Lisbon School of Economics & Management
Universidade de Lisboa

MASTER IN
CONTABILIDADE, FISCALIDADE E FINANÇAS EMPRESARIAIS

MASTER'S FINAL WORK
DISSERTATION

THE IMPACT OF U.S. ELECTIONS ON THE TECHNOLOGY SECTOR AND CRYPTOCURRENCY MARKETS

BENJAMIM PONTE PASCOAL LEANDRO DE MEDEIROS

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GLOSSARY

AAPL – Apple Inc

AAR – Average Abnormal Return

ADA – Cardano

AMZN – Amazon.com Inc

AR – Abnormal Return

BMP Test – Boehmer, Musumeci, and Poulsen Test

BNB – Binance Coin

BTC – Bitcoin

CAAR – Cumulative Average Abnormal Return

CAR – Cumulative Abnormal Return

DOGE – Dogecoin

EMH – Efficient Market Hypothesis

EPU – Economic Policy Uncertainty

ETH – Ethereum

GOOGL – Alphabet Inc

MAG-7 – Magnificent Seven (group of seven leading U.S. technology companies: Alphabet, Amazon, Apple, Meta, Microsoft, Nvidia, and Tesla)

META – Meta Platforms Inc

MSFT – Microsoft Corporation

MVIS – MVIS CryptoCompare Digital Assets 100 Index

NAV – Normalized Abnormal Volume

NVDA – NVIDIA Corporation

SHIB – Shiba Inu

SOL – Solana

TON – Toncoin

TRX – Tron

TSLA – Tesla Inc

U.S. – United States of America

UCRY – Cryptocurrency Uncertainty Index

XRP – XRP (Ripple)

ABSTRACT, KEYWORDS AND JEL CODES

This dissertation investigates the impact of the 2024 U.S. presidential election on financial markets, focusing on two segments particularly sensitive to political transitions: the stocks of the seven largest U.S. technology firms (MAG-7) and the ten leading cryptocurrencies by market capitalization. Motivated by the election of Donald Trump, whose policy record includes unpredictability and a clearly pro-crypto stance, this study applies an event study methodology to assess whether the political shift triggered statistically significant abnormal returns in these markets.

The market model was estimated over a 250-day window preceding the election, and abnormal returns (AR), average abnormal returns (AAR), and cumulative abnormal returns (CAR) were computed across multiple short-term event windows. To assess statistical significance, three tests were applied: the classical t-test, the Boehmer–Musumeci–Poulsen (BMP) test, and the non-parametric sign test.

Findings reveal that, overall, MAG-7 stocks did not exhibit significant reactions. An exception was Tesla, which showed strong positive returns and volume around the event, likely influenced by Elon Musk's visible political engagement. In contrast, the cryptocurrency market responded more strongly. Significant CAARs were observed in several windows, suggesting a positive sector-wide reaction to the expectation of deregulation under Trump. These results highlight the different levels of sensitivity between traditional equities and decentralized digital assets, shaped by their exposure to political risk, regulation, and investor sentiment.

This research contributes to the literature on political uncertainty and financial markets. It offers insights for investors, policymakers, and regulators regarding how ideological transitions in leadership can influence asset behaviour.

KEYWORDS: Event study; U.S. elections; MAG-7; Cryptocurrencies; Political uncertainty; Market Efficiency.

JEL CODES: C12; C22; G12; G14; G18

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1. INTRODUCTION

U.S. presidential elections usually attract global attention and have a strong impact on financial markets. A change in political leadership in the United States is not just administrative. It can bring shifts in fiscal, trade, and regulatory policies that affect investor expectations and market risk. Understanding how markets react to this kind of political information is especially important during periods of uncertainty, like the 2024 election.

This study examines market reactions to the 2024 U.S. presidential election, in which Donald Trump defeated Kamala Harris, who entered the race after Joe Biden's withdrawal. The Republican Party also gained control of both the Senate and the House of Representatives, giving Trump strong legislative support, similar to his first term. While his presidency from 2017 to 2021 was notably pro-business, featuring tax cuts, deregulation, and incentives for corporate investment. It also brought instability and uncertainty through actions like the trade war with China, tariff impositions, and isolationist rhetoric ("America First"). These actions affected industries that rely on international trade, such as technology. As a result, Trump's return in 2024 raised concerns about a possible repeat of such policies and how they might affect financial assets.

This dissertation focuses on two segments of the financial market likely to be sensitive to the 2024 election outcome: the stocks of the seven largest U.S. technology companies (collectively known as the MAG-7: Alphabet, Amazon, Apple, Meta, Microsoft, Nvidia, and Tesla) and the ten largest cryptocurrencies by market capitalization (excluding stablecoins). The MAG-7 firms are globally integrated and particularly exposed to shifts in trade and regulatory policy (Bouoiyour and Selmi, 2016; Ahmed et al., 2025). Cryptocurrencies, in contrast, are decentralized assets that are highly volatile and often driven by investor sentiment (Almeida and Gonçalves, 2023; Chokor and Alfieri, 2021). During the campaign, Trump adopted a pro-cryptocurrency stance, promising deregulation and support for digital innovation, in contrast to the opposing candidate's more cautious regulatory position on digital assets. This divergence heightened uncertainty about future crypto policies, making digital assets potentially more sensitive to the election outcome.

The study is grounded in the semi-strong form of the Efficient Market Hypothesis (Fama, 1970; Fama, 1991), which assumes that markets promptly reflect public information. However, political events often create ambiguity that challenges this process (Pástor and Veronesi, 2012). Prior research indicates that highly polarized elections frequently spike economic policy uncertainty and potentially leading to market inefficiencies (Baker *et al.*, 2020). Empirical findings have been mixed: historically, some studies found that markets initially respond favorably to Republican victories, reflecting optimism about pro-business policies, while others emphasize that election outcomes can create volatility depending on the context (Niederhoffer, Gibbs and Bullock, 1970; Riley and Luksetich, 1980). These insights motivate an examination of whether market reactions to the 2024 election align with or deviate from efficient market predictions. Against this backdrop, this dissertation aims to investigate market reactions to the 2024 U.S. presidential election. The central research questions are: Did MAG-7 stock prices exhibit statistically significant abnormal returns around the 2024 election? And did the top cryptocurrencies experience significant abnormal returns during the same period? Addressing these questions will reveal whether the election triggered measurable departures from expected price behaviour and thus test market efficiency in these contexts.

To answer these questions, an event study methodology is employed. The market model is estimated over a 250-day pre-election window to compute expected returns for each asset. Abnormal returns (AR) are calculated by comparing actual returns to these expectations during event windows around the election (MacKinlay, 1997). These are aggregated into average abnormal returns (AAR) and cumulative abnormal returns (CAR) for each window. Statistical significance is assessed through multiple tests, including the standard t-test, the Boehmer–Musumeci–Poulsen (BMP) volatility-adjusted test, and a nonparametric sign test for robustness under potential non-normality.

The analysis of these market reactions holds both economic and regulatory relevance. From an academic perspective, it contributes to the literature on how election uncertainty and political transitions impact asset pricing in both markets. From a practical standpoint, the findings provide valuable insights for investors, regulators and policymakers by highlighting the sensitivity of large technology firms and cryptocurrencies to political event. The presence of statistically significant abnormal returns may indicate the need for revised regulatory oversight and updated risk management practices in sectors exposed to trade disruptions, technological innovation, and evolving regulatory frameworks.

The dissertation is structured in five chapters. Chapter 1 introduces the context, objectives and methodology. Chapter 2 reviews the literature on elections and financial markets with a focus on tech and crypto. Chapter 3 presents the dataset and methodology. Chapter 4 analyzes the empirical results. Chapter 5 concludes with a discussion of implications, limitations and suggestions for future research.

2. LITERATURE REVIEW

2.1. Market Efficiency

The Efficient Market Hypothesis (EMH), introduced by Fama (1970), is one of the most influential theories in finance. It states that asset prices reflect all available information, making it impossible to consistently achieve abnormal risk-adjusted returns. Under this view, markets are efficient, meaning that neither technical analysis, based on historical prices, nor fundamental analysis, focused on financial data, can reliably predict future price movements. Fama (1970) identified three forms of market efficiency: weak, semi-strong, and strong. In the weak form, current prices incorporate all past market data. The semi-strong form goes further, including all publicly available information such as earnings reports and economic indicators. The strong form assumes that even insider information is already reflected in prices, eliminating arbitrage opportunities.

A key empirical issue is determining how and when new public information is incorporated into prices. Event study methodology responds to this by analyzing market reactions to well-defined events. Fama (1991) emphasized that testing semi-strong efficiency involves observing how quickly and accurately markets respond to new information. Originally developed in the context of corporate finance, over time, event study methodology has become one of the most widely used tools for analyzing how markets respond to specific events (MacKinlay, 1997; Campbell, Lo and MacKinlay, 2012). So, this method aims to detect inefficiencies by assessing whether asset prices adjust immediately, react with delay, or generate abnormal returns, directly testing the EMH. Applying it across different market contexts helps understand how specific structures influence the processing of information. This study applies the method to two such contexts: the stock market and the cryptocurrency market, each with features that may lead to inefficiencies.

2.2. Limitations of market efficiency and possibility for abnormal returns

As previously discussed, real-world markets often diverge from EMH assumptions. Grossman and Stiglitz (1980) demonstrated through their informational paradox, if markets fully incorporated all available information, active investors would have no incentive to acquire it. Yet without informed investors, prices could not adjust efficiently. This paradox exposes a core limitation of the EMH and helps explain why real-world markets often exhibit inefficiencies. Yet, without these investors, markets would not adjust efficiently. In practice, several structural and behavioural limitations can prevent prices from reflecting information accurately or promptly. These include transaction costs, taxes, regulatory barriers, information asymmetries, and low liquidity (Fama, 1991; Malkiel, 2003). Behavioural finance also identifies psychological biases such as overconfidence, herding, and loss aversion, which can drive irrational investor behaviour and mispricings (Kahneman and Tversky, 1979; Shleifer, 2000). These dynamics have been observed in episodes like the 2008 Volkswagen short squeeze and the 2021 GameStop rally (Allen et al., 2017; Klein, 2022).

Cryptocurrency market further amplify these inefficiencies due to their structural features. Introduced with Bitcoin, these decentralized ecosystems operate on blockchain technology and are traded across multiple online platforms without institutional oversight (Nakamoto, 2008). Traded globally on various online platforms rather than centralized exchanges, cryptocurrencies enjoy relative autonomy from regulatory and monetary authorities. Their appeal lies in technological innovation and potential high returns, but also in high volatility, speculative nature, and fragmented legal treatment across jurisdictions (Chokor and Alfieri, 2021). Additionally, crypto markets are dominated by retail investors and are heavily influenced by sentiment, emotion, and behavioural biases. Overconfidence, herding, and risk-seeking are prevalent, driving momentum-driven surges and crashes (Almeida and Gonçalves, 2023; Papadamou et al., 2021). The lack of intrinsic value anchors, as seen in events like the ICO boom or Tesla's Bitcoin acquisition, magnifies divergent beliefs and hype cycles (Cheah and Fry, 2015; Eom, 2021;Szetela et al., 2021;Li et al., 2024). Moreover, information asymmetry is exacerbated by heavy reliance on unstructured sources, such as tweet volume, search trends, and forum discussions, rather than standardized disclosures, further weakening efficiency (Mai et al., 2018; Kraaijeveld and De Smedt, 2020; Abraham et al., 2018; Liu and Tsyvinski, 2018; Gurdgiev and O'Loughlin, 2020). These features challenge the EMH, making it possible to obtain abnormal returns in crypto markets (Gregoriou, 2019, Fousekis and Grigoriadis, 2021). Some scholars, however, argue that efficiency may evolve over time. Khuntia and Pattanayak (2018), for example, support the Adaptive Market Hypothesis developed by Lo (2004), which suggests that market efficiency is not static but evolves as investors adapt to changing environments.

2.3. Uncertainty, Elections, and Market Reactions

Understanding how markets respond to elections requires considering the limitations of market efficiency, especially under uncertainty. When information is ambiguous, delayed, or unevenly processed, prices may fail to adjust fully and promptly. Political uncertainty, particularly surrounding presidential elections, is a critical factor in this dynamic, as it introduces unpredictability about future leadership, economic strategy, and institutional stability (Pástor and Veronesi, 2012). This form of uncertainty overlaps with, but is distinct from, policy uncertainty. As noted by Pasquariello and Zafeiridou (2014), policy uncertainty relates to ambiguity about future macroeconomic and fiscal decisions, while political uncertainty encompasses doubts about electoral outcomes, governance continuity, and the credibility of future policy implementation.

To quantify these effects, Baker et al. (2016) developed the Economic Policy Uncertainty (EPU) Index, based on the frequency of policy-related news articles. Their findings show sharp EPU spikes before and during elections, particularly in highly polarized environments, and these spikes correlate with increased market volatility, reduced investment, and slower job growth. Although both the equity and cryptocurrency markets react to such uncertainty, their responses differ in timing, intensity, and structure. The following sections explore these reactions in each market.

2.3.1. Stock Market

In the stock market, uncertainty plays a significant role in shaping investor expectations and asset prices. The Political Uncertainty Hypothesis, proposed by Goodell, McGee and McGroarty (2020), posits that expectations regarding election outcomes function as proxies for anticipated macroeconomic policy changes. Their study shows that an increasing probability of a candidate's victory is associated with heightened volatility, reflecting investor anxiety over policy shifts. Similarly, Mnasri and Essaddam (2021) argue that political uncertainty influences stock markets primarily through macroeconomic channels, especially when the leading candidate represents the opposition. Białkowski, Gottschalk and Wisniewski (2008) added that when the political orientation of the government changes, volatility may persist over time, as new authorities issue policy reversals and alter economic direction.

Investor behaviour under uncertain conditions is further explained by the Uncertain Information Hypothesis (UIH), introduced by Brown, Harlow and Tinic (1988). This hypothesis suggests that when unexpected information is released, investors, being risk-averse, tend to react cautiously, even when the news is objectively favorable. Over time, as uncertainty diminishes and expectations adjust, prices correct upward, producing a temporary mispricing effect. Pantzalis, Stangeland and Turtle (2000), examining elections in 33 countries, found that pre-election effects depend on variables such as election timing, press freedom, and the likelihood of incumbent re-election. Abnormal returns were strongest in early elections that led to incumbent defeats, particularly in countries with limited freedom. In the U.S., Li and Born (2006) concluded that stock market volatility and average returns increase when no candidate has a clear lead. Conversely, when outcomes are perceived as certain, volatility remains subdued, highlighting the relevance of perceived uncertainty in shaping investor responses.

The political orientation of candidates also influences market reactions. Snowberg, Wolfers and Zitzewitz (2007), analyzing U.S. elections from 1880 to 2004, suggested that financial markets historically perform better under Republican presidents. However, studies by Santa-Clara and Valkanov (2003), using data from the US presidential elections between 1927 and 1998, and Guru (2024), covering the period from 1928 to 2020, found that long-term market performance tends to be stronger under Democratic administrations. Short-term reactions, however, often favor Republican victories. Niederhoffer, Gibbs and Bullock (1970) and Riley and Luksetich (1980) observed that markets respond positively to Republican wins and negatively to Democratic ones. Oehler, Walker and Wendt (2013), studying elections from 1980 to 2008, confirmed this trend, noting a generally negative short-term impact from Democratic victories, although the response to Republican outcomes was more mixed. Also, The growing divergence between the two main U.S. political parties reflects increasing political polarization, often accompanied by tight electoral margins. According to Baker et al. (2020), such conditions are associated with significant spikes in the EPU index. Moreover, Baker et al. (2016) further show that higher policy uncertainty correlates with reduced investment, slower job growth, and heightened market volatility, as measured by the CBOE Volatility Index (VIX). While the EPU captures election-related uncertainty, it also reflects the broader macro-financial environment that markets respond to.

The U.S. elections of 2016, 2020, and 2024 exemplify these dynamics. Each was marked by heightened polarization and closely contested outcomes, with Donald Trump as the Republican candidate. In 2016, his surprise victory led to immediate stock market gains and lower volatility, largely driven by expectations of tax cuts, deregulation, and fiscal expansion (Sun, Qiao and Wang, 2021;Wagner et al., 2017). Nonetheless, Wagner et al. (2017) observed that investors were slow to react to anticipated protectionist trade policies, with multinational firms being penalized only after more concrete signals emerged. In 2024, investor optimism returned with Trump's re-election. Ahmed et al. (2025) found that stock markets exhibited positive abnormal returns, aligned with the Hope Hypothesis, reflecting expectations of pro-business and deregulatory measures. This reaction was supported by Jain et al. (2025), who reported that portfolios linked to Trump's policy agenda showed strong gains after the election. Bouoiyour and Selmi (2016) emphasized that such reactions are not uniform across sectors. Political uncertainty during the 2016 election, for instance, divided the market into clear groups of winners and losers depending on sectoral exposure and policy sensitivity.

2.3.2. Cryptocurrency Market

The cryptocurrency market reacts differently to political and regulatory uncertainty due to its decentralized structure and distinct investor base. Unlike traditional markets, which respond strongly to macroeconomic indicators, cryptocurrencies are primarily influenced by micro-level sentiment and retail investor behaviour. Pyo and Lee (2020) found that macroeconomic announcements, including the Consumer Price Index, Producer Price Index, and statements from the Federal Open Market Committee, have negligible effects on Bitcoin prices, while Glas (2019) suggests that the cryptocurrency market operates largely independently from the macroeconomic environment. Instead, microeconomic sentiment such as concerns about unemployment and job security has a greater influence, largely due to the dominance of retail investors in the cryptocurrency market, who tend to react more emotionally to personal financial fears (Burggraf *et al.*, 2021). Supporting this, Almeida and Gonçalves (2025) show that the crypto market acts as a net transmitter of greed, underscoring its sensitivity to sentiment-driven dynamics.

The decentralized and unregulated nature of cryptocurrencies also makes them highly responsive to regulatory announcements. Xiong, Liu and Zhao (2020) find that weaker regulation leads to higher herding and a greater presence of irrational investors, while stricter regulation mitigates these behaviours. Auer and Claessens (2018), similarly showed that regulatory bans and restrictions often destabilize prices, while regulatory clarity fosters legitimacy and stabilizes volatility. Furthermore, Chokor and Alfieri (2021) observed that announcements raising the likelihood of regulatory adoption are typically associated with negative short-term abnormal returns in crypto assets. However, these effects vary depending on market-specific features such as liquidity and information asymmetry.

The EPU index by Baker et al. (2016), though developed for traditional markets, has also been applied to cryptocurrencies, especially Bitcoin, to evaluate whether these decentralized assets reflect or resist the same uncertainty shocks that influence traditional financial system. Findings remain mixed and tend to depend on macro-financial regimes, investor sentiment, and geopolitical conditions. Some studies suggest that cryptocurrencies such as Bitcoin act as hedges or safe havens during high EPU, particularly in the U.S., China, or Japan (Bouri, Jalkh, et al., 2017; Bouri, Molnár, et al., 2017;Bouri, Gupta, et al., 2017; Bouri et al., 2018; Bouri, Gkillas and Gupta, 2020; Bouri and Gupta, 2021; Cheng and Yen, 2020; Fang, Su and Yin, 2020; Mokni, 2021). Conversely, a significant body of research disputes the hedging capacity of cryptocurrencies. Studies by Fasanya et al. (2021), Hasan et al. (2022), Lucey et al. (2022) and Almeida, Gaio and Gonçalves (2024) conclude that cryptocurrencies do not serve as effective hedges or safe havens against policy risk.

To better capture crypto-specific policy uncertainty, Lucey et al. (2022) developed the Policy Cryptocurrency Uncertainty Index (UCRY Policy), which measures uncertainty surrounding regulatory and policy-related news affecting cryptocurrencies such as regulatory debates, government bans or approvals, central bank positions on crypto and legal ambiguity or announcements of new laws. Their study shows that the UCRY index reacts strongly to cryptocurrency-specific events like exchange hacks, legal announcements, and market bubbles, and that it correlates closely with Bitcoin price movements. Foglia and Dai (2022), further showed that global macro-financial stress, as measured by the EPU, can spill over to the UCRY index, reinforcing that even decentralized assets are affected by broader economic and political uncertainty.

2.4. The Role of Elections in Shaping Market Dynamics

2.4.1. Stock Market: Focus on Technology Sector

As Bouoiyour and Selmi (2016) suggests, political uncertainty can lead to differentiated sectoral outcomes. Within this context, the technology sector emerges as a particularly relevant case for closer analysis. This relevance stems from the sector's acute sensitivity to macroeconomic variables, regulatory frameworks, and global policy shifts.

Bouoiyour and Selmi (2016) and Selmi and Bouoiyour (2020) highlights that during and after the 2016 election, the tech industry emerged as one of the primary sectoral losers, reflecting a lack of engagement with key policy areas such as high-skilled immigration. The administration's opposition to visa programs like H1B signaled a broader indifference to the sector's structural reliance on global talent. This contradiction between the administration's pro-growth narrative and its neglect of innovation-enabling policies was compounded by targeted criticism of major firms like Apple and Amazon. Moreover, Selmi and Bouoiyour (2020) notes the administration's inconsistent political messaging and the resulting elevation in the EPU index, signaling enduring ambiguity for market actors. Building on this, Ahmed et al. (2025) interprets the 2024 election through the lens of renewed structural pressures on the tech sector. The study underscores that Trump's return to office revived fears surrounding trade wars, an "America First" doctrine, and the possibility of renewed tariffs and isolationist policies, conditions that significantly increase volatility for industries dependent on global supply chains. In addition, the continuation of restrictive stances on immigration and foreign relations further exacerbated investor concerns, particularly for technology firms reliant on international talent and open markets.

2.4.2. Cryptocurrency market

In the 2024 U.S. presidential race, Donald Trump and Kamala Harris represent sharply divergent approaches to cryptocurrency regulation. Trump, having shifted from earlier skepticism, now embraces a pro-crypto stance, opposing central bank digital currencies (CBDCs), promising to end regulatory crackdowns, and supporting mining rights and financial privacy, and even the creation of a strategic Bitcoin reserve (Anthony, 2024). His campaign's use of Bitcoin donations and promotion of a family-backed crypto platform further cement this shift. Harris, by contrast, signals continuity with the Biden administration, which has advocated for a 30% tax on crypto mining, proposed a CBDC to crowd out private digital assets, and exerted pressure on banks to limit crypto involvement. While Harris has expressed vague support for innovation in "digital assets" her emphasis lies in regulatory safeguards, particularly for minority investors, and lacks concrete pro-market commitments. Thus, voters face a clear contrast: Trump promoting deregulation and adoption, Harris leaning toward control and restriction. However, as Chohan (2025) warns, these positions must be understood within the broader context of a rising crypto lobbying force. Super PACs like Fairshake spent over $200 million backing pro-crypto candidates from both parties, aiming to reshape the regulatory landscape. This signals a shift in the crypto space from a decentralized, anti-establishment nature to a more institutionalized and politically entrenched industry. In this light, the 2024 election marks not only a clash of regulatory ideologies but also the consolidation of crypto interests within the U.S. political economy.

2.5. Investigation Hypothesis

Given the distinct structural and behavioural characteristics of equity and cryptocurrency markets, this study adopts a dual-track approach, formulating and testing two separate hypotheses tailored to each market.

2.5.1. Investigation Hypothesis 1

This study applies an event study methodology focused on the 2024 U.S. presidential election, limiting the analysis to the Magnificent Seven (MAG-7) stocks. These large-cap, tech-oriented U.S. firms account for nearly one-third of the S&P 500's market capitalization and exert considerable influence over global markets due to their integration in international supply chains and sensitivity to macroeconomic, trade, and regulatory shifts.

The methodology is grounded in the semi-strong form of the Efficient Market Hypothesis (EMH), which asserts that asset prices fully and promptly reflect all publicly available information (Fama, 1970; Fama, 1991). If markets are efficient, political events such as presidential elections should be rapidly priced in. However, elections often generate policy uncertainty that distorts or delays this process. Event studies are commonly used to capture such market reactions, though their reliability can be challenged under heightened uncertainty. In particular, political uncertainty, which especially when the likely winner is from the opposition, tends to increase volatility due to ambiguous expectations regarding future fiscal, macroeconomic, and regulatory policies (Goodell, McGee and McGroarty, 2020; Mnasri and Essaddam, 2021). Historically, Republican victories typically trigger initial market gains, reflecting optimism around tax cuts, deregulation, and pro-business reforms (Sun, Qiao and Wang, 2021; Wagner et al., 2017; Ahmed et al., 2025). However, these broad effects often mask divergent sectoral responses. The technology sector, for example, is highly dependent on high-skilled immigration, stable trade relations, and regulatory predictability, making it especially vulnerable to protectionist policies and political volatility (Bouoiyour and Selmi, 2016; Selmi and Bouoiyour, 2020; Ahmed et al., 2025). These dynamics are particularly relevant for the MAG-7 stocks, globally integrated tech firms whose dominant role in market indices makes them key indicators of investor sentiment in periods of political transition.

Given this context, this study postulates the following hypothesis:

H1: The election of Donald Trump as U.S. President in 2024 is associated with statistically significant short-term abnormal returns in the MAG-7 stocks.

2.5.2. Investigation Hypothesis 2

Regarding the second investigation hypothesis, this study applies an event study methodology to the 2024 U.S. presidential election, focusing on the top 10 cryptocurrencies by market capitalization (excluding stablecoins). Prior to the election, these assets collectively represented $1.90 trillion USD, with Bitcoin alone accounting for approximately 72%, according to CoinMarketCap.

Political uncertainty during elections generates ambiguity about future macroeconomic, fiscal, and regulatory policies (Pasquariello and Zafeiridou, 2014). Unlike traditional assets, cryptocurrency prices tend to respond more to microeconomic sentiment, such as job insecurity, due to the dominance of retail investors (Burggraf *et al.*, 2021). Their decentralized nature and lack of standardized regulation make them highly sensitive to regulatory developments, including government bans, central bank announcements, and legal changes, which often substitute macroeconomic signals in shaping expectations (Chokor and Alfieri, 2021). These events are commonly associated with short-term negative abnormal returns, especially when the probability of regulatory intervention increases although the response varies by cryptocurrency depending on liquidity and information asymmetry.

Also, Trump promoted a pro-crypto agenda and, in July 2024 during a speech in Nashville, even declared his intention to become the first "crypto president", pledging deregulation and digital asset adoption, contrasted with Harris's preference for tighter oversight (Anthony, 2024). This divergence may have reinforced the perception of cryptocurrencies as a hedge against institutional uncertainty, especially as the industry gains political influence through lobbying efforts and becomes increasingly entangled in the political process.

Given this context, this study postulates the following hypothesis:

H2: The election of Donald Trump as U.S. President in 2024 is associated with statistically significant short-term abnormal returns in the top 10 cryptocurrencies.

3. DATA & METHODOLOGY

This study uses event study methodology and Normalized Abnormal Volume (NAV) to evaluate the impact of the 2024 U.S. presidential election on MAG-7 stocks and the top 10 cryptocurrencies. The event study approach is particularly suitable as it isolates the immediate market reaction attributable specifically to the election, while NAV complements price analysis by capturing shifts in trading activity, reflecting investor response beyond price movements alone. Both methods rely on the semi-strong form of the Efficient Market Hypothesis, which assumes prices quickly reflect public information.

3.1. Data

The analysis focuses on two distinct segments of the financial market. This sample was specifically selected due to the high sensitivity of MAG-7 companies to trade, regulatory, and immigration policies directly impacted by the presidential election outcome. The top 10 cryptocurrencies were chosen due to their decentralized nature and heightened responsiveness to regulatory uncertainty, especially given the divergent positions of the candidates on digital asset regulation.

On one hand, the stock market analysis examines the MAG-7 companies, namely Alphabet (GOOGL), Amazon (AMZN), Apple (AAPL), Meta Platforms (META), Microsoft (MSFT), NVIDIA (NVDA), and Tesla (TSLA) daily stock prices and trading volumes sourced from Bloomberg. On the other hand, the study includes the ten largest cryptocurrencies by market capitalization prior to the 2024 U.S. presidential election, excluding stablecoins. This selection comprises a diversified set of digital assets, including major cryptocurrencies such as Bitcoin (BTC) and Ethereum (ETH), prominent altcoins such as Binance Coin (BNB), Solana (SOL), Ripple (XRP), Tron (TRX), Toncoin (TON), and Cardano (ADA), as well as memecoins, namely Dogecoin (DOGE) and Shiba Inu (SHIB). Daily closing prices and trading volumes for the cryptocurrencies were retrieved from CoinMarketCap.

In this study, different benchmarks were selected to represent market returns. For stocks, the UBS Mega Cap Technology Index was chosen for its focus on U.S.-listed tech firms with market caps over $200 billion, aligning closely with the MAG-7. Compared to broader indices like the S&P 500 or Nasdaq-100, it offers a more accurate reflection of large-cap tech performance. For cryptocurrencies, the MVIS CryptoCompare Digital Assets 100 Index (MVDA) was used. It tracks the top 100 cryptocurrencies by market cap, excluding stablecoins to better capture actual price movements. This makes it well-suited for assessing real market dynamics during the election period.

3.2. Descriptive Statistics and Correlation Structure

Descriptive statistics for the daily returns of the MAG-7 stocks, the ten largest cryptocurrencies by market capitalization, and the two benchmark indices, the UBS Mega Cap Technology Index and the MVIS CryptoCompare Digital Assets 100 Index (MVDA), are presented in Appendix 1. Each return series includes 261 daily observations, covering both the estimation and event windows. The descriptive statistics (mean, standard deviation, minimum, maximum, median, skewness, kurtosis) provide a comprehensive overview to support result interpretation.

MAG-7 stocks exhibit low average returns, with AAPL and MSFT at the lowest end, while NVDA and META show higher means than the benchmark (0.49% and 0.25%). Among cryptocurrencies, DOGE, SHIB, and TON stand out with mean returns above 0.30%, in contrast to BTC, which aligns more closely with the MVIS index (0.19%). ADA and ETH report the lowest means. The gap between mean and median is wider in crypto, suggesting more irregular price jumps.

In terms of dispersion, MAG-7 stocks show moderate volatility, with TSLA and NVDA posting the widest spreads. Cryptocurrencies display significantly higher risk, with SHIB and DOGE having standard deviations above 5%, and some daily returns approaching +47%. Compared to the MVIS index (2.67%), most cryptos are more volatile, except TRX and BTC. These results confirm the literature on the differences between equity and crypto markets. As discussed in Section 2, equities tend to show greater informational efficiency and lower volatility, especially among large-cap firms. In contrast, the higher average returns, dispersion, and skewness seen in cryptocurrencies reflect structural inefficiencies, retail-driven sentiment, and speculative behaviour. These characteristics reinforce the need to employ both parametric and non-parametric tests, particularly in short-term event studies due to frequent deviations from normality. These features reinforce the need to use both parametric and non-parametric tests, especially for short-term election reactions, as abnormal returns often deviate from normality and non-parametric tests offer better robustness and power (Serra, 2002).

Building on these return characteristics, it is also important to examine how assets co-move within and across markets. Understanding these relationships informs portfolio diversification and helps interpret aggregate results. The Pearson correlation matrix presented in Appendix 2 summarizes the return co-movements between MAG-7 stocks, the top 10 cryptocurrencies, and their respective benchmarks.

Among MAG-7 stocks, strong positive correlations are observed, both within the group and with the Mega Cap Tech Index, indicating synchronized price movements influenced by common sectoral drivers. This confirms the benchmark's representativeness of large tech firms.

Cryptocurrencies exhibit even higher internal correlations, suggesting they move closely together in response to shared market sentiment. The MVIS Index also shows strong alignment with major cryptocurrencies, supporting its role as a reliable market proxy. A few exceptions emerge, such as TSLA, NVDA and Mega Cap Tech Index, which display slightly higher correlations with certain cryptocurrencies, aligning with evidence of co-jump dynamics in crypto-exposed tech stocks (Xu, Bouri and Cepni, 2022).

Given that MAG-7 stocks are primarily influenced by macroeconomic factors, sector-specific news, and policy expectations, while cryptocurrencies are more driven by regulatory uncertainty, market sentiment, and speculative dynamics, their distinct market reactions justify a separate analytical approach.

3.3. Event Study Methodology for Return-Based Analysis

The event study methodology was chosen due to its robustness in isolating immediate financial market reactions to specific events in this case, the 2024 U.S. presidential election enabling a precise assessment of the event's direct and short-term impact on MAG-7 stocks and cryptocurrencies. Although the election occurred on November 5, 2024, the event day is set as November 6 (Day 0), since the outcome was not yet priced in on the 5th. Based on this, the study defines both the estimation and event windows. Following MacKinlay (1997), the event window is the period set to capture the impact of the event occurring on day 0 and will be defined as (-5,+5). So, the main window spans day -5 to +5, capturing five days before and after the event. This design aligns with Brown and Warner (1985) and ensures that overlapping events are minimized. Additional windows are tested in both markets to assess robustness and detect possible anticipation or delayed effects. However, as the initial window overlaps with earnings releases from MAG-7 firms until Day +3, the main stock market window is adjusted to (-2,+5) to reduce contamination and improve reliability. The estimation window, as defined by MacKinlay (1997), precedes and does not overlap with the event window, allowing for the calculation of normal return parameters unaffected by the event. A 250-day window is adopted for both markets: from -255 (Nov 1, 2023) to -6 (Oct 29, 2024) for stocks, and from -255

(Feb 25, 2024) to -6 (Oct 31, 2024) for cryptocurrencies.This discrepancy arises from the fact that the cryptocurrency market operates continuously, including weekends, unlike the traditional stock market. The Figure 1 demonstrates the event study timeline, including the estimation period, pre-event window, event day, and post-event window.

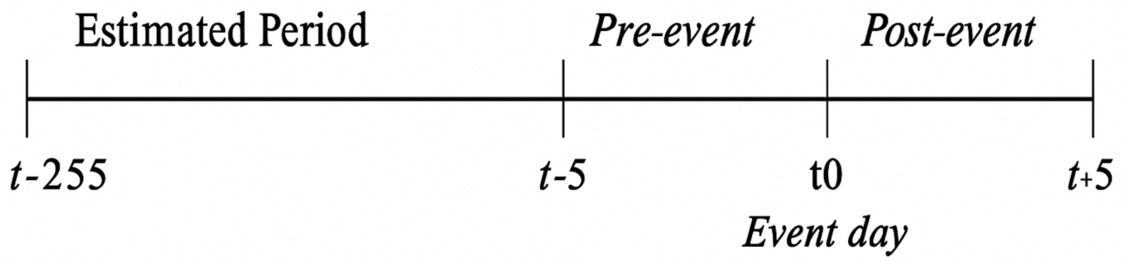

Figure 1- Event Study Timeline

Several models are available for estimating normal returns, including the Mean-Adjusted, Market Adjusted, Market Model, CAPM-based, and Fama-French multi-factor models (MacKinlay, 1997; De Jong, 2007). The Mean-Adjusted model is excluded due to its simplicity. Next, we can differentiate the models based on the number of factors included in their calculations. The multi-factor models (e.g., Fama-French), which incorporates multiple factors to explain the returns of the asset under study, such as the size of the company, its book-to-market value, its profitability, and its investment intensity are suited for long-horizon event studies (De Jong, 2007). Since this study focuses on short-term abnormal returns around the U.S. presidential election, single-factor models are more appropriate. Among these, the Market Model is preferred as it estimates asset-specific Betas, unlike the Market Adjusted model which assumes the Beta and Alpha parameters are equal to 1 and 0, respectively. (MacKinlay, 1997;De Jong and De Goeij, 2007). Supporting this, Holler (2014), through meta-research, showed that 79.1% of event studies used the Market Model.

Before presenting the event study formulas, this study uses the logarithmic function to compute daily returns for each stock, cryptocurrency, and benchmark.

$$R_t = ln(\frac{P_t}{P_{t-1}}) \tag{1}$$

Where R_t is the logarithmic return on day *t* , and P_t and P_{t-1} are the closing prices on days *t* and *t-1*, respectively.

To apply the event study methodology, abnormal returns (AR) must be calculated as the difference between actual and expected returns. Actual returns R_{it} are obtained using logarithmic returns, while expected returns $E(R_{it})$ are estimated using the market model based on the estimation window. The abnormal return for asset *i* on day *t* is given by:

$$AR_{it} = R_{it} - E(R_{it}) \tag{2}$$

The expected return $E(R_{it})$ is calculated as:

$$E(R_{it}) = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{3}$$

Where R_{mt} is the market return on day *t* and α_i and β_i are parameters estimated via Ordinary Least Squares regression of the asset's returns on market returns during the estimation window. The estimated α_i and β_i coefficients for each asset are reported in Appendix 3 (MAG-7 stocks) and Appendix 4 (Top 10 cryptocurrencies).

After computing Abnormal Returns (AR) for each asset, Cumulative Abnormal Returns (CAR) are calculated to assess the total impact over the multi-day event window. Although Buy-and-Hold Abnormal Returns, an alternative metric, are often used in long-term studies (De Jong, 2007; El Ghoul et al., 2022) CAR is more suitable here due to the short-term focus of this analysis.

Thus, the CAR reflects the sum of abnormal returns for each asset between two defined days, t_1 and t_2, within the event window (MacKinlay, 1997; De Jong, 2007). The equation below shows how the CAR is calculated:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{it} \tag{4}$$

Beyond individual asset analysis, a cross-sectional approach assesses the average impact on MAG-7 stocks and the top ten cryptocurrencies. This reveals whether these groups show abnormal returns on each day t, within the event window. The Average Abnormal Return (AAR) is calculated as follows:

$$AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{it} \tag{5}$$

Its variance is also calculated to statistically validate the results, as shown in the following formula.

$$S^2{}_{AAR_t} = \frac{1}{N-1}\sum_{i=1}^{N}(AR_{it} - AAR_t)^2 \tag{6}$$

Where $S^2{}_{AAR_t}$ is the cross-sectional variance of the AAR on day *t*. The term AR_{it} denotes the abnormal return of asset *i* on day *t*, while AAR_t is the mean abnormal return across all *N* assets in the sample.

Next, the Cumulative Average Abnormal Return (CAAR) is computed to capture the overall impact of the event on a group of assets over a defined window. It is calculated by summing the CARs of all assets in the group between two points in time, t_1 and t_2. The formula is given by:

$$CAAR = \sum_{i=1}^{N} CAR_i \tag{7}$$

It will also be necessary to calculate its variance in order to statistically validate the results.

$$S^2{}_{CAAR_{(t_1,t_2)}} = \frac{1}{N-1}\sum_{i=1}^{N}(CAR_{i,(t_1,t_2)} - CAAR_{(t_1,t_2)})^2 \tag{8}$$

Where $S^2{}_{CAAR(t_1,t_2)}$ denotes the variance of the CAAR over the event window from day t_1 to t_2. *N* represents the number of assets in the group.

To assess the significance of the abnormal returns computed during the event windows, several statistical tests were applied to both individual and aggregate measures. According to MacKinlay (1997) and Campbell, Lo and MacKinlay (2012) these tests aim to determine whether the observed abnormal performance differs significantly from zero, thereby validating the impact of the event under study, assuming a normal distribution:

$$AAR_t \sim N(0, S^2{}_{AAR_t}) \tag{9}$$

$$CAAR_{(t_1,t_2)} \sim N(0, S^2{}_{CAAR_{(t_1,t_2)}}) \tag{10}$$

The parametric t-test was used to evaluate whether the AAR and CAAR significantly deviate from zero. For the AAR, the test statistic is defined as:

$$t = \frac{AAR_t}{S_{AAR_t}} \sim t_{N-1} \tag{11}$$

For the CAAR, the test statistic is defined as:

$$t = \frac{CAAR(t_1, t_2)}{S_{CAAR_{(t_1,t_2)}}} \sim t_{N-1} \tag{12}$$

To enhance robustness, this study applies the standardized abnormal return method by Boehmer, Masumeci and Poulsen (1991), known as the BMP test. This approach adjusts for event-induced volatility using estimation window variance and is used in recent studies (Tomić, Todorovic and Jaksic, 2023).

Initially, the standardized abnormal return (SAR) for asset *i* at event time t is computed as:

$$SAR_{i,0} = \frac{AR_{i,0}}{S_{AR_{i,0}}} \tag{13}$$

Where, $AR_{i,0}$ is the abnormal return for asset *i* at time t and $S_{AR_{i,0}}$ is the adjusted variance of the abnormal return at time t, calculated as:

$$S^2{}_{AR_{i,0}} = S^2{}_{AR_i} \times \left(1 + \frac{1}{M_i} + \frac{(R_{m,0} - \bar{R}_m)^2}{\sum_{t=T_0}^{T_1}(R_{m,t} - \bar{R}_m)^2}\right) \tag{14}$$

In this formula, $S^2{}_{AR_i}$ is the unadjusted variance of abnormal returns for asset *i*, estimated over the estimation window. The adjustment accounts for event-induced volatility and small-sample bias. M_i is the number of days in the estimation period, $R_{m,0}$ is the market return at time *t*, and $\sum_{t=T_0}^{T_1}(R_{m,t} - \bar{R}_m)^2$ captures the total variance of the market returns during the estimation window. The average market return $\bar{R}_m$ is calculated as:

$$\bar{R}_m = \frac{1}{M_i}\sum_{t=T_0}^{T_1}(\bar{R}_{m,t})^2 \tag{15}$$

The Average Standardized Abnormal Return (ASAR), which is the cross-sectional average of the SAR for a group of assets on day t within the event window, calculated as:

$$ASAR_t = \sum_{i=1}^{N} SAR_{i,0} \tag{16}$$

To assess the dispersion of SARs across assets at each time t, the cross-sectional variance is computed as:

$$S^2{}_{ASAR,0} = \frac{1}{N-1} \times \sum_{i=1}^{N} (SAR_{i,0} - \frac{ASAR_t}{N})^2 \tag{17}$$

This standardization also applies to cumulative returns. The Standardized Cumulative Abnormal Return (SCAR) for asset i, over a chosen event window from T_1 to T_2, is defined as:

$$SCAR_i = \frac{CAR_i}{S_{CAR_i}} \tag{18}$$

Where CAR_i is the cumulative abnormal return of asset i over the event window, and S_{CAR_i} is its adjusted variance, calculated as:

$$S^2{}_{CAR_i} = S^2{}_{AR_i} \times \left(L_2 + \frac{L_2}{M_i} + \frac{\sum_{t=T_{1+1}}^{T_2} \left(R_{m,t} - \bar{R}_m\right)^2}{\sum_{t=T_0}^{T_1} \left(R_{m,t} - \bar{R}_m\right)^2} \right) \tag{19}$$

$S^2{}_{CAR_i}$ is the adjusted variance of the cumulative abnormal return for asset i over the selected event window. It is based on the unadjusted abnormal return variance $S^2{}_{AR_i}$, estimated from the estimation window. L_2 s the number of days in the event window. M_i is the number of days in the estimation window. The term $\sum_{t=T_{1+1}}^{T_2} \left(R_{m,t} - \bar{R}_m\right)^2$ captures the total variance of the market returns during the selected event window, the $\sum_{t=T_0}^{T_1} (R_{m,t} - \bar{R}_m)^2$ captures the total variance of the market returns during the estimation window.

The Average Standardized Cumulative Abnormal Return ($\overline{SCAR}$) is computed as the mean SCAR across all assets:

$$\overline{SCAR} = \frac{1}{N} \times \sum_{i=1}^{N} SCAR_i \tag{20}$$

And its cross-sectional variance is given by:

$$S^2_{\overline{SCAR}} = \frac{1}{N-1} \times \sum_{i=1}^{N} (SCAR_i - \overline{SCAR}) \tag{21}$$

Finally, to test the significance of ASAR and $\overline{SCAR}$, a standard t-test is applied under the null hypothesis that their means equal zero. The test statistic for ASAR is:

$$t = \frac{ASAR}{\sqrt{N} \times S_{ASAR,0}} \sim t_{M-1} \tag{22}$$

And for $\overline{SCAR}$,

$$t = \sqrt{N} \times \frac{\overline{SCAR}}{S_{\overline{SCAR}}} \sim t_{M-1} \tag{23}$$

So, these statistics are approximately normally distributed under the null hypothesis, assuming cross-sectional independence. Significance is assessed at 1%, 5%, and 10% confidence levels.

To strengthen robustness, this study complements parametric tests with a non-parametric Sign Test on aggregated abnormal returns. Frequently used in financial research (Tomić, Todorovic and Jaksic, 2023), the Sign Test offers a distribution-free alternative suited for volatile data where t-test assumptions like normality and homoscedasticity may not hold. It tests whether positive and negative abnormal returns occur with equal probability under the null hypothesis. In this study, it is applied to both AAR (cross-sectionally by day) and CAAR (across firms per window), serving as a robust check for statistically consistent positive returns. The test statistic is computed as follows:

$$z = \frac{w - N \times 0.5}{\sqrt{N \times 0.5 \times 0.5}} \sim N(0,1) \tag{24}$$

Where w is the number of positive AR_i or the CAR_i during the event window. The resulting Z-score is compared against the standard normal distribution to assess statistical significance at conventional levels (e.g., 1%, 5%, 10%).

Additionally, a Z-test for the difference in means was applied to statistically assess whether Tesla's CAR significantly differed from the average CAR of the remaining MAG-7 firms, considering Elon Musk's unique political involvement during the election period. Given his status as a major campaign donor and his public alignment with Trump, it was important to test whether investor reaction to Tesla was significantly distinct from its peers in the tech sector.

$$Z = \frac{CAR_{Tesla} - \overline{CAR}_{MAG-7\ without\ Tesla}}{\sqrt{\frac{S^2_{Tesla}}{n_1} + \frac{S^2_{MAG-7\ without\ Tesla}}{n_2}}} \tag{25}$$

Where, CAR_{Tesla} is the cumulative abnormal return of Tesla and $\overline{CAR}_{MAG-7\ without\ Tesla}$ is the average CAR of the other six MAG-7 firms. The terms S^2_{Tesla} and $S^2_{MAG-7\ without\ Tesla}$ correspond to the variance of the CARs for Tesla and for the MAG6, respectively. The parameter n_1 equals 1, referring to Tesla as a single observation, and n_2 equals 6, reflecting the number of firms in the MAG6 subgroup.

3.3. Abnormal Trading Volume Analysis

This study adopts the Normalized Abnormal Volume (NAV) to detect significant deviations in trading activity, following the approach by Jarrell and Poulsen (1989). This metric does not aim to signal high volume levels in absolute terms, but rather to capture significant deviations from the asset's historical behaviour. According to Bajo (2010), the NAV allows the identification of moments when volume departs from normality, which may reflect the incorporation of new information by investors.

For each asset *i* and day t, the NAV is defined as:

$$NAV_{i,t} = \frac{TV_{i,t} - \mu_{i,t}}{\sigma_{i,t}} \tag{26}$$

Where, $TV_{i,t}$ is the trading volume of asset *i* on day *t*. $\mu_{i,t}$ mean volume over the preceding N days, calculated as $\mu_{i,t} = \frac{1}{N}\sum_{t=1}^{N} TV_{i,t}$ and $\sigma_{i,t}$ is the corresponding standard deviation: $\sigma_{i,t} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(TV_{i,t} - \mu^{TV}_{i,t})^2}$

In stock markets, Bloomberg provides volume in units. For cryptocurrencies, however, unit-level volume data is unavailable. Therefore, daily monetary volume is divided by the asset's closing price to estimate the number of units traded, using the CoinMarketCap data.

The NAV is statistically useful because, once normalized, its values approximate a standard normal distribution. This allows deviations to be interpreted using critical values: NAV magnitudes above 1.28, 1.64, and 2.33 correspond to significance levels of 90%, 95%, and 99%, respectively. Thus, positive or negative deviations above these thresholds suggest abnormal behaviour in trading volume, potentially associated with the incorporation of new, relevant information by investors.

4. RESULTS

The following section interprets the effects of the 2024 U.S. presidential election on MAG-7 stocks and the top 10 cryptocurrencies, based on the event study methodology. Both AAR and CAAR are analyzed to assess whether the election induced statistically significant market reactions.

4.1. MAG-7 Results

Starting with the MAG-7, Tables 1 and 2 present the AAR and CAAR results, together with the corresponding statistical test outcomes described earlier.

Table 1- Mag-7 AAR Results

Day	AAR (%)	t-test (p-value)	BMP (p-value)	Sign Test (p-value)
-2	-0.27%	0.47	0.35	0.06*
-1	0.19%	0.57	0.90	0.71
0	0.43%	0.81	0.85	0.71
1	0.26%	0.52	0.41	0.71
2	0.02%	0.99	0.31	0.06*
3	-0.04%	0.98	0.34	0.26
4	0.42%	0.70	0.13	0.06*
5	0.29%	0.60	0.46	0.71

AAR (%) represents the Average Abnormal Return, measuring the mean of daily abnormal returns across all assets in the sample on each event day.

AARs were computed using the Event Study Methodology with the Market Model and a 250-day estimation window prior to the event. Statistical tests include the t-test, BMP test and Sign test to assess significance of abnormal returns on each day.

*, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively. P-values are two-tailed.

Table 2- Mag-7 CAAR Results

Event windows	CAAR (%)	t-test (p-value)	BMP (p-value)	Sign Test (p-value)
Before the event				
(-2,-1)	1.17%	0.80	0.50	0.71

During the event				
(-2,2)	0.62%	0.84	0.58	0.06*
(-2,3)	0.57%	0.90	0.48	0.06*
(-2,4)	0.99%	0.77	0.73	0.26
(-2,5)	1.28%	0.73	0.95	0.26
(-1,3)	0.85%	0.86	0.57	0.26
(-1,4)	1.27%	0.73	0.85	0.71
(-1,5)	1.56%	0.69	0.96	0.71
After the event				
(0,3)	0.66%	0.88	0.55	0.26
(0,4)	1.08%	0.76	0.83	0.26
(0,5)	1.37%	0.71	0.97	0.71
(1,3)	-0.02%	0.99	0.30	0.06*
(1,4)	0.66%	0.71	0.83	0.26
(1,5)	0.95%	0.63	0.79	0.26

CAAR (%) represents the Cumulative Average Abnormal Return, capturing the average abnormal return over a given event window across all assets in the sample.

CAARs were computed using the Event Study Methodology, based on the Market Model and a 250-day estimation window. Statistical significance was assessed using the t-test, BMP test and the non-parametric Sign test.

*, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively. P-values are two-tailed.

The AAR for the MAG-7 around the 2024 U.S. election was mostly positive, with +0.43% on day 0 and further gains on days +1, +2, and +4, except for a slight decline on day +3. However, none were statistically significant under the t-test or BMP test, suggesting random variation. The Sign Test showed marginal significance on days –2, +2, and +4, hinting at a potential directional trend. CAAR results were similarly modest, peaking at +1.56% in (–1, +5) and +1.25% in (0, +5), with weak significance in windows (–2, +2), (–2, +3), and (+1, +3) under the Sign Test alone.

The results suggest Trump’s 2024 victory did not generate statistically significant abnormal returns for the MAG-7 as a group, failing to support Hypothesis 1. While some firms showed gains, the lack of consistent significance indicates no clear collective market reaction. A likely explanation is the heterogeneity in investor expectations: despite their shared tech dominance, MAG-7 firms differ in sensitivity to policy areas like skilled immigration, trade, and regulation. Some were perceived as benefiters under Trump, others not. These contrasting views may have offset one another, resulting in no net effect, as illustrated in Figure 2 for the (–2, +5) window.

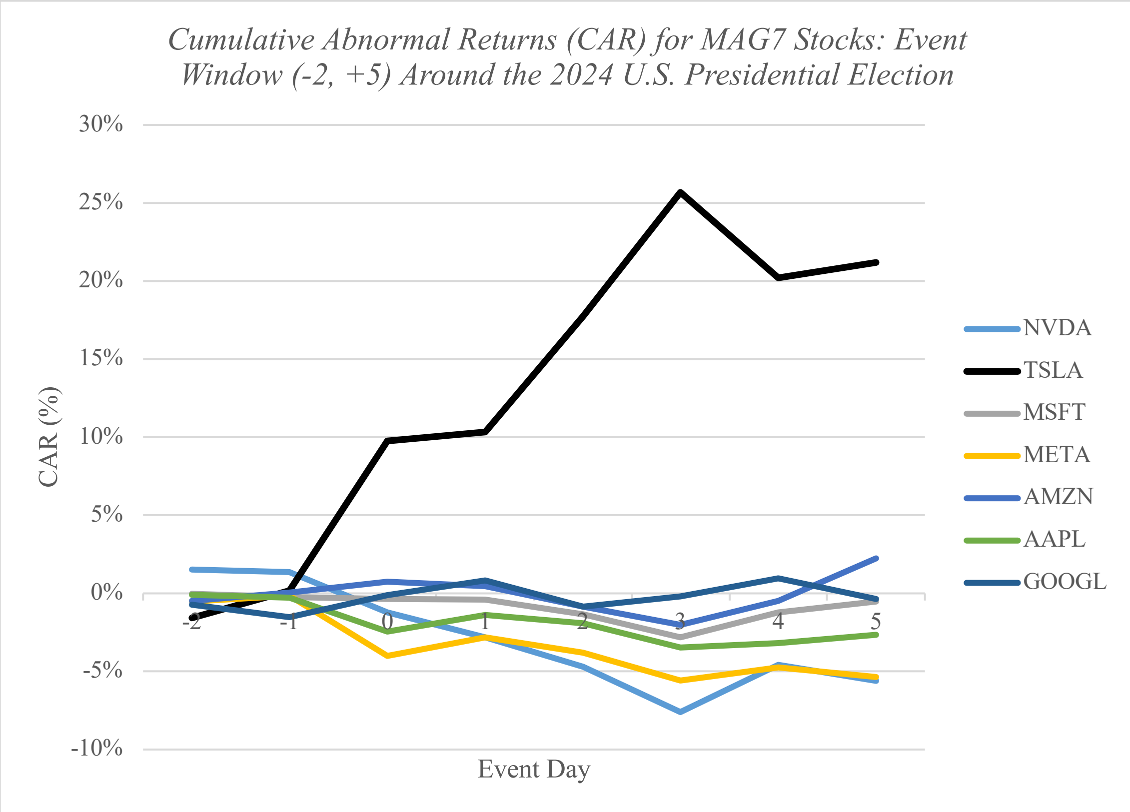

Figure 2– Cumulative Abnormal Returns (CAR) for MAG-7 Stocks: Event Window (-2, +5) Around the 2024 U.S. Presidential Election

As shown in Figure 2, TSLA was the only MAG-7 firm with a significantly positive CAR in the (–2, +5) window, while others remained flat or negative. Also a Z-test confirmed this deviation ($Z = 7.53$, $p < 0.01$). This unique market reaction may reflect investor expectations that TSLA stood to benefit from favorable regulatory and fiscal policies more than other companies under Trump administration. A key reason is Elon Musk's strong political involvement. Musk reportedly donated nearly $300 million to Trump's campaign through his America PAC, becoming the biggest individual donor. After the election, Trump selected him to lead the "Department of Government Efficiency" (DOGE), a proposal to cut federal spending. Musk also used his social media platform X to promote this initiative, which may have influenced investor sentiment in favor of TSLA.

To better assess Hypothesis 1, TSLA was excluded from the analysis, with results for the remaining MAG-7 firms shown in Tables 3 and 4.

Table 3- Mag-7 excluding Tesla AAR Results

Day	AAR (%)	t-test (p-value)	BMP (p-value)	Sign Test (p-value)
-2	-0.06%	0.86	0.58	0.10
-1	-0.07%	0.71	0.69	0.41
0	-1.11%	0.21	0.25	0.41
1	0.21%	0.62	0.48	1.00
2	-1.21%	0.00***	0.00***	0.01**
3	-1.37%	0.03**	0.00***	0.10
4	1.40%	0.01***	0.00***	0.01**
5	0.17%	0.77	0.53	1.00

AAR (%) represents the Average Abnormal Return, measuring the mean of daily abnormal returns across all assets in the sample on each event day.

AARs were computed using the Event Study Methodology with the Market Model and a 250-day estimation window prior to the event. Statistical tests include the t-test, BMP test and Sign test to assess significance of abnormal returns on each day.

*, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively. P-values are two-tailed.

Table 4- Mag-7 excluding Tesla CAAR Results

Event windows	CAAR (%)	t-test (p-value)	BMP (p-value)	Sign Test (p-value)
Before the event				
(-2,-1)	1.16%	0.72	0.48	0.41
During the event				
(-2,2)	-2.24%	0.01**	0.00***	0.01**
(-2,3)	-3.61%	0.01**	0.00***	0.01**
(-2,4)	-2.21%	0.05**	0.01***	0.10
(-2,5)	-2.04%	0.13	0.14	0.10
(-1,3)	-3.55%	0.03**	0.00***	0.10
(-1,4)	-2.15%	0.09*	0.05**	0.41
(-1,5)	-1.98%	0.20	0.25	0.41
After the event				
(0,3)	-3.48%	0.04**	0.00***	0.10
(0,4)	-2.08%	0.12	0.08*	0.10
(0,5)	-1.91%	0.21	0.27	0.41
(1,3)	-2.58%	0.00***	0.00***	0.01**
(1,4)	-0.97%	0.12	0.05*	0.10

(1,5)	-0.80%	0.32	0.44	0.10

CAAR (%) represents the Cumulative Average Abnormal Return, capturing the average abnormal return over a given event window across all assets in the sample.

CAARs were computed using the Event Study Methodology, based on the Market Model and a 250-day estimation window. Statistical significance was assessed using the t-test, BMP test and the non-parametric Sign test.

*, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively. P-values are two-tailed.

After excluding TSLA, several statistically significant abnormal returns emerged. For AARs, days +2 (–1.21%) and +4 (+1.40%) were significant across all tests, reflecting a sentiment reversal. Day +3 (–1.37%) was also significant under the t-test and BMP test. As for CAARs, the (–2, +2), (–2, +3), and (1, +3) windows showed consistent negative significance across all tests. Other windows such as (–2, +4), (–1, +3), (–1, +4), and (0, +3) also presented negative CAARs, though confirmed only by parametric tests.

These results suggest MAG-6 stocks underperformed relative to expectations. While Republican wins are often linked to short-term market optimism driven by investor optimism regarding tax cuts, deregulation, and pro-business reforms (Sun, Qiao and Wang, 2021; Wagner et al., 2017; Ahmed et al., 2025), Trump's 2024 campaign emphasized protectionist policies, higher tariffs, and reduced multilateralism (Weisman, 2024). For globally integrated firms like those in the MAG6, these stances may have amplified concerns over trade and regulatory risks (Bouoiyour and Selmi, 2016; Selmi and Bouoiyour, 2020; Ahmed et al., 2025), which helps explain the statistical negative abnormal returns recorded.

So, these findings offer partial support for Hypothesis 1. While the full MAG-7 group showed no significant abnormal returns, the MAG6 subsample revealed consistent and statistically significant underperformance around the election. This suggests that, excluding TSLA, the U.S. 2024 presidential election did have a measurable negative impact on MAG6.

Regarding the trading volume, Table 5 presents the results from the application of the NAV for each MAG-7 stock during the event window (-2,+5).

Table 5- Mag-7 NAV Results

Days	NVDA	TSLA	MSFT	META	AMZN	AAPL	GOOGL

-2	-1.73*	-1.12	-0.28	-0.49	-0.36	-0.50	-0.60
-1	-1.92*	-1.10	-0.53	-0.74	-0.83	-1.07	-0.90
0	-1.34	2.07**	0.57	0.19	1.63	-0.18	0.52
1	-1.59	0.49	-0.25	-0.21	0.49	-0.59	-0.25
2	-1.81*	3.38***	-0.61	-0.78	-0.50	-0.72	-0.56
3	-1.77*	3.57***	0.30	-0.69	-0.54	-0.60	-0.98
4	-1.65*	1.76*	-0.31	-0.03	-0.33	-0.65	-0.27
5	-1.70*	0.76	-0.06	-0.63	0.09	-0.38	-0.45

NAV represents the standardized trading volume deviation from its historical mean, calculated over the 250-day estimation window prior to the event.

*, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

A NAV above |1.645| indicates abnormal volume at the 10% level, |1.960| at the 5% level, and |2.576| at the 1% level.

The NAV results for MAG-7 stocks reveal differing market reactions to the 2024 U.S. election. TSLA recorded statistically significant positive NAVs on Day 0 (+2.07), Day +2 (+3.38), and Day +3 (+3.57), reflecting surges in trading volume aligned with its significant CARs, suggesting strong investor sensitivity to the political context. This response likely stems from perceptions of regulatory benefits under Trump, amplified by Musk's political involvement. In contrast, NVDA showed marginally significant negative NAVs throughout the event window, indicating subdued trading activity. For the remaining MAG-7 stocks, NAVs remained within normal ranges, implying stable trading volumes and suggesting that the election outcome did not meaningfully disrupt broader large-cap tech fundamentals.

4.2. Top 10 Cryptocurrency results

The impact of Donald Trump's presidential victory on the Top 10 cryptocurrencies is assessed in Tables 6 and 7, which report the AAR and CAAR results, respectively, along with the corresponding statistical test outcomes based on the event study methodology.

Table 6- Top 10 Cryptocurrencies AAR Results

Day	AAR (%)	t-test (p-value)	BMP (p-value)	Sign Test (p-value)
-5	0.41%	0.51	0.49	0.53
-4	-0.24%	0.30	0.20	0.21
-3	-0.71%	0.07*	0.07*	0.06*
-2	-0.59%	0.43	0.17	0.21
-1	0.52%	0.45	0.80	0.21

0	3.01%	0.01**	0.00***	0.06*
1	-0.06%	0.96	0.97	0.53
2	1.58%	0.14	0.09*	0.21
3	3.73%	0.01**	0.00***	0.06*
4	3.99%	0.18	0.19	1.00
5	4.05%	0.03**	0.00***	0.00***

AAR (%) represents the Average Abnormal Return, measuring the mean of daily abnormal returns across all assets in the sample on each event day.

AARs were computed using the Event Study Methodology with the Market Model and a 250-day estimation window prior to the event. Statistical tests include the t-test, BMP test and Sign test to assess significance of abnormal returns on each day.

*, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively. P-values are two-tailed.

Table 7- Top 10 Cryptocurrencies CAAR Results

Event windows	CAAR (%)	t-test (p-value)	BMP (p-value)	Sign Test (p-value)
Before the event				
(-5,-1)	-0.61%	0.55	0.30	0.53
(-4,-1)	-1.02%	0.41	0.19	0.53
(-3,-1)	-0.78%	0.46	0.21	0.21
(-2,-1)	-0.07%	0.96	0.55	0.53
During the event				
(-5,5)	15.69%	0.03**	0.01**	0.06*
(-4,4)	11.23%	0.06*	0.05**	0.21
(-3,3)	7.48%	0.05**	0.04**	0.06*
(-2,3)	8.19%	0.04**	0.04**	0.06*
(-2,4)	12.18%	0.05*	0.04**	0.21
(-2,5)	16.23%	0.03**	0.01***	0.06*
(-1,3)	8.78%	0.03**	0.02**	0.01**
(-1,4)	12.77%	0.03**	0.02**	0.06*
(-1,5)	16.82%	0.02**	0.00***	0.06*
After the event				
(0,3)	8.26%	0.03**	0.02**	0.01**
(0,4)	12.25%	0.03**	0.02**	0.06*
(0,5)	16.30%	0.02**	0.00***	0.00***
(1,3)	5.25%	0.09*	0.09*	0.06*
(1,4)	9.24%	0.07*	0.07*	0.21
(1,5)	13.29%	0.03**	0.01***	0.00***

CAAR (%) represents the Cumulative Average Abnormal Return, capturing the average abnormal return over a given event window across all assets in the sample.
CAARs were computed using the Event Study Methodology, based on the Market Model and a 250-day estimation window. Statistical significance was assessed using the t-test, BMP test and the non-parametric Sign test.
*, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively. P-values are two-tailed.

The AARs around the 2024 U.S. presidential election reveal a clear pattern. In the pre-event period, only day –3 (–0.71%) was marginally significant across the t-test, BMP, and Sign Test, suggesting weak anticipatory behaviour. On the event day (day 0), AAR surged to +3.01%, significant across all tests, indicating an immediate market reaction. Post-event, AARs remained positive, with day +3 (+3.73%) and day +5 (+4.05%) showing strong significance in all tests. CAAR results confirm sustained abnormal price behaviour. Pre-event windows were generally negative and insignificant. In contrast, event windows during the event period revealed increasingly positive and significant CAARs. The (–5,+5) window recorded +15.69%, significant in the t-test and BMP, and marginally in the Sign Test. The (–4,+4), (–3,+3), and (–2,+3) windows showed CAARs between +7.48% and +11.23%, with significance across t-tests and BMP, and marginally in the Sign Test. The (–1,+3) and (–1,+4) windows stood out with CAARs of +8.78% and +12.77%, both significant across all tests, confirming a cumulative reaction to the election. In the post-event period, CAARs remained significantly positive. The (0,+3) window recorded +8.26%, significant across all tests. The (0,+4) and (0,+5) windows reached +12.25% and +16.30%, respectively, with strong significance. Subsequent windows like (+1,+3), (+1,+4), and (+1,+5) showed CAARs up to +13.29%. The final (1,+5) window was statistically significant in all tests, indicating persistent market optimism.

The lack of consistent significant abnormal returns before the event suggests that markets did not fully anticipate Trump's victory or its implications for cryptocurrencies. Although day –3 showed marginally significant negative returns, overall pre-event signals were mixed, reflecting investor uncertainty amid divergent candidate views on digital regulation. After Trump's win was confirmed, day 0 showed a sharp, significant positive return across all tests. The post-event period reinforced this trend, with persistently high and statistically significant CAARs across several windows. This indicates growing investor optimism, likely driven by Trump's pro-crypto stance and expectations of favorable regulatory shifts. These findings support Hypothesis 2 (H2), which posited that the election of a pro-cryptocurrency candidate would lead to statistically and economically significant reactions in digital asset prices.

However, aggregate results may conceal notable disparities across individual assets. To address this, Figure 4 displays the CARs for the top 10 cryptocurrencies during the (–5, +5) window. Table 9 complements this by detailing CARs across pre-event, post-event, and full-event windows, enabling a more granular assessment of asset-specific responses.

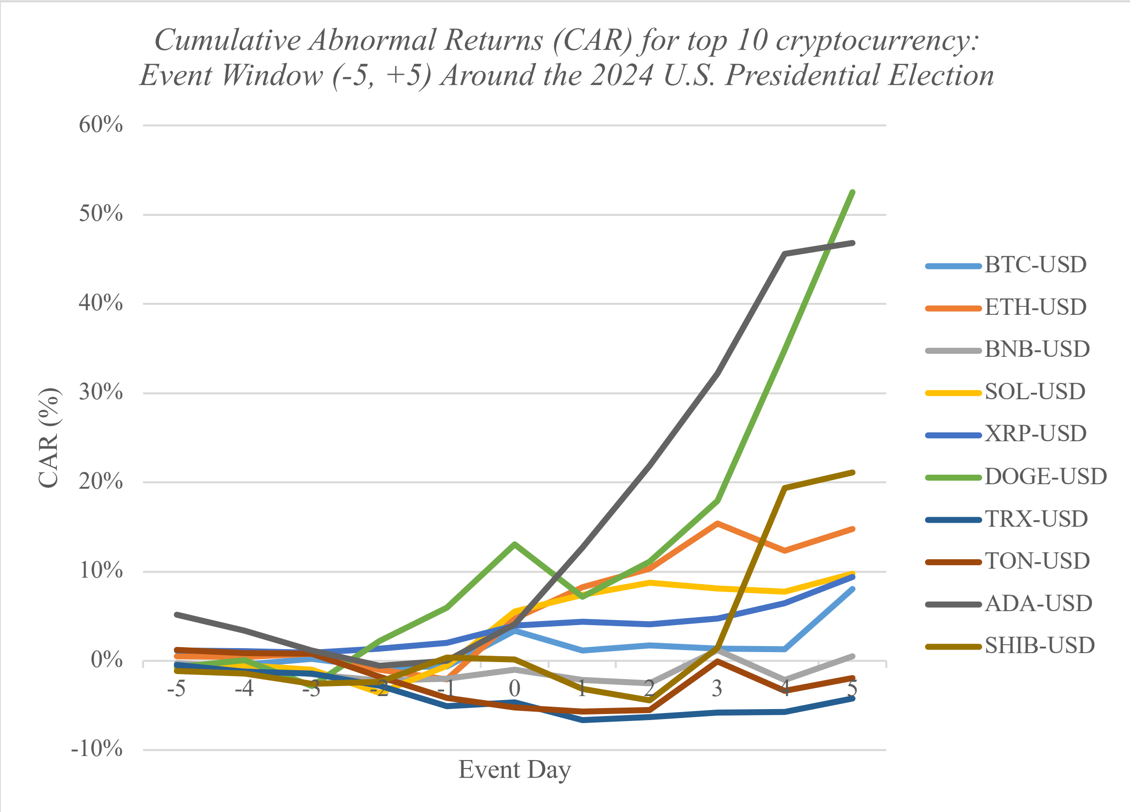

Figure 3– Cumulative Abnormal Returns (CAR) for top 10 Cryptocurrency: Event Window (-5, +5) Around the 2024 U.S. Presidential Election

Table 8- CAR (%) for Top 10 Cryptocurrencies Across Event Windows

	Event Windows		
TOP 10 Cryptocurrencies	**(-5,-1)**	**(1,5)**	**(-5,5)**
BTC-USD	-0.62%	4.65%	8.05%
ETH-USD	-2.08%	10.06%	14.81%
BNB-USD	-1.99%	1.49%	0.50%
SOL-USD	-0.58%	4.27%	9.77%
XRP-USD	2.01%	5.44%	9.40%

DOGE-USD	5.99%	39.45%	52.52%
TRX-USD	-5.06%	0.47%	-4.20%
TON-USD	-4.15%	3.35%	-1.91%
ADA-USD	0.01%	42.74%	46.83%
SHIB-USD	0.35%	20.97%	21.11%

CAR (%) represents the Cumulative Abnormal Return for each individual cryptocurrency, capturing the total abnormal return over the specified event window.

CARs were computed using the Event Study Methodology, based on the Market Model with a 250-day estimation window prior to the event.

As Figure 3 and Table 8 show, the top 10 cryptocurrencies responded heterogeneously during the (–5,+5) window. DOGE (+52.52%) and ADA (+46.83%) notably outperformed peers, likely due to specific political connections. DOGE's surge appears linked to Elon Musk's support for Trump and the viral "DOGE" acronym (Department of Government Efficiency), fostering investor enthusiasm. Musk's involvement with both DOGE and TSLA may reflect shared political sentiment and investor speculation about future favorable treatment. Cardano's strong performance may be linked to its founder, Charles Hoskinson, who publicly supported pro-crypto regulation and was reportedly considered for an advisory role in a Trump-led administration, fueling speculation that ADA could benefit from a more favorable regulatory environment. (Lee, 2024). SHIB also rose (+21.11%), driven by meme dynamics and community engagement, especially after day +3. This reflects its sensitivity to cultural sentiment and retail investor enthusiasm.

Moderate but positive reactions were observed for ETH (+14.81%), SOL (+9.77%), XRP (+9.40%), and BTC (+8.05%), possibly reflecting their larger market capitalizations and more institutional investor bases. In BTC's case, gains may appear muted due to its heavy weighting in the MVIS benchmark, which introduces a benchmark contamination effect, dampening its own measured abnormal returns due to its simultaneous role as both target and reference asset.

Conversely, BNB (+0.50%) posted more modest gains, while TON (-1.91%) TRX (–4.20%) was the only asset to close the window in negative territory. Its weak correlation with the MVIS index and the lowest beta in the market model suggest a low responsiveness to broad market movements, which may have contributed to its distinct underperformance. Despite these lackluster cumulative results during the full event window, both TON and TRX exhibited modest positive abnormal returns in the post-event period. This suggests that, although initially unresponsive, these assets later followed the broader post-election crypto rally, as supported by their positive correlation with the MVDA index

Regarding to the trading volume, the Table 9 demonstrates the results from application of NAV for each stock in the event window (-5,+5).

Table 9- Top-10 Cryptocurrencies NAV Results

Days	BTC-USD	ETH-USD	BNB-USD	SOL-USD	XRP-USD	DOGE-USD	TRX-USD	TON-USD	ADA-USD	SHIB-USD
-5	0.90	1.05	-0.31	-0.14	-0.11	0.68	-0.27	-0.45	0.30	-0.25
-4	-1.09	-0.63	-0.64	-0.86	-1.13	-0.23	-1.03	-0.69	-0.48	-0.52
-3	-0.02	0.38	-0.41	-0.35	-0.55	0.61	-0.65	-0.26	-0.11	-0.37
-2	0.41	0.68	-0.40	-0.23	-0.44	0.80	-0.50	-0.39	-0.21	-0.36
-1	0.66	0.78	-0.52	-0.11	-0.46	1.88*	-0.33	-0.10	-0.38	-0.12
0	4.59***	3.99***	0.37	2.46**	0.97	6.99***	0.60	0.66	1.86*	0.75
1	1.41	2.72***	-0.10	0.24	0.51	1.66*	0.15	0.44	1.42	-0.02
2	0.91	2.20**	-0.20	0.59	0.02	1.36	-0.62	-0.18	5.22***	-0.04
3	-0.58	1.56	0.67	-0.31	-0.31	1.28	-0.76	0.54	1.26	0.04
4	2.23**	3.79***	0.90	1.54	3.07***	5.83***	1.25	1.40	17.85***	4.55***
5	3.55***	4.41***	1.17	1.97**	2.68***	6.19***	1.60	1.23	8.84***	3.22***

NAV represents the standardized trading volume deviation from its historical mean, calculated over the 250-day estimation window prior to the event.

*, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

A NAV above |1.645| indicates abnormal volume at the 10% level, |1.960| at the 5% level, and |2.576| at the 1% level.

The NAV analysis shows that abnormal trading volume in the cryptocurrency market only emerged after the election result was confirmed, with no signs of anticipation in the pre-event period. A coordinated surge in volume began on Day 0 and persisted through Day +5, indicating that the 2024 U.S. presidential election acted as a significant information shock.

This reaction was most pronounced in DOGE and ADA, which recorded the highest NAV values in the sample. DOGE spiked immediately on Day 0 and remained elevated, likely fueled by Elon Musk's association and meme-driven momentum. ADA experienced a delayed but extreme volume increase, possibly linked to speculation around its founder's political visibility. BTC and ETH also showed NAVs on the event day and beyond, though more moderate, reflecting their broader investor base and institutional exposure. In contrast, BNB, TON, and TRX showed no significant volume changes, aligning with their modest or negative abnormal returns. This results suggests weaker investor engagement and lower sensitivity to political developments.

5. CONCLUSION

The main objective of this study was to analyse the impact of the 2024 U.S. presidential election on financial markets, with a particular focus on the MAG-7 companies' stocks and the ten largest cryptocurrencies by market capitalization. Using an event study methodology, abnormal returns were estimated around the election event in order to test market efficiency under conditions of heightened political uncertainty. This analysis made it possible to understand how investors interpreted and reacted to Donald Trump's victory in a context of ideological polarisation and institutional reconfiguration in the U.S..

Based on a 250-day estimation window and several short-term event windows, abnormal returns, cumulative abnormal returns for each of the assets analysed, and the average daily returns of the aggregate of the assets analysed were calculated, such as the AAR and CAAR. The results were subjected to three statistical tests, namely the classical t-test, the BMP test, and the non-parametric sign test, in order to reinforce the robustness of the analysis. This methodological approach allowed for a rigorous evaluation of the existence of statistically significant reactions to Trump's election.

In the stock market, the analysis of the MAG-7 companies revealed heterogeneous results. Most stocks did not show statistically significant cumulative abnormal returns in the central windows around the event date, suggesting a limited reaction or lack of surprise on the part of investors. The exception was Tesla, whose behaviour indicated a significantly positive reaction, not only in terms of return but also in volume, associated with Elon Musk's direct involvement in the political-electoral discourse and his ideological alignment with the new administration. These results corroborate the idea that investors assign different political value depending on the degree of sectoral exposure and reputational sensitivity of each company.

In the cryptocurrency market, whose decentralised and behavioural structure can amplify the effects of events contributing not only to episodes of market inefficiency but also to the emergence of opportunities for abnormal returns the reaction was much more pronounced at the aggregate level, the CAAR proved to be statistically significant in several windows, including the main window (-5, +5), indicating a joint positive response from the sector to Trump's victory. This collective behaviour contrasts with the more individualised response of the stocks and seems to reflect a general perception that a Trump administration could adopt a more favourable stance towards the crypto industry. Dogecoin and Cardano stood out with very high abnormal returns and volumes, and their movements appear to have been driven by both political factors and the speculative and sentiment-sensitive nature of these assets. In contrast, cryptocurrencies such as Binance Coin, Toncoin, and TRON did not show significant reactions, suggesting less connection to the political event in question. However, they exhibited small to moderate positive abnormal returns in the post-event window, reflecting the broader optimistic sentiment observed across the entire market.

This study presents several limitations. First, the focus on MAG-7 stocks and the top 10 cryptocurrencies restricts generalizability, as it excludes other sectors and smaller assets that may react differently to political events. Second, the use of short-term event windows captures immediate reactions but omits medium and long-term effects. Third, the event study methodology assumes normality and stability, which may not hold in highly volatile crypto markets. The limited number of assets also prevents the application of more complex techniques, such as panel regressions with multiple explanatory variables. Finally, the absence of qualitative analysis, such as investor sentiment or regulatory narratives, may limit the interpretation of asset-specific reactions, especially in cases where abnormal behaviour could stem from non-quantifiable factors.

Future research could broaden the asset universe to include other stock market sectors, mid-cap cryptocurrencies, or traditional safe havens, enhancing cross-market comparisons. Extending the time horizon could capture whether election impacts persist or reverse. Considering the current U.S. political climate and instability during Donald Trump's post-election researchers could investigate whether such developments shape investor sentiment and asset volatility. Integrating sentiment proxies or macroeconomic controls would clarify market behaviour under uncertainty. Finally, applying nonlinear and dynamic models such as GARCH or regime-switching techniques could reveal deeper patterns of return and volatility, especially in decentralized and sentiment-driven markets like cryptocurrencies.

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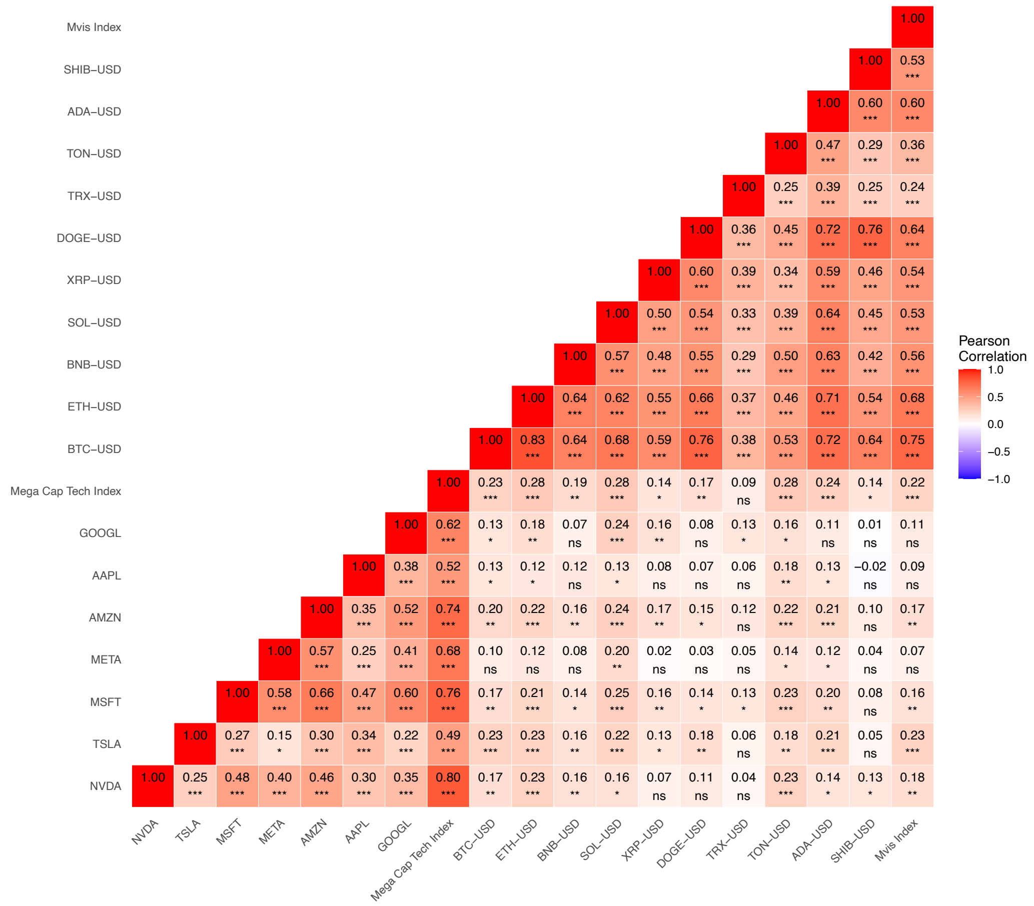
APPENDICES

Appendix 1- Descriptive Statistics of Daily Returns for MAG-7 Stocks, Top 10 Cryptocurrencies, and Benchmark Indices

Variable	N	Mean	SD	Min	Median	Max	Skewness	Kurtosis
NVDA	261	0.49%	3.20%	-10.54%	0.59%	15.19%	0.113473	2.397855
TSLA	261	0.19%	3.76%	-13.16%	0.17%	19.82%	0.654175	4.250611
MSFT	261	0.09%	1.24%	-6.24%	0.13%	2.63%	-0.8752	2.29974
META	261	0.25%	2.20%	-11.16%	0.16%	18.50%	1.550891	19.59958
AMZN	261	0.18%	1.69%	-9.19%	0.09%	7.57%	-0.20597	4.365211
AAPL	261	0.11%	1.41%	-4.94%	0.13%	7.01%	0.377006	3.264307
GOOGL	261	0.14%	1.65%	-7.80%	0.37%	9.73%	0.008796	6.150701
Mega Cap Tech Index	261	0.24%	1.55%	-5.71%	0.20%	5.31%	-0.28241	1.406671
BTC-USD	261	0.21%	2.92%	-8.71%	0.11%	11.46%	0.483243	1.656539
ETH-USD	261	0.05%	3.47%	-10.81%	0.18%	17.62%	0.541117	3.655613
BNB-USD	261	0.21%	3.13%	-9.27%	0.12%	15.90%	0.48686	3.078718
SOL-USD	261	0.29%	4.38%	-14.22%	0.13%	11.93%	0.032757	0.327887
XRP-USD	261	0.05%	3.49%	-13.15%	0.10%	17.23%	0.345958	4.685778
DOGE-USD	261	0.54%	5.68%	-17.24%	0.04%	24.36%	0.686091	2.271966
TRX-USD	261	0.08%	1.89%	-9.91%	0.11%	12.16%	0.45927	9.161275
TON-USD	261	0.37%	4.67%	-12.84%	0.35%	21.65%	0.630069	2.650553
ADA-USD	261	0.01%	3.96%	-15.19%	-0.11%	17.88%	0.067324	2.466614
SHIB-USD	261	0.41%	6.30%	-16.48%	-0.40%	46.66%	2.510178	14.10876
MVIS Index	261	0.15%	2.73%	-8.58%	0.23%	7.95%	0.138147	0.184351

Appendix 2- Pearson Correlation Matrix for Daily Returns of MAG-7 Stocks, Cryptocurrencies and Benchmarks



Appendix 3- Estimated Alpha and Beta Coefficients for MAG-7 Stocks

Stocks	NVDA	TSLA	MSFT	META	AMZN	AAPL	GOOGL
β	1.70	1.13	0.59	0.98	0.81	0.48	0.67
α	0.0010	-0.0016	-0.0004	0.0004	-0.0005	0.0001	-0.0003

Appendix 4- Estimated Alpha and Beta Coefficients for Top 10 Cryptocurrencies

Cryptocurrencies	BTC-USD	ETH-USD	BNB-USD	SOL-USD	XRP-USD	DOGE-USD	TRX-USD	TON-USD	ADA-USD	SHIB-USD
β	0.69	0.76	0.57	0.80	0.53	1.09	0.15	0.5480691	0.70	1.01
α	0.0008	-0.0012	0.0012	0.0014	-0.0006	0.0018	0.0007	0.0029398	-0.0027	0.0018