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Profitability and risk in cryptocurrency markets: testing the Halloween effect and investment strategies

Evangelos Vasileiou
Department of Financial and Management Engineering, University of the Aegean, Chios, Greece
Christos Floros
Department of Accounting and Finance, Hellenic Mediterranean University, Heraklion, Greece, and
Konstantinos Gkillas
Department of Management Science and Technology, University of Patras, Patra, Greece and
Prague University of Economics and Business, Prague, Czech Republic

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Abstract

Purpose – The purpose of this study is to investigate the presence of the Halloween effect in the cryptocurrency market and assess its practical implications for investors. By focusing on five major cryptocurrencies (BTC, ETH, XRP, BNB and ADA), the study aims to determine whether returns during the Halloween period (October 31–April 30) outperform the rest of the year and identify associated risks. It also seeks to evaluate investment strategies based on the Halloween effect, providing insights for investors on the viability of seasonal trading strategies in the context of high-risk, high-volatility assets like cryptocurrencies.

Design/methodology/approach – Using data from 2018 to 2024, we examine five major cryptocurrencies (BTC, ETH, XRP, BNB and ADA), excluding stablecoins for more accurate results. Descriptive statistics reveal leptokurtosis, volatility clustering and asymmetric volatility, guiding the use of GARCH family models for further analysis. We compare returns and volatility during the Halloween period (October 31–April 30) with the rest of the year, evaluating investment strategies and their performance in relation to risk profiles across different cryptocurrencies.

Findings – The empirical evidence shows that cryptocurrencies exhibit higher returns during the Halloween period (October 31–April 30) compared to the rest of the year, although this period is associated with increased risk. Volatility analysis reveals significant differences between Halloween and non-Halloween periods, with most cryptocurrencies (except BTC) showing outperformance during Halloween. Additionally, a leverage effect is observed in BTC, ETH and BNB, while XRP demonstrates an anti-leverage effect. The Halloween-based investment strategy outperforms both the No-Halloween and Buy-and-Hold strategies for most assets, suggesting that, depending on risk tolerance, investors may benefit from a Halloween-focused approach.

Originality/value – This study explores inefficiencies in the cryptocurrency market, specifically focusing on calendar anomalies, with an emphasis on practical investment strategies. It excludes high-frequency trading strategies due to the potential impact of transaction costs on profitability. The Halloween effect is examined, as it requires only two transactions per year and has been less studied in the context of cryptocurrencies. The study reveals that Halloween periods generally offer higher returns, though at an increased risk. It also identifies a leverage effect in BTC, ETH and BNB, while XRP shows an anti-leverage effect. The findings suggest that a Halloween-based strategy could outperform traditional investment strategies, depending on risk tolerance.

Keywords Calendar anomalies, Halloween effect, Investment strategies, Asymmetric volatility

Paper type Research article

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1. Introduction

Cryptocurrencies, particularly Bitcoin (BTC), have captivated investor interest since their inception in 2008. One of the key drivers of this popularity was the aftermath of the subprime mortgage crisis and the subsequent sovereign debt crises. Over the years, periods of heightened interest in the crypto market have coincided with global financial events, such as the COVID-19 pandemic. Throughout these fluctuations, Bitcoin has remained the dominant force in the market.

In recent months, particularly after the U.S. presidential election in late 2024, the popularity of cryptocurrencies has surged again, with prices soaring to unprecedented heights. A contributing factor to this surge may be the rhetoric of President Donald Trump, who, in his campaign for a second term, expressed his intention to position the U.S. as the "crypto capital of the planet" and a "Bitcoin superpower" [1]. Following his remarks, Bitcoin reached all-time high prices, and many other cryptocurrencies also saw significant gains.

As of early 2025, the total cryptocurrency market is valued at approximately $3.5 trillion, with Bitcoin alone accounting for around $1.9 trillion [2]. This means Bitcoin currently represents about 55% of the entire crypto market. Ethereum (ETH), the second-largest cryptocurrency, holds a market capitalization of $437 billion, or roughly 12.5% of the total. The remaining portion of the market is shared among various other digital assets.

The growing interest and rapid expansion of the cryptocurrency market have drawn considerable scholarly attention, particularly regarding its financial utility. A substantial body of research has explored cryptocurrencies' roles as safe havens, hedges, and portfolio diversifiers. For instance, Shahzad *et al*. (2019) and Mariana *et al*. (2021) investigate the safe haven characteristics of cryptocurrencies during periods of market turmoil. Building on this, Kliber *et al*. (2019) highlight the context-dependent nature of Bitcoin's role, noting that it functions as a safe haven in economically distressed countries like Venezuela, but serves only as a weak hedge or diversifier in more stable economies. Similarly, Bouri *et al*. (2017a) find that Bitcoin exhibits safe haven, hedge, and diversification properties in Asia-Pacific stock markets, with these effects varying across investment horizons. In a complementary study, Bouri *et al*. (2017b) provide evidence that Bitcoin can hedge global equity market uncertainty, particularly over short investment periods. Using quantile and quantile-on-quantile regression, they show that Bitcoin's hedging capacity is most significant during extreme fluctuations in both its returns and global uncertainty.

Aligned with the recent trend in financial research emphasizing the role of investor sentiment across asset classes, an emerging body of work has highlighted the behavioral underpinnings of cryptocurrency markets, especially under conditions of uncertainty and emotional volatility. Youssef (2022) employs both static and time-varying versions of the cross-sectional absolute deviation (CSAD) model to investigate herding behavior in the crypto market between 2013 and 2019. While the static model indicates anti-herding behavior overall, the time-varying analysis reveals persistent herding beginning in late 2013. Chowdhury *et al*. (2024) reveal that investor emotions—particularly fear and greed—drive dynamic connectivity patterns in the cryptocurrency market, significantly influencing price behavior and inter-asset relationships. The findings highlight the importance of sentiment-aware strategies for navigating emotionally sensitive crypto environments.

Notably, herding intensifies in response to higher market volatility, rising S&P500 values, and dollar index movements, but is dampened by increases in trading volume, gold prices, and economic policy uncertainty (EPU). Complementing this, da Gama Silva *et al*. (2019) analyze both herding and contagion effects among 50 highly liquid cryptocurrencies between 2015 and 2018. Using CSAD, CSSD, and the Hwang and Salmon (2004) model, they find strong evidence of adverse herding during periods of elevated risk aversion. Their findings also highlight the systemic influence of Bitcoin, identifying widespread contagion effects across other digital currencies using extensions of the Forbes and Rigobon (2002) test.

Together, these studies underscore the importance of behavioral forces—particularly herding and contagion—in shaping the dynamics of cryptocurrency markets. Moreover, recent studies have adopted novel methodological approaches to sentiment analysis in cryptocurrency markets, particularly those leveraging internet-based information sources such as search trends, social media activity, and online news (e.g. Kristoufek, 2013; Vasileiou, 2021).

A substantial portion of the literature focuses on the presence of calendar anomalies in the crypto market, including effects like the day-of-the-week effect (Caporale and Plastun, 2019; Ma and Tanizaki, 2019), the turn-of-the-month effect (Qadan *et al.*, 2022; Vasileiou, 2023a), and the month effect (Baur *et al.*, 2019; Plastun *et al.*, 2019). Calendar anomalies, such as Halloween, January, and Friday effects, play a key role in shaping the association between stock returns and dividend announcements, as documented in equity markets (see Hasan and Al-Najjar, 2025). It is important to emphasize that, as in many areas of empirical research, certain patterns may emerge in the short term in specific contexts, while in others they may not be observed at all (Vasileiou, 2017). This study aims to examine the Halloween effect for two main reasons: (a) there is a relatively limited body of research on this particular anomaly (Kaiser, 2019; Kinateder and Papavassiliou, 2021), and (b) while many studies focus solely on the existence of such anomalies, few have explored whether these anomalies can be beneficial for investors, and more specifically, which types of investors may benefit from them.

Calendar anomalies, such as Halloween, January, and Friday effects, play a key role in shaping the association between stock returns and dividend announcements. The Halloween effect refers to the observed anomaly where stock returns tend to be higher during the period from November to April compared to the rest of the year [3]. The Halloween effect, also known as "Sell in May and go away", first identified by Bouman and Jacobsen (2002), this effect has led to a popular trading rule: sell stocks in early May, invest in T-bills, and reinvest in stocks on Halloween. The Halloween effect is of particular interest to investors because, unlike many other market anomalies that require frequent transactions—which can often erode the potential benefits due to transaction costs (Vasileiou, 2018)—this strategy involves only two transactions per year, making it simple to implement and potentially profitable. In contrast to other anomalies, this reduced frequency of trading minimizes transaction costs and makes it easier to capitalize on the market outperformance observed during this period. Some scholars argue that the Halloween effect may be driven by outliers or could merely represent a variation of the January effect (Lucey and Zhao, 2008). However, Haggard and Witte (2010) demonstrate that a Halloween-based investment strategy can deliver superior risk-adjusted returns compared to a Buy-and-Hold (BnH) approach, even after accounting for transaction costs.

Taking the above into consideration, this study aims to contribute meaningfully to the literature by addressing a notable gap: while the Halloween effect has been extensively examined in traditional equity markets, only a limited number of studies have explored its presence in cryptocurrency markets (e.g. Kaiser, 2019; Kinateder and Papavassiliou, 2021). To the best of our knowledge, this paper is among the first to both test for the existence of the Halloween effect in a broad set of major cryptocurrencies and to assess the real-world viability of a corresponding trading strategy.

This dual focus—detecting the anomaly and evaluating its exploitable potential—extends the current literature beyond purely observational findings. By including a diverse portfolio of leading cryptocurrencies such as Bitcoin (BTC), Ethereum (ETH), XRP, Binance Coin (BNB), and Cardano (ADA), we offer a broader market perspective, capturing both mature and emerging digital assets. Furthermore, our study investigates whether variations in market capitalization correspond with differences in anomaly strength, following the logic of earlier findings in equity markets (e.g. Vasileiou, 2017). Cryptocurrency price data for this analysis were sourced from Yahoo Finance.

Importantly, the sample period spans from January 1, 2018, to December 31, 2024, covering full calendar years to avoid distortions from partial-year anomalies [4]. This enhances the robustness of our results and minimizes interference from other calendar effects. In sum, this research advances the field by bridging the gap between seasonal effects literature and the rapidly evolving domain of cryptocurrency, offering both academic insights and practical implications for investors and policymakers.

The rest of the paper goes as follows: Section 2 presents the theoretical background and analysis of the preliminary data, Section 3 covers the econometric analysis, Section 4 discusses the results of investment strategies derived from our findings, and Section 5 concludes the study.

2. Theoretical background and preliminary data

A growing body of literature has explored the informational efficiency of cryptocurrency markets, with increasing focus on how this efficiency evolves over time and across varying market conditions. Fernandes *et al*. (2022) assess the efficiency of five major cryptocurrencies—Bitcoin, BNB, Cardano, Ethereum, and XRP—both before and during the COVID-19 pandemic using permutation entropy and Fisher information measures. By employing the Shannon–Fisher causality plane and a sliding window approach, their results reveal consistently high levels of informational efficiency across assets and time periods, with Cardano emerging as the most efficient. These findings suggest a maturing market structure and declining potential for price predictability, reinforcing the suitability of cryptocurrencies in liquidity risk diversification strategies. Similarly, Tiwari *et al*. (2018) extend earlier studies by examining long-range dependence in Bitcoin prices using several computationally efficient estimators. Their findings, in line with prior research by Urquhart (2016), Bariviera (2017), and Nadarajah and Chu (2017), indicate that Bitcoin has transitioned from inefficiency toward increasing informational efficiency over time. Collectively, these studies support the notion that as the cryptocurrency market matures, its behavior increasingly resembles that of traditional financial assets, particularly in terms of efficiency and robustness during external shocks.

In parallel with this discussion, the study of calendar anomalies provides a complementary lens for assessing market efficiency. Calendar effects refer to recurring patterns in financial returns tied to specific temporal intervals—such as days of the week, months, or particular seasons. Their presence directly challenges the Efficient Market Hypothesis (Fama, 1970), especially in its weak form, which asserts that asset prices fully reflect all past information. If certain time-based return patterns can be systematically exploited, this would imply predictability and, hence, a deviation from efficiency. However, the literature also points to the ephemeral nature of such anomalies. Schwert (2003), for instance, argues that many anomalies diminish or disappear after being widely documented, possibly due to arbitrage or adaptive market behavior. Thus, the detection and persistence of calendar anomalies remain critical for evaluating whether markets, including cryptocurrencies, behave efficiently or exhibit exploitable inefficiencies over time.

The debate over the existence of calendar anomalies can be attributed to several factors, such as the market capitalization of the assets examined (Sharma and Narayan (2014)) or the use of inappropriate econometric models for empirical analysis (Connolly (1989)). However, even if an anomaly or trading pattern exists, it does not necessarily mean that investors can capitalize on it. This is especially true when the strategy requires a high volume of transactions, leading to increased transaction costs that can erode the potential benefits of exploiting the anomaly (Vasileiou (2015)).

The objective of this study is not only to statistically examine whether a specific time period outperforms the rest of the year, but also to assess whether such a calendar anomaly could serve as the basis for a practical investment strategy. For instance, even if certain weekdays yield higher returns, the benefits may be offset by frequent trading and associated transaction costs (at least 2 transactions per week). In contrast, the Halloween effect—requiring only two trades per year (buy on October 31 and sell in May)—offers a low-frequency strategy that is inherently more accessible and cost-efficient, especially for individual investors. Unlike studies that assume transaction costs arbitrarily, our approach allows investors to estimate real-world implementation costs relative to their capital.

To robustly examine the presence of the Halloween effect in the cryptocurrency market, we evaluate both large-cap and small-cap cryptocurrencies, accounting for differences in market maturity and capitalization. We employ appropriate statistical models selected through diagnostic testing, and we apply a trading strategy designed to minimize transactions, thereby enhancing the practical relevance and applicability of our findings. Notably, the Halloween effect in cryptocurrencies has received limited attention in the existing literature (Kaiser, 2019; Kinateder and Papavassiliou, 2021) [5], possibly due to methodological limitations or the use of incomplete datasets. This study addresses these gaps by using full calendar-year data and a rigorous methodological framework, aiming to provide new insights into seasonal anomalies within cryptocurrency markets.

Figure 1 displays the performance and daily returns of BTC, ETH, XRP, BNB, and ADA over the period from 2018 to 2024. The data reveals a clear pattern of volatility clustering, where periods of high volatility are followed by additional high volatility, and similarly, low volatility

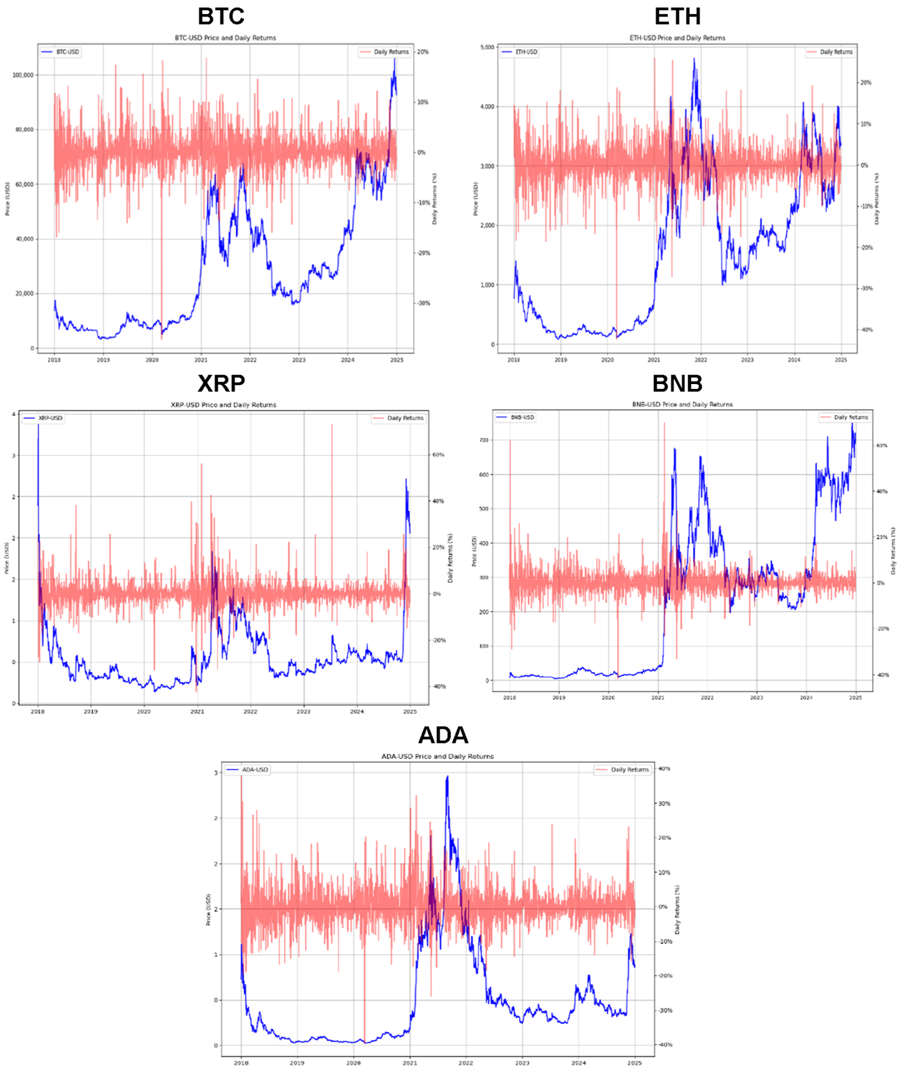


Figure 1. Performance and the daily of BTC, ETH, XRP, BNB, and ADA for the period 2018–2024. Source: Authors' own work

follows periods of low volatility. This pattern is evident across all the cryptocurrencies in the analysis. Furthermore, there are indications of a leverage effect, as described by Black (1976), which suggests that volatility tends to increase more sharply when prices fall than when they rise at the same magnitude. This behavior is observed in most of the cryptocurrencies, except for XRP, where volatility increases when prices rise rather than fall. Figure A1 in Appendix shows the autocorrelation of daily returns squared, highlighting the presence of volatility clustering. The plots reveal that large price changes are often followed by larger price changes -whether up or down-demonstrating the persistence of volatility over time.

Table 1 presents the descriptive statistics for the daily returns of the cryptocurrencies in our study. The results indicate that the return distributions are leptokurtic, with kurtosis values greater than 3, suggesting heavy tails compared to a normal distribution. This is further confirmed by the Jarque-Bera test, which rejects the hypothesis of normality. Additionally, the time series are stationary, implying that no further adjustments, such as differencing, are necessary. Figure A2 in Appendix displays both the theoretical and actual distributions, visually confirming the departure from normality.

The descriptive statistics suggest that Ordinary Least Squares (OLS) models may not be suitable for our analysis due to several issues, including departures from normality, volatility clustering, and the presence of leverage effects. Given these stylized facts, a model from the GARCH family-whether symmetric or asymmetric-may be more appropriate for capturing the dynamics of volatility in our study.

Table 2 presents the descriptive statistics for daily returns during Halloween and non-Halloween days for the cryptocurrencies in our sample, covering the period from 2018 to 2024. A key observation from the table is that Halloween days tend to have higher average returns compared to non-Halloween days. However, they also exhibit greater volatility, as evidenced by higher standard deviations, as well as higher kurtosis [6], indicating a wider range of extreme values (fat tails). This suggests that while Halloween days offer higher potential returns, they also come with increased risk. Additionally, Figure A3 in Appendix presents the corresponding Box-and-Whisker plots [7], which visually illustrate the differences between the two periods under analysis. These plots display the variations in volatility, mean values, and the presence of outliers. Notably, both the highest and lowest values are observed during the Halloween period, with the exception of XRP's maximum value. Volatility is also markedly higher during this period. The prevalence of positive outliers during the Halloween window may contribute to the observed effect and could be indicative of behavioral factors associated with the Halloween anomaly.

Table 1. Descriptive statistics of the daily returns of BTC, ETH, XRP, BNB, and ADA for the period 2018–2024

Statistic	BTC	ETH	XRP	BNB	ADA
Mean	0.00137	0.00162	0.00149	0.00300	0.00153
Std	0.03527	0.04513	0.05656	0.05163	0.05432
Min	−0.37170	−0.42347	−0.42334	−0.41905	−0.39567
$Q1$	−0.01379	−0.01872	−0.02048	−0.01739	−0.02581
Median	0.00081	0.00063	−0.00055	0.00104	−0.00023
$Q3$	0.01620	0.02202	0.01950	0.02172	0.02477
Max	0.18746	0.25948	0.73075	0.69760	0.37960
Kurtosis	10.837	9.275	26.528	33.366	8.291
Skewness	−0.314	−0.246	1.943	2.064	0.59141
Jarque-Bera Statistic	6,554.22***	4,199.78***	60,319.37***	99,617.83***	3,115.84***
ADF Statistic	−34.997***	−15.438***	−18.923***	−13.374***	−24.198***
Count	2,556	2,556	2,556	2,556	2,556

Note(s): *** indicates statistical significance at the 1% statistical level

Source(s): Authors' own work

Table 2. Descriptive statistics of daily returns for Halloween and non-Halloween days for BTC, ETH, XRP, BNB, and ADA from 2018 to 2024

	Halloween	No-Halloween
BTC		
Mean	0.00188	0.00086
Median	0.00099	0.00063
Maximum	0.18747	0.15576
Minimum	−0.37170	−0.15975
Std. Dev.	0.03803	0.03230
Skewness	−0.48972	−0.03921
Kurtosis	12.67	6.53
Jarque-Bera	5,016.61***	666.92***
Observations	1,275	1,281
ETH		
Mean	0.00288	0.00036
Median	0.00095	0.00029
Maximum	0.25948	0.25314
Minimum	−0.42347	−0.27200
Std. Dev.	0.04711	0.04305
Skewness	−0.37133	−0.09766
Kurtosis	10.57	7.28
Jarque-Bera	3,074.54***	980.01***
Observations	1,275	1,281
XRP		
Mean	0.00255	0.00044
Median	−0.00054	−0.00057
Maximum	0.56011	0.73075
Minimum	−0.42334	−0.32716
Std. Dev.	0.06252	0.04993
Skewness	1.37716	2.90785
Kurtosis	17.12	45.20
Jarque-Bera	10,988.46***	96,877.55***
Observations	1,275	1,281
BNB		
Mean	0.00573	0.00029
Median	0.00161	−0.00014
Maximum	0.69760	0.31324
Minimum	−0.41905	−0.33266
Std. Dev.	0.06035	0.04102
Skewness	2.58	−0.18
Kurtosis	32.82	11.66
Jarque-Bera	48,650.91***	4,006.28***
Observations	1,275	1,281
ADA		
Mean	0.00359	−0.00052
Median	0.00071	−0.00083
Maximum	0.37960	0.24530
Minimum	−0.39567	−0.26009
Std. Dev.	0.05935	0.04873
Skewness	0.68	0.35
Kurtosis	8.53	6.66
Jarque-Bera	1,722.48***	742.36***
Observations	1,275	1,281

Note(s): *** indicates statistical significance at the 1% confidence level

Source(s): Authors' own work

From Table 2, we observe notable differences between the statistics of the two sub-groups (Halloween and No-Halloween). Consequently, the next step is to test whether the mean returns, deviations, and distributions of these two time-series are statistically similar. To do so, we conducted several tests, ultimately adopting the following:

(1) Welch's Test (Welch (1951)) is more robust than the standard two-sample *t*-test for cases where there are unequal variances (heteroscedasticity) and unequal sample sizes. It is ideal when the assumption of equal variances is violated.

(2) Kolmogorov-Smirnov (KS) Test (Lara-Astiaso *et al.* (2014)) is appropriate for comparing two distributions to determine if they originate from the same population. It is particularly useful when the data are non-normal, as it does not rely on any specific distributional assumptions.

(3) Brown-Forsythe Test (Brown and Forsythe (1974)) is preferred when testing for the equality of variances across groups, especially when the data are skewed or contain outliers (see Figure A3 in Appendix). It is a more robust alternative to Levene's test (Levene (1960)), making it suitable when normality assumptions are in doubt, which makes it appropriate for our sample.

The results of the statistical tests are summarized in Table 3, which compares the means, variances, and distributions of the daily returns for the two sub-groups. The Brown-Forsythe test reveals statistically significant differences in the variances across the two sub-groups for all the cryptocurrencies analyzed ($p < 0.05$ for all cases). This finding indicates that the assumption of equal variances is violated, making the Welch's test more appropriate than the standard two-sample *t*-test for mean comparison.

The results of Welch's test suggest that, for the high-market capitalization cryptocurrencies, BTC, ETH, and XRP, there is no statistically significant evidence to conclude that the means of returns differ between the Halloween and No-Halloween sub-groups. However, for the smaller capitalization coins, BNB and ADA, there is statistically significant variation in the mean returns between the two sub-groups, with the means differing at the 5 and 10% significance levels, respectively.

The Kolmogorov-Smirnov test assesses whether the two sub-groups come from the same distribution. Again for the high capitalization cryptos, BTC and ETH, the results indicate no significant differences in the distributions of returns between the two sub-groups ($p > 0.05$), suggesting that the returns for these high-capitalization coins are similarly distributed across the two periods. However, for lower capitalization cryptos, BNB and ADA, the Kolmogorov-Smirnov test reveals significant differences in the return distributions between the two sub-groups, suggesting that these cryptocurrencies exhibit distinct statistical properties in the Halloween and No-Halloween periods. For XRP, the statistical evidence is not significantly strong.

Table 3. Return distributions, mean, and variance comparison for Halloween vs. No-Halloween sub-groups (2018–2024)

	BTC	ETH	XRP	BNB	ADA
Welch's Test	0.7400	1.4124	0.9411	2.6611***	1.9111*
Brown-Forsythe Test	10.1516***	4.3642**	20.9065***	30.0993***	23.4905***
Kolmogorov-Smirnov Test	0.0425	0.0454	0.0507*	0.7734***	0.0707***

Note(s): ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively
Source(s): Authors' own work

3. Econometric analysis

The preliminary results suggest that the return distributions of the cryptocurrencies do not follow a normal distribution. Instead, they exhibit several common stylized facts typically observed in financial time series, including leptokurtosis, volatility clustering, and the leverage effect. These characteristics are consistent with the well-established patterns seen in financial markets.

Furthermore, our analysis reveals the presence of heteroskedasticity between the returns of the Halloween and No-Halloween periods. This indicates that the variance of returns differs significantly between the two sub-groups, which may lead to unreliable results if standard methods assuming constant variance are applied. Given this, a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family model is likely more appropriate for capturing the time-varying volatility in the return series, and could provide a better fit for the data.

The mean equation used in this study aligns with those commonly applied in research on calendar anomalies. It is specified as follows:

$$\mathrm{d}r_t = a_0 + a_1 \times \mathrm{Hall}_t + \varepsilon_t \tag{1}$$

where $\mathrm{d}r_t$ represents the daily returns time series on day t, α_0 is the constant term, α_1 is the coefficient of the Hall_t, Hall_t is a dummy variable indicating whether day t falls within the Halloween effect period (from October 31 to April 30), and ε_t is the error term, assumed to follow a normal distribution.

We employed models from the GARCH family, which are well-suited for addressing issues of heteroscedasticity and autocorrelation commonly observed in financial time series data. Model selection among the GARCH variants, as well as the determination of optimal lag lengths, was guided by the Akaike (1974) and Schwarz (1978) information criteria, in line with most similar studies. The results indicated that asymmetric GARCH models, and particularly the Exponentially GARCH (EGARCH) model (Nelson (1991)), offered a superior fit, primarily due to the presence of the leverage effect (and, in one instance, the anti-leverage effect). The conditional variance for the EGARCH(1,1,1) model is

$$\log\left(\sigma_\mathrm{t}^2\right) = \mathrm{c} + \mathrm{c}_1 \times \left|\frac{\varepsilon_{\mathrm{t}-1}}{\sigma_{\mathrm{t}-1}}\right| + \mathrm{c}_2 \times \frac{\varepsilon_{\mathrm{t}-1}}{\sigma_{\mathrm{t}-1}} + \mathrm{c}_3 \times \log\left(\sigma_{\mathrm{t}-1}^2\right) \tag{2}$$

where the logarithmic form ensures the non-negativity of σ_t^2. A negative and statistically significant coefficient (c_2) indicates the presence of a leverage effect, whereas a positive and statistically significant value suggests an anti-leverage effect. The ARCH and GARCH coefficients are represented by the terms c_1 and c_3, respectively.

The results, presented in Table 4, support our hypothesis regarding the existence of the Halloween effect in the cryptocurrency market. Specifically, there is a strong statistical indication of the Halloween effect for Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), and Cardano (ADA), with p-values below 0.01. This suggests that these cryptocurrencies tend to experience positive returns during the half of the year between October 31 to April, in line with the Halloween effect, while no statistically significant returns (positive or negative) are observed on the remaining days of the year.

Furthermore, there is robust evidence of the leverage effect in these cryptocurrencies, except for the ADA. This implies that when prices decrease, volatility tends to increase, which is consistent with established market dynamics. The presence of the Halloween effect, combined with the leverage effect, points to potential market inefficiencies within the examined cryptocurrencies.

In contrast, the results for XRP (Ripple) diverge from this pattern. Notably, the returns on non-Halloween days are positive and statistically significant, whereas the Halloween effect is only marginally significant at the 10% confidence level, indicating a weaker effect compared to the other cryptocurrencies analyzed. Additionally, the volatility results for XRP reveal the presence of an anti-leverage effect, as evidenced by a positive and statistically significant coefficient for the conditional volatility term (c_2). This anti-leverage effect is an unusual

Table 4. Econometric analysis of the Halloween effect for BTC, ETH, XRP, BNB, and ADA from 2018 to 2024

Mean equation	BTC	ETH	XRP	BNB	ADA
α_0	0.000716	2.88E−05	0.004072***	0.000575	−0.001598
	(0.000890)	(0.001094)	(0.001168)	(0.000916)	(0.001252)
α_1	0.004566***	0.003994***	0.003394*	0.003772***	0.004935***
	(0.000985)	(0.001301)	(0.001766)	(0.000154)	(0.001783)
Conditional Variance					
c	−0.553696***	−0.252696***	−2.025521***	−0.339288***	−0.400165***
	(0.050424)	(0.023479)	(0.111169)	(0.019619)	(0.033654)
c_1	0.171844***	0.141947***	0.492362***	0.255132***	0.222106***
	(0.013480)	(0.009311)	(0.020964)	(0.010426)	(0.014008)
c_2	−0.055933***	−0.020989***	0.050088***	−0.025821***	−0.009177
	(0.005873)	(0.005508)	(0.012153)	(0.005461)	(0.006420)
c_3	0.936119***	0.976086***	0.713488***	0.975447***	0.960256***
	(0.006256)	(0.003025)	(0.016895)	(0.002356)	(0.004569)
Q-stat and LM (F-statistic)					
*Q*1	0.4554	1.5343	0.3455	0.0172	0.0133
*Q*2	4.1960	2.0563	1.1453	3.0189	4.0602
*Q*3	6.4750	2.5127	3.1987	4.5572	6.6938
*Q*4	7.1829	2.5697	3.4877	5.0185	7.5339
*Q*5	9.4030	3.7881	4.1041	5.1475	9.0480
ARCH LM1	0.0297	0.8662	0.0321	0.6444	0.3501
ARCH LM2	0.0961	0.6137	0.0173	0.7440	0.3671
ARCH LM3	0.5147	0.4895	0.0199	0.9492	0.2598

Note(s): ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The standard deviations of the coefficients are reported in parentheses. For the autocorrelation and ARCH LM tests, the Q-statistics and F-statistics are provided

Source(s): Authors' own work

stylized fact, as it suggests that volatility increases more when prices rise than when they fall, which deviates from the conventional leverage effect. The existence of the anti-leverage effect should be considered an additional market inefficiency (Vasileiou (2022, 2023b [8])).

To test the robustness of our results, we apply the EGARCH model with the same mean equation as in Eq. (1). However, in the conditional variance equation, we introduce a Hall dummy variable to account for the potential influence of the Halloween effect on volatility. The modified conditional variance equation is as follows:

$$\log\left(\sigma_t^2\right) = c + c_1 \times \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + c_2 \times \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + c_3 \times \log\left(\sigma_{t-1}^2\right) + c_4 \times Hall_t \tag{3}$$

where is a dummy variable that takes the value of 1 during the Halloween period and 0 otherwise. If the coefficient c_4 is positive and statistically significant, it suggests that volatility increases during the Halloween period, i.e. when the Hall dummy variable is active ($Hall_t = 1$). The results of this robustness test are presented in Table 5.

The results of the robustness test are largely consistent with the initial findings, with only minor changes in the level of statistical significance. The mean equations robustly confirm the presence of the Halloween effect for BTC, ETH, BNB, and ADA, but no such effect is observed for XRP, where the previously weak evidence is now marginally rejected. Regarding the leverage

Table 5. Robustness test of the econometric analysis of the Halloween effect for BTC, ETH, XRP, BNB, and ADA from 2018 to 2024

Mean equation	BTC	ETH	XRP	BNB	ADA
α_0	−0.000151	0.000142	0.003189**	0.000814	−0.001534
	(0.000843)	(0.001054)	(0.001325)	(0.000885)	(0.001171)
α_1	0.002785**	0.003376**	0.002587	0.002852**	0.004492**
	(0.001327)	(0.001453)	(0.001817)	(0.002852)	(0.001854)
Conditional Variance					
c	−0.621936***	−0.262140***	−1.919730***	−0.358291***	−0.437841***
	(0.056825)	(0.023683)	(0.108971)	(0.020159)	(0.037416)
c_1	0.176653***	0.138166***	0.485765***	0.247543***	0.218884***
	(0.014437)	(0.009281)	(0.020746)	(0.011051)	(0.014515)
c_2	−0.049632***	−0.019057***	0.050599***	−0.027838***	−0.008500
	(0.006316)	(0.005443)	(0.011719)	(0.005575)	(0.006926)
c_3	0.929090***	0.975000***	0.727508***	0.973184***	0.955414***
	(0.006838)	(0.003024)	(0.016581)	(0.002400)	(0.005119)
c_4	0.034388***	0.010699***	0.036680***	0.019898***	0.021583***
	(0.006540)	(0.003132)	(0.012377)	(0.004764)	(0.005064)
Q-stat and LM (F-statistic)					
$Q1$	0.3149	1.2788	0.1817	0.0102	0.0007
$Q2$	4.1758	2.0052	1.3253	3.1841	4.2475
$Q3$	5.4995	5.5517	3.6628	4.6409	5.2332
$Q4$	5.9922	7.5643	4.1727	4.9942	6.7250
$Q5$	9.2468	8.8154	4.8100	5.1469	8.2790
ARCH LM1	0.0361	0.9213	0.0288	0.5784	0.2531
ARCH LM2	0.0611	0.5643	0.0161	0.9441	0.2054
ARCH LM3	0.4775	0.3974	0.0190	1.0468	0.1520

Note(s): ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The standard deviations of the coefficients are reported in parentheses. For the autocorrelation and ARCH LM tests, the Q-statistics and F-statistics are provided

Source(s): Authors' own work

effect, it is strongly confirmed for BTC, ETH, and BNB. However, while the coefficient for ADA is negative, it is not statistically significant. In contrast, the anti-leverage effect persists for XRP.

4. Investment strategies based on the Halloween effect

The analysis of the Halloween effect suggests that this calendar anomaly is statistically significant, pointing to a potential challenge to the Efficient Market Hypothesis (EMH). However, what practical advantages could this anomaly offer to investors? To examine this, we assume an initial investment at the beginning of the time period and compare the performance of a Buy-and-Hold (BnH) strategy with an alternative strategy based on the Halloween effect (or the No-Halloween period). In this alternative approach, the investment is made only during the Halloween period (or the No-Halloween period), while in non-investment periods, the funds are kept in a non-interest-bearing bank account to ensure a conservative approach.

The results of this comparison include cumulative returns, daily standard deviation, and the Coefficient of Variation (CV), which is calculated by dividing the mean return by the standard deviation. It is important to note that the standard deviations for the Halloween and No-Halloween strategies are expected to be lower than that of the Buy-and-Hold strategy, as these strategies involve fewer investment days, with many months of zero returns. As a result, the standard deviations for these strategies will be lower than those reported for the respective periods in Table 2. Additionally, a higher CV is more desirable, as it indicates that for each unit of risk, the return is greater. Thus, the higher the CV, the better the strategy. The results of these tests are presented in Figure 2.

The results show that the Halloween strategy outperforms all other strategies in terms of cumulative returns and CV for all cryptocurrencies, except for Bitcoin (BTC). Additionally, the returns for cryptocurrencies (ETH, XRP, BNB, and ADA) are negative under the No Halloween strategy, indicating that the "Sell in May and Go Away" Halloween effect not only holds for these assets but also represents the most profitable period of the year compared to the No-Halloween period.

In contrast, for BTC, the Halloween period is the most profitable between the two alternative strategies in terms of cumulative returns and CV. However, the positive cumulative returns of the No-Halloween strategy and its lower standard deviation compared to the Halloween period do not lead to outperformance of the Halloween strategy over the Buy-and-Hold (BnH) strategy for BTC.

Table 6 presents the maximum drawdowns for the Buy-and-Hold and Halloween strategies across five major cryptocurrencies over the period 2018–2024. Maximum drawdown (MDD) is a widely used risk metric that captures the largest peak-to-trough decline in portfolio value during a given period. Unlike standard deviation—which reflects the dispersion of returns around the mean—MDD provides a more intuitive and psychologically relevant measure of downside risk, particularly from the perspective of investor sentiment. While standard deviation treats gains and losses symmetrically, drawdown focuses solely on the worst-case loss, which can trigger panic selling or hesitation among investors.

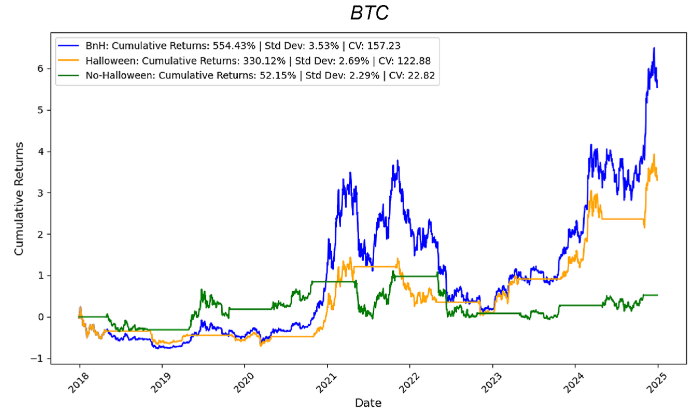
The results show that the Halloween strategy consistently mitigates the severity of drawdowns compared to the Buy-and-Hold approach. For instance, ADA experienced a dramatic −97.85% drawdown under Buy-and-Hold, which was reduced to −87.49% under the Halloween strategy. Similarly, Ethereum's drawdown improved from −93.96% to −79.53%, and BNB from −80.10% to −70.54%. Even in cases like XRP, where both strategies experienced their worst drawdowns on the same date (12/03/2020), the Halloween approach still resulted in a less severe decline. Notably, Bitcoin's largest drawdown also improved under the seasonal strategy by over 5% points. These results suggest that the Halloween strategy may offer practical advantages in managing tail risk and preserving capital during extreme downturns—benefits that standard deviation alone may not fully capture. The reduced drawdowns can provide psychological comfort and increase the likelihood of investors remaining invested during turbulent periods, thus supporting long-term strategy adherence.

5. Concluding remarks

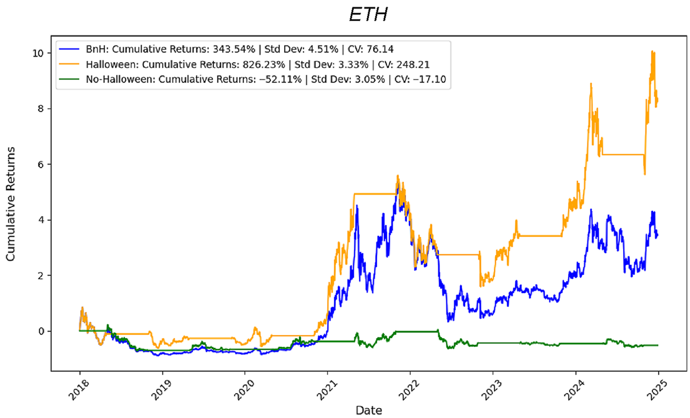
This study investigates the inefficiencies in the cryptocurrency market, specifically focusing on calendar anomalies, with an aim to suggest practical investment strategies suitable for a wide range of investors. Strategies that involve frequent transactions are excluded, as the potential benefits from statistical confirmations could be outweighed by the high transaction costs associated with frequent trading.

The calendar anomaly explored in this study is the Halloween effect. This anomaly not only fits the scope of the study, due to requiring only two transactions per year, but it has also been less explored in the context of cryptocurrency markets compared to other calendar effects. The analysis focuses on cryptocurrencies with higher market capitalizations, excluding stablecoins, and considers data from 2018 to 2024 to ensure a sufficiently large sample. The final sample includes BTC, ETH, XRP, BNB, and ADA.

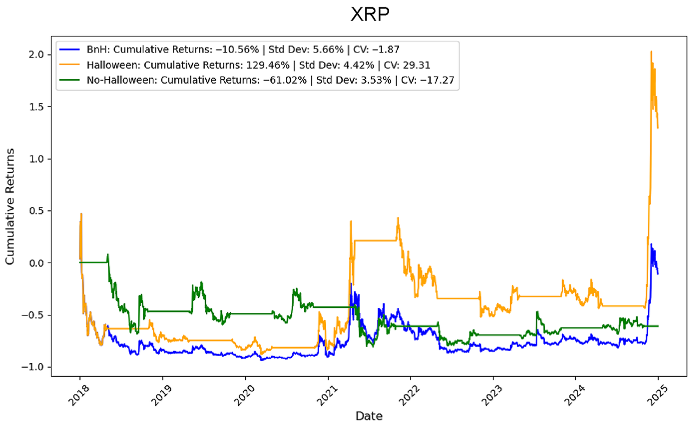
Descriptive statistics reveal that the time series for these cryptocurrencies do not follow a normal distribution, exhibiting key stylized facts such as leptokurtosis, volatility clustering, and asymmetric volatility. These characteristics suggest that a GARCH family model, which



(a)

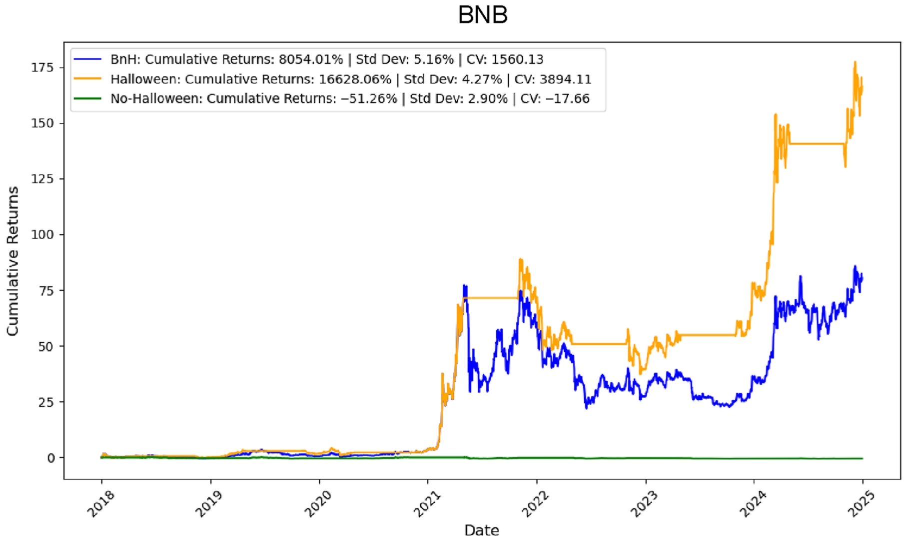


(b)

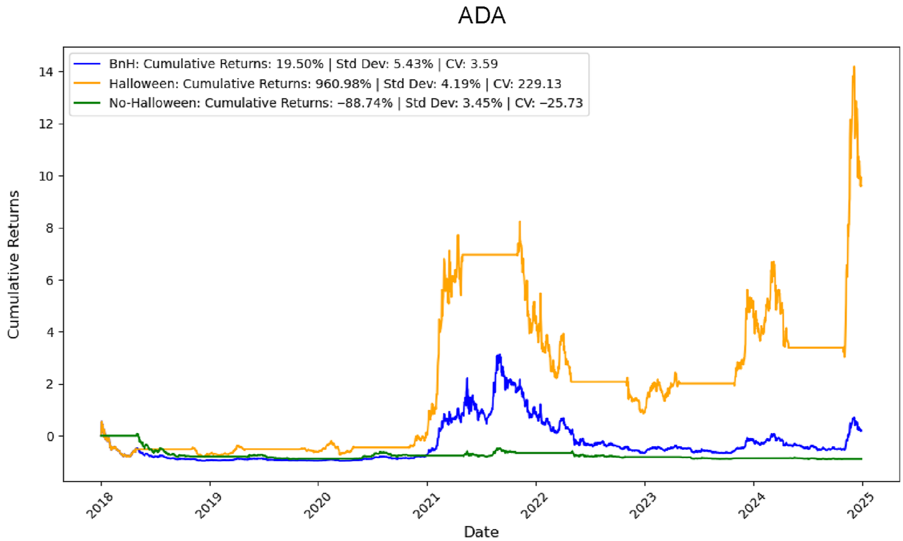


(c)

Figure 2. Cumulative returns of the Buy-and-Hold, Halloween, and No-Halloween investment strategies during the period 2018–2024. Source: Authors' own work



(d)



(e)

Figure 2. (*continued*)

captures volatility dynamics, would be more appropriate. The sample was divided into two time periods: Halloween (October 31 to April 30) and No-Halloween (the remainder of the year). The results show that Halloween periods tend to be more profitable on average than the No-Halloween periods, but also come with higher risk, as indicated by greater standard deviations of Halloween returns. Equality tests reveal significant differences between the two periods in terms of variance, but only BNB and ADA showed a statistically significant difference in mean returns.

Table 6. Maximum drawdown comparison between buy-and-hold and halloween strategies

Cryptocurrency	Max drawdown (buy and hold)	Date (buy and hold)	Max drawdown (Halloween)	Date (Halloween)
BTC	−81.53%	15/12/2018	−75.95%	12/3/2020
ETH	−93.96%	14/12/2018	−79.53%	14/12/2018
XRP	−95.87%	12/3/2020	−91.87%	12/3/2020
BNB	−80.10%	7/12/2018	−70.54%	5/2/2018
ADA	−97.85%	12/3/2020	−87.49%	15/12/2018

Source(s): Authors' own work

For the econometric analysis, several models were tested, with the EGARCH model emerging as the most suitable for this analysis. The Halloween effect was statistically confirmed for all cryptocurrencies except XRP. Additionally, the leverage effect was confirmed for BTC, ETH, and BNB, while ADA exhibited signs of a leverage effect that was not statistically significant. XRP, on the other hand, displayed a statistically significant anti-leverage effect, suggesting the presence of a distinct anomaly beyond the Halloween effect. This anti-leverage effect, if considered contrary to the typical leverage effect, could indicate abnormal market behavior for XRP.

The divergent behavior of XRP compared to the other cryptocurrencies during the Halloween and non-Halloween periods warrants further investigation. A possible explanation may lie in the presence of outliers during specific timeframes, particularly given that XRP records its maximum return during the non-Halloween period—unlike all other cryptocurrencies in the sample, which reach their maximum values during the Halloween period (Table 2). This distinct pattern suggests that extreme values may be disproportionately influencing XRP's results, highlighting the importance of conducting additional robustness checks or a sub-period analysis.

However, as our primary objective is not only to test econometric models but also to assess the practical implications for investors, we aim to provide empirical evidence on the effectiveness of a Halloween-based investment strategy. Specifically, the study evaluates whether investing during the Halloween period and holding funds in a zero-interest bank account during the rest of the year yields better performance compared to a No-Halloween strategy and a traditional Buy-and-Hold (BnH) approach.

Our findings indicate that the Halloween strategy outperforms both the No-Halloween and Buy-and-Hold (BnH) strategies for all cryptocurrencies in the sample, with the sole exception of Bitcoin (BTC). This deviation may be attributed to BTC's relatively lower price volatility and the behavior of its investors, who appear to be less influenced by seasonal patterns. Notably, during the No-Halloween period, BTC's return distribution exhibits skewness close to zero (−0.03921) and a kurtosis of 6.53—the lowest among the examined cryptocurrencies—indicating a more symmetric and stable distribution of returns. This behavior may reflect a more mature and efficient market structure, potentially explaining why BTC is the only cryptocurrency in the sample to deliver positive returns under the No-Halloween strategy.

As illustrated in Figure 2, No-Halloween strategies yield negative returns across all other cryptocurrencies, reinforcing the conclusion that investing during the Halloween period and exiting the market in May yields superior results. These findings highlight that the Halloween period offers not only higher profitability but also reduced risk when compared to a traditional BnH strategy. Consequently, investors can use this seasonal anomaly to tailor their strategies according to their individual risk tolerance and return expectations.

Moreover, the maximum drawdown (MaxDrawdown) analysis reveals that while price deviations are more pronounced during the Halloween period, the most severe drawdowns also occur during this timeframe. However, the MaxDrawdown values for the Halloween-based strategy are lower compared to the BnH strategy—mirroring the behavior of standard deviation—suggesting that the most significant price corrections are concentrated within the Halloween window. This raises an important implication: if the Halloween effect is so pronounced in cryptocurrency markets, could this suggest that investors are treating cryptocurrencies as investment assets akin to, or as substitutes for, traditional stocks?

This question opens a valuable avenue for future research—specifically, investigating how investors have come to perceive and classify cryptocurrencies in recent years. Understanding whether they are viewed more as speculative instruments, inflation hedges, or traditional investment assets could offer deeper insights into market behavior and asset pricing dynamics in the digital economy.

Future research could build on these findings by incorporating cryptocurrency investments into a portfolio during specific periods to maximize returns. Additionally, further investigation into the anti-leverage effect could explore whether it signals overvalued asset prices and if the influence of a calendar anomalies varies according to the market capitalization of different cryptocurrencies.

About the author

Evangelos Vasileiou is currently affiliated with the Department of Accounting and Finance, Hellenic Mediterranean University, Heraklion, Crete, Greece.

Appendix

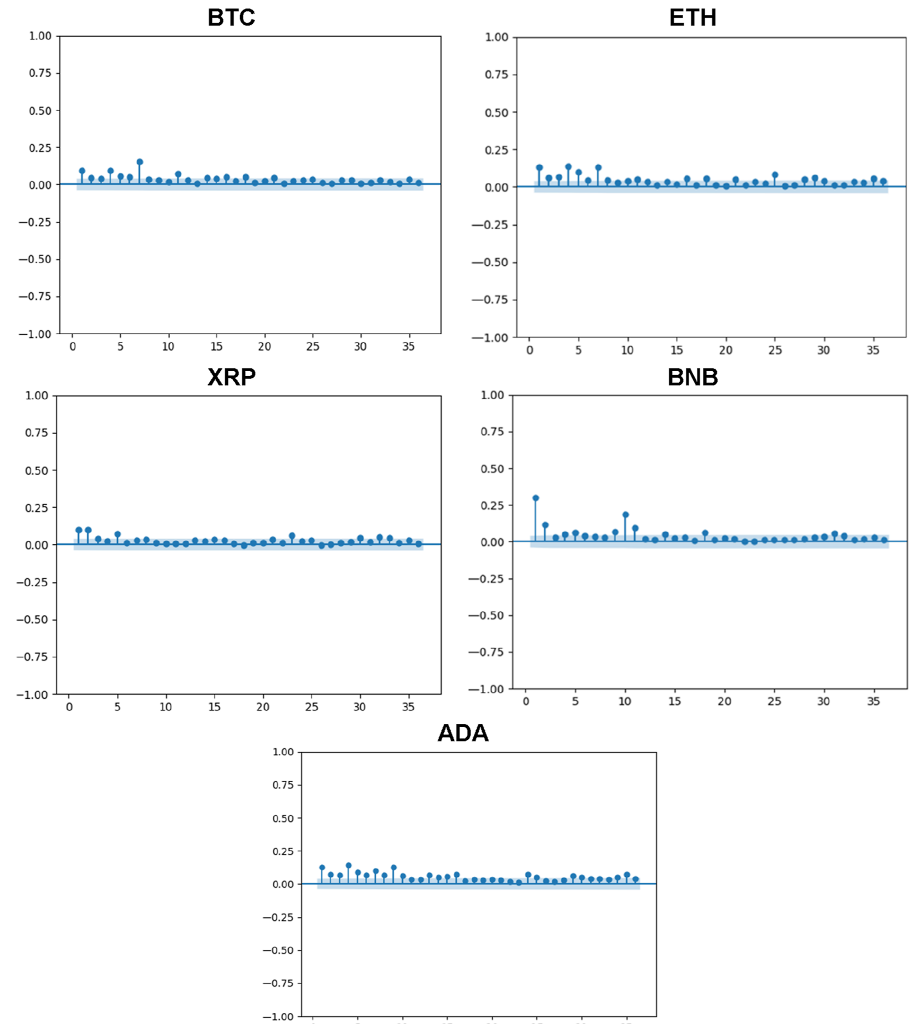


Figure A1. autocorrelation of the squared daily returns of BTC, ETH, XRP, BNB, and ADA for the period 2018–2024. Figures below present the autocorrelation of squared daily returns for BTC, ETH, XRP, BNB, and ADA. The presence of persistent autocorrelation in squared returns confirms volatility clustering across the cryptocurrencies, suggesting that large price movements are often followed by further high-volatility periods.
Source: Authors' own work

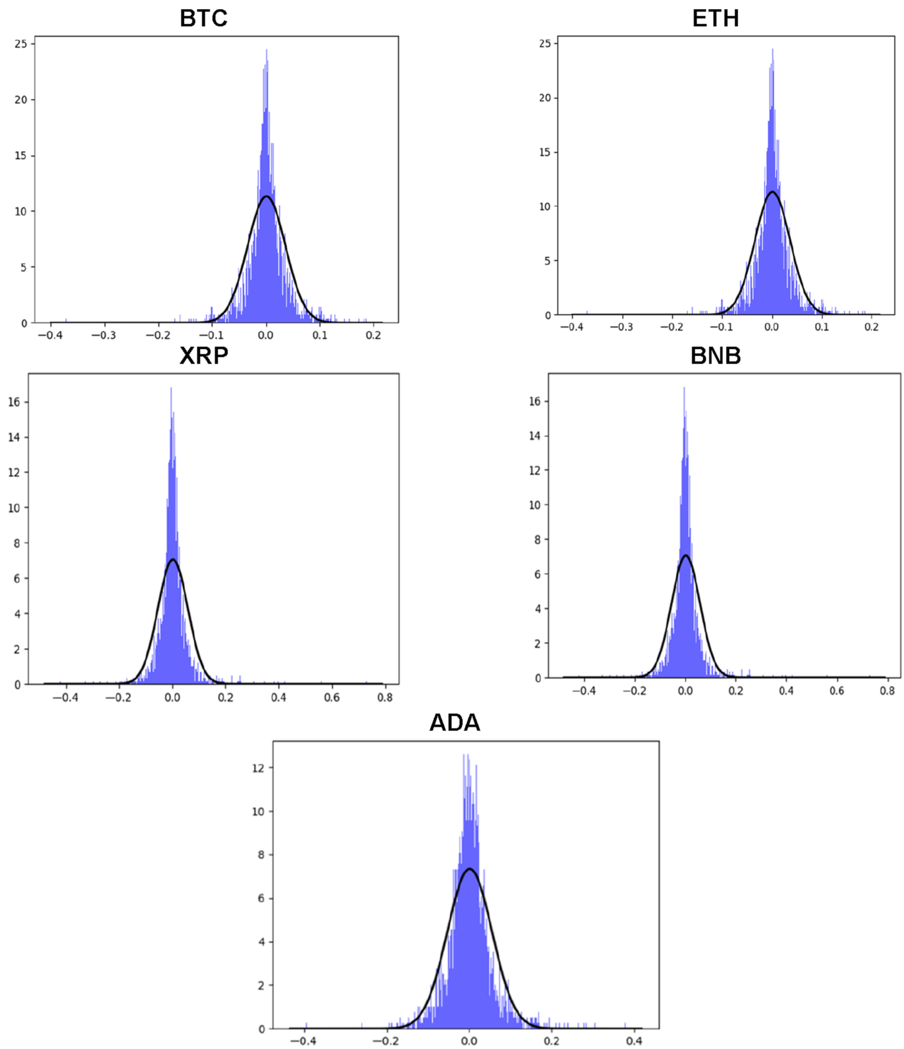


Figure A2. Comparison of the theoretical normal distribution with the actual daily returns of BTC, ETH, XRP, BNB, and ADA from 2018 to 2024. The following figures present comparisons between the actual distribution of returns and a fitted normal distribution reveals significant deviations from normality, further supporting the use of non-linear volatility models in subsequent analysis. Source: Authors' own work

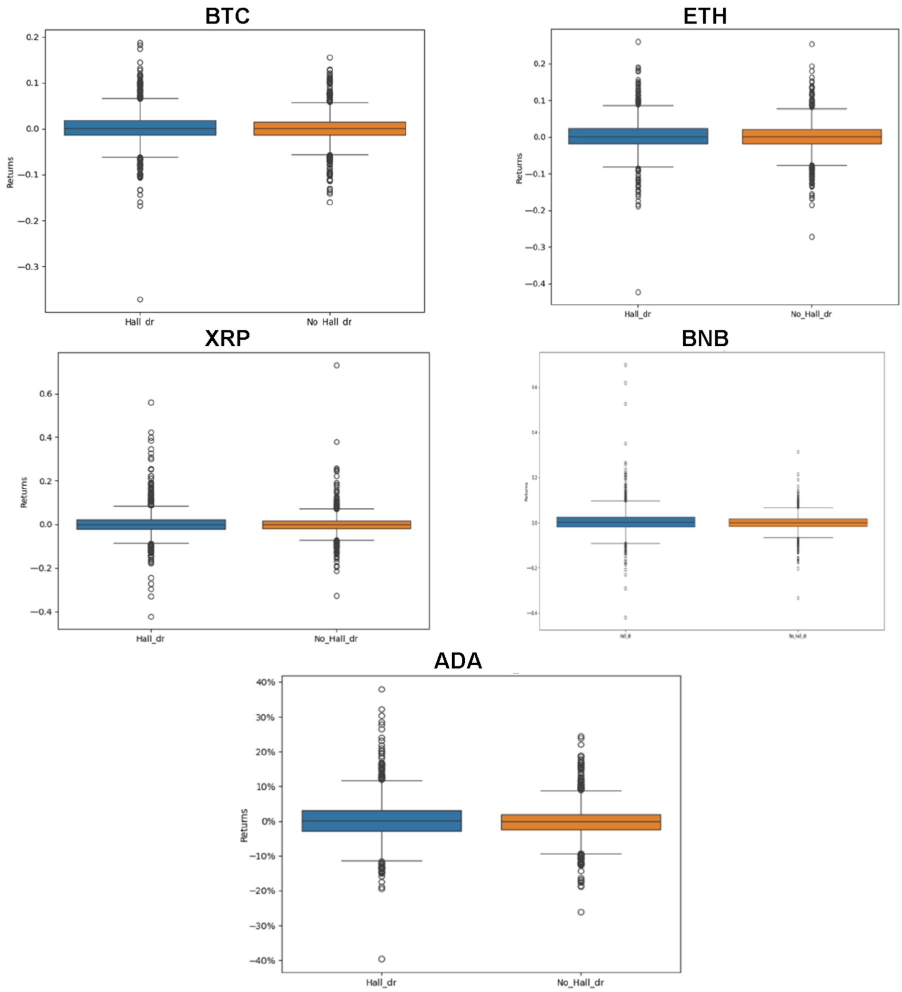


Figure A3. Box-and-Whisker plots of daily returns for Halloween and non-Halloween days for BTC, ETH, XRP, BNB, and ADA from 2018 to 2024. A Box-Whisker plot summarizes a dataset using five key statistics: minimum, first quartile (Q1), median (Q2), third quartile (Q3), and maximum, effectively showing the spread and center of the data. The box represents the interquartile range (IQR $= Q3 - Q1$), capturing the middle 50% of the data, while the "whiskers" extend to the smallest and largest non-outlier values, with any outliers plotted individually. This figure visually compares the distribution of daily returns across the two calendar-based sub-periods. While high-market-cap cryptocurrencies (BTC, ETH, and XRP) exhibit relatively stable dispersion and median values, smaller-cap assets (BNB and ADA) display noticeable variation, particularly in terms of spread and outliers. These visual cues reinforce the statistical evidence of differing return characteristics across the two regimes and support the presence of seasonal effects in lower-cap cryptocurrencies. Source: Authors' own work

Notes

1. https://apnews.com/article/donald-trump-bitcoin-cryptocurrency-stockpile-6f1314f5e99bbf47cc3ee6fc6178588d
2. https://coinmarketcap.com/
3. The Halloween strategy is a market timing approach based on the empirical observation that stock market returns are generally higher from October 31 to May 1 than during the rest of the year. The

strategy derives its name from its starting date—Halloween—reflecting the seasonal anomaly often summarized by the saying, "Sell in May and go away".

4. The selection of cryptocurrencies was based primarily on their substantial market capitalization, as reported in CoinMarketCap's (https://coinmarketcap.com/historical/20250315/), and the availability of complete calendar-year data for a minimum period of five years. Assets such as Solana were excluded due to their relatively recent introduction to the market, which would not allow for consistent and comprehensive full-year analysis. This selection criterion ensures the robustness of our results by avoiding potential biases associated with the inclusion of newer or less established cryptocurrencies.
5. Moreover, since previous studies have rejected the existence of the Halloween effect in cryptocurrencies, re-examining this anomaly using a more recent and comprehensive dataset may yield new evidence and potentially stimulate further research in this area.
6. The only exception, where kurtosis is higher on non-Halloween days is XRP.
7. A Box-Whisker plot summarizes a dataset using five key statistics: minimum, first quartile ($Q1$), median ($Q2$), third quartile ($Q3$), and maximum, effectively showing the spread and center of the data. The box represents the interquartile range (IQR $= Q3 - Q1$), capturing the middle 50% of the data, while the "whiskers" extend to the smallest and largest non-outlier values, with any outliers plotted individually.
8. Moreover, as suggested in these studies, such behavior indicates market conditions where prices may be higher than expected, potentially reflecting overvaluation.

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Corresponding author
Evangelos Vasileiou can be contacted at: evasileiou@hmu.gr