasticity (ARCH) model, where heteroscedasticity could be included in the estimation process.

In the following equation (2), which describes GARCH (p,q), σ_t and σ_{t-j} are the conditional variance of returns at time t and t-j, respectively; and α_0, α_I, and β are the GARCH model coefficients. In the model, the conditional variance depends on the q lags of the squared error and the p lags of the conditional variance (Brooks, 2014: 428).

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{2}$$

Before employing the GARCH model, ARCH effects are controlled with the ARCH-LM test. Then, by comparing the different combinations of p and q, the most appropriate GARCH (p, q) models are selected for each cryptocurrency based on their Akaike Information (AIC), Schwartz criteria (SIC), and R-squared values. While the lowest values of AIC and SIC are preferred, the highest value is desirable for the R-squared statistic. Additionally, the model has to obtain positive and statistically significant ARCH (α) and GARCH (β) variables. Moreover, if the autocorrelation is observed in the selected model, the ARMA (p, q) terms could be included into the model. After approving whether the ARCH effect and autocorrelation problem have disappeared, the selected models are employed to investigate the anomalies with the following equations.

First, the DoW effect is examined for each dataset. To avoid the dummy variable trap, Sunday is excluded from the analysis. In equation (3), the dummy variables d1, d2, d3, …, and d6 take the value of 1 on Monday, Tuesday, Wednesday, …, and Saturday, respectively, and 0 otherwise.

$$R_{i,t} = \alpha_0 + \partial_1 d_1 + \partial_2 d_2 + \partial_3 d_3 + \partial_4 d_4 + \partial_5 d_5 + \partial_6 d_6 + \varepsilon_{i,t} \tag{3}$$

Second, the MoY effect is analyzed with the following equation. To avoid the dummy variable trap, September is excluded from the analysis. In equation (4), the dummy variables d1, d2, d3, …, and d12 take the value of 1 on January, February, March, …, and December, respectively, and 0 otherwise.

$$\begin{aligned} R_{i,t} = \alpha_0 &+ \partial_1 d_1 + \partial_2 d_2 + \partial_3 d_3 + \partial_4 d_4 + \partial_5 d_5 + \partial_6 d_6 + \partial_7 d_7 + \partial_8 d_8 + \partial_{10} d_{10} \\ &+ \partial_{11} d_{11} + \partial_{12} d_{12} + \varepsilon_{i,t} \end{aligned} \tag{4}$$

Third, the ToM effect is analyzed with equation (5) where d1 is the dummy variable that takes 1 on the last day and the first three days of the month, and 0 otherwise (Kumar, 2022).

$$R_{i,t} = \alpha_0 + \partial_1 d_1 + \varepsilon_{i,t} \tag{5}$$

4. Empirical Results

The descriptive statistics of BTC, MANA, STX, and XTZ are presented in Table 3. There are a total of 1451 observations during the data period. When the minimum and maximum returns are compared while STX has the lowest minimum value, MANA has the highest maximum value.

The standard deviations show that MANA and STX obtain the highest volatility among others. The Jarque-Bera test statistics indicate that none of the cryptocurrencies are normally distributed.

Table 3. Descriptive Statistics

	BTC	MANA	STX	XTZ
Mean	0.000768	0.001504	0.000681	-0.000236
Max.	0.171821	0.935067	0.799405	0.305869
Min.	-0.464730	-0.629841	-0.712411	-0.607260
Std. Dev.	0.035542	0.071961	0.071390	0.058862
Jarque-Bera	30961.70***	43773.20***	27546.05***	9090.79***
Obs.	1451	1451	1451	1451

Notes: *** denotes the statistical significance at the %1 level.

In the second phase, the unit roots of the cryptocurrencies are controlled with the Augmented-Dickey Fuller (ADF) test to control whether the series is stationary. As exhibited in Table 4, the null hypothesis "there is a unit root in the model" is rejected for both intercept and trend & intercept models, and hence it is found that all cryptocurrencies are stationary at their levels.

Table 4. ADF Test Results

	Intercept	Trend & Intercept
BTC	-40.24284***	-40.25116***
MANA	-36.78430***	-36.83614***
STX	-40.32989***	-40.32115***
XTZ	-41.88533***	-41.94982***

Notes: *** denotes the statistical significance at the %1 level.

In the third phase, to find out whether the series are homoscedastic the ARCH LM test is applied for each variable, and the results are exhibited in Table 5 for various lags. According to the F-statistics, the null hypothesis "the residuals exhibit no conditional heteroscedasticity" is rejected for each lag (only STX seems homoscedastic after the 10th lag). Since the results indicate heteroscedasticity and an ARCH effect for all variables, the ARCH/GARCH model is employed in the following process.

Table 5. ARCH LM Test Results

	BTC	MANA	STX	XTZ
1^{st} Lag	4.240235**	76.34410***	6.463157***	30.81631***
5^{th} Lag	2.041451*	15.58032***	1.893361*	9.824806***
10^{th} Lag	2.998108***	7.835242***	1.089319	6.017821***
20^{th} Lag	1.624314**	3.973065***	0.578604	3.351714***

Notes: This table shows the F-statistics of various lags. *, **, *** denote the statistical significance at %10, %5 and %1 level, respectively.

In the next step, R-squared, SIC, and AIC criteria are evaluated for all variables to determine which GARCH model is best suited. As mentioned before, while the lowest values of AIC and SIC are preferred, the highest value is desirable for the R-squared statistic. Additionally, the model has to obtain positive and statistically significant ARCH (α) and GARCH (β) variables.

Models that do not fulfill these conditions are automatically excluded from the evaluation and the values are presented in Table 6.

First, for the BTC, according to the statistical findings, there are negative β and α values in the GARCH (1,2) and GARCH (3,1) models, and the β_1 in the GARCH (2,2) model does not exhibit statistical significance. Therefore, the values for the GARCH (1,1) and GARCH (2,1) models are compared, and the GARCH (1,1) model is chosen for BTC since its AIC and SIC are lower. Second, for the MANA, there are negative β and α values in GARCH (2,1), GARCH (2,2) and GARCH (3,1). When the remaining models are compared, the GARCH (1,1) model has the highest R-squared and the lowest SIC, while the GARCH (1,2) model has the lowest AIC value. Therefore, the GARCH (1,1) model is selected for MANA.

Third, for the STX, there are negative β and α values in the GARCH (1,2) and GARCH (3,1) models, and the β_1 and β_2 in the GARCH (2,2) model are not statistically significant. The best values of AIC and SIC are observed for the GARCH (2,1) model. Finally, only XTZ had an autocorrelation problem based on the Ljung-Box test (Q-test) statistics of correlograms[2]; this issue is resolved by adding the AR(1) term to the selected model. The AR(1)-GARCH(1,1) model is chosen for the XTZ because the other models include parameters that are not statistically significant. To sum up, GARCH (1,1) is selected for BTC, MANA, and XTZ. For STX, on the other hand, GARCH (2,1) is the most suitable model.

Table 6. Model Selection

	GARCH(1,1)	**GARCH(1,2)**	**GARCH (2,1)**	**GARCH (2,2)**	**GARCH (3,1)**
BTC					
c	0.001533*	0.001397*	0.001512*	0.000111***	7.01E-05***
α_1	0.121843***	0.062584***	0.098194***	0.062949***	0.108159***
α_2	-	-	0.029928**	0.201956***	-0.087911***
α_3	-	-	-	-	0.123855***
β_1	0.857328***	1.482892***	0.847242***	0.013223	0.820583***
β_2	-	-0.562131***	-	0.677863***	-
AIC	**-3.939069**	-3.944009	-3.938117	-3.954604	-3.951083
SIC	**-3.924514**	-3.925815	-3.919923	-3.932771	-3.929250
R-squared	**-0.000464**	-0.000314	-0.000439	-0.000224	-0.000359
MANA					
c	0.000183***	0.000188***	8.13E-05***	1.21E-05***	4.81E-05***
α_1	0.245389***	0.262261***	0.323943***	0.306326***	0.306347***
α_2	-	-	-0.202383***	-0.285555***	-0.075131*
α_3	-	-	-	-	-0.153541***
β_1	0.756091***	0.562207	0.875237***	1.508322***	0.920193***
β_2	-	0.176156**	-	-0.529430***	-
AIC	**-2.815594**	-2.816223	-2.823473	-2.837558	-2.835140
SIC	**-2.801038**	-2.798028	-2.805279	-2.815725	-2.813306
R-squared	**-0.000845**	-0.000935	-0.001408	-0.001368	4.81E-05

[2] Before adding the AR(1) term, the Q statistics were 3.3820, 10.165, 19.526 for 1st, 5th, and 10th lags, respectively, which were statistically significant at %10 level for the 1st and 5th lags, and %5 level for the 10th lag.

Table 6. Continued

STX	GARCH(1,1)	GARCH(1,2)	GARCH (2,1)	GARCH (2,2)	GARCH (3,1)
c	0.000945***	0.000887***	0.001921***	0.001858***	0.000806**
α_1	0.442014***	0.394058***	0.259104***	0.245649***	0.248331***
α_2	-	-	0.491771***	0.499140***	0.360222***
α_3	-	-	-	-	-0.274827***
β_1	0.504382***	0.711098***	0.086859**	0.033138	0.599744***
β_2	-	-0.163812***	-	0.063653	-
AIC	-2.562941	-2.574066	**-2.601200**	-2.601374	-2.601746
SIC	-2.548386	-2.555871	**-2.583006**	-2.579541	-2.579912
R-squared	-0.000258	-0.000092	**-0.000065**	-0.000040	-0.000069
XTZ					
c	5.76E-05***	5.90E-05***	5.46E-05***	0.000126***	3.97E-05***
α_1	0.112906***	0.116282***	0.122479***	0.080128***	0.116113***
α_2	-	-	-0.013724	0.152713***	0.038846
α_3	-	-	-	-	-0.065363**
β_1	0.882543***	0.840965***	0.886980***	0.080336	0.908089***
β_2	-	0.038106	-	0.676905***	-
AIC	**-3.037574**	-3.036223	-3.036267	-3.039969	-3.037379
SIC	**-3.019380**	-3.014390	-3.014434	-3.014497	-3.011907
R-squared	**0.008201**	0.008191	0.008172	0.007606	0.008154

Notes: α and β indicate ARCH and GARCH variables, respectively. *,**,*** denote the statistical significance at %10, %5, and %1 level, respectively. The numbers in bold show the best values for each statistic. The lowest value is preferable for AIC and SIC and the highest value is preferable for R-squared. For the XTZ AR(1) term is included in the model, and the GARCH parameters show the AR(1)-GARCH(p,q) model results.

Furthermore, for the selected GARCH models, the correlograms are checked for the potential autocorrelation problem and the ARCH-LM tests are re-employed to figure out if the effect had disappeared. As shown in Table 7, the selected models do not have heteroscedasticity and autocorrelation problems, hence the calendar anomalies are examined using these models.

Table 7. ARCH-LM and Correlogram Statistics for the Selected Models

		ARCH-LM	Q-stats
BTC	1st Lag	0.031046	0.3580
	5th Lag	0.815865	3.9192
	10th Lag	0.482371	12.427
	20th Lag	0.311113	18.278
MANA	1st Lag	1.251733	2.4971
	5th Lag	0.757871	3.3795
	10th Lag	0.761361	6.9936
	20th Lag	0.769026	17.209
STX	1st Lag	0.311856	7.E-05
	5th Lag	0.293265	5.3747
	10th Lag	0.191465	9.1279
	20th Lag	0.197379	18.967
XTZ	1st Lag	1.94E-05	1.3470
	5th Lag	0.282556	6.4961
	10th Lag	0.439523	14.952
	20th Lag	0.339026	21.498

Notes: The GARCH (1,1) model is applied for BTC. MANA and XTZ. The GARCH (2,1) model is applied for STX. AR (1) term is included in the model for XTZ to control for the residual autocorrelation. This table shows the F and Q statistics of various lags. *, **, *** denote the statistical significance at %10, %5, and %1 level, respectively.

The DoW results are exhibited in Table 8. In the variance equations of all series, the coefficients of the constant term (ω), ARCH terms (α), and GARCH term (β) are positive and statistically significant. Therefore, the coefficients of each model match the predictions of $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$. The results indicate that BTC has significantly lower returns on Thursdays and Fridays. Additionally, STX has significantly lower returns on Wednesdays. On the other hand, MANA and XTZ do not have a significant DoW anomaly on any day.

Table 8. Day of the Week Effect Results

	BTC	MANA	STX	XTZ
Constant	0.004445	-0.001696	0.002115	-0.000541
(C)	[1.885446]**	[-0.522554]	[0.516113]	[-0.156514]
Monday	-0.001800	-0.004632	0.001154	-0.002584
(d1)	[-0.609690]	[-1.075591]	[0.243057]	[-0.538480]
Tuesday	-0.001497	-0.005900	-0.005979	-0.002370
(d2)	[-0.484763]	[-1.314456]	[-1.138315]	[-0.529867]
Wednesday	-0.000494	0.002585	-0.009434	-0.002507
(d3)	[-0.157153]	[0.583915]	[-1.732032]*	[-0.577086]
Thursday	-0.009208	0.002060	-0.001121	-0.004314
(d4)	[-3.061864]***	[0.457039]	[-0.196854]	[-1.033079]
Friday	-0.005030	0.006315	-0.002102	0.002461
(d5)	[-1.728272]*	[1.504773]	[-0.391972]	[0.519142]
Saturday	-0.002934	0.006974	0.004067	0.005173
(d6)	[-0.624248]	[1.265952]	[0.932830]	[0.962468]
AR(1)	-	-	-	-0.072422 [-2.475712]**
Variance Equation				
Constant	4.80E-05	0.000191	0.001886	6.14E-05
(ω)	[6.936452]***	[6.870617]***	[13.03245]***	[5.487704]***
α_1	0.124643 [9.920496]***	0.253174 [15.05128]***	0.262619 [10.89985]***	0.116012 [10.94412]***
α_2	-	-	0.496941 [14.61693]***	-
β_1	0.856334 [65.85071]***	0.737318 [51.46711]***	0.083726 [2.101006]**	0.878439 [82.96138]***
AIC	-3.941297	-2.816562	-2.598946	-3.034250
SIC	-3.904909	-2.780173	-2.558918	-2.994222

Notes: *, **, *** denote the statistical significance at %10, %5, and %1 level, respectively. The statistics in brackets show the z-statistics for each variable. The dummy variables d1, d2, d3, …, and d6 are equal to 1 on Monday, Tuesday, Wednesday, …, and Saturday, and zero otherwise, respectively. The GARCH (1,1) model is applied for BTC, MANA, and XTZ. The GARCH (2,1) model is applied for STX. AR (1) term is included in the model for XTZ to control for residual autocorrelation. ω is the constant for variance equation. α and β show the ARCH and GARCH parameters, respectively. AIC is the Akaike and SIC is the Schwarz-Bayesian information criteria.

The MoY results are shown in Table 9. In the variance equations of all series, the coefficients of the constant term (ω), ARCH terms (α), and GARCH term (β) are positive and statistically significant. Therefore, the coefficients of each model match the predictions of $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$. According to the results, the returns of BTC are significantly positive in January, February, and March. Similarly, the returns of MANA and XTZ are significantly positive in January and February. Besides January, STX returns are statistically significant and positive in April and May.

Table 9. Month of the Year Effect Results

	BTC	MANA	STX	XTZ
Constant	-0.001214	-0.004563	-0.008781	-0.003212
(C)	[-0.559362]	[-1.178178]	[-2.041707]**	[-0.704985]
January	0.008158	0.008816	0.013291	0.010158
(d1)	[2.173675]**	[1.840216]*	[1.864985]*	[1.778003]*
February	0.006631	0.014583	0.009477	0.011239
(d2)	[2.087358]**	[2.266472]**	[1.456872]	[1.822411]*
March	0.018450	0.010298	0.002840	0.009587
(d3)	[5.534846]***	[1.570933]	[0.478184]	[1.452532]
April	0.001584	0.002818	0.019090	0.000758
(d4)	[0.452250]	[0.467061]	[3.621654]***	[0.131509]
May	-0.002148	0.003355	0.011016	-0.000923
(d5)	[-0.554096]	[0.482505]	[1.747611]*	[-0.159039]
June	0.000680	0.004864	0.009608	-0.003577
(d6)	[0.171510]	[0.933607]	[1.416428]	[-0.601439]
July	0.003180	0.008775	0.009778	0.006433
(d7)	[0.864922]	[1.406011]	[1.475380]	[1.065154]
August	-0.000376	0.001712	0.008804	0.000660
(d8)	[-0.104760]	[0.274016]	[1.261613]	[0.108795]
October	0.005304	0.002359	0.008908	0.000373
(d10)	[1.475152]	[0.420698]	[1.083249]	[0.063661]
November	-0.000248	0.002302	0.008166	0.007451
(d11)	[-0.074229]	[0.374911]	[1.134693]	[1.346449]
December	0.000942	0.000200	0.003975	-0.007935
(d12)	[0.272477]	[0.030805]	[0.582242]	[-1.491676]
AR(1)	-	-	-	0.004111 [0.099268]
Variance Equation				
Constant	4.51E-05	0.000196	0.001858	0.000942
(ω)	[7.209872]***	[7.030471]***	[12.17940]***	[9.482089]***
α_1	0.133066 [9.320783]***	0.252038 [15.29057]***	0.255609 [10.75779]***	0.452839 [11.33001]***
α_2	-	-	0.497305 [13.01129]***	-
β_1	0.851131 [64.39016]***	0.746762 [50.60269]***	0.092330 [2.227992]**	0.498067 [13.88252]***
AIC	-3.946296	-2.806861	-2.593868	-2.550583
SIC	-3.891713	-2.752277	-2.535646	-2.492361

Notes: *. **. *** denote the statistical significance at %10, %5 and %1 level, respectively. The statistics in brackets show the z-statistics for each variable. The dummy variables d1, d2, d3, …, and d11 are equal to 1 on January, February, March, …, and November, and zero otherwise, respectively. The GARCH (1,1) model is applied for BTC, MANA, and XTZ. The GARCH (2,1) model is applied for STX. AR (1) term is included in the model for XTZ to control for residual autocorrelation. ω is the constant for variance equation. α and β show the ARCH and GARCH parameters, respectively. AIC is the Akaike and SIC is the Schwarz-Bayesian information criteria.

The ToM results are shown in Table 10. In the variance equations of all series, the coefficients of the constant term (ω), ARCH terms (α), and GARCH term (β) are positive and statistically significant. Therefore, the coefficients of each model match the predictions of $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$.The results indicate that only STX has statistically significant and positive returns on the last day of the month, and the consecutive three days of the following month which represent the ToM anomaly. The remaining cryptocurrencies do not have such an anomaly.

Table 10. Turn of the Month Effect Results

	BTC	MANA	STX	XTZ
Constant	0.001957	-0.000283	-0.002758	-0.001659
(C)	[2.178219]**	[-0.222202]	[-1.773178]*	[-1.312128]
ToM	-0.002927	-0.002050	0.016126	0.003019
(d1)	[-1.088011]	[-0.446511]	[5.009966]***	[0.793808]
AR(1)	-	-	-	-0.071920 [-2.501586]**
Variance Equation				
Constant	5.03E-05	0.000185	0.001872	5.68E-05
(ω)	[7.172004]***	[7.477304]***	[12.87450]***	[5.494633]***
α_1	0.122616 [12.55908]***	0.246758 [15.69538]***	0.255941 [11.94436]***	0.112240 [11.25684]***
α_2	-	-	0.487147 [15.85620]***	-
β_1	0.856932 [69.06433]***	0.744703 [55.00464]***	0.090397 [2.262189]**	0.883332 [89.32348]***
AIC	-3.938810	-2.814435	-2.612934	-3.036759
SIC	-3.920615	-2.796241	-2.591101	-3.014926

Notes: *. **. *** denote the statistical significance at %10, %5 and %1 level, respectively. The statistics in brackets show the z-statistics for each variable. The dummy variable d1 equals 1 on the last day of the month and the consecutive three days of the following month, and zero otherwise. The GARCH (1,1) model is applied for BTC, MANA, and XTZ. The GARCH (2,1) model is applied for STX. AR (1) term is included in the model for XTZ to control for residual autocorrelation. ω is the constant for variance equation. α and β show the ARCH and GARCH parameters, respectively. AIC is the Akaike and SIC is the Schwarz-Bayesian information criteria.

5. Conclusion

This study examines the effect of DoW, MoY, and ToM anomalies on NFT coins. To represent the NFT coin market STX, XTZ, and MANA are selected. Additionally, BTC is added to the analysis to compare the findings of the NFT coin market with the traditional cryptocurrency market. For this purpose, the GARCH model is used as an econometric model, and the daily data ranges from 2019 to 2023. When prior studies are scrutinized, it is observed that none of them investigated NFT coins for the analysis of calendar anomalies, hence this research is supposed to address that gap. Furthermore, the outcomes of this study provide insight into whether the anomalies for BTC returns within the specified timeframe vanish over time.

Based on the DoW anomaly results, BTC has lower returns on Thursdays and Fridays, and STX has lower returns solely on Wednesdays. These findings are consistent with those of Susana et al. (2020) and Lopez-Martin (2022b), who revealed that most coins had significantly lower returns on Thursdays. However, the findings are partially contradicted with those of Eyuboglu (2018), who observed high abnormal returns on Fridays. On the other hand, the remaining coins did not exhibit a statistically significant DoW effect which is consistent with the findings of Yaya and Ogbonna (2019). Although most studies detected the Monday effect on cryptocurrency returns (i.e., Eyuboglu, 2018; Aharon and Qadan, 2019; Caporale and Plastun, 2019), the findings of this study did not observe it. Briefly, it could be stated that the Monday effect has diminished in the market in recent years, the Friday impact has shifted to the negative, and only one NFT coin (Stacks) has shown negative returns on Wednesdays. Hence, in terms of the DoW effect, conventional coins seem to be more prone to this anomaly.

According to the MoY effect results, in line with the findings of Dumrongwong (2021), all evaluated coins generated abnormal returns in January. Moreover, positive returns were also reported in February for XTZ, MANA, and BTC, which is consistent with the findings of Eyuboglu (2018) and Ossola (2022). Additionally, BTC experienced positive returns in March as well, thus it had abnormal returns during the first three months of the year. Furthermore, aside from January, STX had significantly positive returns in April and May, which is in line with Ossola's (2022) findings. As a result, the MoY effect does not distinguish between conventional and NFT coins; and it occurs for all coins in similar months. Particularly, it may be suggested that the January anomaly persisted over time and is a feature of the whole market. Finally, the results of the ToM anomaly suggest that only STX has statistically significant and positive returns on the last day of the month, and the next three days. The remaining cryptocurrencies do not have such an anomaly. Previously, Qadan et al. (2022) reported that BTC exhibited abnormal returns associated with the ToM effect. The absence of such an effect in the current research reveals that the anomaly has diminished over the years for BTC.

In conclusion, the ToM anomaly is only seen for STX, the DoW anomaly is only present for BTC and STX, and the MoY anomaly is evident for all examined coins. Overall, the findings of this study suggest the presence of calendar anomalies in the cryptocurrency market that violate the assumptions of market efficiency and indicate that returns are predictable. Moreover, considering the outcomes varied according to the cryptocurrency under investigation, it is possible to draw the inference that each coin's market efficiency is unique. Though, by using these outcomes, investors may develop trading strategies for their portfolio selection, hence by taking advantage of the market, they could earn unusual profits. However, market participants should also consider that these effects may change, and the efficiency of the market fluctuates over time depending on the sample period and method used, or they may completely disappear over time. Therefore, investors should dynamically alter their investment strategies following the current situation of the market.

Finally, this study has three primary drawbacks and suggestions. First, the cryptocurrency market has a shorter data history than the stock market. As a result, larger datasets may offer more insight about return patterns; so, more prolonged datasets may be used in future research. Second, in addition to GARCH models, additional volatility models (such as EGARCH and TGARCH) could also be considered in subsequent studies. Moreover, in this study, calendar anomalies are tested only in the mean model, investigation of the volatility model is left for the further analysis. Third, because of the nonlinear patterns in cryptocurrency returns, nonlinear models may be preferred in future research.

Declaration of Research and Publication Ethics
This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher's Contribution Rate Statement
I am a single author of this paper. My contribution is 100%.

Declaration of Researcher's Conflict of Interest
There is no potential conflicts of interest in this study.

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