

Calendar Anomalies in DeFi Assets and Their Competitive Implications

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Abstract

This paper investigates the presence, characteristics, and potential competitive implications of calendar anomalies within the decentralized finance (DeFi) sector, an area largely overlooked in existing financial literature. Previous research has predominantly focused on bitcoin or other cryptocurrencies selected purely based on market capitalization. In contrast, this article uniquely examines a specific sector within the cryptocurrency market, analyzing five leading DeFi assets by market capitalization, namely LINK, AAVE, MKR, SNX, and UNI, using daily data spanning November 2017 to November 2023 and estimating a GJR-GARCH model to assess day-of-the-week (DoW), month-of-the-year (MoY), and Halloween effects. The findings reveal no evidence of a consistent Halloween effect in returns or volatility. However, a strong and consistent Tuesday effect is observed in volatility, with four out of five assets exhibiting statistically significant excess volatility. A less pronounced Wednesday effect is identified in three assets, highlighting distinct volatility patterns unique to DeFi markets. The MoY analysis uncovers a pronounced January effect, with all assets except MKR exhibiting positive excess returns. This finding aligns with traditional finance yet is unprecedented within cryptocurrencies. Additionally, volatility clustering is evident, with periods of high or low volatility persisting and strongly linked to historical levels across all assets. These results enhance understanding of the competitive dynamics of DeFi markets, offering insights into how calendar anomalies influence risk, returns, and competitiveness within this rapidly evolving ecosystem.

Keywords: *Calendar anomalies, DeFi, GARCH dummy model, Seasonalities, Competitive*

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1. INTRODUCTION

Bitcoin's emergence marked a key challenge to traditional banking and financial structures, aiming to decentralize currency management (Rech et al., 2022). In the years that followed,

newer crypto assets sought to address bitcoin's limitations or introduce innovative solutions aimed at further transforming and liberating the financial landscape. Among these advancements, decentralized finance (DeFi) assets have recently gained significant traction, positioning themselves as a key force in the ongoing evolution of financial systems.

DeFi provides on-chain financial services like borrowing, investing, and lending, operating independently of traditional centralized intermediaries (Werner et al., 2022). Built on open-source software, it leverages smart contracts to automate processes and facilitate stakeholder participation (Jensen et al., 2021; Werner et al., 2022). DeFi's decentralized and algorithmic foundations create unique temporal complexities, distinct from traditional financial markets and other cryptocurrencies.

This complexity is further intensified by the algorithmic execution of transactions through smart contracts, which generate intricate patterns shaped by code-driven decision-making. Moreover, the collateralized nature of assets within DeFi protocols, often tied to the value of underlying cryptocurrencies, amplifies the relevance of examining calendar anomalies. Understanding these temporal patterns offers valuable insights into the behavior of collateralized assets and highlights potential risks or opportunities associated with asset-backed transactions. This investigation into calendar anomalies thus serves as a crucial step toward deciphering the temporal dynamics and risk profiles inherent in the DeFi ecosystem.

Calendar anomalies are systematic return patterns that recur on particular days, months, or seasons, contradicting the randomness implied by the weak-form efficient-market hypothesis (Fama, 1965, 1970) and, by extension, reshaping the competitive landscape for informed traders and liquidity providers. Classic illustrations include the day-of-the-week (DoW) or Monday effect (e.g., Chiah & Zhong, 2021; Khan et al., 2023), in which average Friday returns are higher than Monday returns; the January effect (e.g., Aslam et al., 2022; Chen et al., 2021), marked by unusually strong first-month gains; and the Halloween, or "sell in May," effect (e.g., Almeida et al., 2022; Lobão & Costa, 2023; Plastun et al., 2020), where returns from November through April systematically outpace those from May through October. Because such patterns create predictable risk-return profiles, they open profitable windows for arbitrage, influence portfolio rebalancing schedules, and ultimately affect the relative competitiveness of market participants who can—or cannot—exploit them.

Calendar anomalies have largely disappeared or significantly weakened in developed equity markets (Plastun et al., 2019; Grebe & Schiereck, 2024), rendering cryptocurrencies as an

emerging asset class a uniquely compelling case for studying anomaly persistence. Yet research remains hobbled by bitcoin-centrism (Decourt et al., 2017; Aharon & Qadan, 2019; Baur et al., 2019; Ma & Tanizaki, 2019; Hamurcu, 2022; Kinatader & Papavassiliou, 2021; Liu, 2024). Studies including more cryptocurrencies frequently select assets using top market capitalization (Caporale & Plastun, 2019; Kaiser, 2019; Qadan et al., 2021; Sahu et al., 2024; Mueller, 2024), despite this approach's inherent weakness given extreme volatility in cryptocurrency valuation rankings. Relying solely on market capitalization groups structurally dissimilar cryptocurrencies, including payment coins such as bitcoin, smart-contract platforms like ethereum, meme tokens exemplified by dogecoin, and exchange tokens such as binance coin, thereby conflating asset classes that differ fundamentally in technology, purpose, and potentially risk–return characteristics.

We contend that the cryptocurrency market has now reached a stage of structural maturity that warrants a sector-specific approach. This maturity is evidenced by a growing literature that scrutinizes DeFi's microstructure, governance, and risk channels from multiple angles (Gudgeon et al., 2020; Capponi & Jia, 2021; Zhang & Chan, 2022; Wang et al., 2022; Yousaf et al., 2022; Corbet et al., 2023), yet conspicuously, no work has undertaken a sector-focused analysis of calendar anomalies. These studies have already identified some forms of inefficiency in DeFi, such as trading systems often benefit informed arbitrageurs at the expense of passive liquidity providers (Capponi & Jia, 2021), market efficiency depends on protocol usage, with liquidity appearing mainly during periods of high activity (Gudgeon et al., 2020) and shifting market efficiency over time (Zhang & Chan, 2022). Others show that price dynamics are shaped by imitation and herding (Corbet et al., 2023; Wang et al., 2022; Yousaf et al., 2022). This paper adds to this literature by examining whether time-based patterns, like calendar anomalies, represent another layer of market inefficiency.

This paper investigates the presence, characteristics, and competitive implications of calendar anomalies in the five largest DeFi assets: LINK, AAVE, MKR, SNX, and UNI. The research examines three anomalies, namely the DoW, MoY, and HE. No evidence of a Halloween effect is found in returns or volatility, aligning with prior bitcoin studies. However, a strong and consistent Tuesday volatility effect is observed in four assets, followed by a less pronounced Wednesday effect in three. These findings carry significant implications for DeFi trading risk management. A pronounced January effect in returns is observed across all assets except MKR, paralleling traditional financial markets while introducing a novel perspective to

cryptocurrencies. Volatility clustering and strong links between current and past volatility highlight DeFi's complex temporal dynamics. These findings provide key insights into DeFi's competitive and risk landscape, emphasizing the need for further research into the mechanisms driving these anomalies and their implications.

The remainder of the paper is organized as follows. Section 2 briefly introduces DeFi, sketches the sector's key features, defines calendar anomalies and outlines their potential implications in DeFi sector. Section 3 presents the research design and data used in the analysis. In section 4, the results are presented and discussed in detail. Finally, section 5 concludes the article, summarizing the key findings and suggesting directions for future research.

2. LITERATURE REVIEW

DeFi has emerged as a transformative paradigm in financial services, leveraging blockchain infrastructure to offer permissionless, peer-to-peer financial interactions without reliance on traditional intermediaries such as banks (Bourveau et al., 2024; Xu et al., 2024, Sockin & Xiong, 2023). At its foundation, DeFi is built on a layered architecture: the base layer consists of blockchain protocols like ethereum that enable smart contract functionality (Schär, 2021), while upper layers include decentralized applications (dApps), oracles, and user interfaces that facilitate various financial services (Cai et al., 2018; Dunbar et al., 2025). These smart contracts act as autonomous agents executing financial transactions, such as lending, borrowing, and trading without centralized oversight (Yousaf et al., 2022; Negara et al., 2021). DeFi protocols eliminate the need for conventional hub-based systems, instead allowing scale through distributed ledger technology (Zetzsche et al., 2020). This disintermediation enhances financial transparency, inclusivity, and efficiency, particularly for users in underbanked or high-compliance jurisdictions where traditional financial access is constrained (Schär, 2021; Zetzsche et al., 2020). However, decentralization does not equate to complete disintermediation; many blockchain systems still operate within hierarchical governance structures that restrict permissionless participation (Zetzsche et al., 2020).

The DeFi Sector

Traditionally, centralized financial models concentrated authority within institutions such as banks and regulatory bodies, which oversaw transactions, safeguarded assets, and facilitated capital allocation. While effective in maintaining systemic oversight, these institutions often imposed entry barriers, constrained innovation, and limited financial inclusivity (Xu et al.,

2024). The advent of internet-based platforms improved accessibility and user interaction, yet retained the hierarchical and centralized architecture of legacy finance, all factors that can undermine dynamic competitiveness within financial markets (Biancone et al., 2024). Moreover, even with significant advancements in information technology, the unit cost of financial intermediation remains as high today as it was in the early 20th century, possibly due to oligopolistic competition (Philippon, 2014), which underscores the entrenched inefficiencies and limited competitive pressure in traditional systems. A significant turning point arrived with the introduction of bitcoin, which offered a decentralized, peer-to-peer mechanism for transferring monetary value outside the control of traditional intermediaries. Despite this breakthrough, bitcoin's functionality remained confined to monetary transactions and digital asset storage. Building upon this foundation, decentralized finance (DeFi) significantly broadened the vision of financial decentralization by replicating a wide array of traditional financial instruments and fostering alternative market structures that intensify competitive dynamics across financial services.

DeFi's rise has been rapid. Although virtually nonexistent before 2017, the sector grew explosively during 2019–2021. Total value locked (TVL) in DeFi smart contracts – a common aggregate measure of the sector's size – surged from roughly \$4 billion to over \$100 billion USD within the span of three years (Meyer et al., 2022). This spectacular growth, coupled with the emergence of truly innovative protocols, has made DeFi increasingly relevant in discussions of competitive transformation within the financial industry, and has sparked intense interest among policymakers, researchers, and financial institutions (Schär, 2021). Functionally, DeFi has evolved into a diversified ecosystem comprising several distinct yet interoperable categories. Decentralized exchanges (DEXs) like Uniswap and Curve utilize automated market makers (AMMs) and smart contract-managed liquidity pools to bypass centralized order books for crypto-assets trading (Bhambhwani & Huang, 2024; Schär, 2021). By eliminating traditional intermediaries, DEXs enhance market accessibility and foster price competition among liquidity providers. Lending protocols such as Aave and Compound allow users to access overcollateralized, crypto-backed loans. The interest generated from these loans is distributed among liquidity providers and holders of the platform's native tokens (Dunbar et al., 2025; Gudgeon et al., 2020). However, Gudgeon et al. (2020) show that under conditions of limited liquidity, lending protocols can become undercollateralized in less than a month, exposing the system to considerable risk and revealing potential vulnerabilities that may hinder the sector's competitive resilience. Stablecoins, which include fiat-backed tokens like USDC

as well as algorithmically stabilized assets, play a foundational role within the DeFi ecosystem by helping to reduce price volatility and acting as mediums of exchange and units of account (Sood et al., 2023; Saengchote & Samphantharak, 2024). Despite their central importance, empirical evidence suggests that stablecoins frequently face difficulties in maintaining their pegs during periods of market turbulence. As a result, they require strong collateralization models and stabilization mechanisms to function reliably in a highly competitive and rapidly shifting financial environment (Pernice et al., 2019).

In addition to core transactional services, DeFi has expanded into derivatives and synthetic asset markets. Platforms such as Synthetix allow users to gain synthetic exposure to commodities, indices, and other financial instruments by issuing tokens pegged to these assets through collateralized pools and decentralized oracles (Schär, 2021). These synthetic instruments enable the creation of complex financial products—including options, futures, and swaps—on-chain, thereby extending DeFi’s functionality to mirror traditional derivatives markets. Another critical segment is on-chain asset management, which includes yield aggregators such as Yearn.finance. These protocols algorithmically deploy user funds across lending pools, liquidity farms, and staking mechanisms to maximize returns. Often governed by smart contracts, these platforms perform dynamic portfolio rebalancing, effectively replicating the role of traditional asset managers in a decentralized context, enhancing competitive efficiency by reducing management costs and human intervention (Jensen et al., 2021; Schär, 2021; Allen et al., 2023).

A key feature of DeFi is the high degree of interoperability among protocols, often described as “money Lego” blocks. These are modular components that can be combined to create complex financial products. For example, a token acquired from a decentralized exchange can be used as collateral in a lending platform, and the borrowed funds can then be deployed into a yield farm. This composability, supported by open-source code and standardized APIs, enables permissionless innovation and accelerates the development of new financial services, a dynamic that lowers entry barriers and intensifies innovation-based competition within the sector (Chen & Bellavitis, 2020). Addressing the broader implications of this rapidly evolving system, Werner et al. (2022) offer one of the first comprehensive assessments of DeFi’s challenges, examining both the technological foundations and the economic vulnerabilities that arise within such an open and composable architecture.

Calendar Anomalies

Calendar anomalies refer to systematic patterns in asset returns that correspond to specific periods in the calendar year, which appear to challenge the EMH. According to EMH, asset prices fully reflect all available information, leaving no consistent opportunity for excess returns based on historical patterns (Fama, 1965, 1970). The most extensively studied calendar anomalies include the day-of-the-week (DoW) effect, typically illustrated by lower returns on Mondays and higher returns on Fridays (Cross, 1973; French, 1980), the month-of-the-year (MoY) effect, most famously captured by the “January effect,” in which January returns exceed those of other months (Rozeff & Kinney, 1976), and the Halloween effect, where returns from November to April tend to outperform those from May to October (Bouman & Jacobsen, 2002).

Various explanations have been proposed to account for calendar anomalies, typically addressing each anomaly individually rather than offering a unified theoretical framework. Although the explanations differ by anomaly, behavioral biases emerge as the most promising explanation across studies Jacobs and Levy (1988). For the DoW effect in particular, the most popular explanations include the timing of negative news releases and that short sellers often close their positions on Fridays to avoid holding them over the weekend, when markets are closed and uncertainty increases. They then reopen these positions on Mondays, creating upward pressure on prices at the end of the week and downward pressure at the start of the new week (Chen & Singal, 2003; Jacobs & Levy, 1988). Grebe and Schiereck (2024) provide a comprehensive overview of theories behind the DoW effect but conclude that so far, all of them remain insufficient to explain its inconsistent empirical patterns. The January effect has been linked to tax-loss selling, whereby investors offload underperforming assets in December, leading to a rebound in January (Jacobs & Levy, 1988). Although Gultekin and Gultekin (1983) found support for this hypothesis in several countries, Australia stood as a notable exception. Window-dressing and cash-flow effects around month-ends further contribute to these anomalies (Jacobs & Levy, 1988). While not focused specifically on the Halloween effect, Kamstra et al. (2003) provide compelling evidence that investor mood, influenced by seasonal changes in daylight, known as the seasonal affective disorder (SAD) effect, contributes to cyclical patterns in asset returns.

However, recent evidence suggests these calendar effects have largely dissipated in developed markets. Plastun et al. (2019), in a century-long analysis of the Dow Jones Industrial Average, report that calendar effects peaked mid-20th century and have since largely disappeared. Meta-analyses corroborate this decline, indicating that while Mondays and Fridays still exhibit

slightly lower and higher returns, respectively, these effects are far weaker and largely confined to historical data (Grebe & Schiereck, 2024).

Following the emergence of bitcoin in 2009, researchers began exploring whether classical calendar anomalies persist in cryptocurrency markets, which differ fundamentally from traditional equities. Their decentralized structure, 24/7 trading, low entry barriers, and inelastic supply create unique price dynamics. Yi et al. (2023) argue that these features promote rapid information absorption, supporting greater market efficiency even in early, low-liquidity phases.

Nonetheless, evidence of calendar anomalies in cryptocurrencies, particularly bitcoin, remains mixed. A number of studies support the existence of DoW effects in bitcoin returns (Decourt et al., 2019; Kurihara & Fukushima, 2017; Aharon & Qadan, 2019; Caporale & Plastun, 2019; Ma & Tanizaki, 2019; Qadan et al., 2022; Hamurcu, 2022; Tosunoğlu et al., 2023; Sahu et al., 2024; Liu, 2024; Mueller, 2024), with further anomalies observed in volatility, trading volume, and spreads (Aharon & Qadan, 2019; Kaiser, 2019; Hamurcu, 2022; Kinatader & Papavassiliou, 2021). Notably, more recent studies by Sahu (2024) and Mueller (2024) find evidence of DoW effects in a wider set of cryptocurrencies beyond bitcoin.

However, several studies fail to replicate these findings, reporting no consistent evidence of calendar anomalies in bitcoin or other cryptocurrencies. Baur et al. (2019) and Kinatader and Papavassiliou (2021) find no consistent DoW effects in bitcoin. Analyses of other cryptocurrencies similarly fail to detect significant anomalies in daily returns (Caporale & Plastun, 2019; Qadan et al., 2022; Tosunoğlu et al., 2023). The evidence surrounding the MoY effect is equally inconclusive. While Kaiser (2019) finds no return-based MoY effect across various cryptocurrencies, he notes anomalies in volatility and trading volume. In bitcoin specifically, Baur et al. (2019) find no MoY effect, while Kinatader and Papavassiliou (2021) and Hamurcu (2022) report modest return and volatility seasonality in select months. Interestingly, the traditional focus on January has shifted toward a broader examination of month-level effects—likely due to the absence of a tax calendar analogue in cryptocurrency markets. Regarding the Halloween effect, although no significant pattern has been identified in bitcoin (Kaiser, 2019; Kinatader & Papavassiliou, 2021; Qadan et al., 2022), some studies have detected its presence in other crypto assets (Kaiser, 2019; Kinatader & Papavassiliou, 2021).

Implications of Calendar Anomalies in the DeFi Sector

Most studies of crypto calendar anomalies still center on bitcoin. When other tokens are included, researchers usually select the coins that happen to have the largest market value at the beginning of the sample, even though those rankings change rapidly. This practice yields fragmented evidence for assets other than bitcoin and tends to examine only a single pattern, such as the DoW in returns. Such methodological limitations constrain our understanding of how temporal inefficiencies may differentially affect tokens within a highly competitive and evolving DeFi landscape. The distinctive automated-market-maker architecture and self-contained on-chain ecosystem of DeFi have already spurred a focused research stream that probes various areas.

Capponi and Jia (2021) provide formal evidence that constant-function automated market makers, the dominant liquidity mechanism in DeFi, systematically transfer surplus from passive liquidity providers to informed arbitrageurs, thereby embedding a persistent layer of allocational inefficiency. Gudgeon et al. (2020) corroborate this micro-structural diagnosis by documenting that DeFi tokens are weak-form inefficient and that liquidity depth materializes chiefly during periods of elevated protocol utilization, while Zhang and Chan (2022) further demonstrate that market efficiency oscillates over short horizons in a manner consistent with the adaptive market hypothesis. Calendar anomalies would add another layer of predictability that bots and MEV seekers could exploit, prompting liquidity providers to pull capital at known high-drift intervals and raising the risk of synchronized collateral stress across lending and derivative protocols. This introduces new challenges for sustaining robust and competitive market infrastructures within DeFi, where sudden capital reallocation may undermine liquidity resilience.

Complementing these structural frictions, recent behavioral studies highlight when such inefficiencies may intensify. The demonstration by Corbet et al. (2023) and Wang et al. (2022) that self-reinforcing price explosions are driven by investor imitation, coupled with Yousaf et al.'s (2022) finding that herding clusters on deceptively low-volatility days, strongly suggests that if calendar anomalies exist in DeFi, they would likely be manifestations of these herding and imitation behaviors exhibiting predictable temporal patterns, potentially amplified during seemingly calm conditions. Such temporally concentrated behaviors could degrade competitive market conditions by introducing asymmetric risks and speculative cycles that disadvantage less agile participants. Furthermore, Maouchi et al.'s (2021) evidence linking bubble formation

to coinciding volume and news spikes implies that calendar anomalies could be particularly pronounced or triggered during periods of scheduled high-impact events or when exogenous shocks intersect with specific calendar-related market conditions.

3. METHODOLOGY AND DATA

3.1 Data sample

The dataset analyzed in this paper consists of daily closing prices in USD for the five DeFi assets with the highest market capitalization at the time of data collection: LINK (Chainlink), AAVE (Aave), MKR (Maker), SNX (Synthetix), and UNI (Uniswap). The data was sourced from the coingecko.com website, spanning from each asset's earliest available data point to November 15, 2023. Due to differences in the inception dates of these DeFi assets and limitations in data availability, the starting point for each asset was determined based on the earliest accessible data: LINK (November 10, 2017), AAVE (October 4, 2020), MKR (December 21, 2017), SNX (March 22, 2018), and UNI (September 18, 2020). Daily returns R_t are calculated as $R_t = \log\left(\frac{P_t}{P_{t-1}}\right)$, where P_t represents the closing price on date t .

3.2 Methodology: The GJR-GARCH Model

Numerous studies investigating the impact of calendar effects on returns frequently employ the standard ordinary least squares (OLS) methodology. However, this approach is associated with several significant limitations. First, the presence of potential autocorrelation in the model's residuals can lead to biased and misleading inferences. Second, the assumption of constant error variance (homoskedasticity) may not hold, as the variance of error terms often varies over time (Kiyamaz & Berument, 2003). Third, conditional volatility of returns may change in response to both unexpected positive and negative shocks, introducing asymmetry into the process (Glosten et al., 1993).

To address these issues, incorporating lagged values of the return variable into the model offers a viable solution for mitigating autocorrelation. In this framework, the stochastic process for returns is expressed as:

$$R_t = \alpha_0 + \alpha_{1,c}D_{t,c} + \sum_{i=1}^n \alpha_i R_{t-i} + \varepsilon_t \quad (1)$$

where R_t represents returns of a selected DeFi asset, while $D_{t,c} \in \{D_{t,h}, D_{t,d}, D_{t,m}\}$ denotes the dummy variables corresponding to one of the three calendar effects at time t . The lag

order is represented by n . During the Halloween period (November to April), the Halloween dummy ($D_{t,h}$) is assigned a value of one for these months and zero otherwise. This variable captures potential variations in returns and/or volatility during non-summer months. The DoW dummy ($D_{t,d}$) is assigned a value of one for a specific day d , where $d = 1$ corresponds to Monday and $d = 7$ corresponds to Sunday, and zero otherwise. This setup enables an investigation of the DoW effect for each weekday individually, hypothesizing that certain weekdays may exhibit abnormal returns or heightened risk. Similarly, the MoY dummy ($D_{t,m}$) is assigned a value of one for a specific month m , where $m = 1$ corresponds to January and $m = 12$ corresponds to December, and zero otherwise. This facilitates the examination of abnormal returns during specific months and potential disparities in volatility across the year.

To address the second limitation of non-constant error variance, the model incorporates a mechanism that allows the variance of errors to become time-dependent. This adjustment introduces conditional heteroskedasticity, effectively capturing the dynamic changes in the variance of returns over time. Consequently, the error terms are characterized by a mean of zero and a time-varying variance, represented as $h_t^2[\varepsilon_t \sim (0, h_t^2)]$.

Over the years, various methodologies have been proposed to model the time-dependent nature of conditional variances in financial time series. Among these, the generalized autoregressive conditional heteroskedasticity (GARCH) model has emerged as a particularly prevalent approach. Initially introduced by Engle (1982) and later refined by Bollerslev (1986), the GARCH model extends the foundational autoregressive conditional heteroskedasticity (ARCH) framework by incorporating p lags of the conditional variance into its formulation, thereby enhancing its ability to capture persistent volatility clustering.

The GARCH (p, q) model is specifically designed to account for the time-dependent nature of conditional variances, making it particularly suitable for financial time series characterized by volatility clustering. In this context, the lagged returns in the model are referred to as autoregressive (AR) terms and are included in the mean equation to capture the temporal dependencies in returns. The order p in the AR (p) process is determined by analyzing the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots for each dataset, ensuring model specification is tailored to the underlying data structure. The precise formulations of the mean equation (Eq. 2) and the variance equation (Eq. 3) are provided as follows:

$$R_t = \mu + \sum_{i=1}^n p_i R_{t-1} + \phi_{1,c} D_{t,c} + \varepsilon_t \quad (2)$$

and

$$h_t^2 = \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^q \beta_i h_{t-1}^2 + \phi_{2,c} D_{t,c}, \quad (3)$$

In the model, h_t^2 represents the conditional variance of ε_t , ω denotes the constant term, and α and β are coefficients. The term h_{t-1}^2 signifies the lagged value of h_t^2 , capturing the persistence of volatility over time. To prevent issues associated with the dummy variable trap, meticulous consideration of both the constant terms μ and ω and their coefficients is crucial. This issue arises when binary variables exhibit redundancy with the intercept, leading to multicollinearity. Such problems are particularly pronounced in models that include dummy variables for every category of a categorical variable without a designated baseline category.

To mitigate the dummy variable trap, a common approach in the literature on calendar effects involves strategically omitting one category when executing the model. This practice is particularly useful when the researcher seeks to focus on specific categories, such as the January effect. For instance, by excluding January from the set of month dummy variables, the model implicitly uses January as the baseline category. This allows the coefficients for other months to represent deviations from January, with January being absorbed into the constant term.

However, relying on this approach to confirm an anomaly can be problematic, as observed returns may differ significantly from only one or a few specific months rather than demonstrating a broader calendar effect. An alternative and more robust strategy involves using all months except January as the baseline category, which is represented by the constant term, and including a single dummy variable for January. This method significantly reduces the likelihood of observing statistically significant differences in returns by chance and, if an anomaly is detected, provides stronger evidence of a robust calendar effect applicable across all categories—specifically, in this case, months.

To address the third limitation, an additional term is incorporated into the standard GARCH (p, q) model, as proposed by Glosten et al. (1993). The conventional GARCH (p, q) model assumes a symmetric response in conditional volatility, irrespective of whether returns are positive or negative. However, Glosten et al. (1993) argue that unexpected positive returns typically lead to a decrease in conditional volatility, whereas unexpected negative returns tend to result in an

increase in conditional volatility. This asymmetry is particularly relevant in financial markets, where negative shocks often have a more pronounced effect on volatility than positive ones.

This modification culminates in the final equations of the asymmetric AR (p)-GJR-GARCH (1,1) model, the specific model employed for empirical analysis in this research. While the mean equation retains its structure from the standard GARCH (1,1) model (refer to Eq. 2), the variance equation is adapted to capture the asymmetric response. The variance equation for the AR (p)-GJR-GARCH (1,1) model is articulated as follows:

$$h_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{[\varepsilon_{t-1} < 0]} + \beta h_{t-1}^2 + \phi_{2,c} D_{t,c}, \quad (4)$$

where, $I_{[\varepsilon_{t-1} < 0]}$ denotes the indicator function, and its associated coefficient γ is commonly referred to as the “leverage effect” in the literature. This term allows for the inclusion of an asymmetric response in the conditional variance h_t^2 , where volatility is hypothesized to increase more significantly following negative shocks than positive shocks of equivalent magnitude.

4. EMPIRICAL RESULTS AND DISCUSSION

Figure 1 illustrates the time dynamics of the daily closing prices for the selected DeFi assets. The empirical investigation reveals a distinct pattern among these assets. A notable episode of bubble-like dynamics is observed in DeFi asset prices from early 2020 to the third quarter of 2021, followed by a downward trend that persisted until mid-2022. While the broad cryptocurrency market exhibited a generalized price decay during this period, a divergence emerged during the post-COVID-19 recovery. The broader market not only recovered but surpassed its previous record high, achieving a new peak in the latter half of 2021. In contrast, DeFi assets failed to undergo a comparable recovery, instead experiencing a sustained decline until mid-2022. Post-2022, LINK and MKR showed a modest recovery, though not entirely aligned with the broader cryptocurrency market's trajectory. Meanwhile, the prices of AAVE, SNX, and UNI exhibited relative stability. These dynamics highlight the distinct behavior of DeFi assets compared to the broader cryptocurrency market during critical market phases.

Figure 2 depicts the time-varying returns of the selected assets, offering further insights into their volatility dynamics. The analysis identifies volatility clustering across all markets, characterized by notable spikes at various points in time. These observations challenge the assumptions of simple random walk models, emphasizing the need for advanced econometric modeling to capture the underlying dynamics of these markets.

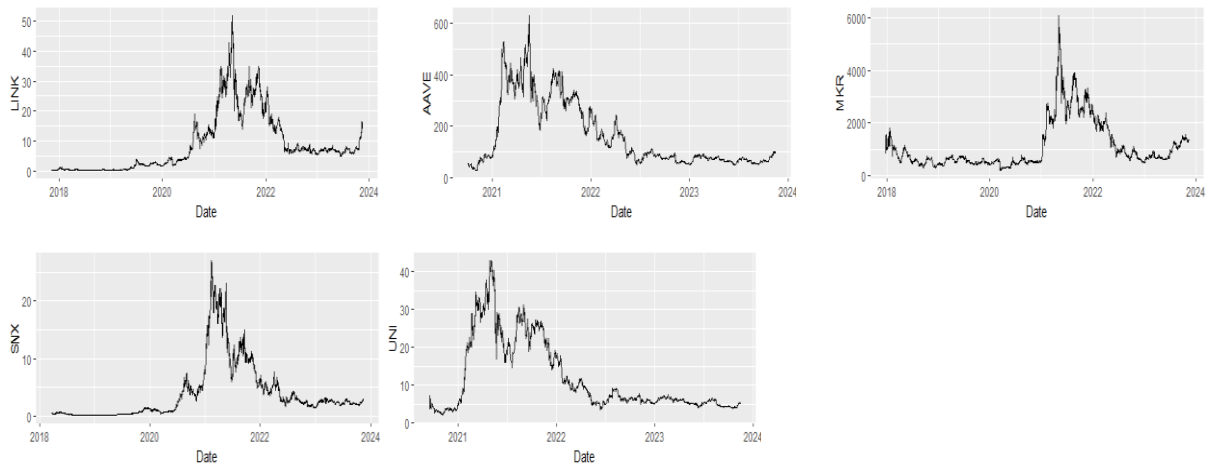


Fig. 1 – DeFi Assets Daily Closing Prices

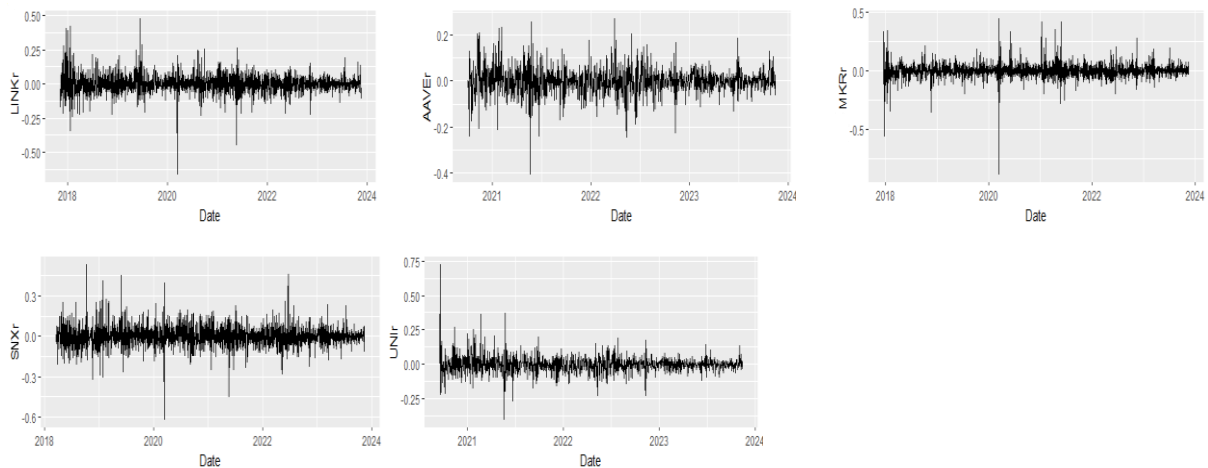


Fig. 2 – DeFi Assets Returns

Table 1 provides key descriptive statistics characterizing the daily return distributions of the selected DeFi assets. These statistics include the mean, median, standard deviation, minimum, maximum, skewness, kurtosis, and augmented–Dickey–Fuller (ADF) test outcomes, offering insights into the central tendency, dispersion, and shape of the return distributions.

The mean daily return values for all DeFi assets are positive; however, their respective standard deviations are notably high, reflecting significant variability in daily returns. Given this high variability, the median might serve as a more representative measure of central tendency. Notably, two assets, namely MKR and SNX, exhibit negative median daily returns. These assets also show the highest range of observed returns, with MKR experiencing a decline as steep as 88.1 percent in a single day. In contrast, AAVE exhibited the lowest range of motion

among the assets analyzed. The skewness and kurtosis statistics provide additional insights into the symmetry and tail characteristics of the return distributions. These metrics are critical for selecting an appropriate error distribution when fitting the AR (1)-GJR-GARCH model. As emphasized by Boubaker et al. (2017), appropriate distributional assumptions for model errors are essential to avoid fragile econometric findings and ensure robust statistical inferences in financial data analysis. In light of this, the authors suggest using either the student t-distribution or the generalized error distribution (GED), as popularized by Nelson (1991). Based on the observed data characteristics and the Akaike information criterion (AIC), we chose the skewed Student T-distribution for all AR (1)-GJR-GARCH models employed in this article. Finally, the ADF test results indicate that all the selected DeFi assets follow a unit root process, underscoring the need for further transformations to ensure stationarity in the modeling process.

Tab. 1 – Descriptive statistics. Source: own processing

	Mean	Median	St. Dev.	Min	Max	Skewness	Kurtosis	ADF
LINK	.0019	.0009	.0674	-.6608	.4761	-.0439	8.9665	-12.552***
AAVE	.0004	.0005	.0634	-.4076	.2725	-.1488	3.3769	-10.208***
MKR	.0001	-.0006	.0624	-.8810	.4420	-.9548	27.5737	-12.018***
SNX	.0008	-.0011	.0773	-.6190	.5323	.1960	5.9966	-11.496***
UNI	.0003	.0002	.0645	-.3996	.7232	1.3603	17.2778	-9.981***

Note: Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

4.1 The Halloween Effect

The AR (p)-GJR-GARCH (1,1) model results for the Halloween effect in the selected DeFi assets are displayed in Table 2. The mean equation includes a constant term (μ), an autoregressive term of order 1 (AR1), and the Halloween period dummy variable ($D_{t,h}$), which captures the potential effects of the Halloween period on asset returns. The variance equation incorporates a constant term (ω) and coefficients (α , β , γ) to model the conditional variance dynamics. These terms account for the persistence and asymmetry in volatility, where the parameter γ specifically reflects the leverage effect. Additionally, the Halloween dummy variable ($D_{t,h}$) is also included in the variance equation to identify any volatility changes associated with the Halloween period.

To evaluate the robustness and reliability of the models, a comprehensive set of diagnostic tests was performed. Specifically, the weighted Ljung-box tests on standardized residuals (WL-B SR) and squared residuals (WL-B SR²) were utilized to detect serial correlation in the residuals. The results indicated no significant autocorrelation in either the standardized residuals or their squares, confirming that the models effectively capture the temporal dependencies and dynamics present in both the mean and variance equations.

The inclusion of autoregressive (AR) terms varied across the DeFi assets analyzed. For LINK, MKR, SNX, and UNI, a single AR (1) term adequately modeled temporal dependencies, suggesting that the AR (1)-GJR-GARCH (1,1) model effectively captures the conditional return and volatility dynamics for these assets. In contrast, AAVE required no AR term, indicating that its temporal behavior is sufficiently described by the GJR-GARCH (1,1) framework without additional lagged terms. The models' ability to capture conditional heteroskedasticity and volatility clustering was further validated using the weighted autoregressive conditional heteroskedasticity Lagrange multiplier test (WARCH LM), which confirmed the models' efficacy. Parameter stability over time was established by the Nyblom stability test (NST), with consistent acceptance across all assets. Moreover, the sign bias test (SBT) revealed no significant biases in predicting return signs, underscoring the adequacy of the models. Finally, the adjusted Pearson goodness-of-fit test (AP-GOF) demonstrated a strong fit of the models to the data, affirming their statistical soundness. Collectively, these diagnostic tests validate the models' reliability and robustness in capturing the underlying market processes during the Halloween period.

In the mean equation, the constant term (μ) exhibits variability across assets, with the highest value observed in LINK (0.0019) and the lowest in UNI (-0.0018). Notably, all constant term coefficients are statistically insignificant. Interestingly, three out of five assets display negative baseline returns, suggesting a potential inherent downward bias in expected returns during the specified period. For AAVE (-0.0008) and UNI (-0.0018), this can be attributed to economic conditions surrounding their initial coin offerings (ICOs), which occurred during the COVID-19 period—a time marked by significant market price losses for all DeFi assets. In contrast, LINK (0.0019) and SNX (0.0011), whose ICOs took place before the COVID-19 period, experienced longer durations of positive returns. MKR, with a notably negative baseline return of -0.0110 and a longer data span, stands out as an exception. Additionally, all AR (1) terms in the mean equation are negative, indicating an inverse relationship between current returns and

their lagged values. This observation is consistent with the concept of mean reversion, whereby returns tend to move in the opposite direction of their prior values. For all DeFi assets except AAVE, this tendency is reinforced by the statistical significance of the AR (1) coefficients, highlighting the role of mean reversion dynamics in shaping return behavior. From a competitive perspective, the prevalence of mean reversion suggests that short-horizon contrarian strategies could be viable, but only for assets where the effect is statistically reliable.

The Halloween dummy variable ($D_{t,h}$) in the mean equation was not statistically significant for any DeFi asset, indicating no evidence of excess returns during the Halloween period. However, in the variance equation, a weakly statistically significant Halloween effect was observed for SNX, where the conditional variance increased during the Halloween period. The constant term (ω) for SNX was statistically significant, with the highest value among the DeFi assets at 0.0003. During the Halloween period, this risk was further elevated by 0.0001, marking the highest increase among all DeFi assets. Although the magnitude is small, this asset-specific spike implies that liquidity providers in SNX may demand a higher risk premium between late October and early May, potentially widening spreads or reducing leverage during that window.

The α and β coefficients provide valuable insights into the short-term and long-term influences on volatility, capturing the dynamics of market shocks and the persistence of volatility over time. All α and β coefficients for the DeFi assets were statistically significant at the 1% significance level. However, substantial differences were observed across the assets. AAVE (0.1240), MKR (0.1198), and SNX (0.1211) exhibited the highest α coefficients, indicating a relatively stronger short-term influence of market shocks on volatility. In contrast, UNI displayed the lowest short-term impact with an α coefficient of 0.0455. The β coefficients revealed a high degree of persistent volatility clustering across the DeFi assets. UNI demonstrated the highest level of persistence at 0.9219, closely followed by LINK (0.9022) and AAVE (0.8783). SNX (0.8256) and MKR (0.7679) exhibited relatively lower levels of volatility clustering. The inclusion of the γ coefficients introduced asymmetry into the model. Among the DeFi assets, only UNI had a statistically significant γ coefficient (0.0560) at the 10% significance level, indicating mild evidence of asymmetric responses to positive and negative shocks. For the remaining DeFi assets, γ coefficients were not statistically significant. These cross-sectional differences signal that traders face heterogeneous volatility–return trade-offs, for instance, UNI’s high persistence but low α may favor longer-horizon volatility targeting, whereas SNX’s higher α and Halloween-related variance bump could reward shorter-

term gamma-scalping strategies. Due to space constraints, the results for the remaining calendar anomalies are limited to the dummy variables. These results closely resemble the coefficients presented in Table 2, further supporting the consistency of the model's findings across other calendar anomalies.

Tab. 2 – The Halloween Effect. Source: own processing

	LINK	AAVE	MKR	SNX	UNI
Mean equation					
μ	.0019	-.0008	-.0010	.0011	-.0018
AR1	-.0528**		-.0697***	-.1111***	-.0784***
$D_{t,h}$	-.0001	.0010	.0023	.0008	.0017
Variance equation					
ω	.0001***	.0001*	.0003***	.0003*	.0000
α	.0955***	.1240***	.1198***	.1211***	.0454**
β	.9022***	.8783***	.7679***	.8256***	.9219***
γ	-.0186	-.0273	.0604	.0208	.0560*
$D_{t,h}$	2.4e-05	.0001	4.1e-05	.0001*	4.3e-05
skew	1.0352***	.9578***	1.0266***	1.0786***	0.9505***
shape	4.8937***	5.4735***	3.2751***	4.1577***	4.1010***
Diagnostics tests					
WL-B SR	Not Rejected	Not Rejected	Not Rejected	Not Rejected	Not Rejected
WL-B SR ²	Not Rejected	Not Rejected	Not Rejected	Not Rejected	Not Rejected
WARCH	Not Rejected	Not Rejected	Not Rejected	Not Rejected	Not Rejected
LM					
NST	Not Rejected	Not Rejected	Not Rejected	Not Rejected	Not Rejected
SBT	Not Rejected	Not Rejected	Not Rejected	Not Rejected	Not Rejected
Goodness-of-Fit Tests					
AP-GOF Test	Not Rejected	Not Rejected	Not Rejected	Not Rejected	Not Rejected

Note: Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

As noted, research on the HE in traditional financial markets has produced conflicting findings regarding the existence and significance of this anomaly. In the context of cryptocurrency

assets, our findings align with those of Kinatader and Papavassiliou (2021), who found no evidence of the HE in bitcoin.

4.2 The Day-of-the-Week Effect

The mean equation in Table 3 results reveal no DoW anomalies for AAVE, SNX, and UNI. However, for LINK, a weak positive DoW effect (0.0054) is observed on Wednesday's returns, statistically significant at the 10% level. Additionally, Friday exhibits a moderate negative DoW effect (-0.0067), while Saturday shows a moderate positive effect (0.0058). These findings align with the presence of a negative AR (1) term, reinforcing the concept of mean reversion, where current returns tend to move inversely to their historical values—a behavioral pattern consistently observed across all analyzed DeFi assets. Similarly, MKR returns display a weak negative DoW effect (-0.0052) on Tuesday and a moderate positive effect (0.0050) on Sunday.

In contrast to returns, the analysis of volatility reveals a more pronounced DoW effect. Notably, Tuesdays across all DeFi assets, excluding UNI, demonstrate statistically significant excess volatility, making it the most prominent day for volatility anomalies. Although the Tuesday coefficients in the mean equation generally lack statistical significance, returns tend to be negative across all DeFi assets on this day. Furthermore, short-term volatility clustering is evident for LINK, AAVE, MKR, and SNX, as these assets exhibit consecutive days of elevated volatility. AAVE exhibits excess volatility spanning from Tuesday to Thursday, while LINK, MKR, and SNX demonstrate heightened volatility over two consecutive days: Tuesday and Wednesday for LINK and MKR, and Monday and Tuesday for SNX. These observations collectively highlight excess Tuesday volatility as a DeFi-specific DoW anomaly.

On an individual asset basis, LINK emerges as the most susceptible to DoW anomalies, characterized by deviations in both returns and volatility. In contrast, UNI shows no evidence of DoW anomalies, either in returns or volatility, underscoring its relative stability among the analyzed DeFi assets.

Tab. 3 – The Day-of-the-Week Effect. Source: own processing

	LINK	AAVE	MKR	SNX	UNI
Mean equation					
Monday	-.0031	-.0009	.0002	.0015	.0009
Tuesday	-.0039	-.0026	-.0052*	-.0020	-.0060

Wednesday	.0054*	.0033	.0011	-.0001	.0019
Thursday	.0008	.0052	-.0026	.0016	.0033
Friday	-.0067**	-.0032	-.0010	-.0060	-.0043
Saturday	.0058**	.0031	.0024	.0042	.0034
Sunday	.0021	-.0047	.0050**	.0031	.0007
Variance equation					
Monday	0e+00	.0003	.0002	.0018**	0e+00
Tuesday	.0008***	.0006**	.0014***	.0030***	.0004
Wednesday	.0006***	.0005**	.0008**	.0003	.0004
Thursday	0e+00	.0005**	.0006	.0008	.0004
Friday	0e+00	0e+00	0e+00	0e+00	0e+00
Saturday	0e+00	0e+00	0e+00	0e+00	0e+00
Sunday	0e+00	0e+00	0e+00	0e+00	0e+00

Note: Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

In cryptocurrency-related research, the DoW effect has been the most extensively studied anomaly, likely due to the 24/7 trading nature of these assets. Notably, scholarly attention has predominantly focused on bitcoin, as other cryptocurrency assets have only risen to prominence relatively recently. Pioneering studies by Decourt et al. (2019) and Kurihara and Fukushima (2017) revealed intriguing patterns, noting notably higher positive returns during bitcoin's early stages, particularly on Tuesday, Wednesday, and Thursday, with Thursday emerging as the most significant day. More recent findings by Liu (2024) identified higher positive returns on Fridays, whereas Mueller (2024) observed that prices and returns tend to be lowest on Fridays for various native cryptocurrencies and tokens. Adding further nuance, Qadan et al. (2022) reported that in 4 of the 8 cryptocurrencies they examined, the strongest returns actually materialize on Tuesdays, suggesting that day-of-the-week patterns can vary considerably across assets and over time. In addition to these return patterns, studies have highlighted consistent trading volume for bitcoin throughout the week (Hansen et al., 2024; Kurihara & Fukushima, 2017) and increased Google search interest on Tuesday, Wednesday, and Thursday (Aharon & Qadan, 2019). These studies underscore not just the presence but the shifting strength and timing of weekly patterns, hinting at time-varying competitive advantages for traders who can adapt quickly.

Our investigation into DeFi assets uncovers a more nuanced landscape. Specifically, Tuesday consistently exhibits heightened volatility across four out of five DeFi assets, suggesting this anomaly may hold particular relevance within the DeFi domain. Additionally, notable DoW effects are observed on Wednesday and Thursday across the majority of the DeFi assets analyzed, although their magnitude is weaker than Tuesday's, implying a diminishing yet still actionable pattern for short-term strategies.

An examination of trading volume distribution throughout the week (see Fig. 3) further enriches these findings. Bitcoin's trading volume dynamics in recent years display a discernible shift, with decreased activity on Mondays and Sundays and relatively stable volumes from Tuesday through Saturday. The observed surge in trading volume from Monday to Tuesday may partially explain the pronounced increase in volatility on Tuesdays across DeFi assets, which in turn encourages market makers to widen spreads or increase margin buffers at the start of the trading week.

Indeed, corroborating evidence from several studies investigating the DoW effect in bitcoin highlights a consistent pattern of increased volatility on Tuesdays (Hamurcu, 2022; Kinatader & Papavassiliou, 2021; Ma & Tanizaki, 2019). Similarly, an examination of Google search trends (Fig. 4) reveals a notable drop in attention during weekends, followed by a sharp rebound on Mondays and relative stability thereafter. This pattern may contribute to heightened volatility, as multiple studies have reported increased volatility on Mondays (Aharon & Qadan, 2019; Hamurcu, 2022; Kaiser, 2019; Kinatader & Papavassiliou, 2021; Ma & Tanizaki, 2019; Tosunoğlu et al., 2023), adding further complexity to the DoW effect puzzle.

For DeFi assets, a distinct trading volume pattern emerges: trading activity begins to rise on Tuesday, peaks on Thursday, and then declines. This trend provides a potential explanation for the heightened volatility observed on Tuesday, Wednesday, and Thursday. As shown in Table 3, Tuesday exhibits the most significant volatility increase, primarily driven by the surge in trading activity transitioning from Monday to Tuesday. While volatility continues to rise through Thursday due to elevated trading activity, the day-over-day increases diminish in intensity, causing the anomaly to dissipate by the end of Thursday. Practically, this tapering profile suggests that any competitive edge from exploiting the DoW effect narrows rapidly after mid-week, steering algorithmic strategies toward short holding periods and encouraging liquidity providers to recalibrate fee tiers by Thursday afternoon.

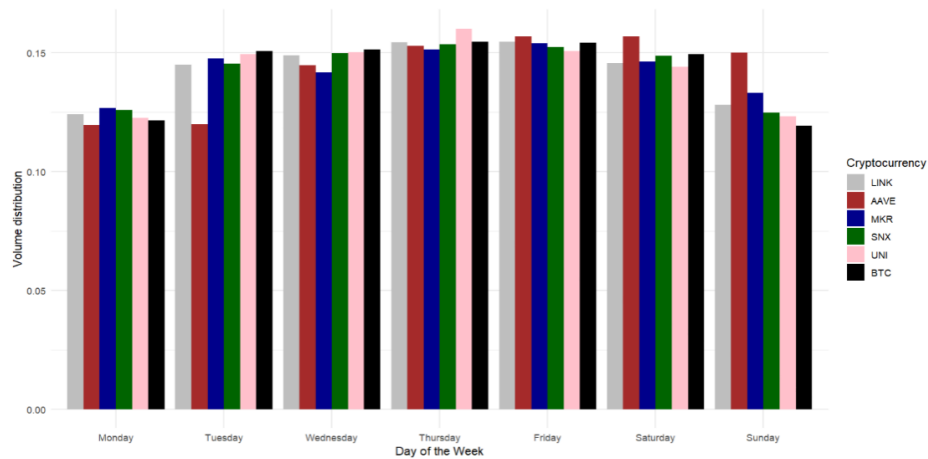


Fig. 3 –Trading volume weekly distribution. Source: own processing

Upon closer examination of Google search trends (see Fig. 4), we observe a notable divergence from the patterns previously reported by Aharon and Qadan (2019) for bitcoin. For bitcoin, search interest is relatively evenly distributed from Monday to Friday, with a decline over the weekend. In contrast, DeFi assets display a more balanced distribution of search interest across weekdays, with a notable peak on Thursday. This provides additional context for the heightened volatility observed leading up to Thursday, suggesting a potential link between search activity and market dynamics.

While Google search trends and trading volume distributions offer valuable insights into the DoW effect on volatility, conflicting findings from prior studies underscore the complex and enigmatic nature of this phenomenon within cryptocurrency markets. Furthermore, it is essential to investigate the potential impact of the DoW effect on the spread of DeFi assets. Given the consistent volatility patterns observed, it is crucial to determine whether exchanges systematically adjust spreads in response to these trends. Such an investigation would provide critical insights into the market microstructure of the DeFi ecosystem, highlighting potential strategies employed by exchanges to mitigate or capitalize on DoW effects. These findings could significantly enhance our understanding of market dynamics and inform both academic research and industry practices.

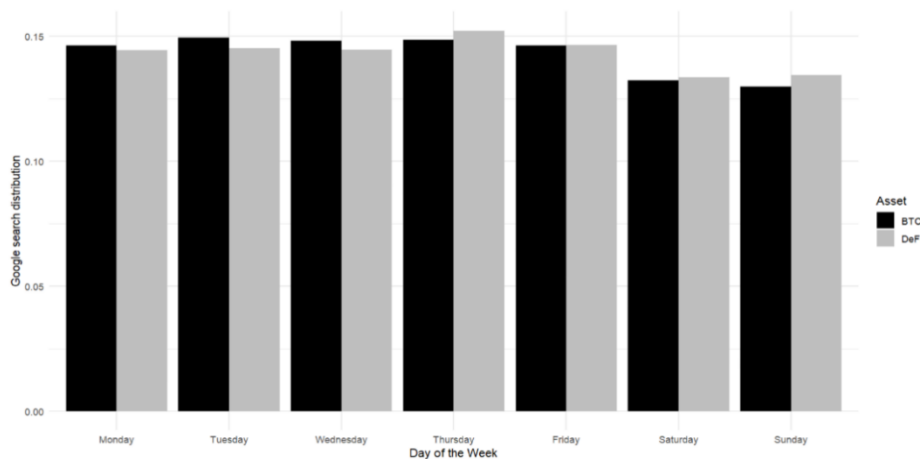


Fig. 4 –Google search weekly distribution for “bitcoin” and “DeFi”. Source: own processing

4.3 The Month-of-the-Year Effect

Table 4 summarizes the results of the MoY effect analysis. The mean equation reveals a notable January effect across all DeFi assets, with the exception of MKR. This January effect generally exhibits a moderate positive impact, with AAVE showing the highest excess returns (0.0135), followed by UNI (0.0097), SNX (0.0092), and LINK (0.0089). Although the January coefficient for MKR is not statistically significant, the returns remain positive. Based on these findings, we infer the presence of a January effect within DeFi assets, supported by moderate yet consistent evidence. Beyond the January effect, additional MoY anomalies are observed, albeit with weaker significance. MKR exhibits a weak positive February effect (0.0059) and a weak positive July effect (0.0050). Similarly, UNI shows a weak positive July effect (0.0073). Negative effects are also noted, with MKR demonstrating a moderate negative August effect (-0.0065) and LINK experiencing a moderate negative December effect (-0.0087). These secondary signals are sporadic and token-specific, implying that any strategic response should be highly selective rather than portfolio-wide.

Tab. 4 – The Month-of-the-Year Effect. Source: own processing

	LINK	AAVE	MKR	SNX	UNI
Mean model					
January	.0089**	.0135**	.0035	.0092*	.0097**
February	.0005	-.0040	.0059*	-.0057	-.0011
March	-.0009	.0001	-.0016	-.0029	.0016

April	.0005	.0011	.0039	.0031	-.0013
May	-.0014	-.0022	-.0026	.0028	-.0040
June	-.0021	-.0096	-.0035	-.0019	-.0035
July	.0022	.0050	.0050*	.0032	.0073*
August	-.0043	-.0030	-.0065**	-.0025	-.0063
September	.0023	.0007	.0001	-.0015	-.0012
October	.0035	.0024	-.0001	-.0006	-.0002
November	.0002	-.0008	-.0007	.0032	3e-05
December	-.0087**	-.0020	-.0019	-.0035	.0004
Variance model					
January	2.7e-05	.0002	.0001	.0003	.0001*
February	3.9e-05	0e+00	.0002	.0002	.0001
March	0e+00	4.3e-05	0e+00	.0001	0e+00
April	0e+00	0e+00	0e+00	4.7e-05	0e+00
May	0e+00	0e+00	0e+00	.0001	0e+00
June	0e+00	.0001	1.8e-05	.0004	.0001
July	0e+00	0e+00	2.7e-05	.0002	0e+00
August	0e+00	0e+00	4.8e-05	0e+00	0e+00
September	0e+00	0e+00	.0001	0e+00	0e+00
October	0e+00	0e+00	0e+00	0e+00	0e+00
November	.0001	6.8e-05	1e-05	2.9e-05	.0001
December	0e+00	1.7e-05	0e+00	0e+00	0e+00

*Note: Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.*

The variance equation reveals a weak January effect (0.0001) for UNI. Volatility across months is relatively uniform, contrasting with pronounced day-of-the-week variability. Because the return premium is sizeable while the volatility shift is minimal, January temporarily improves the risk-adjusted profile of AAVE, UNI, SNX, and LINK, which creates an opportunity for market makers to tighten spreads or for leverage-seeking traders to raise position size with only a modest adjustment to collateral buffers.

The MoY effect investigation reveals a statistically significant January effect, a phenomenon well-documented in traditional finance but largely unexplored in cryptocurrency markets. Notably, Kinatader and Papavassiliou (2021) provide the only prior evidence, identifying a reverse January effect in bitcoin returns. Similarly, Kaiser (2019) reported support for the January effect, though limited to metrics such as volatility, trading volume, and spread. This article is the first to document a consistent January effect across multiple DeFi assets.

While the January effect is linked to window dressing and tax-loss selling, these explanations face scrutiny in cryptocurrency markets. Firstly, the borderless nature of cryptocurrency trading, coupled with the lack of uniformity in capital gains tax regulations across jurisdictions, complicates the plausibility of tax-driven explanations. Secondly, the decentralized nature of crypto transactions complicates tax enforcement, enabling potential deferrals by retail investors. The most compelling challenge to traditional explanations for calendar anomalies, however, stems from the dynamic and volatile nature of cryptocurrency markets. Erratic crypto price movements suggest dominance by speculative short-term investors, rather than long-term portfolio strategies.

Monthly Google search data from 2017–2023 offers insights similar to the DoW effect (see Fig. 5). Bitcoin search activity spiked in December 2017 due to a trading bubble. Excluding this outlier, January emerges as the month with the highest average Google search interest. In contrast, DeFi assets display a more uniform Google search pattern, characterized by heightened interest during the initial months of the year, followed by a gradual decline.

These patterns suggest that Google search activity may play a pivotal role in shaping market dynamics. Supporting this hypothesis, previous studies by Kinatader and Papavassiliou (2021) and Hamurcu (2022) have highlighted reduced volatility in bitcoin during September, coinciding with the lowest Google search traffic. This alignment between search behavior and market outcomes underscores the potential influence of public attention on volatility and reinforces the need for further exploration of its role in explaining calendar anomalies within cryptocurrency markets.

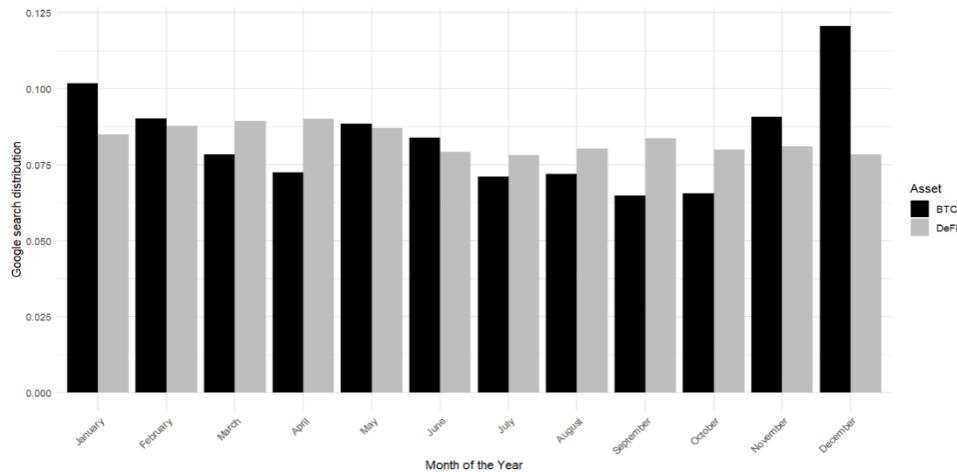


Fig. 5 – Google search monthly distribution for “bitcoin” and “DeFi”. Source: own processing

Analyzing Google search traffic for “how to invest” from 2004 to 2023 also revealed a pronounced spike in January, indicating heightened investment interest at the start of the year. This trend may drive increased activity in speculative assets favored by retail investors during this period. While search trends provide valuable insights into behavioral patterns and calendar anomalies, these phenomena stem from a complex interplay of factors, including market structure, investor psychology, and external conditions. Further research is needed to disentangle these elements and better understand their impact on market dynamics.

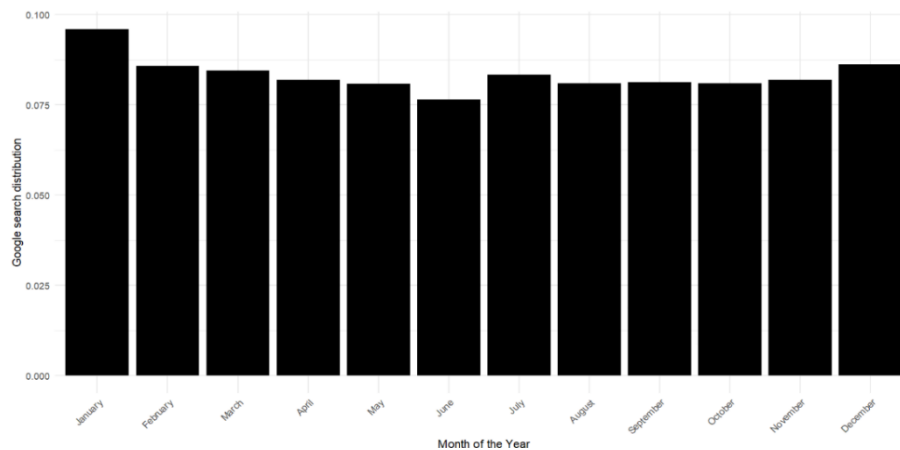


Fig. 6 – Google search monthly distribution for “How to invest.” Source: own processing

4.4 Theoretical and Practical Contributions

This research fundamentally advances the theoretical discourse on calendar anomalies by demonstrating their persistence in decentralized finance markets despite the absence of traditional drivers commonly cited in equity market studies. As Grebe and Schiereck (2024) <https://doi.org/10.7441/joc.2025.03.10>

catalogued, conventional explanations for seasonality such as tax calendars, institutional window-dressing, month-end cash-flow shocks, and strategic news timing are inapplicable in DeFi's borderless, automated, and continuously operating environment. Nevertheless, we document statistically significant Tuesday-related volatility patterns and a consistent January return anomaly. These findings challenge the weak-form efficient market hypothesis (Fama, 1965, 1970), which posits that asset prices fully reflect all available information, thereby precluding the possibility of persistent, exploitable patterns. Our results instead corroborate the view of Bennett et al. (2023), who demonstrate that asset pricing in DeFi adheres more closely to behavioral finance models than to traditional rational expectations frameworks. This also aligns with the earlier argument by Jacobs and Levy (1988), who concluded that human psychology offers a more compelling and broadly applicable explanation for these anomalies. Moreover, our findings complement the AMH perspective advanced by Zhang et al. (2022), which posits that DeFi market efficiency is not static but fluctuates over time based on investor behavior, technological shifts, and market evolution. The recurrence of predictable anomalies in an algorithmically governed system aligns with AMH predictions, further suggesting that periods of inefficiency and behavioral pricing dynamics are endogenous features of DeFi.

In addition, by pioneering a sector-specific analytical lens, our article reveals that calendar anomalies vary systematically across cryptocurrency subsectors. This represents a critical theoretical advancement over prior approaches that relied on market-capitalization-based sampling, which tends to obscure structural differences among asset classes. While earlier studies on bitcoin by Caporale and Plastun (2019), Kaiser (2019), and Kinatader and Papavassiliou (2021) report inconsistent or absent day-of-the-week and month-of-the-year effects, our analysis uncovers a pronounced and consistent Tuesday excess volatility pattern in LINK, AAVE, MKR, and SNX, and a robust January return effect in LINK, AAVE, SNX, and UNI. These results directly contradict the reverse January pattern reported in bitcoin by Kinatader and Papavassiliou (2021), underscoring that grouping payment coins, smart-contract platforms, and DeFi tokens under a unified crypto umbrella overlooks crucial sectoral distinctions.

Our findings also carry important implications for various DeFi stakeholders. Liquidity providers can use this information to manage exposure during high-risk periods, aligning with concerns about value extraction in AMMs (Capponi & Jia, 2021). Traders and arbitrageurs may exploit these predictable patterns to optimize timing, consistent with research showing cyclical

efficiency in DeFi (Gudgeon et al., 2020; Zhang & Chan, 2022). Risk managers can integrate calendar effects into collateral and stress models to better anticipate liquidation risk. Protocol designers may consider time-sensitive adjustments to fees or buffers to improve resilience. Finally, under the efficient market hypothesis (Fama, 1970), making these anomalies public should hasten their disappearance, thus contributing to long-term market efficiency.

An additional practical implication relates to the future viability of these patterns. Under the efficient market hypothesis (Fama, 1965, 1970), once calendar anomalies become widely known, their predictive power should dissipate as rational agents arbitrage them away. By documenting and publicly sharing these patterns, our research contributes not only to academic discourse but also to market efficiency itself, potentially accelerating the absorption and eventual elimination of these anomalies through broader participant awareness.

6. CONCLUSION

This paper investigates calendar anomalies in the daily returns and volatility of five prominent DeFi assets: LINK, AAVE, MKR, SNX, and UNI. Recognizing the sensitivity of seasonality analysis to model specifications, we employ a robust estimator designed to capture the stylized facts characteristic of DeFi returns. Our analysis focuses on three well-established calendar effects—the day-of-the-week effect, the month-of-the-year effect, and the Halloween effect—with the objective of providing robust insights into their presence, characteristics, and potential competitive implications within the dynamic DeFi landscape.

The findings reveal no evidence of a consistent Halloween effect in DeFi, aligning with existing research on bitcoin returns and volatility. However, the analysis of the DoW effect uncovers a distinct and DeFi-specific pattern. While DoW anomalies in returns are inconsistent and asset-specific, volatility dynamics present a clearer picture. Tuesdays exhibit the most significant and consistent excess volatility across the majority of DeFi assets, with evidence of short-term clustering around this day. This highlights Tuesday as a prominent anomaly within the DeFi market, underscoring its potential implications for risk management and trading strategies. Among individual assets, LINK demonstrates the strongest susceptibility to DoW anomalies, while UNI remains notably stable, showing no significant patterns in either returns or volatility.

The analysis of the MoY anomaly reveals a statistically significant and consistent January effect across all DeFi assets except MKR, with AAVE showing the strongest effect. This aligns with traditional financial markets but is unprecedented in cryptocurrencies. Other months show

weaker and inconsistent effects, such as positive February and July effects for MKR, and negative effects in August and December for specific assets. Volatility, in contrast, is relatively uniform across months, diverging from the pronounced DoW effects. UNI is the only asset to exhibit a weak January effect in volatility. While Google search data and trading volume offer valuable supplementary insights, further research is needed to explore the underlying drivers of these anomalies.

While this paper offers valuable insights into calendar anomalies in the DeFi market, it has limitations, focusing on a specific set of assets over a constrained timeframe. Future research should explore the causal mechanisms behind these anomalies, their market and behavioral drivers, and their competitive implications. Investigating how anomalies influence spread dynamics and assessing their long-term persistence are vital to understanding their role in shaping the competitive landscape. Such research would aid stakeholders in making informed decisions and enhance understanding of these patterns and their broader impact on the competitiveness of the DeFi market.

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REFERENCES

- Allen, D. W. E., et al. (2023). The exchange theory of web3 governance. *Kyklos*, 76(4), 659–675. <https://doi.org/10.1111/kykl.12345>
- Aharon, D. Y., & Qadan, M. (2019). Bitcoin and the day-of-the-week effect. *Finance Research Letters*, 31, 415–424. <https://doi.org/10.1016/j.frl.2018.12.004>
- Aslam, F., et al. (2022). Calendar anomalies in Islamic frontier markets. *SAGE Open*, 12(2). <https://doi.org/10.1177/21582440221097886>
- Baur, D. G., Cahill, D., Godfrey, K., & Liu, Z. (2019). Bitcoin time-of-day, day-of-week and month-of-year effects in returns and trading volume. *Finance Research Letters*, 31, 78–92. <https://doi.org/10.1016/J.FRL.2019.04.023>

- Bennett, D., Mekelburg, E., & Williams, T. H. (2023). BeFi meets DeFi: A behavioral finance approach to decentralized finance asset pricing. *Research in International Business and Finance*, 65, 101939.
- Bhambhwani, S., & Huang, A. (2024). Auditing decentralized finance. *British Accounting Review*, 56(2), 101270. <https://doi.org/10.1016/j.bar.2023.101270>, 2024, ISSN 0890-8389.
- Biancone, P., Brescia, V., Chmet, F., and Lanzalonga, F. (2024). The evolution of integrated popular financial reporting: Toward a digital-driven collaborative approach using sentiment analysis tool. *EuroMed Journal of Business*, 20(5), 75–97. <https://doi.org/10.1108/EMJB-11-2023-0298>
- Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3). [https://doi.org/10.1016/0304-4076\(86\)90063-1](https://doi.org/10.1016/0304-4076(86)90063-1)
- Boubaker, S., Essaddam, N., Nguyen, D. K., & Saadi, S. (2017). On the robustness of week-day effect to error distributional assumption: International evidence. *Journal of International Financial Markets, Institutions and Money*, 47. <https://doi.org/10.1016/j.intfin.2016.11.003>
- Bouman, S., & Jacobsen, B. (2002). The Halloween indicator, “sell in May and go away”: Another puzzle. *American Economic Review*, 92(5). <https://doi.org/10.1257/000282802762024683>
- Bourveau, T., Brendel, J., & Schoenfeld, J. (2024). Decentralized finance (DeFi) assurance: Early evidence. *Review of Accounting Studies*, 29, 2209–2253. <https://doi.org/10.1007/s11142-024-09834-8>
- Cai, C. (2018). Disruption of financial intermediation by FinTech: A review on crowdfunding and blockchain. *Accounting and Finance*, 58, 965–992.
- Capponi, A., & Jia, R. (2021). The adoption of blockchain-based decentralized exchanges [Unpublished manuscript]. arXiv. <https://doi.org/10.48550/arXiv.2103.08842>
- Caporale, G. M., & Plastun, A. (2019). The day of the week effect in the cryptocurrency market. *Finance Research Letters*, 31, 258–269. <https://doi.org/10.1016/j.frl.2018.11.012>

- Chen, H., & Singal, V. (2003). Role of speculative short sales in price formation: The case of the weekend effect. *Journal of Finance*, 58(2), 685–705.
<http://www.jstor.org/stable/3094554>
- Chen, Y., & Bellavitis, C. (2019). Blockchain disruption and decentralized finance: The rise of decentralized business models. *Journal of Business Venturing Insights*, forthcoming.
<https://doi.org/10.2139/ssrn.3483608>
- Chiah, M., & Zhong, A. (2021). Tuesday blues and the day-of-the-week effect in stock returns. *Journal of Banking & Finance*, 133, 106243.
<https://doi.org/10.1016/J.JBANKFIN.2021.106243>
- Corbet, S., Goodell, J. W., Gunay, S., & Kaskaloglu, K. (2023). Are DeFi tokens a separate asset class from conventional cryptocurrencies? *Annals of Operations Research*, 322(2), 609–630.
- Cross, F. (1973). The behavior of stock prices on Fridays and Mondays. *Financial Analysts Journal*, 29(6), 67–69. <https://doi.org/10.2469/faj.v29.n6.67>
- De Almeida, J. R., et al. (2022). An analysis of “sell in May and go away” Strategy in Latin American stock markets. *Latin American Business Review*, 23(3).
<https://doi.org/10.1080/10978526.2021.1997334>
- Decourt, R., Chohan, U. W., & Perugini, M. L. (2019). Bitcoin returns and the weekday effect. *SSRN Electronic Journal*, 1931, 1–16. <https://doi.org/10.2139/ssrn.3435176>
- Dunbar, K., Treku, D. N., & Owusu-Amoako, J. (2025). The decentralization enigma in DeFi: Impact of U.S. federal funds rate changes. *British Accounting Review*. Advance online publication. <https://doi.org/10.1016/j.bar.2025.101613>
- Fama, E. F. (1965). The Behavior of stock-market prices. *Journal of Business*, 38(1).
<https://doi.org/10.1086/294743>
- Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance*, 25(2). <https://doi.org/10.2307/2325486>
- French, K. R. (1980). Stock returns and the weekend effect. *Journal of Financial Economics*, 8, 55–69.
- Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the
<https://doi.org/10.7441/joc.2025.03.10>

- expected value and the volatility of the nominal excess return on stocks. *Journal of Finance*, 48(5). <https://doi.org/10.1111/j.1540-6261.1993.tb05128.x>
- Grebe, L., Schiereck, D. (2024). Day-of-the-week effect: A meta-analysis. *Eurasian Economic Review*, 14, 1057–1094. <https://doi.org/10.1007/s40822-024-00293-9>
- Gudgeon, L., et al. (2020). DeFi protocols for loanable funds: Interest rates, liquidity and market efficiency. In *2020 Crypto Valley Conference on Blockchain Technology*, 1–15. IEEE. <https://doi.org/10.1109/CVCBT50464.2020.00005>
- Hamurcu, C. (2022). Examining the existence of day-of-week and month-of-year anomalies in bitcoin. *Kırklareli University Journal of the Faculty of Economics and Administrative Sciences*, 11(1), 162–183. <https://doi.org/10.53306/KLUJFEAS.1062270>
- Jacobs, B. I., & Levy, K. N. (1988). Calendar anomalies: Abnormal returns at calendar turning points. *Financial Analysts Journal*, 44(6), 28–39.
- Jensen, J. R., von Wachter, V., & Ross, O. (2021). How decentralized is the governance of blockchain-based finance: Empirical evidence from four governance token distributions. <http://arxiv.org/abs/2102.10096>
- Kaiser, L. (2019). Seasonality in cryptocurrencies. *Finance Research Letters*, 31, 232–238. <https://doi.org/10.1016/J.FRL.2018.11.007>
- Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2003). Winter blues: A SAD stock market cycle. *American Economic Review*, 93(1), 324–343. <https://doi.org/10.1257/000282803321455322>
- Khan, B., Aqil, M., Alam Kazmi, S. H., & Zaman, S. I. (2023). Day-of-the-week effect and market liquidity: A comparative study from emerging stock markets of Asia. *International Journal of Finance and Economics*, 28(1). <https://doi.org/10.1002/ijfe.2435>
- Kinateder, H., & Papavassiliou, V. G. (2021). Calendar effects in bitcoin returns and volatility. *Finance Research Letters*, 38, 101420. <https://doi.org/10.1016/j.frl.2019.101420>
- Kiymaz, H., & Berument, H. (2003). The day of the week effect on stock market volatility and volume: International evidence. *Review of Financial Economics*, 12(4). <https://doi.org/10.7441/joc.2025.03.10>

[https://doi.org/10.1016/S1058-3300\(03\)00038-7](https://doi.org/10.1016/S1058-3300(03)00038-7)

- Kurihara, Y., & Fukushima, A. (2017). The market efficiency of bitcoin: A weekly anomaly perspective. *Journal of Applied Finance & Banking*, 7(3), 57-64.
- Liu, C.-H. (2024). Exploring calendar effects in bitcoin returns: An analysis of market efficiency. *Journal of Applied Finance & Banking*, 14(4), 33–52.
<https://doi.org/10.47260/jafb/1443>
- Lobão, J., & Costa, A. C. (2023). The adaptive dynamics of the Halloween effect: Evidence from a 120-year sample from a small European market. *International Journal of Financial Studies*, 11(1). <https://doi.org/10.3390/ijfs11010013>
- Ma, D., & Tanizaki, H. (2019). On the day-of-the-week effects of bitcoin markets: International evidence. *China Finance Review International*, 9(4), 455–478.
<https://doi.org/10.1108/CFRI-12-2018-0158>
- Maouchi, Y., Charfeddine, L., & El Montasser, G. (2022). Understanding digital bubbles amidst the COVID-19 pandemic: Evidence from DeFi and NFTs. *Finance Research Letters*, 47(A), 102584. <https://doi.org/10.1016/j.frl.2021.102584>
- Meyer, E., Welp, I., & Sandner, P. (2022). Decentralized Finance – A systematic literature review and research directions. *Proceedings of the European Conference on Information Systems*, 1–17.
- Mueller, L. (2024). Revisiting seasonality in cryptocurrencies. *Finance Research Letters*, 64, 105429. <https://doi.org/10.1016/j.frl.2024.105429>
- Negara, E. S., Hidayanto, A. N., Andryani, R., & Syaputra, R. (2021). Survey of smart contract framework and its application. *Information*, 12(7), 257. <https://doi.org/10.3390/info12070257>
- Pernice, I. G., et al. (2019). Monetary stabilization in cryptocurrencies – Design approaches and open questions.” *2019 Crypto Valley Conference on Blockchain Technology*, 47–59.
- Philippon, T. (2014). Has the finance industry become less efficient? On the theory and measurement of financial intermediation *American Economic Review*, 105(4), 1408–1438.
- Plastun, A., Sibande, X., Gupta, R., & Wohar, M. E. (2019). Rise and fall of calendar
<https://doi.org/10.7441/joc.2025.03.10>

- anomalies over a century. *North American Journal of Economics and Finance*, 49, 181–205. <https://doi.org/10.1016/j.najef.2019.04.011>
- Plastun, A., Sibande, X., Gupta, R., & Wohar, M. E. (2020). Halloween effect in developed stock markets: A historical perspective. *International Economics*, 161. <https://doi.org/10.1016/j.inteco.2019.11.009>
- Qadan, M., Aharon, D. Y., & Eichel, R. (2022). Seasonal and calendar effects and the price efficiency of cryptocurrencies. *Finance Research Letters*, 46. <https://doi.org/10.1016/j.frl.2021.102354>
- Rech, F., et al. (2022). Bitcoin transaction fees, miners' revenue, concentration and electricity consumption: A failing ecosystem. *Prague Economic Papers*, 31(5), 377–397. <https://doi.org/10.18267/j.pep.817>
- Rozeff, M. S., & Kinney, W. R. (1976). Capital market seasonality: The case of stock returns. *Journal of Financial Economics*, 3(4). [https://doi.org/10.1016/0304-405X\(76\)90028-3](https://doi.org/10.1016/0304-405X(76)90028-3)
- Saengchote, K., & Samphantharak, K. (2024). Digital money creation and algorithmic stablecoin run. *Finance Research Letters*, 64, 105435. <https://doi.org/10.1016/j.frl.2024.105435>
- Sahu, S., Fonseca Ramírez, A., & Kim, J.-M. (2024). Exploring calendar anomalies and volatility dynamics in cryptocurrencies: A comparative analysis of day-of-the-week effects before and during the COVID-19 pandemic. *Journal of Risk and Financial Management*, 17(8), 351. <https://doi.org/10.3390/jrfm17080351>
- Schar, F. (2021). Decentralized finance: On blockchain- and smart contract-based financial markets. *Review*, 103(2), 153–154. <https://doi.org/10.20955/r.103.153-74>
- Sockin, M., & Xiong, W. (2023). Decentralization through tokenization. *Journal of Finance*, 78(1), 247–299. <https://doi.org/10.1111/jofi.13192>
- Sood, K., et al. (2023). Identification and prioritization of the risks in the mass adoption of artificial intelligence-driven stable coins: The quest for optimal resource utilization. *Resources Policy*, 81, 103235. <https://doi.org/10.1016/j.resourpol.2022.103235>
- Tosunoğlu, N., Abacı, H., Ateş, G., & Saygılı Akkaya, N. (2023). Artificial neural network analysis of the day of the week anomaly in cryptocurrencies. *Financial Innovation*, 9(1). <https://doi.org/10.7441/joc.2025.03.10>

<https://doi.org/10.1186/s40854-023-00499-x>

- Wang, Y., et al. (2022). Bubbles all the way down? Detecting and date-stamping bubble behaviours in NFT and DeFi markets. *Journal of Chinese Economic and Business Studies*, 20(4), 415–436. <https://doi.org/10.1080/14765284.2022.2138161>
- Werner, S., et al. (2022). SoK: Decentralized finance (DeFi). *Proceedings of the Fourth ACM Conference on Advances in Financial Technologies*, 30–46. <https://doi.org/10.1145/3558535.3559780>
- Yousaf, I., Nekhili, R., & Gubareva, M. (2022). Linkages between DeFi assets and conventional currencies: Evidence from the COVID-19 pandemic. *International Review of Financial Analysis*, 81, 102082. <https://doi.org/10.1016/j.irfa.2022.102082>
- Zetsche, D., Arner, D., & Buckley, R. (2020). Decentralised finance. *Journal of Financial Regulation*, 6(2), 172–203. <https://doi.org/10.1093/jfr/fjaa010>
- Zhang, Y., Chan, S., Chu, J., & Shih, S. (2022). The adaptive market hypothesis of decentralized finance (DeFi). *Applied Economics*, 55(42), 4975–4989. <https://doi.org/10.1080/00036846.2022.2133895>
- Zhang, J., Lai, Y., & Lin, J. (2017). The day-of-the-week effects of stock markets in different countries. *Finance Research Letters*, 20, 47–62. <https://doi.org/10.1016/J.FRL.2016.09.006>
- Xu, R., et al. (2024). Decentralized finance (DeFi): A paradigm shift in the fintech. *Enterprise Information Systems*, 18(9). <https://doi.org/10.1080/17517575.2024.2397630>

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