School of Economics and Management

"Impact of staking policy on returns in the crypto market: A Comprehensive Analysis of the 'dividends' of the crypto market"

Master Thesis Finance

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Abstract

Cryptocurrencies have become increasingly popular as an investment due to their diversification role and potential use in innovative projects. A distinctive characteristic of many currencies is the ability to lock currencies to earn passive rewards, known as staking. Most existing studies have focused on the theoretical advantages of these Proof-of-Stake coins, but little effort has been made to examine their practical effects on returns. This paper aims to fill this gap by analyzing staking-specific variables, such as the staking yield and ratio gathered from StakingRewards.com, to examine the effects of staking on daily returns. Furthermore, prior research suggests that other variables, such as sentiment and regulatory changes, may also generate high volatility spikes. Ten currencies are selected for the sample, all with unique characteristics enabling a comprehensive examination of staking effects. The results indicate mixed results, with Solana and Ethereum both providing evidence that increased staking returns are associated with higher returns of 0.0662% and 0.6368%, respectively. In contrast, Cardano, Ton, and Tron exhibit mixed results, where higher yields lead to lower returns. This indicates that staking effects are not uniform and depend on currency-specific conditions.

Additionally, GARCH(1,1) models are used to evaluate the impact of these variables on volatility. The findings indicate that changes in trading volume affect volatility across most currencies, while Polkadot and Cosmos, the currencies with the longest lockup periods in the sample, show increased volatility linked to lockup duration. This may reflect investors' tendency to reinvest or sell the staked tokens rewards. These insights offer valuable empirical evidence for policymakers, investors, and institutions to explore blockchain technology, informing on strategic decisions and risk management in the cryptocurrency market.

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1. Introduction

The rise of cryptocurrencies as an alternative asset class began with Bitcoin and it's mining-based consensus mechanism, has interested investors, policymakers, and institutions. As the ecosystem of cryptocurrencies evolved, attention expanded to staking, an alternative to mining, which offers both economic and network incentives. Through staking, cryptocurrency holders lock their tokens, which enhances network stability and supports the validation of blockchain transactions. In return, these holders earn passive periodic rewards, similar to a dividend payout in traditional finance. However, unlike the extensive research conducted in traditional finance, there has been little to no empirical research exploring the impact of staking metrics on returns. Since these metrics may present an additional return, they may influence investment strategies and staking policies.

The existing literature on staking remains theoretical, with a minimal focus on empirical studies. Theoretical studies offer valuable insights into the potential impacts of staking. However, empirical investigation is necessary to understand the implications on returns fully. Previous study suggests that higher staking ratios lead to higher returns, with market indices serving as a key indicator of these returns, highlighting the strong correlation among currencies (Cong et al. 2025). However, these studies leave out the impact of staking yields on returns, suggesting that not all staking metrics are accounted for.

Understanding the empirical effects of staking metrics on returns is crucial for developing optimal investment strategies, implementing blockchain technology, and optimizing policies related to staking. Staking metrics may not be fully priced in, offering additional returns on investments. However, these staking metrics may introduce risks that require careful consideration.

The exploration of staking's impact on cryptocurrency returns forms the core of this thesis, motivated by a research gap where empirical evidence is limited despite robust theoretical foundations. In traditional finance, studies such as those by Modigliani and Miller (1961) establish dividends being irrelevant to firm value, with Black and Scholes (1974) suggesting that dividends may impact stock prices because of signaling, but note that if dividends adjust value, firms may adjust policies for its valuations. In contrast, DeAngelo and DeAngelo (2006) and Baker et al. (2002) show that dividends do impact firm value, based on input from managers, or contradicting assumptions made by prior studies. Literature on cryptocurrencies, such as John et al. (2021) and Riposo and Gupta (2024), focus on the role of staking in Proof-of-Stake systems, prioritizing its benefits, like network security and adoption, but provides limited empirical insights into its direct effects on returns. This shortcoming in literature inspires the central research question: "*Do staking rewards enhance returns on cryptocurrencies?"* This question aims to quantify whether staking yields function as a return-enhancing mechanism, and whether they shape investor behavior or market stability due to the decentralized nature of cryptocurrencies.

Beyond examining the direct impact of staking on returns, the thesis will also investigate the volatility implications of staking, as formed via a complementary question inspired by Catalini and Gans (2020): *"Does the duration of staking lockups reduce the volatility of cryptocurrencies?"* This question will evaluate whether more extended lockup periods, which reduce circulating supply, mitigate volatility or risk of supply shocks, as cautioned by Budish (2022). These research questions support two hypotheses: first, *Higher staking reward rates positively affect cryptocurrency returns,* which mirrors the return-enhancing effect of dividends noted by Iftikhar et al. (2017) and supported by Cong et al.'s (2025) concept of crypto carry, and second, *Cryptocurrencies with longer staking lockup durations exhibit lower price volatility compared to those with shorter, or no lockups.* This hypothesis reflects Fama and French's (2001) findings on the stability effects of dividends. Together, these questions and hypotheses provide a narrative to evaluate the economic significance of staking, offering empirical insights that could guide investment strategies and inform staking policies in decentralized finance.

The research questions are addressed by employing a robust empirical framework, selecting data and techniques based on prior studies that examine the economic impacts of staking on returns and volatility in cryptocurrencies. The thesis focuses on ten staking cryptocurrencies: Ethereum, Solana, Cardano, Cosmos, Algorand, Tron, Ton, Binance, Polkadot, and Avalanche. These cryptocurrencies were selected based on their market capitalization exceeding $1 billion in 2024 and their launch before 2022, as per data from CoinMarketCap. This selection ensures robust price dynamics and significant staking activity, thereby minimizing noise in smaller-cap coins. Since the sample features unique staking systems with distinct mechanisms, such as liquid staking in Ethereum, the governance-based system of Algorand, and long lockup durations in Polkadot and Cosmos, it enables a comprehensive exploration of staking's effects across different network designs and investor behavior. Returns are calculated using logarithmic returns based on daily price data obtained from Coinbase, a major exchange with strict regulations ensuring independence and reliability (Bobin, 2022). Staking metrics, including yields, ratios, and lockup durations, are sourced from StakingRewards.com and cross-verified against blockchain explorers, ensuring accurate and consistent data for the period from 2022 to 2024. These datasets are ideal for testing both hypotheses, as they directly capture the incentives and constraints of staking, which are crucial for understanding the impact on returns and volatility.

To enhance the robustness of the findings, the analysis incorporates market and macroeconomic data to control external influences on cryptocurrency markets. The S&P Cryptocurrency Broad Digital Market Index tracks market-wide trends, with weekend returns interpolated to align with daily cryptocurrency trading. Market sentiment is captured via the Fear & Greed Index, obtained from Alternative.me, along with currency-specific sentiment from LunarCrush, effectively addressing endogeneity from investor behavior that could dilute the impact of staking. Macroeconomic variables are accounted for by a regulatory dummy, with the U.S. Federal Reserve's daily effective rate initially considered as a variable but excluded due to concerns about multicollinearity, as identified through Variance Inflation Factor analysis. The empirical techniques include an OLS regression for Hypothesis 1. Hypothesis 2 is addressed using a GARCH(1,1) model, which captures time-varying volatility, an ideal approach for cryptocurrencies due to volatility clustering (Chu et al., 2017).

The empirical analysis shows mixed results for Hypothesis 1, revealing the subtle effect of staking across cryptocurrencies. The regression analysis reveals significant positive effects for Ethereum and Solana, where a 1% increase in staking yield boosting daily returns by 0.0662% and 0.6368%, respectively. This supports Cong et al.'s (2025) "crypto carry" concept, which posits that staking incentives reduce sell pressure and enhance returns. However, Ton, Tron, and Cardano exhibit significant negative effects, with a 1% increase in yield, lowering returns by 0.0051%, 0.0079%, and 0.6552%, respectively, suggesting that high yields may signal risk or trigger selloffs as stakers liquidate rewards, aligning with Schär's (2021) observations of speculative behavior in staking systems. For other currencies, the effects of staking yield are insignificant, indicating that staking rewards do not consistently drive returns, possibly due to differences in network maturity, lockup structures, or investor behavior. The staking ratio shows positive effects for Algorand, Solana, and Cardano, with a 1% increase in the ratio increasing returns by 0.0762%, 0.0001%, and 0.0051%, respectively, reflecting investor confidence in mature networks, supporting findings of Cong et al. (2025), but negative effects for Ton and Tron suggest selling pressure from reward distribution. The S&P Cryptocurrency Broad Digital Market Index is a significant driver of returns for most currencies, underscoring market correlation. Meanwhile, sentiment and trading volume have significant effects on Tron and Binance, highlighting the role of liquidity. These findings are relevant as they extend Baker et al.'s (2002) dividend analogy, revealing that staking's return-enhancing potential is dependent on currencies shaped by network-specific dynamics and market conditions.

However, volatility in cryptocurrency markets complicates consistent pricing, as noted by Liu and Tsyvinski (2021).

For Hypothesis 2, the GARCH(1,1) models present a complex picture that partially contradicts the expectations. Across most currencies, trading volume emerges as a dominant driver of volatility, with significant p-values reflecting increased price swings resulting from supply-demand shifts, consistent with Foroutan and Lahmiri (2022). However, lockup durations significantly increase volatility in Polkadot, Cardano, and Cosmos, with coefficients of 0.000003%, 0.000006%, and 0.00000003% per unit change, respectively, contradicting the hypothesis. These currencies offer unique lockup structures, with Polkadot and Cosmos being among the currencies in the sample with the most extended lockup periods. Cardano, on the other hand, offers both liquid and fixed staking structures, which may experience volatility due to periodic reward reinvestment or selling, potentially amplifying market activity rather than stabilizing prices, as cautioned by Budish (2022). For other currencies, the lockup duration has no significant effect, suggesting that currency-specific factors, such as liquidity and staking flexibility, outweigh the impact of lockups. Additionally, the GARCH(1,1) models are plotted in volatility graphs, which reveal shared spikes across all currencies, notably after the 2024 U.S. presidential election and the implementation of MiCA, indicating that macroeconomic and regulatory events have more impact compared to the volatility effects of staking, aligning with Liu and Tsyvinski's (2021) findings on the regulatory impacts. These results are noteworthy as they challenge Catalini and Gans' (2020) assertion that lockups stabilize prices, highlighting the criticism of staking design and external shocks, which demands further research into staking protocol variations and their interaction with market conditions.

These findings have substantial academic and practical implications, enriching our understanding of the economic role of staking in cryptocurrencies. Academically, the study fills a gap in the literature by empirically testing staking metrics absent in prior work by Cong et al. (2025) and Liu and Tsyvinski (2021), confirming that staking's effects on returns and volatility are not universal but depend on network design and market maturity. The positive yield effects for Ethereum and Solana support Buterin's (2020) and Saleh's (2021) theoretical models of staking's stabilizing incentives, while negative effects in Ton, Tron, and Cardano underscore speculative risks noted by Schär (2021). Practically, investors can leverage these insights to prioritize mature networks with stable staking yields, such as Ethereum, while remaining cautious of the volatility risks associated with currencies that have longer lockups, like Polkadot and Cosmos. Policymakers may use the findings on volatility to design regulations that enhance transparency in reward distribution, thereby mitigating supply uncertainty during turbulent periods, such as future U.S. elections or the implementation of new laws. Institutions exploring blockchain integration can favor networks with balanced staking designs to minimize volatility risks while leveraging the benefits of staking, such as energy efficiency. The mixed results underscore the complexity of staking dynamics, highlighting the need for future research to investigate how maturing cryptocurrency markets, and evolving regulatory frameworks influence the economic impacts of staking.

The thesis finds that staking in cryptocurrencies has a limited impact on returns and volatility, with significant positive effects on returns for mature networks, such as Ethereum and Solana, but negative or insignificant effects elsewhere. Additionally, it unexpectedly reveals increased volatility from longer lockup durations in currencies like Polkadot and Cosmos. The key finding is that staking's economic benefits, similar to dividends in traditional finance, are currency-dependent, shaped by network design, market maturity, and external shocks, offering valuable insights for investors to prioritize stable networks and for policymakers to enhance reward transparency. However, limitations include the reliance on a 2022 to 2024 dataset, which may not capture long-term trends as cryptocurrency markets mature, and the potential for unobserved variables, such as network usage or accounting for whales, which may influence results. Econometric challenges, like heteroskedasticity addressed with robust standard errors and the exclusion of the Federal Reserve rate due to multicollinearity, suggest model refinements. Future research should extend the time frame, incorporate additional staking-specific metrics, such as validator concentration, and explore advanced models, including panel regressions or machine learning, to capture dynamic interactions better and address endogeneity, thereby enhancing the generalizability of staking's economic implications.

The rest of the thesis is organized as follows: Chapter 2 presents a detailed literature review, building on traditional finance theories related to dividend impacts and bridging them to cryptocurrency research on staking, thereby establishing the theoretical foundation for this study. Chapter 3 defines the research questions and hypotheses, focusing on the empirical impact of staking's effects on returns and volatility. Chapter 4 discusses the data selection process, outlining the selection of ten cryptocurrencies based on specific thresholds and describing key variables, including staking metrics, market sentiment, and macroeconomic variables, for the 2022-2024 period. Chapter 5 presents the empirical methodology for testing Hypothesis 1, using an OLS regression and implementing a GARCH(1,1) model to examine Hypothesis 2. Chapter 6 continues on the empirical models presented in Chapter 5, detailing both models used to test the hypotheses. Chapter 7 presents empirical findings, examining whether the hypotheses are supported. Finally, Chapter 8 concludes this thesis, summarizing key findings and discussing key limitations that offer potential for future research.

2. Literature Review

The evolution of the cryptocurrency market has introduced mechanisms that challenge traditional financial theory, with staking being a key feature of Proof-Of-Stake (PoS) blockchain protocols. Staking allows investors to lock up their holdings to support network operations. As compensation, investors receive periodic rewards comparable to dividends in stocks or coupon payments with bonds. In traditional finance, researchers have established the influence of periodic payments on asset pricing, investor behavior, and market dynamics. Studies by Modigliani and Miller, as well as Black and Scholes, demonstrate how periodic payments affect liquidity and impact returns and firm value (Modigliani & Miller, 1961; Black & Scholes, 1974). In the domain of cryptocurrency, however, the direct impact of staking on asset returns and dynamics remains underexplored.

2.1 Theory of traditional finance

In traditional finance, periodic payments play a crucial role in asset valuation, market dynamics, and investor behavior. Since these periodic payouts to stockholders are comparable to payments to stakers, the literature on traditional finance offers a framework for evaluating the economic impact of staking.

Modigliani and Miller (1961) established a theory, assuming a perfect market, that dividend policy is irrelevant to firm value. Returns should only depend on investment decisions rather than payouts. However, they acknowledged that in the presence of market imperfections, such as taxes or asymmetric information, dividend policy could become relevant, suggesting that periodic payments may enhance returns, a mechanism that staking rewards in cryptocurrency prices may mirror.

Black and Scholes (1974) argue that if payout policies impact values, firms can increase their share price by adjusting their payout ratio. This would saturate demand for different dividend-yielding stocks, leading to an equilibrium in which the policy would not affect the stock price. They confirm this by presenting empirical evidence that different dividend yields result in variations in stock returns, suggesting that dividend policies do not consistently impact stock prices.

The statements about the irrelevance of dividends contradict valuation models that consider dividends, such as the Dividend Discount Model (DDM), which was founded by Williams (1938). This model values assets based on the present value of future dividends, formulated as $p = \sum_{t=1}^{\infty} \frac{D^t}{(1+r)^t}$. This model was later refined by Gordon (1959), where the author introduced the Gordon Growth Model (GGM), formulated as $p_0 = \frac{D_1}{r-g}$. Within the model, constant dividend growth is assumed. In his paper, Gordon quantified the role of stable payouts on returns, providing a foundational link between periodic payments and asset valuation.

Bhattacharya (1979) extended the dividend debate by introducing a signaling model where dividends convey private information. In his framework, dividends serve as a signal of firm quality in the presence of asymmetric information. High-quality firms use dividends to differentiate themselves from lower-quality firms, making the payout policy informative for investors. This signaling logic, particularly relevant for staking, offers a key insight into the importance of dividend policies in the finance sector.

DeAngelo and DeAngelo (2006) support the findings that dividend policies impact value in the paper "The Irrelevance of the M&M Dividend Irrelevance Theorem." The researchers argue that payout policies do impact firm value and highlight different frictions overlooked in M&M's original model, such as taxes, agency costs, and cash flow asymmetries. These real-world frictions explain why dividends can influence asset prices. The critique suggests that dividend payments do influence firm value and returns, which is a relevant perspective to consider when evaluating staking rewards.

Rozeff (1982) extends research into the relevance of dividends. The author found that dividend policies can mitigate agency conflicts by distributing free cash flows, thereby aligning the interests of managers and shareholders, suggesting that high dividend payouts signal good governance and enhance firm value. This perspective on agency problems suggests that staking policies could align the interests of holders and protocol developers, thereby boosting investor confidence and returns. Rozeff's findings strengthen the need to assess the economic impact of staking, as he highlighted the governance role of payouts.

Baker et al. (2002) surveyed managers of firms that pay cash dividends to investigate the relationship between dividend policy and value, their views on dividend policies, and the explanations for paying dividends. They find that managers support statements that suggest dividend policy matters and stress the importance of dividend continuity. The managers offer no support for the tax preferences and agency cost explanations for dividend payouts, instead suggesting that dividends should serve as a signal to investors of private information, similar to Bhattacharya (1979).

Fama and French (2001) link a decline in paid dividends to firm maturity. They suggest that established firms are more likely to pay dividends, whereas growth firms prefer to reinvest profits or distribute value through capital gains. This lifecycle perspective implies that staking may be more common or more valued in mature blockchain ecosystems, mirroring dividend behavior in established companies.

Baker and Weigand (2015) offer modern research on dividend policy and its impact on firm valuation. The authors provide a comprehensive overview of all the important literature on dividend policies. They find that there is no universal theory explaining why firms pay dividends or the quantity of dividends they pay.

Iftikhar et al. (2017) continue on the theoretical research in traditional finance and provide empirical evidence that dividend payouts impact stock prices. The authors use a regression to show that with a one-unit increase in dividend payout, stock prices increase by 19.38730. Similarly, an increase in dividend per share leads to a 5.373796 increase in stock prices.

The debate within traditional finance underscores the need to evaluate the effects of staking in cryptocurrency finance, as the formulas used in traditional finance may also have an impact on staking cryptocurrencies. Staking rewards resemble dividends, which means that DDM or GGM may be used to value tokens. However, the variability in staking and the risks of locking up tokens, such as market manipulation, challenge the traditional literature, making perfect market assumptions less applicable.

Cong, He, and Tang (2025) bridge the findings from traditional finance to cryptocurrencies in their paper "The Tokenomics of Staking." The authors develop a model of tokenomics that introduces "crypto carry" to link staking rewards to price changes. Crypto carry refers to the yield from token lockups, similar to dividends, and is shown to reduce supply and increase adoption, potentially enhancing returns. They suggest that staking rewards influence prices beyond traditional cash flows, indicating a combination of periodic income and speculative growth.

The rising participation among institutional and retail investors shows the growing adoption of staking. Literature in traditional finance shows both empirical and theoretical evidence of the impact that dividends payout has on stock prices. Based on these results, the gap in crypto finance needs to be investigated to fully understand market dynamics.

2.2 Proof-Of-Stake

To understand the role of staking in cryptocurrencies, an analysis of the staking mechanisms and their economic implications is crucial. PoS is a protocol where token holders lock their assets, which validates transactions and increases network security in exchange for periodic rewards. This section reviews studies on the comparison of PoS with Proof-of-Work (PoW). Also, the impact of staking via periodic rewards and locked tokens on the market is studied. Findings are found in theoretical frameworks and empirical research.

Research in PoS shows that this is an energy-efficient alternative to PoW, which depends on data mining. Saleh (2021) examines PoS using a theoretical model that compares PoS and PoW. The model assumes tokens are staked to increase network security and focuses on the process of preventing energy waste. Saleh only uses theoretical evidence to predict the behavior of PoS under specific conditions, such as the number of stakers. The key findings indicate that PoW requires more energy, while PoS requires almost none. This is explained as PoS depends on tokens rather than machines and computers needed in PoW. Saleh also finds that PoS can maintain a consensus, which is a stable agreement regarding transactions if enough tokens are staked. Chiu and Koeppl (2017) provide insights into the comparison between PoS and PoW systems, focusing on their abilities to prevent double spending, a mechanism where holders spend the same tokens multiple times. They examine the consensus mechanisms, and how this aligns with validator behavior and network security, focusing on the importance of penalties, such as slashing, to counter malicious actions, showing the benefits of PoS compared to PoW. Their model remains theoretical, as it explores the theoretical structure of both mechanisms. Empirical data on energy consumption, one of the key benefits of PoS is provided by Digiconomist. The author shows that Bitcoin (PoW) consumes 700-1000 kWh per transaction. Comparing this to Ethereum (PoS), it gets reduced by over 99.95%, estimating to require about 0.03-0.1 kWh per transaction (Digiconomist, 2025)

Buterin (2020), the inventor of Ethereum, explained the reasoning behind the transition of Ethereum from PoW to PoS. One of the primary motivations for the transition to PoS is to address the energy-intensive nature of PoW. Buterin noted the significant requirement for computational power in PoW, which leads to substantial energy consumption. This is replaced by the implementation of PoS, where validators participate in staking, thereby reducing the environmental footprint, as also found by Saleh (2021) and the Digiconomist (2025). Another key reason for the transition of Ethereum to PoS is the robust security, which the authors find to be more efficient compared to PoW. With PoS, investors are incentivized for honest behavior, as staked tokens may be slashed for malicious behavior (Buterin, 2020; Chiu & Koeppl, 2017).

2.3 Economic implications of staking

Staking in PoS systems does more than secure networks, it changes market dynamics as tokens are locked in exchange for a return. This reduction in supply may influence investor behavior and impact price action, much like dividends in traditional finance. This section examines the economic implications of staking, which helps to understand the role of staking in generating returns.

Cong, He, and Li (2021) investigate staking pools, in which token holders combine assets to validate transactions and earn rewards. To show the impact, they create a model that simulates a network based on PoS with staking pools. With the assumption that holders have more tokens staked than others, they evaluate how these pools are formed and how rewards are distributed. The model focuses solely on theoretical aspects, avoiding real-world data. They find that staking pools make rewards more consistent. A reduction of variation in payouts of staking by 2-5% compared to solo staking. The authors provide reasons for this variation, including risk sharing in pools and the benefits of scaling. However, they warn about the risks of manipulation in these pools, as they may lead to centralization, where large holders control a significant portion of the staked assets, potentially influencing prices, or network stability. However, the study only focuses on these pools and does not show the effects on prices or returns.

Catalini and Gans (2020) study the effect of holder behavior. They use a theoretical model that acts like a stablecoin market, where holders lock tokens to stabilize the value of a currency, similar to staking, where holders earn a periodic reward. They solely use theoretical assumptions and test the costs of locking tokens, such as sudden price increases. They evaluate different scenarios, such as changes in returns or varying lockup periods, to observe the behavior of investors. They show that locking up tokens incentives long-term holdings and a decrease in selloffs when the markets go down. They also note the flexibility costs of locking up tokens. During this period, investors are unable to sell tokens if the price increases, but periodic returns offset this. However, as if it were only a theoretical framework, no real-world data is used to demonstrate the impact of staking on prices or returns. These studies provide theoretical evidence for staking and how supply may be reduced, encouraging long-term holding. However, no data is provided to verify whether this affects market prices or returns.

Budish (2022) explores the liquidity implications, suggesting that staking's token lockups reduce market fluidity, potentially indicating strong confidence among holders, as they may be more long-term focused. They found that limiting short-term speculation aids price discovery. However, the authors warn about volatility spikes when the shortage of supply disrupts the market equilibrium. The authors base the findings on a theoretical model which focuses on Bitcoin. The model assumes tokens are locked to improve network functions, which reduces the available supply. Different scenarios are theoretically assessed to see if trading fluidity and price discovery are affected. The findings of Budish are supported by Schär (2021), who notes that projects may rely on governance voting schemes, where token holders grant voting rights, similar to a stock. These tokens may increase active participation in the token but note that the distribution of tokens is highly concentrated. This may lead to a loss of project credibility, result in massive supply shocks, and have a negative impact on liquidity, as noted by Budish. The findings of Budish and Schär differ from those of Catalini and Gans (2020), who suggest that lockups stabilize prices and volatility. Budish highlights the risks in low-volume markets when reduced liquidity increases price swings. The high concentration risk echoes the warning in the paper of Chiu and Koeppl (2017) about the centralization risks of PoS, where a small group of stakers may impact market dynamics.

2.4 Market dynamics and returns

Staking in PoS systems extends beyond network security. It shapes the dynamics of the cryptocurrency market through its impact on supply, liquidity, and investor behavior. By locking up tokens to earn rewards, staking reduces the circulating supply of tokens. As rewards are commonly paid in tokens, mimicking dividend reinvestment by increasing token holdings, returns may increase as the holdings increase.

Gupta and Krishnamachari (2024) provide empirical evidence on staking rewards. They predict staking rewards for top PoS cryptocurrencies, utilizing regression analysis to forecast rewards based on historical data, including reward rates, token prices, and market trends. They use blockchain explorers to collect daily data and price feeds from exchanges. Their study is based on data from 2022 to 2023. They predict rewards and compare them to actual rewards, measuring accuracy using the root mean squared error (RMSE). They show empirical evidence that the rewards of Ethereum can be predicted with an error of 0.7% for 1-day forecasts and 1.1% for 7-day forecasts. Most staking rewards researched in this study are predictable, but currencies like Solana show slightly less accuracy due to faster block times. However, for their research, they leave out crucial factors for staking, such as the distribution of tokens and the volume of staked assets. Another shortcoming is the short-term predictions, as these are only either 1- or 7-day forecasts. The paper also does not link staking to market outcomes.

John, Rivera, and Saleh (2021) offer a return-orientated perspective in which the researchers analyze equilibrium staking levels in PoS systems. The researchers assume that staking participation stabilizes network economics, making staking a lucrative strategy for token holders. These rewards could enhance total returns as staking reduces supply and improves economic performance. They note that "increasing block rewards reduces short-horizon cryptocurrency investment, which, under certain conditions, reduces the overall transfer to long-horizon investment as well" (John et al., 2021). This decreases total investments in cryptocurrencies, leading to a lower value of the staked assets. However, the researchers remain theoretical, lacking empirical evidence of price action or changes in volatility. Biais et al. (2023) extend this discussion by examining the dynamics and risks of staking. The researchers explore the PoS consensus via a theoretical view. They suggest staking aligned incentives but introduces different risks. Dominant holders may manipulate prices or volatility. Coordination among stakes may change the power dynamics between holders. However, the study warns about the usefulness of the findings as the theory is complex, and the empirical evidence is limited.

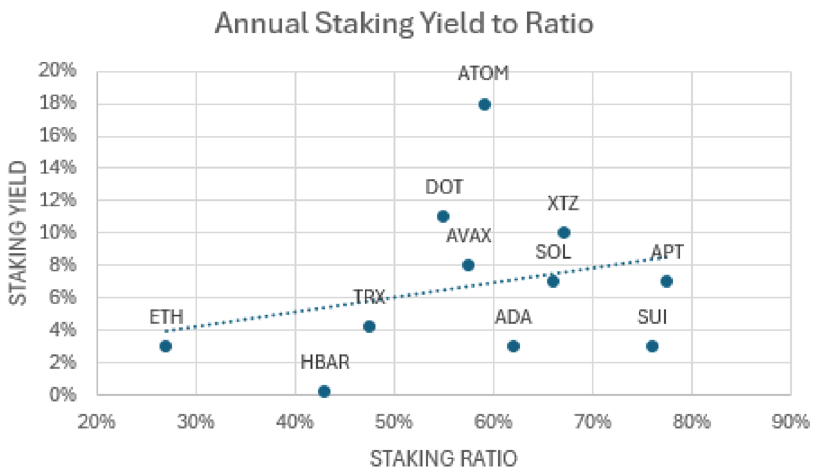

Figure 1: Annual Staking Yield to Staking Ratio (CoinGecko, 2024)

CoinGecko (2024) provides practical insights into staking yields among the top PoS blockchains. In Figure 1, the yields and staking ratios are added, and the staking ratio is the ratio of staked assets compared to total available assets. As shown in the figure, Ethereum has a staking ratio of 28% with an annual yield of 3%, while Polkadot has a staking ratio of 56% with an annual yield of 11%. The figure shows no definite trend between a higher yield and a higher staking ratio, suggesting that investors consider more aspects to stake rather than solely yields.

Cong et al. (2025) provide empirical evidence that a higher aggregate staking reward does increase the staking ratio. For this, the authors use a regression with StakingRatio as the dependent variable, with independent variables being staking reward rate, NotLaunched dummy, value share held by large holders known as whales, and platform productivity. The staking ratio is significantly and positively affected by rewards and whales and negatively by platform productivity. Cong et al. (2025) provides more empirical research on staking ratios. They suggest that the staking ratio positively predicts changes in token prices. Empirical evidence is provided with a regression based on the previous staking ratio. This revealed a significantly positive staking ratio, indicating that a higher staking ratio predicts higher token price appreciation. They also assess portfolio performance based on staking ratio by longing the top 50% of high-staking tokens and shorting the bottom 50%. They prove that this portfolio provides positive cumulative returns with a Sharpe ratio of 0.865. This study shows the impacts of staking ratios on returns and portfolio performance; however, the study is focused on the staking ratio, leaving out the impact of staking yields.

Riposo and Gupta (2024) model staking as a floating rate note to estimate the returns on staking. Empirical evidence is based on Ethereum 2.0. The framework estimates expected returns by considering network-specific variables, such as staking participation and transaction volume. The model also incorporates slashing, a penalty for validator misbehavior that impacts yields, and Maximal Extractable Value (MEV), where validators obtain extra profit from ordering transactions. Thus, offering a complete view of all the economic drivers within staking. They find that staking rewards rise with increased supply lockups and network activity, potentially exceeding traditional yields. However, the model theoretically links staking rates to effects on price or volatility but lacks empirical evidence based on real-world data. The model also focuses solely on Ethereum 2.0, which may show different dynamics compared to other blockchains. Fan, Jiao, Lu, and Tong (2024) analyze an investment strategy in which investors exploit high staking yields in PoS assets, such as ATOM, to achieve excess returns. They found empirical evidence of an average excess return of 1,5% per month. The study employs a cross-sectional approach to demonstrate that carry trades rely on yield differences, which is comparable to a dividend-seeking investment strategy. They note, however, that using this strategy does face a risk of crashing from lockup-induced volatility spikes. Nevertheless, for this thesis, the investor behavior in this strategy helps determine the market influence of staking.

Liu and Tsyvinski (2021) explore the risk and return dynamics of cryptocurrencies over the period 2011 to 2018. They provide empirical evidence that cryptocurrencies exhibit high volatility, with annualized volatilities differing from 60 to 100%. The study also finds a low correlation between cryptocurrencies and traditional assets, like bonds and stocks. Liu and Tsyvinski identify crypto-specific return drivers, including momentum, investor attention, and network effects. For example, they find empirical evidence that past weekly returns predict a 4 to 6% higher return the next week, while investor attention boosts return by 2 to 3%. The authors note that cryptocurrencies are insensitive to macroeconomic variables during the study period.

Chu et al. (2017) investigated the volatility dynamics of cryptocurrencies by applying various GARCH models to several cryptocurrencies, utilizing data from 2014 to 2017. Their study assesses the performance of various GARCH models in capturing the distinctive characteristics of cryptocurrencies, including their high volatility. They find that the GARCH(1,1) models provide the best fit for most cryptocurrencies, effectively capturing the volatility and fat-tailed nature of returns. Their study also highlights the influence of external factors on volatility, such as trading volume or sentiment, with higher volumes being associated with increased volatility because of speculative trading activity. The authors note that cryptocurrencies exhibit asymmetric volatility responses in which negative shocks have a larger impact on volatility than positive shocks. This study is relevant as it enables modeling volatility in PoS currencies, validating the use of GARCH(1,1) models to capture the volatility dynamics of crypto returns. The authors suggest that staking mechanisms, such as lockup durations and reward distribution, may impact liquidity and price stability (Chu et al., 2017). Foroutan and Lahmiri (2022) use an EGARCH model to model volatility during the COVID-19 pandemic. The authors use ten cryptocurrencies to investigate the relationships between return, volatility, and volume. The authors find empirical evidence of a relationship between return and volatility for most of the sample. They find that changes in volume solely influence volatility (Foroutan & Lahmiri, 2022).

2.5 Conclusion

While in traditional finance, both theoretical and empirical research show that periodic payments, such as dividends and coupons, are return drivers, the role of staking rewards in cryptocurrency remains underexplored. Modigliani and Miller (1961) suggest that firm values are irrelevant to dividend policies. This statement has been contradicted by many studies over time, such as DeAngelo and DeAngelo (2006). Evidence is provided both empirical and theoretically confirming that periodic payments increase the price of assets, mainly explained by the signaling principle of private information. However, in crypto finance, most research prioritizes the technical and economic mechanisms of staking but not the returns. Saleh (2021) and Chiu and Koeppl (2017) highlight the benefits of PoS, including energy-efficient mechanisms and increased security, demonstrating how lockups strengthen networks. Cong et al. (2021), Cong et al. (2025), and Catalini and Gans (2020) suggest that staking encourages holding and reduces supply, potentially stabilizing prices. These studies, however, focus on theoretical models, providing limited empirical evidence or leave out staking yields as a potential driver of returns. This research gap is critical as the periodic rewards of staking could drive returns by increasing holdings and signaling an increase in network security. This thesis aims to address this gap by examining the impact staking has on returns in PoS currencies, building on frameworks and principles from traditional finance.

3. Hypothesis

In the literature review, the connection between periodic payments and their impact on asset returns in traditional finance has been established. Studies like those by DeAngelo and DeAngelo (2006) demonstrate how dividend payments signal firm value, a finding supported by many researchers. Research into the cryptocurrency literature reveals that the focus lies on the role of staking in PoS systems and the benefits that PoS currencies offer, such as enhanced network security, adoption dynamics, and the reduced carbon footprint. These researchers pay no attention to the full impact staking metrics have on returns or prices. Studies like those by John et al. (2021) and Riposo and Gupta (2024) have modeled staking payouts as potential enhancers of returns. However, the emphasis of these studies is on theoretical application without empirical evidence to support their findings, which this thesis aims to address.

This chapter will define the research questions and hypotheses guiding the research into the impact of staking on returns. Increased staking participation suggests that staking is more than solely a technical feature, it influences supply, liquidity, and behavior of investors similar to dividends or coupons. However, while there is empirical evidence in traditional finance, current literature on staking falls short of evaluating the practical implications of staking. Gupta and Krishnamachari (2024) demonstrate the predictability of staking rewards, and Riposo and Gupta (2024) model yield by incorporating network activity and lockups into supply. However, no research ties these factors to price or volatility changes. This gap motivates an empirical exploration into the role of staking as a driver of returns.

The main gap this thesis addresses is focused on staking, framing the main research question as: *"Do staking rewards enhance returns on cryptocurrencies?"*

This question builds on the findings in the literature review, in which Cong et al. (2025) suggest that staking reduces supply, potentially leading to an increase in price if demand holds. John et al. (2021) argue that staking rewards stabilizes the blockchain network, offering a lucrative investment strategy akin to dividend returns. In traditional finance, the impact of dividends has been thoroughly examined, with authors noting both the relevance of dividend policies and their irrelevance. Papers like Baker et al. (2002) and Iftikhar et al. (2017) quantify dividends as a return boost, which may indicate the potential impact of staking.

H1: *"Higher staking reward rates show a positive effect on cryptocurrency returns."*

This hypothesis is based on the effect of dividend yields in traditional finance, following the impact of periodic rewards and the reduction in supply resulting from staking, which drives returns. This hypothesis can be empirically evaluated via an analysis of market data.

Another question that complements the main research question this thesis seeks to answer is, *“Does the duration of staking lockups reduce the volatility of cryptocurrencies?”*

Research in traditional finance highlights the additional benefits of dividend payments, which signal firm strength and mitigate agency conflicts (Rozeff, 1982; Fama & French, 2001). Following this research in traditional finance, the assumption is that this dynamic may be mirrored by staking. Budish (2022) has already researched the impact of lockups in staking, finding that lockups indicate the confidence of holders but warns of spikes in volatility from supply shocks resulting from market manipulation. Catalini and Gans (2020) explore how PoS mechanisms align token holders with network success, potentially supporting long-term participation. Riposo and Gupta (2024) suggest that staking rewards enhance network stability but lack empirical evidence. Within PoS systems, lockup durations vary, which allows for a natural experiment to assess the effect on stability.

H2: *“Cryptocurrencies that have longer staking lockup durations show less price volatility compared to currencies with shorter or no lockup durations.”*

This hypothesis is based on traditional finance, where Fama and French (2001) noted that mature firms pay dividends to signal stability, potentially reducing volatility. This trait may also be reflected in cryptocurrencies. Unlike in traditional finance, where dividends have a uniform schedule, the variability within PoS systems offers a unique perspective for assessing specific effects within the cryptocurrency market, such as volatility.

These questions frame the empirical research of this thesis, testing if staking in PoS systems functions as a periodic payment mechanism with empirical impacts in the market. The thesis is based on the literature review, in which theoretical and practical insights are discussed. Following the approach used to establish the impact of dividends and coupons in traditional finance, this thesis aims to provide empirical evidence of the economic significance of staking. If this evidence can be obtained, it will contribute to academic research and may also be utilized in investment strategies involving cryptocurrencies. Evidence of H1 could prioritize high-yielding staking assets for investors, while evidence of H2 may favor investment strategies with a long-term focus. Policymakers can use evidence of the hypotheses to re-evaluate risks within their staking policy.

4. Data

The empirical analysis requires multiple datasets. The most crucial part is selecting currencies that meet the required criteria. These choices need to be well-considered, as the research relies on data based on these currencies, including returns, staking ratios, staking rewards, and market sentiment. Finally, macroeconomic factors, such as interest rates and legal changes, need to be considered, as these are crucial for answering the research questions and ensuring robust results.

4.1 Currency selection

A selected sample of cryptocurrencies meeting specific criteria to ensure a robust analysis of PoS dynamics is chosen. As illustrated in Appendix A, media interest in PoS increased significantly from 2022 onward, with limited attention prior to that. Consequently, only cryptocurrencies launched prior to 2022 are included, covering the study period from 2022 to 2024. To mitigate the high volatility present in the cryptocurrency market, all selected coins have a market capitalization of $1 billion or higher as of 2024. This threshold ensures that the selected currencies offer stable price dynamics, which enhances data reliability. Control variables are incorporated to address endogeneity concerns, which are selected based on established research on cryptocurrencies.

4.1.1. Ethereum

Ethereum (ETH) has the second-largest market cap in cryptocurrencies, behind Bitcoin, making it the largest altcoin. It achieved a maximum market capitalization of almost $472 billion in 2024 (CoinMarketCap, 2025). Ethereum officially transitioned from PoW to PoS in September 2022, a crucial change during the period of this study. Prior to this transition, staking was already possible via Beacon Chain. However, users were unable to withdraw tokens until the full transition (Bitstamp, 2024). For the thesis, staking data prior to the transition is also included, as staking was an active option during that time. Ethereum has high liquidity and extensive validator activity, which minimizes volatility. Ethereum has high lockup requirements, as thirty-two tokens are needed for staking, allowing for an exploration of the supply dynamics in the event of unstaking (EtherScan, 2025).

4.1.2. Solana

Solana (SOL) is also included, reaching a market cap of almost $120 billion in 2024 (CoinMarketCap, 2025). A key aspect of SOL is its high transaction throughput, which is driven by a PoS mechanism (SolScan, 2025). Solana is widely adopted in DeFi, making it suitable for a regression analysis on returns and liquidity effects. SOL has experienced extensive price growth since its ICO in 2020, but this has stabilized since, making it suitable for analysis to determine the economic impact of staking.

4.1.3. Cardano

Cardano (ADA), with a market capitalization of approximately $50 billion USD in 2024, employs an efficient PoS protocol (CoinMarketCap, 2025). Its liquid staking pool eliminates traditional lockup periods, limiting analysis of liquidity impacts, but offers insights into validator dynamics and the economic implications of staking due to its high liquidity and established network (CardanoScan, 2025).

4.1.4. Cosmos

Cosmos (ATOM) is also selected. ATOM offers a high staking yield, offering insights into differences in impacts based on yield. ATOM reached a market capitalization of $5 billion in 2024, falling short of its previous high of around $10 billion in 2022 (CoinMarketCap, 2025). The PoS implemented in ATOM supports interoperability, making its role in the cross-chain ecosystem relevant for studying the economic impacts of staking (AtomScan, 2025).

4.1.5. Algorand

Algorand (ALGO) is also included. ALGO employs a pure PoS protocol, which features an automatic staking mechanism, allowing for easy participation, making it crucial in understanding investor behavior and supply effects (AlloInfo, 2025). Algorand has experienced a significant decline in market capitalization, from $15 billion in 2022 to just over $2 billion in 2024 (CoinMarketCap, 2025).

4.1.6. Tron

Tron (TRX) reached a market cap of thirty-six billion dollars in 2024 (CoinMarketCap, 2025). TRX uses a delegated PoS system, where super representatives are used to stake tokens (TronScan, 2025). The application of TRX in stablecoin transfers, as well as its use in DeFi, makes it suitable for studying the effects on liquidity and returns.

4.1.7. Ton

Ton (TON) is selected for its real-world applications. The currency is integrated with Telegram, enabling users to easily conduct transactions via TON, which ensures high trading volumes (TonScan, 2025). TON reached a market cap of twenty-five billion in 2024, which means it matches the criteria for currency selection (CoinMarketCap, 2025). TON is a PoS currency and operates on an independent blockchain (TonScan, 2025).

4.1.8. Binance

Binance (BNB) is the official token released by exchange Binance. It uses a PoS mechanism and is commonly used on Binance, resulting in high liquidity and trading volume (BNBScan, 2025). The noise of volatility is also limited, as Binance is a global exchange, with the currency achieving a market cap of $100 billion in 2024 (CoinMarketCap, 2025). The appliance of BNB in Defi complements the uses of Solana, which offers a comparison of the differences among currencies.

4.1.9. Polkadot

Polkadot (DOT) is selected for its high yield and solid PoS system, which enables interoperability. Polkadot had a maximum market cap of $15 billion in 2024. Combining this with an active validator network makes it suitable for studying both returns and liquidity dynamics. Compared to different PoS currencies, DOT offers a high yield for staking, making it an interesting currency for this thesis (CoinMarketCap, 2025; PolkadotScan, 2025).

4.1.10. Avalanche

Avalanche (AVAX) is chosen for its high-yielding PoS protocol and fast transactions. As it offers a high yield, the high number of validators makes it a suitable case for analyzing the dynamics of returns and supply. Similar to BNB and SOL, AVAX has seen growth in both the DeFi and institutional adoption markets, achieving a maximum market cap of almost $25 billion in 2024 (CoinMarketCap, 2025). However, similar to ETH, AVAX has a high-stake requirement of 2000 AVAX tokens, offering insights into the impact of lockups (AvaScan, 2025).

This sample of ten cryptocurrencies provides diversity in PoS mechanisms, market dynamics, and staking characteristics. All meet the criteria of an ICO before 2022 and have a market capitalization above $1 billion as of 2024. Their independence from one another excludes dependent tokens, such as Polygon. Cryptocurrencies with low staking yields, such as Chainlink and Hedera, where staking rewards have minimal impact, are also excluded to ensure a meaningful analysis of staking effects.

4.2 Data collection for currencies

Following the selection of cryptocurrencies, specific data for each currency were collected to address the research question, which examines the impact of staking on returns, volatility, and liquidity in PoS cryptocurrencies. Data are obtained for the period from 2022 to 2024, aligning with the surge in PoS interest that began in 2022, as noted in Section 4.1, to maximize the likelihood of significant findings. This section justifies the sources and methods used for data collection, ensuring robust empirical analysis.

4.2.1. Daily prices and returns

The most important piece of data for this thesis is the daily prices, which are used to calculate daily returns and serve as the dependent variable for the study. This data is essential in assessing the impact of staking on returns, the key part of the research question. This data is obtained from Coinbase, a major exchange with no affiliates in the selected currencies, which ensures independence and removes the potential for any biases (Bobin, 2022). The data obtained consists of the daily open, close, high, and low prices. For the consistency of the research, the daily returns are based on daily closing prices, calculated as logarithmic returns with $\ln(p_t) - \ln(p_{t-1})$. Logarithmic returns are used in statistics for properties such as the normalization of price changes. Within the data obtained from Coinbase, the daily volume is also obtained. This data is interesting for the research as the volume can be used as an indicator to show the impact of the lockup periods and investor behavior after this period.

Coinbase was selected as a key source for data because of its extensive market coverage and robust API, which provides reliable data for all selected currencies. Since Coinbase is a large exchange subject to strict regulations, its prices and volume data are robust and continuous, minimizing the potential discrepancies that occur with smaller exchanges (Bobin, 2022). The data collected spans the entire period from 2022 to 2024, eliminating the need for sample adjustments.

4.2.2. Staking data

Staking data is essential for analyzing the economic effects of staking in PoS currencies, as this provides insight into additional returns, changes in volatility, and liquidity dynamics resulting from staking mechanisms. This data is used to address both the primary research question, focusing on returns, and the second question, which focuses on volatility and liquidity. These data include the yield from staking, lockup requirements, and staking ratio for the selected currencies.

Staking yield is expressed as an annual percentage and measures the additional returns that investors earn from staking, similar to dividends in traditional finance. This is essential in determining whether higher yields drive stability or volatility. This data is obtained as effective daily rewards rates, which reflect the change in rewards depending on the amount staked and validator performance, and is sourced from Stakingrewards.com, a leading platform for staking metrics. This site provides reliable and historical information on yields, lockup periods, and minimum staking requirements. Their data is based on various sources to ensure robust results. Staking yields and lockup details are cross-verified with blockchain explorers, which are specific for each currency. These explorers provide real-time statistics on validators and protocols.

The staking ratio measures the proportion of the total coins that are locked for staking, calculated by dividing total staked tokens by total circulating supply. This data is essential in analyzing if lockups and other behavioral changes influence volatility or returns. Data on staked tokens is also obtained from StakingRewards.com. The total token supply is estimated by dividing the daily market cap by the daily closing price of the currency. The data on the market caps is obtained from Coinmarketcap.com.

Lockup requirements provide insights into the volatility and liquidity dynamics of cryptocurrencies. Staking protocols require stakers to lock tokens in order to earn rewards, allowing this data to be sourced from various blockchain explorers. However, as exchanges offer different lockup durations, the data is adjusted based on unlock periods, as determined by explorers, combined with exchange requirements. This adjustment is based on changes in staking ratio's, allowing to capture when supply becomes available. By making the lockup variable time-varying, rather than stationary, the GARCH(1,1) can more accurately estimate the impact of lockup durations on volatility.

The staking data are appropriate for the research questions because they provide a direct measure of both the financial and operational aspects of staking that influence returns, volatility, and liquidity. Higher yielding PoS currencies may attract investors, which can increase returns but also volatility if staking participation fluctuates over time. Lockup requirements restrict the token supply, which may stabilize prices during lockups but introduce other risks, such as massive unstaking events. The selection of diverse staking mechanisms among selected currencies enables a comprehensive analysis of the economic effects of staking, aiming to fill the current gap in the existing literature. With the focus on high-cap coins, the noise from speculative low-cap coins is minimized, ensuring reliable staking metrics.

Data on staking yield and ratio for the selected cryptocurrencies were primarily sourced from StakingRewards.com, a widely cited platform for staking metrics, ensuring consistency across the 2022–2024 study period. However, Algorand lacks comprehensive historical yield and staking ratio data on StakingRewards.com due to its governance-based staking model, which differs from traditional PoS mechanisms. To address this, a constant staking yield of 4.42% was obtained from Coinbase, a major exchange providing standardized yield estimates for Algorand (Coinbase, 2025). Algorand's staking ratio was estimated by dividing its Total Value Locked (TVL), sourced from DefiLlama, by its market capitalization, yielding an average staking ratio of 10% over the study period.

For Ton, which transitioned from PoW to PoS in November 2022, the staking yield and ratio are assumed to be zero prior to the transition due to the absence of a staking mechanism. Post-transition, TON's staking data were sourced from StakingRewards.com, consistent with other cryptocurrencies, ensuring comparability.

4.2.3. Market data

To address endogeneity issues, market data is essential to capture external price fluctuations and investor behavior that may confound the effects of staking. Endogeneity may arise via reverse causality or omitted variables. To control broader market trends, the S&P Cryptocurrency Broad Digital Market Index is used as a control variable. Sentiment indicators are also included to account for market-wide and currency-specific optimism or fear, which may drive price movements independently of staking mechanics.

The Fear & Greed Index, gathered from Alternative.me, is a metric that combines cryptocurrency market indicators, including volatility, trading volume, social media activity, and Bitcoin dominance (Alternative.me, 2025). This index provides a daily measure of overall market sentiment, which influences investor behavior across all selected currencies, making it a robust control variable against external price drivers. For example, a high greed score during bull runs, characterized by a high score, with 100 being extreme greed, may inflate returns. The index is collected daily for the period 2022 to 2024, gathered from Alternative.me.

Currency-specific sentiment is captured through social media analytic tools. LunarCrush offers insight into specific currency sentiment, mentions, and engagements on social media. The data provided by LunarCrush indicates a 100% score when sentiment is exceptionally good, while a lower score indicates a worse sentiment for the currency (LunarCrush, 2025). Currencies with strong sentiment and high engagement may be influenced by external factors that affect investor behavior, potentially leading to omitted variable bias if these factors are not accounted for. By controlling media sentiment, the findings should be robust against external price drivers.

To control market movements, daily log returns of the S&P Cryptocurrency Broad Digital Market (BDM) are included. This helps to capture market-wide trends. The index tracks over 240 cryptocurrencies that meet specific liquidity and market capitalization criteria, providing a comprehensive benchmark for the cryptocurrency market's performance

(SPGlobal, 2025). This data complements specific variables for PoS currencies, such as staking yield and ratio. Because the index only includes weekday trading data, weekend returns are interpolated using the average of preceding and following trading days. This preserves the daily frequency of the datasets and avoids bias by assuming zero or constant weekend returns.

Data quality is ensured through thorough processing of the available data. The Fear & Greed Index is complete for the research period, with no missing values. The sentiment data obtained via LunarCrush is filtered for activity from bots, providing nearly complete data. Some minor gaps are interpolated linearly to maintain the daily frequency used in the research. Outliers, such as the collapse of FTX in November 2022, remain in the data to reflect complete market reactions, as cryptocurrencies are prone to large price swings. Removing events like this, risks introducing bias by removing volatile events, a key feature of crypto markets. The BDM index captures macro-level market trends, which, together with the variables that account for sentiment, help control for addressing endogeneity due to omitted variables. The period of the research contains key PoS events, such as the switch of Ethereum to PoS, which ensures the relevance of staking dynamics. By mitigating external price drivers, these controls enhance the robustness of the findings, aligning with similar studies on cryptocurrency markets.

4.3 Macroeconomic data

Macroeconomic data is essential for analyzing the effects of staking economics on returns, volatility, and liquidity. These data control external economic factors that may impact price movements and investor behavior independent of staking mechanics. For the research questions, certain macroeconomic variables, such as interest rates and regulatory changes, are considered which enhances the robustness of the regression.

Interest rates influence investor risk appetite, with changing rates potentially diverting capital from cryptocurrencies to traditional assets, affecting returns and liquidity (Karadag & Cetin, 2023). To ensure robust results, the U.S. Federal Reserve's fund rate is a key indicator in monetary policy. The daily effective rate is obtained from the Federal Reserve Economic Data (FRED) database, which provides a complete dataset for the thesis' time period.

Regulatory changes can increase volatility or alter returns, potentially biasing findings. While prior studies, such as Feinstein and Werbach (2021), find no evidence that regulatory measures drive traders away, this study uses pre-existing data, making regulatory impact a critical variable to consider. Robustness in the findings are ensured as regulatory events are collected as a dummy variable based on news archives and legal databases. The focus of these events is on U.S. and EU regulatory changes because of their impact on the global market, such as the approval of ETFs and the SEC's ruling against XRP.

4.4 Descriptive statistics

This section summarizes the characteristics of the selected PoS cryptocurrencies to provide context for the empirical analysis. Descriptive statistics for daily returns, staking metrics, trading volumes, market sentiment, and macroeconomic variables are presented to assess the suitability of data for addressing the research questions on the impact of staking on returns, volatility, and liquidity. These statistics ensure the dataset's robustness for regression analysis.

Currency	Mean	Median	Standard deviation	Lowest daily return	Highest daily return
ETH	0.06%	0.02%	3.58%	-17.52%	19.23%
SOL	0.15%	-0.10%	5.27%	-42.25%	32.73%
ADA	0.05%	0.00%	4.29%	-18.65%	23.51%
ATOM	-0.05%	-0.10%	4.66%	-20.54%	24.31%
ALGO	-0.04%	0.05%	4.80%	-23.03%	36.21%
TRX	0.16%	0.15%	3.07%	-18.38%	43.30%
TON	0.13%	-0.04%	4.45%	-18.86%	26.80%
BNB	0.07%	0.04%	3.12%	-18.36%	17.30%
DOT	-0.04%	0.00%	4.25%	-19.98%	29.26%
AVAX	0.02%	-0.12%	5.07%	-30.08%	24.82%

Figure 2: Descriptive Statistics Currency Data

Figure 2 presents the descriptive statistics of the currencies, including the mean, median, standard deviation, and range of daily returns for each cryptocurrency from 2022 to 2024. The figure highlights lower volatility in higher market capitalization coins, consistent with their established market presence. Larger-cap currencies, such as Ethereum and Binance, exhibit smaller extreme daily returns compared to smaller-cap currencies like Algorand.

Currency	Average Yield	Epoch	Lockup period	Average ratio
ETH	4.2%	1	4	17.5%
SOL	6.6%	5	5	12.6%
ADA	3.5%	5	0	67.3%
ATOM	18.4%	7	25	63.9%
ALGO	1.5%	1	0	9.6%
TRX	4.2%	3	14	43.9%
TON	4.2%	1	0	0.8%
BNB	3.5%	1	7	13.1%
DOT	13.5%	1	30	54.4%
AVAX	8.3%	4	9	27.8%

Figure 3: Descriptive Statistics Staking Metrics

Figure 3 summarizes the staking metrics data, including yields, staking ratios, reward epochs, and lockup periods. Annual staking yields range from 2.6% to 18.7%, reflecting diverse incentives across currencies. Contrary to expectations, higher yields do not consistently correlate with higher staking ratios as shown in Figure 3, which is supported by Figure 1, suggesting other factors, such as investor preferences or network design, influence staking behavior. Reward epochs vary among currencies, ranging from 1 to 7 days, while lockup periods range from liquid staking pools to fixed periods of up to one month.

Sentiment	Mean	Median	Standard deviation	Lowest daily score	Highest daily score
ETH	83.49%	85.00%	8.77%	10.00%	99.00%
SOL	81.98%	85.00%	10.69%	10.00%	99.00%
ADA	82.89%	85.00%	9.88%	13.00%	99.00%
ATOM	76.79%	78.00%	12.52%	1.00%	100.00%
ALGO	78.42%	79.00%	11.14%	29.00%	100.00%
TRX	78.03%	79.00%	20.66%	2.00%	100.00%
TON	77.27%	80.00%	14.08%	8.00%	100.00%
BNB	77.22%	79.00%	8.87%	25.00%	100.00%
DOT	82.78%	84.00%	11.64%	10.00%	100.00%
AVAX	79.03%	82.00%	12.92%	22.00%	100.00%

Figure 4: Descriptive Statistics Sentiment Data

The Fear & Greed Index, averaging 47.77 from 2022 to 2024, captures market sentiment dynamics. Peaks align with significant events, such as the U.S. presidential election in late 2024 and the cryptocurrency bull run in late 2022, while lows correspond to bear markets in late 2023 and early 2024. This aligns with currency-specific sentiment scores from LunarCrush, which data is summarized in Figure 4. Larger-cap coins exhibit a lower standard deviation with a high sentiment score.

Key macroeconomic variables include regulatory changes and interest rates. In the U.S., a notable regulatory event occurred in July 2023, when a court ruled in favor of Ripple against the SEC, determining that XRP is not a security. In the European Union, the Markets in Crypto-Assets Regulation (MiCA) was adopted in April 2023, with implementation phases scheduled for July 2023, October 2023, and March 2024. Monthly FRED interest rates averaged 3.95% over the study period, providing a macroeconomic control variable. These variables account for external influences on cryptocurrency returns and volatility, enhancing the robustness of the analysis.

This chapter establishes a robust framework for analyzing the economic implications of staking on returns, volatility, and liquidity in PoS cryptocurrencies. A sample of ten cryptocurrencies was selected based on criteria that ensured significant staking yields, being a market capitalization exceeding $1 billion in 2024, and independent blockchains, as detailed in Section 4.1. These criteria ensure a diverse and representative sample suitable for comparative analysis. Data were sourced from multiple reputable databases, including Coinbase for prices, StakingRewards.com for staking metrics, LunarCrush for market sentiment, and FRED for macroeconomic variables, enabling a comprehensive regression analysis. Descriptive statistics, presented in Section 4.3, confirm the data's suitability, revealing lower volatility in higher market capitalization coins and a wide range of staking yields, which supports the analysis of diverse staking mechanisms. This framework facilitates a precise evaluation of staking's effects, ensuring robust and reliable insights into its economic impacts.

4.5 Data validity

Robustness and validity of the model is ensured by evaluating several statistical assumptions.

First, the assumption of linearity between the dependent variable and independent variables was assessed by examining residual plots. These plots displayed a random scatter of residuals around zero, confirming a linear relationship and supporting the appropriateness of a linear regression framework.

Next, multicollinearity among explanatory variables was evaluated using Variance Inflation Factors (VIF). VIF quantifies the extent to which the variance of an estimated regression coefficient is inflated due to correlations among predictors. A VIF value exceeding five indicates high multicollinearity, which can inflate standard errors, making estimates less precise and statistical less reliable. In this analysis, VIF values were computed for all explanatory variables, leading to the removal of the FRED variable due to problematic multicollinearity. Although this issue was not universal across all currencies, the variable was removed from the models for all to maintain consistency in the estimation process and avoid potential distortions in comparative analyses. The problematic multicollinearity between FRED and cryptocurrency returns reflects their shared sensitivity to macroeconomic conditions. Changes in FRED rates usually signal shifts in liquidity, risk appetite, and inflation expectations, which are key macro-financial dynamics that impact cryptocurrency markets.

The zero-mean residual assumption was verified ensuring the model's residuals have an expected mean of approximately zero. This condition is typically satisfied when the regression includes an intercept term, as was the case here. Confirmation of this assumption ensures that the model is correctly specified and unbiased in its predictions, as non-zero mean residuals could indicate the presence of omitted variables or model misspecification.

Homoskedasticity, the assumption of constant residual variance across observations, was tested using the Breusch-Pagan test. This test assesses whether the residual variance is dependent on the values of the independent variables. Heteroskedasticity, if present, may lead to inefficient estimates and biased standard errors, affecting the validity of hypothesis tests and confidence intervals. The Breusch-Pagan test results showed the presence of heteroscedasticity among all currencies. To account for this, robust standard errors are used. Since a Durbin-Watson test showed no significant autocorrelation, there was no need to use Newey-West robust standard errors.

Finally, the normality of residuals was considered. Given the large sample size of the dataset, the Central Limit Theorem shows that the sampling distribution of the regression coefficients approximates normality, thereby reducing concerns about minor deviations in residual normality.

A key assumption of the GARCH(1,1) model is that the return series must be covariance stationary, implying that the mean, variance, and autocorrelation structure remain constant over time, which are ensured by using daily log returns, which are commonly applied to stabilize variance and achieve stationarity. Furthermore, consistent with the assumptions of OLS, the model requires that residuals exhibit no significant autocorrelation and that the presence of conditional heteroskedasticity justifies the use of a GARCH model. These conditions were evaluated and addressed during the preliminary analysis of the explanatory variables. Lastly, for the GARCH(1,1) model to be valid, the conditional variance process must also be stationary. This requires that the sum of the ARCH and GARCH parameters, indicated by Alpha and Beta, is less than one, ensuring that volatility remains mean-reverting and does not diverge over time.

Together, these diagnostics confirm compliance with the key assumptions of the models, supporting the reliability and interpretability of the results for the hypotheses.

5. Empirical models

This section outlines the empirical models used to test the hypotheses and address the research questions of the thesis. Building on literature in traditional finance and existing studies in cryptocurrency, the hypothesis examines whether the implications of staking mimic the effects of dividends in traditional finance. These models utilize established methodologies in traditional finance and adapt to the characteristics of the cryptocurrency market.

5.1 Hypothesis 1

The literature review examines the impact of dividend payments on stock returns, providing a foundation for analyzing staking rewards in cryptocurrencies. Iftikhar et al. (2017) found evidence that dividends enhance asset returns. Staking rewards mimic dividends by providing periodic payments and additionally, enhancing network security, which incentivizes long-term holding and decreases the circulating supply (Cong et al., 2025). Cong et al. (2025) introduce the concept of "crypto carry", suggesting that staking lockups increase cryptocurrency prices. This study examines whether staking rewards have a similar effect on cryptocurrency returns, drawing parallels with traditional finance.

The hypothesis posits that staking rewards positively affects cryptocurrency returns. If the null hypothesis that staking rewards does not affect returns, cannot be rejected, it would indicate that there is no significant impact. If a positive effect of staking is found, the null hypothesis would be rejected, confirming that staking enhances returns, similar to traditional finance. Hypothesis 1 is tested by employing an OLS regression model, following the traditional research of Iftikhar et al. (2017), who uses an OLS regression to quantify the impact of dividends on stock returns, and Cong et al. (2025), who employ regressions to identify return drivers for cryptocurrencies. The dependent variable will be the daily returns of the currency, with independent variables including staking metrics, such as the yield and ratio. Control variables include the market sentiment and a dummy variable for regulatory events. These variables account for external influences. Due to the simplicity of OLS, it is preferred over similar models, such as the panel regression model. The regression is formulated as follows:

$$R_{it} = ai + \beta_{i1}SR_{it-1} + \beta_{i2}SY_{it-1} + \beta_{i3}FG_{t-1} + \beta_{i4}REG_t + \beta_{i5}Log(MC)_{it} + \beta_{i6}\Delta SENT_{it} + \beta_{i7}Log(Volume)_{it} + \beta_{\mathrm{i}8}\Delta MKT_t + \varepsilon$$

Where:

- R_{it}: Daily logarithmic returns for currency *i* at time *t*,
- SR_{it-1}: Staking ratio for currency *i* at time *t*,

- SY_{it-1}: Staking yield for currency *i* at time *t*,
- FG_{t-1}: Fear & Greed index score on time *t*,
- REG_t: Regulatory event dummy for cryptocurrencies on day *t* where 1 indicates a regulatory event,
- $Log(MC)_{it}$: Log of Market Cap of currency *i* at time *t*,
- $\Delta SENT_{it}$: Change in market sentiment for currency *i* at time *t*,
- $Log(Volume)_{it}$: Trading volume for currency *i* at time *t*,
- ΔMKT_t: Change in Crypto Market Index returns at time *t*,
- ε: Error term

The expectation is that $\beta 1$ and $\beta 2$ will significantly increase returns, as this reduces circulating supply and signals network stability (Cong et al., 2025), similar to findings by Iftikhar et al. (2017) in traditional finance. Cong et al. (2025) showed that the staking ratio has a positive effect on returns, which is also expected in this regression.

The control variables of volume and sentiment are also expected to increase returns, while Fear & Greed remains ambiguous. In times of greed, this variable is likely to have a positive effect on returns, but in times of fear, it may depress returns. Regulatory events are likely to have mixed effects, as such changes can have both negative and positive impacts on the market. Market cap is also expected to influence returns significantly, however, the direction may be ambiguous, similar to volume. Finally, returns are expected to follow the returns in the index, as some currencies are included in them, leading to a correlation with the returns.

5.2 Hypothesis 2

Literature in traditional finance shows that dividend payments reduce stock price volatility by offsetting agency problems (Rozeff, 1982) and signaling firm maturity (Fama & French, 2001). In PoS systems, tokens are typically required to be locked up, which restricts the token supply and encourages long-term holding, potentially stabilizing prices (Catalini & Gans, 2020). However, Budish (2022) warns of sudden volatility shocks when supply becomes available. The currency selection offers variability in lockup durations, enabling experimentation to test the effects. The hypothesis, as formulated in Chapter 3, proposes that longer lockup durations lower price volatility.

This hypothesis is tested using a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (1,1) model to capture the dynamics of return volatility. GARCH models estimate the conditional variance of returns as a function of both past squared residuals and past variances, which is particularly appropriate for cryptocurrencies due to their known volatility and volatility clustering (Chu et al., 2017). The model's ability to estimate volatility dynamically over time makes it well-suited for evaluating the evolving impact of staking lockups. Chu et al. (2017) conducted a comparative study of various GARCH specifications applied to cryptocurrency markets. They found that the GARCH(1,1) model most accurately captures the statistical properties of returns on digital assets. In this analysis, lockup duration is used as the primary explanatory variable on volatility while also controlling staking ratio, staking yield, trading volume, and relevant micro- and macroeconomic variables. A negative and significant effect of lockup duration on conditional variance would reject the null hypothesis, supporting the theoretical insights of Bhattacharya (1979) and Catalini and Gans (2020), who argue that information frictions and commitment mechanisms can stabilize asset pricing dynamics. The GARCH(1,1) model consists of both a mean equation and a variance equation, with the focus of this study being on the variance equation. The mean equation is specified as:

$$R_{it} = \mu + \varepsilon$$

The variance equation is specified as:

$$\sigma_{it}^{2} = wi + \alpha\varepsilon^{2} + \beta i\sigma^{2} + y_{i1}SR_{it-1} + y_{i2}SY_{it-1} + y_{i3}FG_{t-1} + y_{i4}REG_{t} + y_{i5}Log(MC)_{t} + y_{i6}\Delta SENT_{it} + y_{i7}Log(Volume)_{it} + y_{i8}LD_{it} + y_{i9}\Delta MKT_{t} + \varepsilon$$

In this model:

- $\sigma^{2}{}_{it}$: Variance for currency *i* on day *t*,
- LD_{i}: Lockup duration in days for currency *i* on day *t*,
- SR, SY, VOL, FG, SENT, MC, MKT and REG follow the same definition as given in H1,
- ε: Error term

The expectation is that longer lockup durations will reduce volatility, as this limits speculation and sell-offs during bear markets (Catalini & Gans, 2020). Both market sentiment, expressed in the Fear & Greed index, and the microeconomic sentiment, expressed in sentiment, are expected to be ambiguous as swings can move both ways, similar to regulatory events. The staking ratio and yield are expected to show negative signs, as volatility is most stable with fixed staking, which is impacted by these factors. Changes in volume are expected to increase volatility, and an increase in market returns is likely to increase volatility as money flows increase into currencies.

The GARCH(1,1) models are constructed in RStudio using the maximum likelihood method from the rugarch package. This approach estimates the parameters by assuming the models follow a Student's T-distribution, aligning with Chu et al.'s (2017) findings that this distribution provides the best fit for cryptocurrency data. The coefficients and their corresponding standard errors, t-values, and p-values are derived to assess statistical significance, offering insights into the impact of each parameter and external regressor on the mean returns and variance.

The empirical analysis draws on a dataset from Chapter 4, which includes daily returns, staking metrics, sentiment, and macroeconomic factors. By basing the methodology on established frameworks from traditional finance tailored to the dynamics of cryptocurrencies, this study ensures robust and generalized conclusions about the economic implications of staking.

6. Results

This section provides the empirical results of the regression analysis testing both hypotheses. The results of both hypotheses are summarized in Appendix B.

6.1 Hypothesis 1

An OLS regression was conducted for the ten cryptocurrencies over the period from 2022 to 2024. The dependent variable is the daily logarithmic returns, and the explanatory variables include staking metrics, sentiment scores, a regulatory dummy, and macroeconomic variables.

Hypothesis 1 posits that a high staking reward rate has a positive effect on crypto returns. The regression results provide mixed evidence among the sample of currencies. A significant positive effect is observed in Solana and Ethereum, where an increase in staking yield is correlated with higher daily returns. The regression shows a 1% increase in yield, resulting in an increase in returns of 0.6368% and 0.0662%, respectively. This aligns with dividend signaling theory under asymmetric information (Bhattacharya, 1979), where higher dividends signal firm quality, reduce uncertainty and boost stock prices. Similarly, higher staking yields may signal robust network health, incentivizing holding and reducing sell pressure, as supported by Iftikhar et al. (2017), who find an increase in return increases with a higher dividend payout ratio. This is consistent with the economic incentives of staking (Cong et al., 2025) and the Dividend Discount Model (Williams, 1938; Gordon, 1959), where asset value reflects expected future payouts, suggesting staking yields enhance returns for mature cryptocurrencies like Solana and Ethereum. However, Ton, Tron, and Cardano show significant negative results. Tron shows a decrease of 0.0079% when the staking yield increases by 1%, indicating a significant impact. Similarly, Ton and Cardano show a reduction of 0.0051% and 0.6552% in daily returns per 1% increase in staking yield, respectively. These negative effects align with traditional finance findings, which indicate that high dividend yields signal risk or unsustainability (DeAngelo & DeAngelo, 2006). Rozeff (1982) also emphasizes the trade-off between dividends and investment, where excessive payouts may be perceived as agency-driven or detrimental to growth. These parallels suggest that high staking yields indicate network saturation, dilution risks, or anticipated selling pressure following reward distributions.

For the remaining currencies, the effect of staking yield is statistically insignificant, suggesting, as per Modigliani and Miller's (1961) irrelevance theory, that staking rewards may not consistently drive returns in idealized conditions due to market frictions like variable lockup periods or network-specific risks, such as price manipulation, which challenge the applicability of traditional models like Gordon's (1959) Growth Model. This may be explained by differences in network designs or investor behavior, which dilute the signaling effect of staking rewards across all PoS cryptocurrencies.

The staking ratio also shows mixed effects on returns. Algorand, Ethereum, Solana, and Cardano demonstrate a positive impact on returns, which aligns with the findings of Cong et al. (2025). For Ethereum, however, the effect is rounded to 0, while Algorand, Solana, and Cardano show increases in returns of 0.0762%, 0.0001%, and 0.0051%, respectively, with a 1 unit increase in staking ratio. The effects of Algorand can be explained by the strong confidence investors have in the governance-based model of Algorand. Solana, Ethereum, and Cardano may be explained by their maturity compared to the other currencies in the sample. These currencies are among the largest altcoins, which may indicate that this variable is only priced for larger and more mature currencies. This finding, however, is contradicted by Ton and Tron, which both show a negative effect on returns when the ratio increases. This effect may be explained by the selling pressure of the distributed rewards or the reduced market liquidity, which may increase downward price pressure. This would show that during the time period, the selling activity is more significant as the buyers of the currencies.

A key return indicator for almost all currencies is the S&P Cryptocurrency Broad Digital Market Index, which aligns with the findings by Cong et al. (2025). This suggests that the currencies in the sample closely follow broader market trends in cryptocurrency, reflecting an interconnected market. The sentiment of currencies, measured by changes sentiment scores obtained via LunarCrush, shows significant effects on Tron and Cosmos, suggesting that the returns of these currencies are influenced by shifts in sentiment scores. The Fear and Greed index shows no significant impact across all currencies, indicating the limited role of sentiment pricing in determining prices. Key regulatory events have only shown a minor positive effect on Cosmos' returns, possibly due to the increased legitimacy following the regulatory changes. The impact of macroeconomic variables is similar to the findings of Liu and Tsyvinski (2021) in their study, which focuses on the period 2011 to 2018. They also note that cryptocurrencies' returns are largely insensitive to macroeconomic variables. An increase in market cap shows a significant increase in returns for Tron, Algorand, and Binance, while the return of Cardano and Binance are positively affected by an increase in trading volume, reflecting the role of liquidity in returns.

The regression results provide mixed support for the hypothesis, suggesting that staking rewards' impact on returns varies across PoS currencies. Drawing from traditional finance, the positive effect of staking yields on Solana and Ethereum mirrors dividend signaling theory

(Bhattacharya, 1979), where higher yields signal strong network fundamentals, thereby boosting returns, as supported by Iftikhar et al. 's (2017) findings. This aligns with the Dividend Discount Model (Williams, 1938; Gordon, 1959), where asset value is determined by expected payouts, particularly for mature cryptocurrencies. Conversely, the negative findings for Ton, Tron, and Cardano align with the risk-signaling view (DeAngelo & DeAngelo, 2006) and agency-based dividend theories (Rozeff, 1982), indicating that high yields might be perceived as unsustainable or opportunistic. The insignificant effects in other currencies support Modigliani and Miller's (1961) irrelevance theorem, suggesting that staking yields may not drive returns due to crypto-specific frictions like market manipulation or lockup variability, which complicate traditional valuation models (Williams, 1938; Gordon, 1959). Another reason for the results is the maturity and volatility of crypto markets. Several studies have tried to identify key return drivers for cryptocurrencies (Liu & Tsyvinski, 2021; Cong et al., 2025). These studies offer insights about return drivers, showing parallels with dividend policies in traditional finance, which are also implemented in this study. Staking's volatility-dampening potential may be offset by crypto market dynamics, and with the recent rise of interest in staking, not all effects are effectively priced in.

	Returns				
	Ethereum (1)	Solana (2)	Cardano (3)	Cosmos (4)	Algorand (5)
Lagged Staking Ratio	0.0000***	0.0762*	0.0001*	-0.0001	0.0051***
	(0.0000)	(0.0445)	(0.00004)	(0.0011)	(0.0018)
Lagged Staking Yield	0.0662*	0.6368***	-0.6552**	0.0017	
	(0.0396)	(0.2000)	(0.2830)	(0.0012)	
Fear and Greed Index	-0.00002	-0.0001	-0.00003	0.0001	-0.00003
	(0.00003)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Delta Sentiment	0.0116	0.0079	0.0002	0.0161*	0.0133
	(0.0084)	(0.0079)	(0.0051)	(0.0086)	(0.0124)
Regulatory Dummy	0.0153	-0.0007	0.0076	0.0202*	0.0063
	(0.0153)	(0.0122)	(0.0159)	(0.0108)	(0.0119)
Log (Market Cap)	-0.0007	-0.0013	0.0052	0.0031	0.0064
	(0.0009)	(0.0010)	(0.0035)	(0.0031)	(0.0041)
Log (Volume)	0.0021	0.0003	0.0017**	0.0005	0.0004
	(0.0018)	(0.0007)	(0.0007)	(0.0004)	(0.0007)
Delta Market Returns	0.9940***	1.2292***	1.0074***	1.0018***	1.0319***
	(0.0347)	(0.0827)	(0.0513)	(0.0610)	(0.0655)
Constant	0.0093	-0.0197	-0.1233	-0.0790	-0.1418*
	(0.0289)	(0.0286)	(0.0816)	(0.0677)	(0.0814)
Observations	1,094	1,094	1,094	1,094	1,094
R2	0.5278	0.3696	0.3874	0.3210	0.3260
Adjusted R2	0.5243	0.3649	0.3828	0.3160	0.3216
Residual Std. Error	0.0248 (df = 1085)	0.0425 (df = 1085)	0.0331 (df = 1085)	0.0385 (df = 1085)	0.0394 (df = 1086)
F Statistic	151.4755*** (df = 8; 1085)	79.4997*** (df = 8; 1085)	83.4905*** (df = 8; 1085)	64.0498*** (df = 8; 1085)	75.0280*** (df = 7; 1086)
Note:					*p<0.1; **p<0.05; ***p<0.01

Figure 5: Regression H1 for ETH, SOL, ADA, ATOM & ALGO

	Returns				
	Tron (1)	Ton (2)	Binance Coin (3)	Polkadot (4)	Avalanche (5)
Lagged Staking Ratio	-0.0076**	-0.0050**	0.0005	-0.0005	0.0005
	(0.0032)	(0.0020)	(0.0007)	(0.0017)	(0.0028)
Lagged Staking Yield	-0.0079**	-0.0051**	-0.0019	-0.0002	-0.0010
	(0.0031)	(0.0021)	(0.0014)	(0.0021)	(0.0015)
Fear and Greed Index	-0.00002	0.00002	-0.00004	0.00003	0.00001
	(0.00004)	(0.0001)	(0.00004)	(0.0001)	(0.0001)
Delta Sentiment	0.0084**	0.0020	0.0058	0.0095	-0.0101
	(0.0038)	(0.0042)	(0.0164)	(0.0061)	(0.0110)
Regulatory Dummy	-0.0013	0.0330	-0.0072	0.0126	0.0145
	(0.0072)	(0.0262)	(0.0053)	(0.0210)	(0.0226)
Log (Market Cap)	0.0176**	0.0054*	0.0019**	0.0027	0.0022
	(0.0089)	(0.0031)	(0.0008)	(0.0029)	(0.0033)
Log (Volume)	0.0024	0.0021	0.0007*	-0.00001	0.0002
	(0.0028)	(0.0018)	(0.0004)	(0.0004)	(0.0007)
Delta Market Returns	0.5412***	0.6482***	0.7026***	0.9976***	1.1900***
	(0.0418)	(0.0583)	(0.0397)	(0.0459)	(0.0600)
Constant	-0.4464*	-0.1567***	-0.0516**	-0.0656	-0.0546
	(0.2330)	(0.0575)	(0.0213)	(0.0645)	(0.0740)
Observations	1,094	1,094	1,094	1,094	1,094
R2	0.2457	0.1614	0.3463	0.3815	0.3759
Adjusted R2	0.2401	0.1552	0.3415	0.3769	0.3713
Residual Std. Error	0.0262 (df = 1085)	0.0404 (df = 1085)	0.0254 (df = 1085)	0.0335 (df = 1085)	0.0404 (df = 1085)
F Statistic	44.0993*** (df = 8; 1085)	26.0962*** (df = 8; 1085)	71.8535*** (df = 8; 1085)	83.6459*** (df = 8; 1085)	81.6715*** (df = 8; 1085)
Note:					*p<0.1; **p<0.05; ***p<0.01

Figure 6: Regression H1 for TRX, TON, BNB, DOT & AVAX

6.2 Hypothesis 2

GARCH(1,1) models were estimated for the ten selected PoS cryptocurrencies over the period to assess the impact of the variables used in Hypothesis 1 on the volatility of each currency's daily logarithmic returns. The models incorporate the explanatory variables from H1, including lagged staking yield, lagged staking ratio, Fear and Greed Index, change in sentiment, a regulatory dummy, log market capitalization, log trading volume, and change in broader market returns, to evaluate their influence on conditional volatility. These models are added in Appendix C, with several models being highlighted and added in the text.

Hypothesis 2 suggests that currencies with longer lockup durations show less price volatility compared to currencies with shorter or no lockup durations. The empirical results, presented in Appendix C, present a complex picture that partially contradicts the hypothesis.

GARCH(1,1) Coefficients for Cardano Returns

	Estimate	Std. Error	t value	Pr(> | t|)
mu	-0.018852	0.060059	-0.313886	0.753608
mxreg1	0.000128	0.000156	0.820264	0.412066
mxreg2	-0.136983	0.190673	-0.718422	0.472497
mxreg3	0.000021	0.000023	0.883541	0.376944
mxreg4	-0.000778	0.011744	-0.066288	0.947149
mxreg5	0.000780	0.002578	0.302769	0.762066
mxreg6	0.001745	0.004938	0.353433	0.723763
mxreg7	0.000183	0.000408	0.448743	0.653617
mxreg8	-0.000077	0.000088	-0.867150	0.385860
mxreg9	0.868034	0.034085	25.466820	0
omega	0.000072	0.000023	3.136309	0.001711
alpha1	0.260994	0.046229	5.645636	0.00000002
beta1	0.625673	0.023086	27.101280	0
vxreg1	0.00000004	0.000002	0.018272	0.985422
vxreg2	0	0.000578	0.000021	0.999983
vxreg3	0	0.00000003	0.0000001	1.000000
vxreg4	0.00000003	0.000742	0.000038	0.999970
vxreg5	0.00000003	0.00000003	1.214578	0.224527
vxreg6	0.00000003	0.000317	0.000106	0.999916
vxreg7	0.0000001	0.00000003	3.890625	0.000100
vxreg8	0.000006	0.00000003	213.589800	0
vxreg9	0.00000003	0.000874	0.000029	0.999977
shape	4.637008	0.549737	8.434958	0

Figure 7: GARCH(1,1) model on Cardano Returns

GARCH(1,1) Coefficients for Polkadot Returns

	Estimate	Std. Error	t value	Pr(> | t|)
mu	-0.047660	0.053190	-0.896031	0.370236
mxreg1	-0.001149	0.000765	-1.501341	0.133267
mxreg2	0.000353	0.001755	0.201014	0.840688
mxreg3	-0.000007	0.000038	-0.193178	0.846819
mxreg4	0.008640	0.012158	0.710645	0.477304
mxreg5	0.002027	0.002302	0.880634	0.378516
mxreg6	0.009472	0.006517	1.453449	0.146099
mxreg7	-0.000236	0.000115	-2.061276	0.039277
mxreg8	0.000079	0.000112	0.701503	0.482989
mxreg9	0.909955	0.032775	27.763850	0
omega	0.000001	0.000015	0.037846	0.969810
alpha1	0.211739	0.019100	11.085640	0
beta1	0.654009	0.028107	23.268620	0
vxreg1	0.00000004	0.000017	0.002439	0.998054
vxreg2	0	0.000017	0.000850	0.999322
vxreg3	0	0.0000001	0.000050	0.999960
vxreg4	0.0000001	0.000586	0.000121	0.999903
vxreg5	0	0	0.450836	0.652108
vxreg6	0	0.000825	0.000011	0.999991
vxreg7	0.000009	0.0000001	144.971500	0
vxreg8	0.000003	0.0000001	24.095090	0
vxreg9	0	0.000729	0.000004	0.999997
shape	5.639417	0.779913	7.230826	0

Figure 8: GARCH(1,1) model on Polkadot Returns

Among most currencies, a significant explanatory variable for volatility is changes in volume. This relationship is driven by increased trading activity, which tends to cause increased price volatility due to shifts in supply and demand (Foroutan & Lahmiri, 2022). The GARCH(1,1) models consistently show that LogVolume, as represented by vxreg7, is a significant predictor of volatility across the majority of the sample, with p-values typically below 0.05, indicating the dominant role of volume on volatility. For example, Ethereum shows a highly significant p-value of 0.000217, which reinforces this finding.

However, the impact of lockup duration, indicated by vxreg8, challenges the hypothesis. Most currencies show no significant impact, with a p-value being larger than 0.05. However, Polkadot, Cardano, and Cosmos show a significant increase in volatility associated with changes in lockup duration, with the currencies showing increases of 0.000003%, 0.000006%, and 0.00000003% per unit change in lockup duration, as seen in Figure 7 and 8 for Cardano and Polkadot. These coefficients have small p-values, suggesting that longer lockup periods do not reduce volatility as hypothesized. Notably, Polkadot and Cosmos, which rank among the longest lockup durations in the sample, alongside Cardano's dual staking structure, which offers both liquid staking and staking with short lockup durations, provide critical context in understanding the impact of staking on volatility. The increase in volatility for these currencies may be attributed to investor behavior, like the reinvestment or selling of staking rewards upon receiving rather than a stabilizing effect from longer lockups. This behavior may amplify market activity, contradicting the expected reduction in volatility. However, the evidence suggests that currency-specific factors, like market liquidity, staking flexibility, and ecosystem dynamics, dominantly drive volatility outcomes, which overshadows the expected effects of extended lockup periods.

The contradictory findings may reflect the interplay between lockup duration and other volatility drivers. For example, Polkadot has a 28-day unstaking period, and Cosmos has validator-specific lockup periods, which may encourage periodic selling pressure. In contrast, Cardano's liquid staking may mitigate the fixed lockup impacts.

6.3 Additional findings

Beyond the primary results of this study, the empirical analysis revealed several findings that provide deeper insights into the dynamics of PoS cryptocurrencies. These additional findings will be summarized in this section, enhancing the understanding of the economic implications of staking on returns and volatility and offering valuable insights for future research.

Appendix D presents the volatility graphs for the selected cryptocurrencies in this study, covering the period from 2022 to 2024. These graphs are derived from the GARCH(1,1) models used to test the second hypothesis. The graphs reveal similar volatility spikes among all currencies, indicating shared exposure to market-wide events. The most prominent spike was observed after the U.S. presidential election in November 2024, following Trump's appointment as president. This event sparked anticipation of changes in U.S. regulation, which typically leads to a price change, as confirmed by a study conducted by Liu and Tsyvinski (2021). The study found that returns are affected by negative regulatory events but not by positive regulatory events. Additional spikes in volatility are found near the implementations of MiCA. These spikes suggest that external macroeconomic factors, especially regulatory factors, influence the volatility of cryptocurrencies, which go beyond the effects of staking metrics.

The volatility graphs also uncovered interactions between staking lockup periods, liquidity, and market sentiment. Currencies with liquid staking pools, such as Ethereum and Cardano, exhibit high volatility during spikes, which can be attributed to the absence of lockup constraints, allowing investors to make rapid responses. In contrast, currencies with longer lockup durations, such as Cosmos and Atom, exhibited fewer volatility shifts, suggesting that lockup durations help stabilize prices.

These additional findings strengthen the explanation of the complexity of PoS cryptocurrency dynamics and highlight the need to account for macroeconomic events and staking design in analysis. The volatility graphs in Appendix D, together with the regressions from Figures 5 and 6 and the GARCH models in Appendix C, provide a comprehensive view of how staking interacts with external factors.

6.4 Implications

This section serves as an exploration of the findings from both academic and practical perspectives, focusing on the economic implications of staking in PoS currencies and their broader relevance to the market of cryptocurrencies.

Academically, this study contributes to the existing literature on the drivers of return and volatility in cryptocurrencies. The study prioritizes the implications of staking, focusing on the staking ratio and yield and how these variables impact returns. The study builds on Cong et al. (2025) and Liu and Tsyvinski (2021), which employ similar methods and slightly adjusted data to explore return drivers. This study addresses the research gap left by prior studies by incorporating staking-specific metrics absent in prior research. Cong et al. (2025) emphasizes the stabilizing role of staking through reduced circulating supply and network incentives, while Liu and Tsyvinski (2021) highlight factors such as momentum and investor attention as key drivers of returns. The authors also note the insensitivity of cryptocurrency returns to macroeconomic variables, like interest rates. However, these studies do not directly examine staking metrics as return drivers in PoS systems, which is the gap this study aimed to fill.

This gap is filled by revealing effects across several PoS cryptocurrencies over the 2022 to 2024 period. The theory of Cong et al. (2025) suggests that staking induces price stability, which suggests that a higher staking yield would incentivize holding and reduce sell pressure. The findings of H1 are mixed, with Solana and Ethereum showing that a higher yield for staking leads to a higher return. However, the negative effects for Ton, Tron, and Cardano suggest that high yields may indicate risks or increase sell pressure, which aligns with Schär's (2021) observation of speculative behavior in PoS currencies. The author also warns about the highly concentrated distribution of staked tokens. The GARCH models further enrich the existing volatility literature in crypto by finding a positive effect on the volatility for tokens with longer lockup periods. This suggests that longer lockup periods introduce supply uncertainty and liquidity constraints, which is consistent with the findings of Chu et al. (2017)

about the role of factors that influence crypto volatility. However, the key change of volatility for PoS currencies is explained by changes in volume.

The study also contributes a perspective on the impact of several variables on volatility. The models extend prior volatility models from Chu et al. (2017) by incorporating recent data and PoS-specific variables, such as lockup duration, staking ratio, and yield. The observed volatility spikes across all currencies are seen during the implementation of MiCA and the U.S. election, which underscores the impact of market-wide factors and the interplay with staking mechanics, which is backed by the study of Liu and Tsyvinski (2021). The findings of the volatility graphs suggest that staking's economic effects are context-dependent and influenced by network-specific factors and external shocks. This highlights the need for future research, when cryptocurrencies are more mature, to explore the interaction between PoS protocol designs and market conditions, as well as regulatory frameworks.

Furthermore, the findings of this study align with theoretical frameworks on decentralized finance and blockchain economics. Buterin (2020) explained in the whitepaper on Ethereum's transition to PoS that staking mechanisms can enhance network security but influence economic incentives. The perspective of Buterin is empirically tested in this study, enabling policymakers to make informed decisions based on empirical evidence. The theoretical insights of Buterin are supported by Saleh (2021), who provides a theoretical model of PoS economics, suggesting that staking rewards may stabilize prices as they align with the incentives of holders. This is empirically supported by Solana and Ethereum but contradicted by Ton, Tron, and Cardano, where sell pressure is more dominant.

From a practical perspective, the findings of this study offer valuable insights for various stakeholders in the cryptocurrency ecosystem, including investors. For them, the results highlight the importance of evaluating staking metrics alongside other risk factors when investing in PoS currencies. The positive effect of yield on Ethereum and Solana suggests that staking rewards can enhance returns, making them a lucrative option for long-term investors. However, the negative effects in several currencies indicate risks, such as sell pressure and changes in volatility. Another key item investors need to consider is the lockup duration. As seen in the GARCH models, longer lockup durations in Cosmos and Polkadot increase volatility, which can be attributed to supply uncertainty.

Policymakers may use the findings to design policies that strike a balance between staking incentives and market stability. Policymakers may consider guidelines that enhance transparency in trading protocols and reward distribution to reduce uncertainty. This would ensure that the PoS systems remain resilient during turbulent times, like the implementation of MiCA or the U.S. election in 2024.

Institutions exploring potential blockchain integration, such as smart contracts, may benefit from understanding the economic implications of staking. The insignificant yield effects for several currencies suggest that staking rewards may not drive returns in efficient markets. However, the volatility effects indicate potential risks to price stability, which could impact financial blockchain products. Institutions may favor networks that offer stable staking designs to mitigate volatility risks while still using the benefits of PoS, like energy efficiency.

7. Conclusion

Using OLS regression and GARCH(1,1) models to analyze a sample of ten PoS cryptocurrencies over the period 2022 to 2024, I find that staking yields significantly enhance daily returns for Solana and Ethereum. Specifically, a 1% increase in staking yield boosts returns by 0.6368% for Solana and 0.0662% for Ethereum. However, results are mixed, as Ton, Tron, and Cardano show a significant negative effect, reducing returns by 0.0051%, 0.0079%, and 0.6552%, respectively. Additionally, staking ratios positively affect daily returns for Algorand, Solana, and Cardano, which reflects investor confidence in established networks. In contrast, negative effects on Ton and Tron suggest selling pressure from the reward distribution. For Hypothesis 2, I used GARCH(1,1) models and found that lockup durations increase volatility for Polkadot, Cardano, and Cosmos, which contradicts the hypothesis that longer staking lockups reduce volatility. The model shows that, among most currencies, trading volume emerges as a dominant driver of volatility. This research contributes to the academic literature on cryptocurrencies by addressing a gap in prior cryptocurrency studies, which overlook specific staking metrics, and extending frameworks from traditional finance to crypto finance. The study provides practical insights for investors by showing empirical evidence for investing in PoS currencies, showing that investments should not solely be based on staking rewards. Policymakers should use the findings and implement transparent reward distribution policies to enhance market stability.

However, a key limitation of this study is its limited time frame of 2022 to 2024, which may not capture long-term market effects. Leaving out variables such as network changes or validator concentration may also influence outcomes. OLS assumptions have been accounted for by including robust standard errors to address heteroskedasticity and by removing FRED as a variable, as the VIF indicated problematic multicollinearity. Future research should extend the time horizon and incorporate additional metrics on PoS metrics, like validator activity or protocol upgrades. Employing machine learning may also lead to interesting findings by better modelling dynamic interactions and addressing endogeneity concerns, thereby enhancing our understanding of staking’s role in the evolving cryptocurrency markets.

Application of AI during thesis

In preparing this thesis, I utilized AI tools to enhance the quality and efficiency of my work while maintaining my contributions. I used Grammarly to improve the thesis's grammar, sentence structure, and overall readability, ensuring clarity without incorporating entirely generated text. This allowed me to preserve my writing style while ensuring the quality and readability of the text.

AI was also used during statistical analysis conducted in RStudio. When encountering unfamiliar error messages or coding challenges, I used Grok to diagnose issues and suggest solutions, such as debugging syntax errors or optimizing regression models. I evaluated the output and ensured the models aligned with the hypotheses.

AI was also used to adjust the figures. For example, the original Appendix A and Figure 1 used to have a black background, mismatching with the white papers. Because of this, AI was requested to adjust the figures to have a white background to align with the other figures and the coloring of the paper.

Additionally, I used Grok as an analytical aid to refine and improve research methods. For example, Grok helped identify key regulatory changes and brainstorm potential variables to improve model performance. I made all final decisions, ensuring that AI contributions supplemented rather than replaced my independent judgment.

This selective and transparent use of AI tools enhanced the clarity, accuracy, and consistency of my thesis, while adhering to the guidelines of Tilburg University on responsible AI usage.

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Appendix

Appendix A: Engagement PoS Social Media

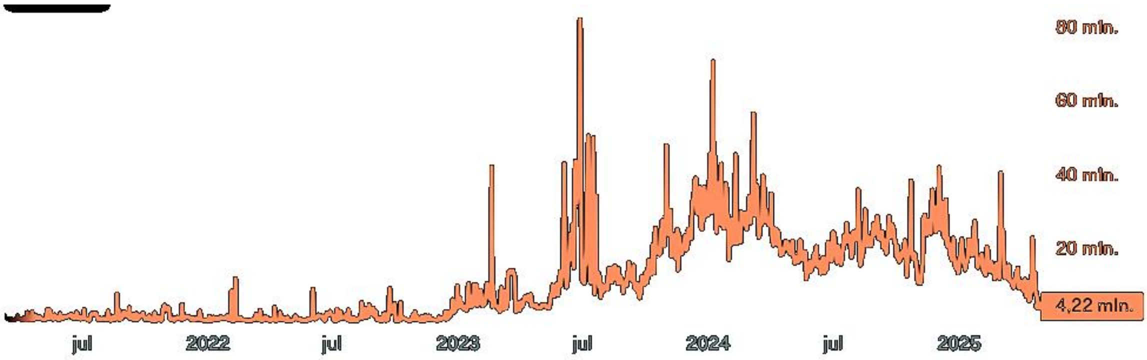

Figure 9: Engagement PoS social media (LunarCrush, 2025)

Appendix B: Summary table

Currency	Hypothesis 1	Hypothesis 2
Ethereum	Reject H0	Do not reject H0
Solana	Reject H0	Do not reject H0
Cardano	Do not reject H0	Do not reject H0
Cosmos	Do not reject H0	Do not reject H0
Algorand	Do not reject H0	Do not reject H0
Tron	Do not reject H0	Do not reject H0
Ton	Do not reject H0	Do not reject H0
Binance	Do not reject H0	Do not reject H0
Polkadot	Do not reject H0	Do not reject H0
Avalanche	Do not reject H0	Do not reject H0

Figure 10: Summary of tested hypotheses

Appendix C: GARCH(1,1) Models

GARCH(1,1) Coefficients for Ethereum Returns

	Estimate	Std. Error	t value	Pr(> | t|)
mu	0.008262	0.007707	1.071915	0.283758
mxreg1	0	0.0000004	0.000649	0.999482
mxreg2	-0.178622	0.091893	-1.943814	0.051918
mxreg3	-0.000003	0.000025	-0.111368	0.911325
mxreg4	-0.035573	0.017116	-2.078377	0.037675
mxreg5	-0.000334	0.000056	-5.945764	0
mxreg6	0.011409	0.003584	3.183239	0.001456
mxreg7	0.001580	0.001646	0.960291	0.336909
mxreg8	-0.000078	0.000073	-1.063319	0.287637
mxreg9	1.054138	0.031387	33.585310	0
omega	0.000001	0.000001	0.412808	0.679747
alpha1	0.162659	0.010686	15.221780	0
beta1	0.789613	0.019279	40.957040	0
vxreg1	0.00000004	0.000001	0.044955	0.964143
vxreg2	0.00000002	0.000065	0.000274	0.999781
vxreg3	0	0.0000001	0.101831	0.918891
vxreg4	0	0.000077	0.000151	0.999879
vxreg5	0.00000002	0.0000001	0.328320	0.742669
vxreg6	0	0.000063	0.000189	0.999849
vxreg7	0	0	3.698323	0.000217
vxreg8	0	0.00000005	0.112454	0.910464
vxreg9	0	0.000078	0.000115	0.999908
shape	21.544880	2.630245	8.191207	0

Figure 12: GARCH(1,1) model on Ethereum Returns

Reg1	Lagged Staking Ratio
Reg2	Lagged Staking Yield
Reg3	Lagged Fear and Greed Index
Reg4	Regulatory Dummy
Reg5	Log(MarketCap)
Reg6	ΔSentiment
Reg7	Log(Volume)
Reg8	Lockup Duration
Reg9	ΔMarket Index

Figure 11: GARCH(1,1) Variable table

GARCH(1,1) Coefficients for Solana Returns

	Estimate	Std. Error	t value	Pr(> | t|)
mu	-0.003348	0.017254	-0.194062	0.846128
mxreg1	0.090029	0.059547	1.511894	0.130561
mxreg2	0.403583	0.162600	2.482063	0.013062
mxreg3	-0.000035	0.000044	-0.814241	0.415507
mxreg4	0.002352	0.014624	0.160825	0.872231
mxreg5	-0.001395	0.000751	-1.856743	0.063348
mxreg6	0.000966	0.007559	0.127840	0.898276
mxreg7	0.000002	0.000442	0.004784	0.996183
mxreg8	-0.000074	0.000239	-0.309553	0.756901
mxreg9	1.116186	0.041882	26.650940	0
omega	0.000001	0.000025	0.033879	0.972974
alpha1	0.205119	0.049933	4.107923	0.000040
beta1	0.634385	0.093551	6.781198	0
vxreg1	0.00000004	0.000477	0.000094	0.999925
vxreg2	0	0.000536	0.000011	0.999991
vxreg3	0	0	0	1
vxreg4	0	0.001293	0.000008	0.999993
vxreg5	0.00000002	0.00000003	0.843326	0.399046
vxreg6	0.00000003	0.000374	0.000068	0.999946
vxreg7	0.000025	0.000012	2.154386	0.031210
vxreg8	0	0.00000003	0.482764	0.629263
vxreg9	0	0.001450	0.000006	0.999995
shape	5.656949	0.988943	5.720196	0

Figure 13: GARCH(1,1) on Solana returns

GARCH(1,1) Coefficients for Cardano Returns

	Estimate	Std. Error	t value	Pr(> | t|)
mu	-0.018852	0.060059	-0.313886	0.753608
mxreg1	0.000128	0.000156	0.820264	0.412066
mxreg2	-0.136983	0.190673	-0.718422	0.472497
mxreg3	0.000021	0.000023	0.883541	0.376944
mxreg4	-0.000778	0.011744	-0.066288	0.947149
mxreg5	0.000780	0.002578	0.302769	0.762066
mxreg6	0.001745	0.004938	0.353433	0.723763
mxreg7	0.000183	0.000408	0.448743	0.653617
mxreg8	-0.000077	0.000088	-0.867150	0.385860
mxreg9	0.868034	0.034085	25.466820	0
omega	0.000072	0.000023	3.136309	0.001711
alpha1	0.260994	0.046229	5.645636	0.00000002
beta1	0.625673	0.023086	27.101280	0
vxreg1	0.00000004	0.000002	0.018272	0.985422
vxreg2	0	0.000578	0.000021	0.999983
vxreg3	0	0.00000003	0.0000001	1.000000
vxreg4	0.00000003	0.000742	0.000038	0.999970
vxreg5	0.00000003	0.00000003	1.214578	0.224527
vxreg6	0.00000003	0.000317	0.000106	0.999916
vxreg7	0.0000001	0.00000003	3.890625	0.000100
vxreg8	0.000006	0.00000003	213.589800	0
vxreg9	0.00000003	0.000874	0.000029	0.999977
shape	4.637008	0.549737	8.434958	0

Figure 14: GARCH(1,1) on Cardano returns

GARCH(1,1) Coefficients for Cosmos Returns

	Estimate	Std. Error	t value	Pr(> | t|)
mu	0.140231	0.032535	4.310098	0.000016
mxreg1	-0.000729	0.001088	-0.670071	0.502813
mxreg2	0.000390	0.001437	0.271393	0.786089
mxreg3	0.000117	0.000052	2.260777	0.023773
mxreg4	-0.008133	0.015124	-0.537708	0.590779
mxreg5	-0.007234	0.001431	-5.056871	0.0000004
mxreg6	-0.009062	0.009959	-0.909943	0.362852
mxreg7	0.000553	0.000428	1.292878	0.196053
mxreg8	0.000314	0.000315	0.995857	0.319320
mxreg9	0.123244	0.047263	2.607598	0.009118
omega	0.000086	0.000024	3.648787	0.000263
alpha1	0.183049	0.042474	4.309637	0.000016
beta1	0.786916	0.037216	21.144500	0
vxreg1	0	0.000019	0.000598	0.999523
vxreg2	0.00000002	0.000015	0.001617	0.998710
vxreg3	0	0.00000003	0.0000001	1.000000
vxreg4	0.00000004	0.000998	0.000044	0.999965
vxreg5	0.0000001	0.0000001	1.228130	0.219398
vxreg6	0	0.000432	0.000012	0.999990
vxreg7	0	0.0000001	0.225884	0.821291
vxreg8	0.00000003	0	3.065175	0.002175
vxreg9	0.00000002	0.001186	0.000018	0.999986
shape	6.728076	1.396139	4.819057	0.000001

Figure 15: GARCH(1,1) on Cosmos returns

GARCH(1,1) Coefficients for Algorand Returns

	Estimate	Std. Error	t value	Pr(> | t|)
mu	-0.014301	0.010448	-1.368791	0.171065
mxreg1	0.001933	0.001551	1.245889	0.212805
mxreg2	0.000043	0.000044	0.998305	0.318132
mxreg3	0.009255	0.012177	0.760044	0.447228
mxreg4	0.000347	0.000553	0.627261	0.530488
mxreg5	0.001430	0.009753	0.146642	0.883415
mxreg6	0.000268	0.000095	2.821444	0.004781
mxreg7	-0.000080	0.000148	-0.541787	0.587965
mxreg8	0.953036	0.038351	24.850620	0
omega	0.000145	0.000027	5.402726	0.0000001
alpha1	0.253448	0.045141	5.614592	0.00000002
beta1	0.664642	0.036573	18.172880	0
vxreg1	0.00000003	0.000019	0.001722	0.998626
vxreg2	0	0	2.342299	0.019165
vxreg3	0.00000002	0.000745	0.000026	0.999979
vxreg4	0.0000001	0	7.022557	0
vxreg5	0.00000002	0.000453	0.000039	0.999969
vxreg6	0.0000002	0.00000002	10.624640	0
vxreg7	0	0.00000002	0.000005	0.999996
vxreg8	0	0.001269	0.000004	0.999997
shape	5.857273	1.049624	5.580354	0.00000002

Figure 16: GARCH(1,1) on Algorand returns

GARCH(1,1) Coefficients for TRON Returns

	Estimate	Std. Error	t value	Pr(> | t|)
mu	-0.078187	0.084987	-0.919978	0.357584
mxreg1	-0.002434	0.001590	-1.530407	0.125916
mxreg2	-0.001420	0.001541	-0.921892	0.356585
mxreg3	-0.000020	0.000023	-0.853694	0.393275
mxreg4	0.005189	0.007965	0.651465	0.514747
mxreg5	0.003816	0.003131	1.218637	0.222982
mxreg6	0.007466	0.002632	2.837303	0.004550
mxreg7	-0.000459	0.000636	-0.722150	0.470202
mxreg8	0.000070	0.000194	0.361991	0.717358
mxreg9	0.375083	0.015187	24.697870	0
omega	0.000057	0.000003	19.683080	0
alpha1	0.190467	0.008609	22.125180	0
beta1	0.697816	0.023082	30.232540	0
vxreg1	0	0.000005	0.000996	0.999206
vxreg2	0.00000003	0.000006	0.005193	0.995857
vxreg3	0	0.0000001	0	1
vxreg4	0.0000001	0.000199	0.000255	0.999796
vxreg5	0.0000001	0.0000002	0.585889	0.557950
vxreg6	0	0.000059	0.000096	0.999923
vxreg7	0.00000003	0.0000002	0.127121	0.898845
vxreg8	0.00000002	0.0000003	0.061797	0.950724
vxreg9	0.00000003	0.000065	0.000436	0.999652
shape	3.771551	0.386750	9.751904	0

Figure 17: GARCH(1,1) on Tron returns

GARCH(1,1) Coefficients for TON Returns

	Estimate	Std. Error	t value	Pr(> | t|)
mu	-0.009773	0.010511	-0.929828	0.352460
mxreg1	-0.001609	0.001190	-1.352081	0.176349
mxreg2	-0.001400	0.001579	-0.886351	0.375428
mxreg3	0.000028	0.000036	0.783518	0.433323
mxreg4	-0.015307	0.012845	-1.191723	0.233370
mxreg5	-0.001053	0.001121	-0.939872	0.347283
mxreg6	-0.000935	0.003168	-0.295270	0.767788
mxreg7	0.001802	0.001189	1.515618	0.129616
mxreg8	0.000055	0.000238	0.229438	0.818529
mxreg9	0.051898	0.039616	1.310019	0.190189
omega	0.000140	0.000026	5.469786	0.00000005
alpha1	0.241089	0.036682	6.572443	0
beta1	0.751131	0.029512	25.452020	0
vxreg1	0.00000004	0.000021	0.002043	0.998370
vxreg2	0.00000002	0.000026	0.000845	0.999326
vxreg3	0	0.00000002	0.312569	0.754608
vxreg4	0.0000001	0.000880	0.000063	0.999950
vxreg5	0.00000002	0.00000002	0.961536	0.336282
vxreg6	0	0.000341	0.000001	0.999999
vxreg7	0.0000001	0.00000002	2.870205	0.004102
vxreg8	0	0.00000005	0.000238	0.999810
vxreg9	0.00000003	0.001206	0.000028	0.999977
shape	3.279077	0.346351	9.467484	0

Figure 18: GARCH(1,1) on Ton returns

GARCH(1,1) Coefficients for Binance Coin Returns

	Estimate	Std. Error	t value	Pr(> | t|)
mu	-0.020533	0.005520	-3.719935	0.000199
mxreg1	0.000361	0.000742	0.485824	0.627092
mxreg2	-0.000554	0.000474	-1.166833	0.243278
mxreg3	0.000002	0.000025	0.092281	0.926475
mxreg4	-0.005117	0.005661	-0.903916	0.366040
mxreg5	0.000718	0.000288	2.493156	0.012661
mxreg6	-0.002881	0.008597	-0.335143	0.737518
mxreg7	0.000239	0.000089	2.694451	0.007050
mxreg8	-0.000526	0.000819	-0.642386	0.520623
mxreg9	0.612814	0.023163	26.456360	0
omega	0.000047	0.000003	18.536300	0
alpha1	0.254382	0.028685	8.868125	0
beta1	0.745040	0.022112	33.693520	0
vxreg1	0	0.000002	0.006996	0.994418
vxreg2	0	0.000008	0.001258	0.998996
vxreg3	0	0.0000002	0.0000001	1.000000
vxreg4	0	0.000339	0.000041	0.999967
vxreg5	0.00000004	0.0000002	0.180996	0.856371
vxreg6	0.00000002	0.000256	0.000081	0.999935
vxreg7	0.00000003	0.0000001	0.453934	0.649876
vxreg8	0.00000002	0.000001	0.018318	0.985385
vxreg9	0.00000002	0.000457	0.000038	0.999969
shape	3.276730	0.302077	10.847330	0

Figure 19: GARCH(1,1) on Binance Returns

GARCH(1,1) Coefficients for Polkadot Returns

	Estimate	Std. Error	t value	Pr(> | t|)
mu	-0.047660	0.053190	-0.896031	0.370236
mxreg1	-0.001149	0.000765	-1.501341	0.133267
mxreg2	0.000353	0.001755	0.201014	0.840688
mxreg3	-0.000007	0.000038	-0.193178	0.846819
mxreg4	0.008640	0.012158	0.710645	0.477304
mxreg5	0.002027	0.002302	0.880634	0.378516
mxreg6	0.009472	0.006517	1.453449	0.146099
mxreg7	-0.000236	0.000115	-2.061276	0.039277
mxreg8	0.000079	0.000112	0.701503	0.482989
mxreg9	0.909955	0.032775	27.763850	0
omega	0.000001	0.000015	0.037846	0.969810
alpha1	0.211739	0.019100	11.085640	0
beta1	0.654009	0.028107	23.268620	0
vxreg1	0.00000004	0.000017	0.002439	0.998054
vxreg2	0	0.000017	0.000850	0.999322
vxreg3	0	0.0000001	0.000050	0.999960
vxreg4	0.0000001	0.000586	0.000121	0.999903
vxreg5	0	0	0.450836	0.652108
vxreg6	0	0.000825	0.000011	0.999991
vxreg7	0.000009	0.0000001	144.971500	0
vxreg8	0.000003	0.0000001	24.095090	0
vxreg9	0	0.000729	0.000004	0.999997
shape	5.639417	0.779913	7.230826	0

Figure 20: GARCH(1,1) on Polkadot returns

GARCH(1,1) Coefficients for Avalanche Returns

	Estimate	Std. Error	t value	Pr(> | t|)
mu	-0.042404	0.032056	-1.322813	0.185897
mxreg1	0.003744	0.002658	1.408922	0.158858
mxreg2	-0.000318	0.000492	-0.647214	0.517493
mxreg3	-0.000013	0.000044	-0.296506	0.766844
mxreg4	0.013934	0.016541	0.842400	0.399564
mxreg5	0.001972	0.001579	1.249090	0.211632
mxreg6	-0.011038	0.008323	-1.326191	0.184776
mxreg7	-0.000383	0.000373	-1.026272	0.304764
mxreg8	-0.000057	0.000157	-0.359602	0.719145
mxreg9	1.147023	0.041255	27.802940	0
omega	0.000106	0.000032	3.301915	0.000960
alpha1	0.208512	0.034830	5.986630	0
beta1	0.748625	0.050588	14.798620	0
vxreg1	0	0.000015	0.000636	0.999492
vxreg2	0	0.000021	0.000711	0.999433
vxreg3	0	0.0000002	0.00000003	1.000000
vxreg4	0	0.000598	0.000017	0.999987
vxreg5	0.0000001	0.00000004	2.625709	0.008647
vxreg6	0	0.000798	0.000013	0.999990
vxreg7	0.0000001	0.00000003	2.494331	0.012619
vxreg8	0	0	0.057384	0.954240
vxreg9	0	0.001201	0.000008	0.999993
shape	4.670057	0.606358	7.701817	0

Figure 21: GARCH(1,1) on Avalanche returns

Appendix D: Volatility graphs

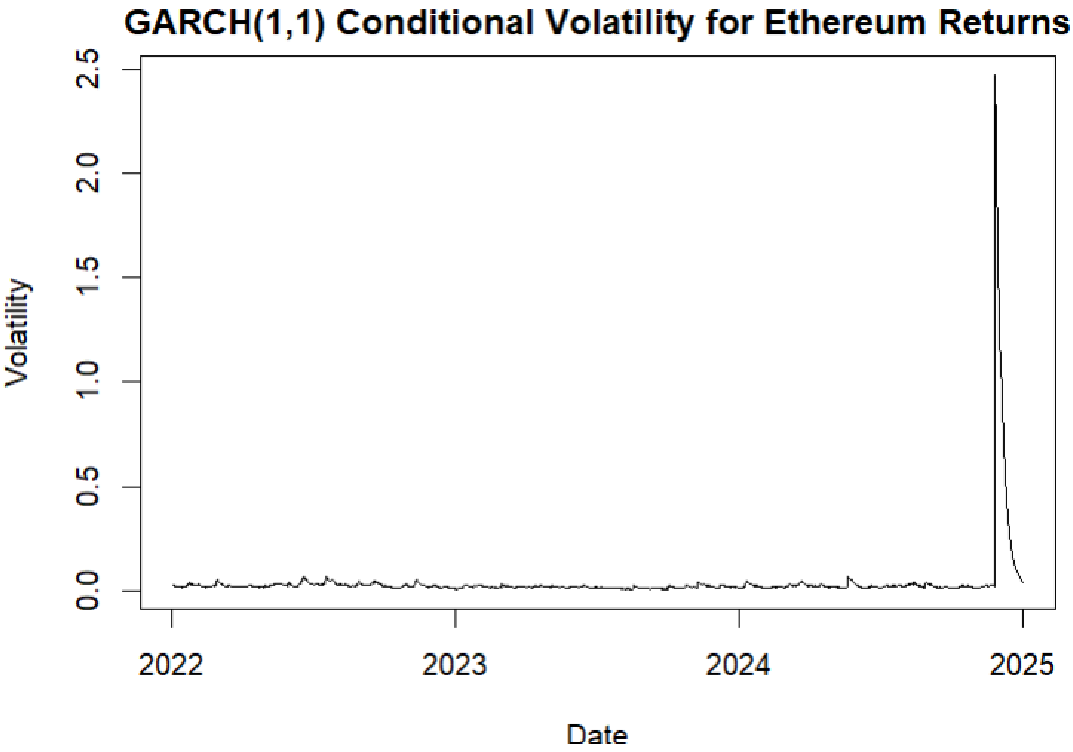

Figure 22: Volatility graph Ethereum Returns

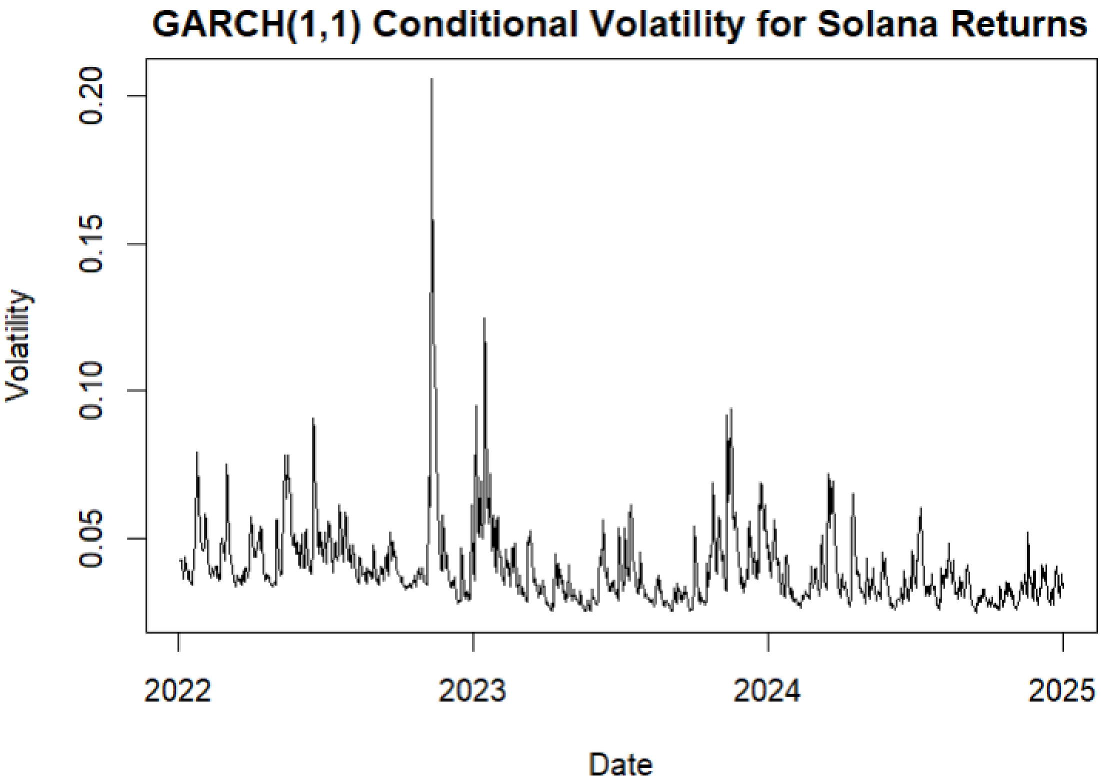

Figure 23: Volatility graph Solana Returns

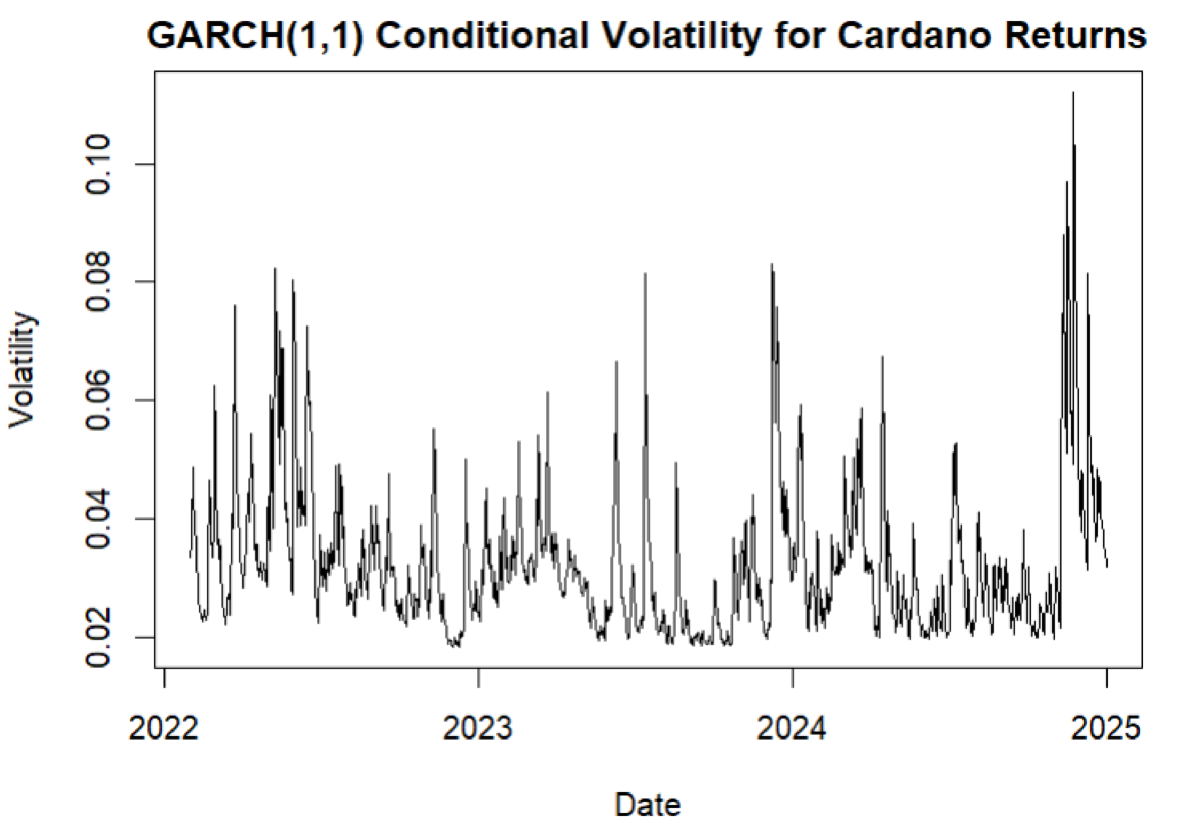

Figure 24: Volatility graph Cardano Returns

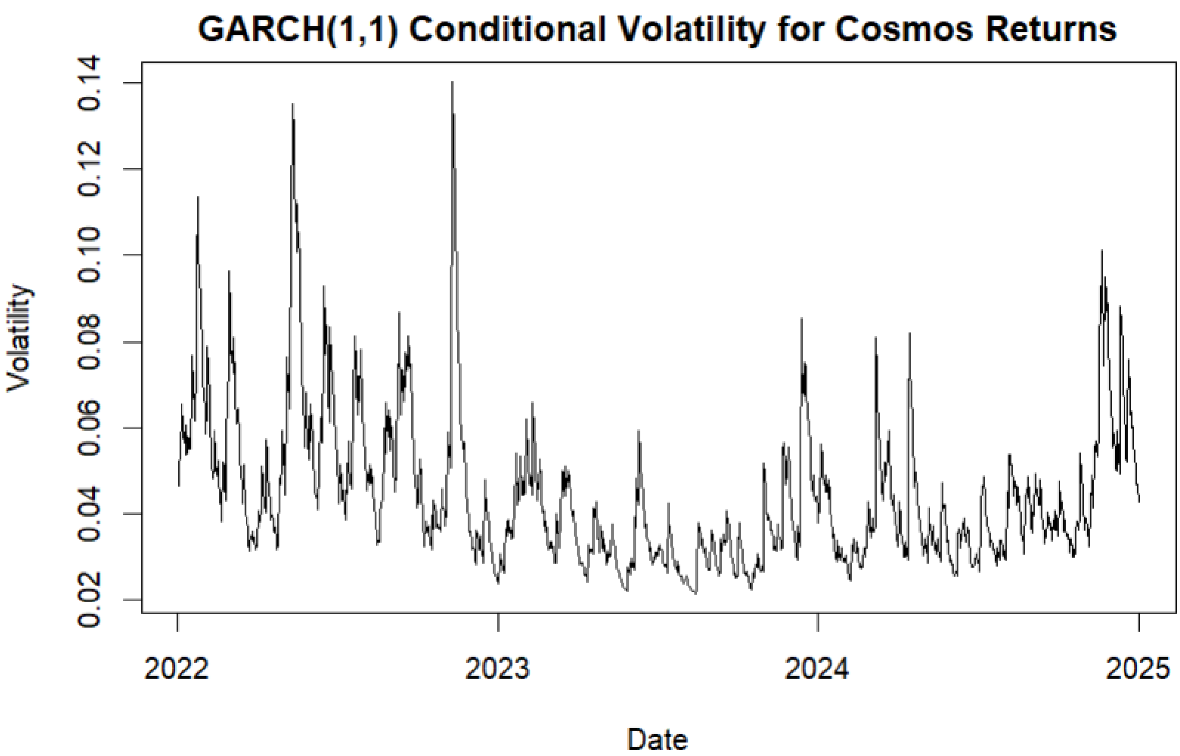

Figure 25: Volatility graph Cosmos Returns

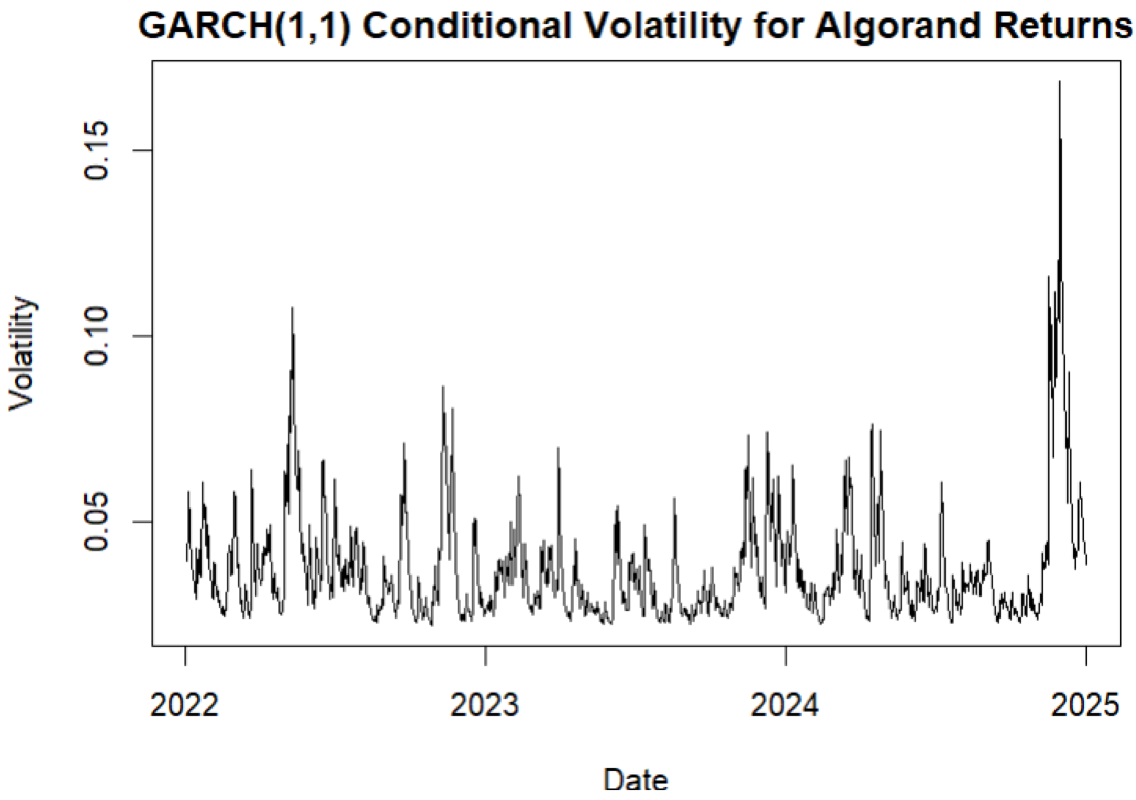

Figure 26: Volatility graph Algorand Returns

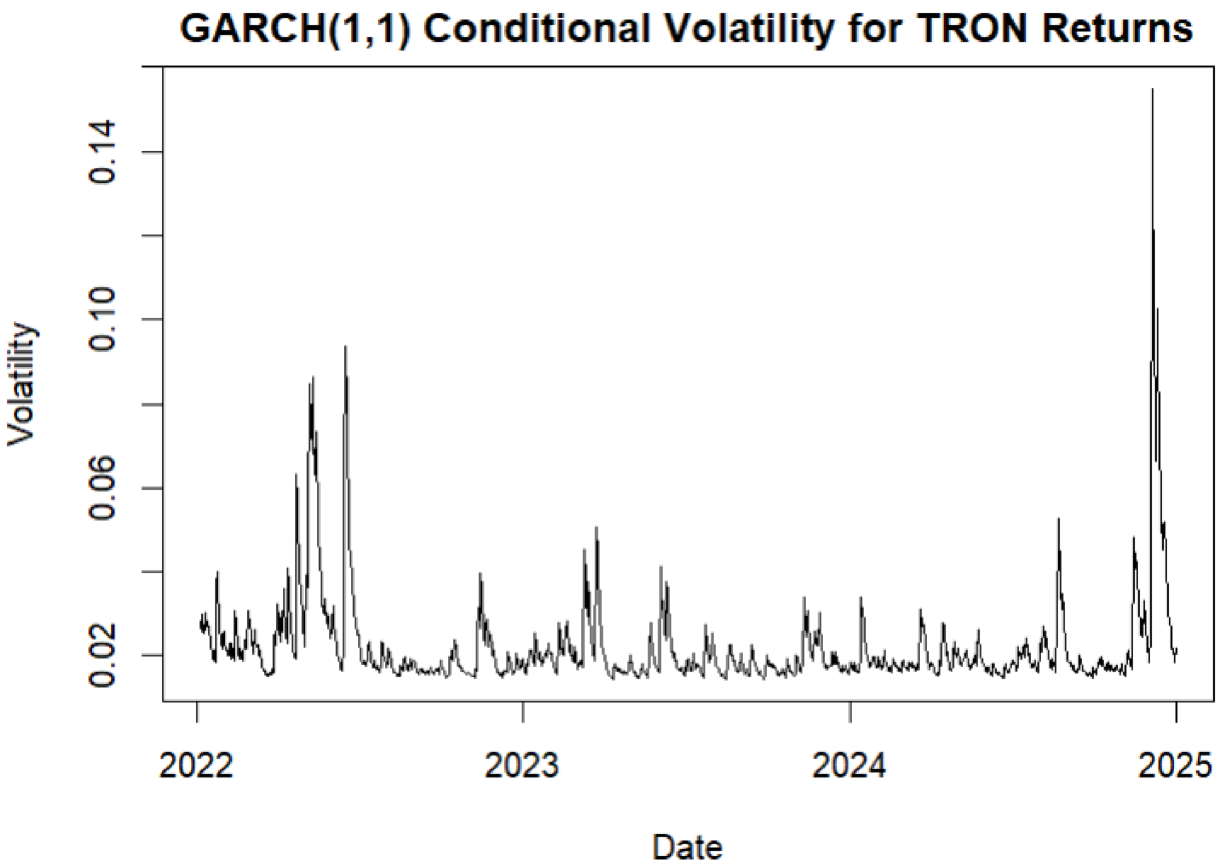

Figure 27: Volatility graph Tron Returns

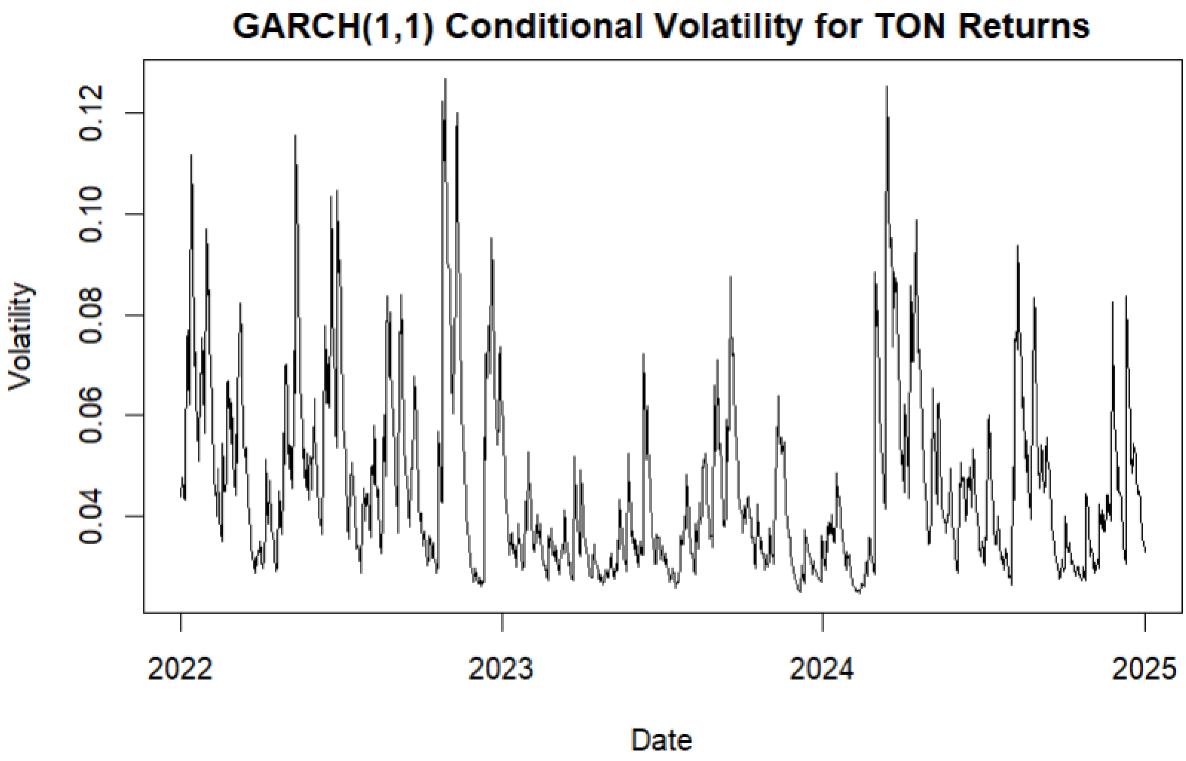

Figure 28: Volatility graph Ton Returns

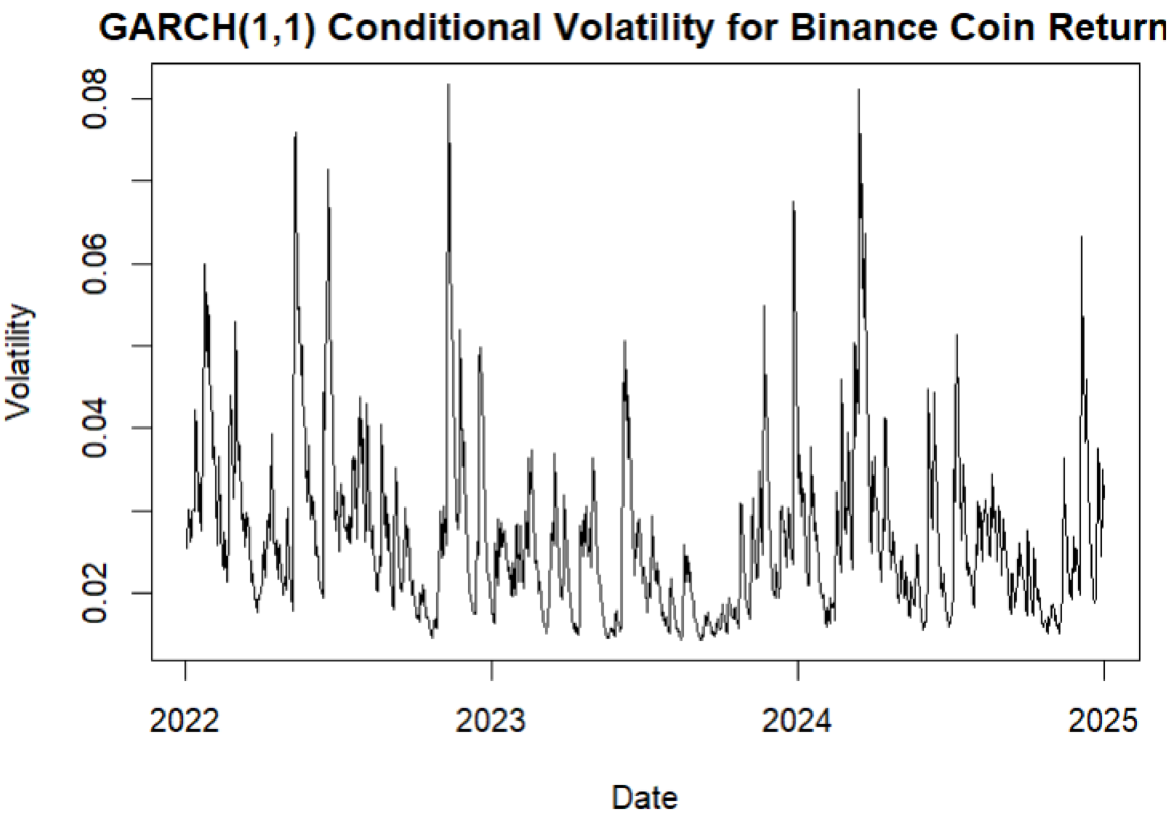

Figure 29: Volatility graph Binance Returns

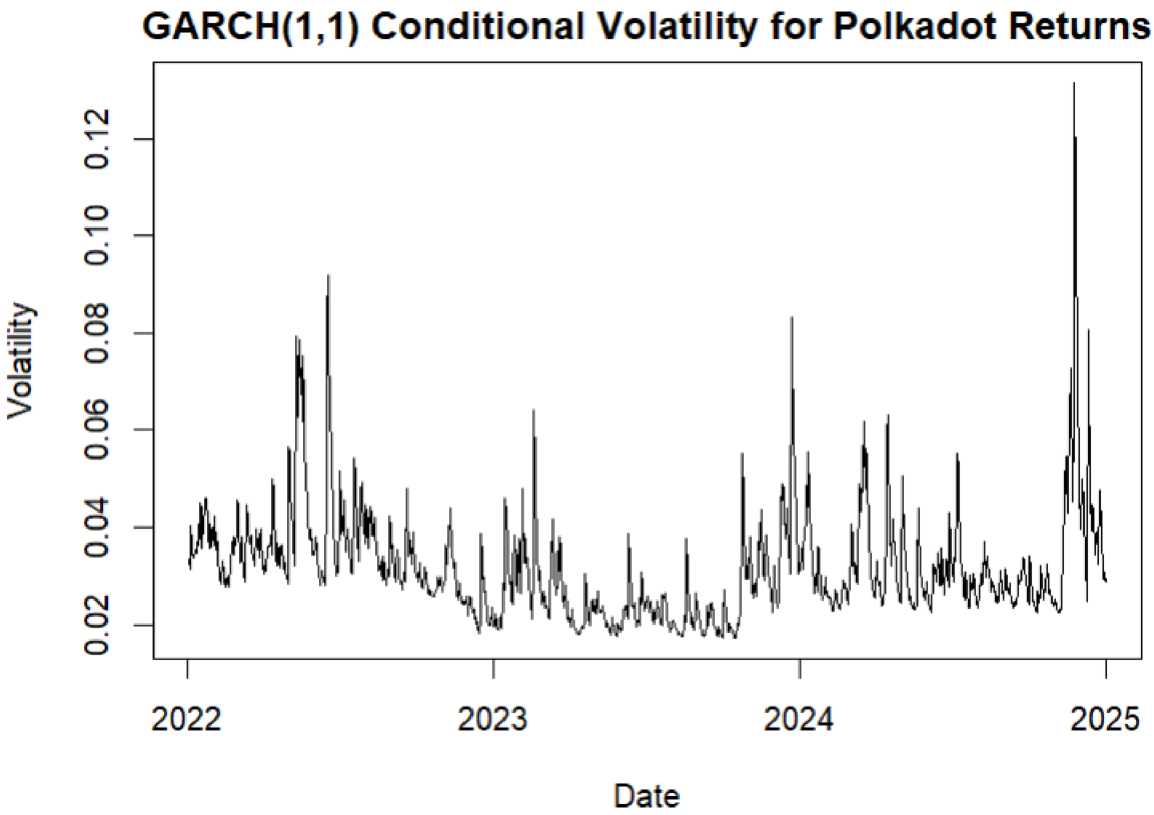

Figure 30: Volatility graph Polkadot Returns

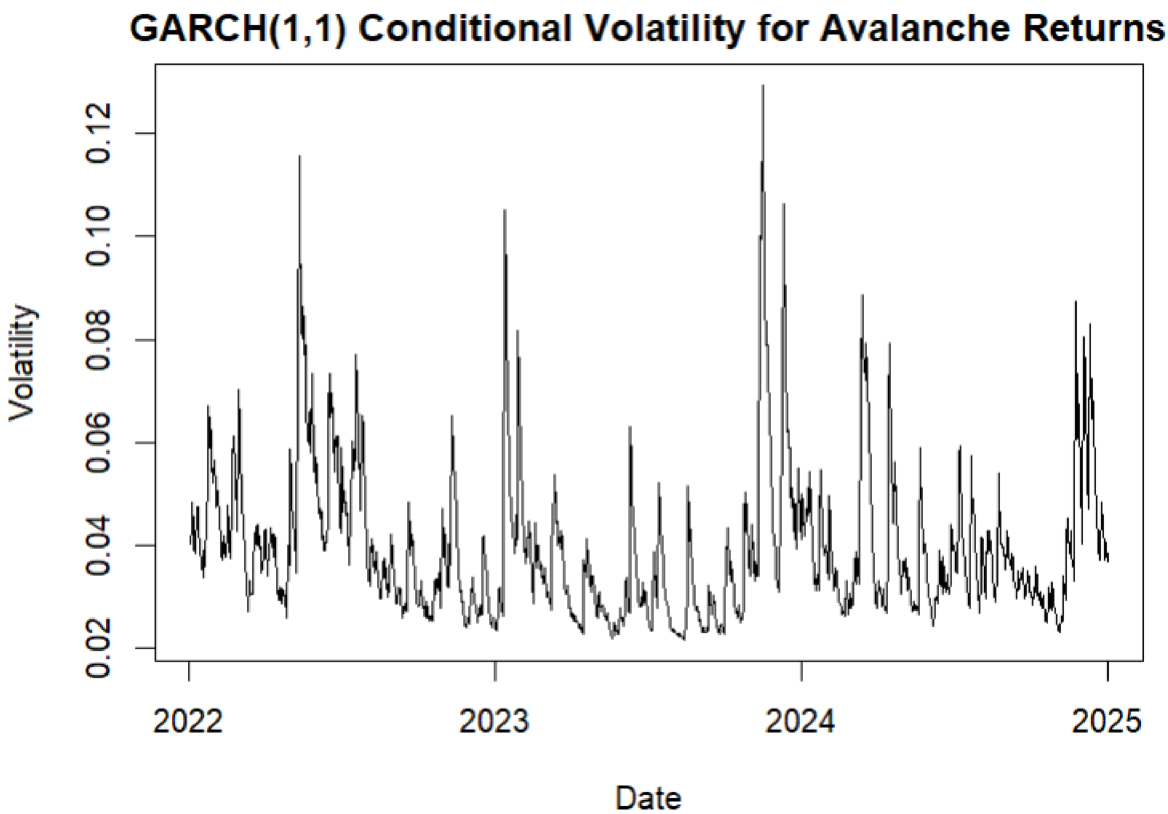

Figure 31: Volatility graph Avalanche Returns