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Faculty I

– Management, Controlling, HealthCare –

International Business Administration with a focus on Management

**Bachelor thesis**

Topic:

# Stock market dynamics and political information

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# 1. Introduction

Financial markets are highly sensitive to political developments, as stock prices continuously adjust to reflect investor expectations regarding economic policy, regulatory shifts, and geopolitical events. The relationship between „stock market dynamics and political information“ has been extensively studied, yet quantifying the precise extent to which political events generate abnormal stock returns remains an empirical challenge. This study employs a systematic event study framework (MacKinlay, 1997) to examine the stock price behavior of selected firms and sectors surrounding the U.S. presidential election of November 5, 2024. Focusing on its impact on six sectors: Solar energy, electric vehicle (EV) battery production, U.S. oil and gas, European oil and gas, banking, and technology.

By applying the capital asset pricing model (CAPM) (Sharpe, 1964), extended by the Fama-French three-factor model (Fama & French, 1993), this research conducts a comprehensive estimation of abnormal asset returns that are realized in the market around the presidential election date. The methodology provides a rigorous statistical framework to assess whether financial markets systematically adjust their valuations of firms in response to a major political event. While financial markets continuously process new information, the 2024 U.S. presidential election was marked by considerable uncertainty, as polling data varied significantly across states and over time, making the final outcome unpredictable. This uncertainty suggests that the election result constituted a source of new information for investors, potentially triggering market adjustments. Understanding these market reactions is crucial, as political decisions - such as subsidies for renewable energy, tax incentives for electric vehicles, or deregulation of fossil fuel industries - can significantly alter investment flows, capital costs, and corporate profitability. Political developments can induce heterogeneous effects across industries, with some firms experiencing favorable market adjustments while others face adverse financial implications contingent upon the prevailing regulatory, economic, and policy landscape.

The financial market’s reaction to political shocks offers valuable insights into investor expectations, policy effectiveness, and sectoral resilience. Prior research has established that financial markets rapidly incorporate new information. The Efficient Market Hypothesis (EMH) (Fama, 1970) posits that asset prices fully and instantaneously reflect available information with different levels of efficiency. Strong-form efficiency asserts that prices incorporate all public and private information, whereas semi-strong efficiency, the most relevant for event studies, contends that markets adjust rapidly to publicly available news. Weak-form efficiency, by contrast, suggests that stock prices only reflect historical data, rendering technical analysis ineffective. MacKinlay (1997) formalized the event study methodology as a robust tool to quantify the impact of specific events on stock prices, which has since been applied to corporate earnings announcements (Ball & Brown, 1968), monetary policy decisions (Bernanke & Kuttner, 2005), and geopolitical risks (Baker, Bloom, & Davis, 2016).

While extensive research has examined the effects of oil price volatility (Kilian, 2009), political uncertainty (Baker et al., 2016; Brogaard & Detzel, 2015), and ESG-related stock performance (Gibson, Krueger, & Schmidt, 2021), few studies have directly compared how fossil fuel companies and renewable energy firms react to political events. Pastor & Veronesi (2012) demonstrated that stock market volatility increases with policy uncertainty, particularly in highly regulated industries, such as energy, healthcare, and finance. Kilian & Zhou (2020) further highlighted the exposure of oil and gas firms to geopolitical risks, while Bolton & Kacperczyk (2021) found that firms with high carbon emissions face increasing capital costs and a rising carbon premium. In contrast, Henriques & Sadorsky (2008) and LuluwahAl-Fagih et al. (2021) identified that renewable energy firms benefit from carbon pricing mechanisms and government incentives. Similarly, Oberndorfer (2008) examined the European Emission Trading Scheme (ETS) and found that fluctuations in carbon prices significantly affect electricity stock returns, underscoring the role of regulatory frameworks in shaping firm valuations in energy markets.

Despite these advancements in the literature, a significant research gap remains, as this study is among the first to examine the effects of the most recent U.S. presidential election on stock market reactions. To address this, the study applies an event study methodology to systematically analyze multiple stocks. The approach is fully transparent and reproducible, allowing for validation and replication through the provided R code (R Core Team, 2024).

Through an empirical analysis of stock price reactions, this study contributes to the finance and energy economics literature by providing evidence on how political information influences stock market dynamics across competing energy sectors. The findings have important implications for investors, policymakers, and corporate decision-makers, offering insights into how government actions shape financial market expectations, capital allocation, and the energy transition.

Given the widespread market discourse surrounding the 2024 U.S. presidential election and its potential implications for energy policy, as well as the broader uncertainty that elections introduce into financial markets (Goodell, McGee, & McGroarty, 2020; Phuc Lam Thy Nguyen et al., 2023), this study examines whether financial markets exhibit abnormal returns in response to the election outcome. If stock prices of the selected companies remain unaffected beyond normal market fluctuations, this could suggest that investors had already incorporated relevant policy expectations into their valuations prior to the election outcome. However, the absence of a market reaction does not necessarily confirm strong-form efficiency, as it may also reflect an expectation that the new administration's policies will not meaningfully alter the profitability of these sectors. This finding aligns with broader discussions on market efficiency (Fama, 1970) and the role of rational expectations in political event studies.

Beyond sector-specific effects, this study further investigates whether stocks of companies with close political affiliations to Donald Trump - such as firms whose executives have publicly supported his administration or industries expected to receive policy advantages - exhibit distinct price behavior. Prior research suggests that politically connected firms may benefit from preferential regulatory treatment, tax incentives, or government contracts (Goldman, Rocholl, & So, 2009; Brown & Huang, 2017). If these firms demonstrate statistically significant abnormal returns compared to their sectoral counterparts, it may indicate that firm-specific political alignment influences investor behavior beyond broad industry expectations.

# 2. Model

## 2.1 Framework

This study employs an event study framework (MacKinlay, 1997) to examine stock market reactions to the 2024 U.S. presidential election, with a particular focus on six sectors: solar energy, electric vehicle (EV) battery production, U.S. oil and gas, European oil and gas, banking, technology and politically affiliated corporations. The underlying methodology rests on the assumption that financial markets are semi-strong efficient (Fama, 1970), meaning that new political information should be rapidly incorporated into asset prices. By estimating abnormal returns (ARs), average abnormal returns (AARs), and cumulative abnormal returns (CARs) around the event date, this approach facilitates an empirical assessment of whether market participants systematically adjust their valuations of firms in response to the election outcome.

## 2.2 Expected Returns Estimation

This study employs logarithmic returns to measure stock price movements. The log return for stock $i$ at time $t$ is computed as the natural logarithm of the ratio of its closing price $P_{i,t}$ to its closing price at the previous time step $P_{i,t-1}$.

The log return for stock $i$ at time $t$ is given by:

(1) $$R_{i,t} = ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

To quantify abnormal returns, the study than estimates expected returns using the Fama-French three-factor model which extends the capital asset pricing model:

1. The capital asset pricing model (CAPM) (Sharpe, 1964; Lintner, 1965; Mossin, 1966), which models excess returns as a function of systematic market risk:

(2) $$R_{i,t} - Rf = \alpha_i + \beta_i(R_{m,t} - Rf) + \epsilon_{i,t}$$

where $R_{i,t}$ represents the return of stock $i$ at time $t$, $Rf$ denotes the risk-free rate, $R_{m,t}$ is the market return and $\beta_i$ captures the systematic risk exposure.

2. The Fama-French three-factor model (Fama & French, 1993), which extends CAPM by incorporating size and value factors:

(3) $$R_{i,t} - Rf = \alpha_i + \beta_m\big(R_{m,t} - Rf\big) + \beta_s SMB_t + \beta_h HML_t + \epsilon_{i,t}$$

where $SMB_t$ represents the size premium (small-minus-big), and $HML_t$ captures the value premium (high book-to-market minus low book-to-market).

For each stock in the sample, the parameters $\alpha_i$, $\beta_m$, $\beta_s$ and $\beta_h$ are estimated using an ordinary least squares (OLS) regression over an estimation window preceding the event date. Obviously, these parameters differ across stocks. For readability, the stock index $i$ is omitted in the parameter notation of the three-factor model.

The OLS estimates for these parameters will be denoted by $\hat{\alpha}_i$, $\hat{\beta}_m$, $\hat{\beta}_s$, and $\hat{\beta}_h$.

The regression model produces residuals, denoted as $\hat{\epsilon}_{i,t}$, which represent the portion of stock returns that cannot be explained by the systematic factors included in the model. Formally, the residuals are defined as:

(4) $$\hat{\epsilon}_{i,t} = \big(R_{i,t} - Rf\big) - \hat{\alpha}_i - \hat{\beta}_m\big(R_{m,t} - Rf\big) - \hat{\beta}_s SMB_t - \hat{\beta}_h HML_t$$

And the residual variance is defined as:

(5) $$\hat{\sigma}_\epsilon^2 = \frac{1}{L_1 - k} \sum_{t=t_0}^{t_1-1} \hat{\epsilon}_{i,t}^2$$

where $L_1$ denotes the number of observations in the estimation window, and $k$ represents the number of estimated parameters in the model.

The CAPM and the Fama-French three-factor model (3) derive the expected return for each stock by applying their factor specifications to the estimation window data, which ensures that the expected returns are based on historical risk-return relationships.

Within this framework, the market risk premium $\beta_m$ captures a stock's sensitivity to overall market fluctuations, reflecting the excess return required by investors for bearing non-diversifiable risk beyond the risk-free rate. The size premium $\beta_s$, commonly referred to as the small-minus-big (SMB) factor, accounts for the empirical observation that smaller firms tend to outperform larger firms on a risk-adjusted basis. This phenomenon is attributed to higher growth potential, reduced liquidity, and increased idiosyncratic risk associated with smaller companies. The SMB factor is constructed by taking the return differential between a portfolio of small-cap stocks and a portfolio of large-cap stocks, thereby isolating the size-related component of stock returns.

The value premium $\beta_h$, denoted as the high-minus-low (HML) factor, quantifies the systematic return differential between value stocks, characterized by high book-to-market ratios, and growth stocks, which exhibit lower book-to-market ratios. The superior long-term performance of value stocks has been attributed to their higher exposure to financial distress and cyclical downturns, requiring greater risk compensation.

While these factor loadings capture systematic sources of risk, the intercept $\alpha_i$ represents stock-specific performance unrelated to these systematic factors, reflecting firm-specific characteristics that are not explained by broader market, size, or value effects. However, under the Efficient Market Hypothesis (EMH), particularly in its semi-strong form, $\alpha_i$ should not be systematically different from zero, as all available information is assumed to be fully reflected in asset prices. Persistent deviations from zero could indicate market inefficiencies or omitted risk factors (Fama 1970; Fama & French, 2010). By incorporating these additional risk factors, the Fama-French model enhances the explanatory power of the capital asset pricing model and provides a more comprehensive framework for analyzing cross-sectional variations in stock returns.

To estimate expected returns over the event window, the Fama-French three-factor model is applied to the observed data. The estimated model parameters, derived from the estimation window, are used to predict the expected return for each stock during the event period. This is achieved by leveraging the fitted regression model to generate out-of-sample forecasts based on prevailing market conditions and factor exposures. Formally, the expected return for stock $i$ at time $t$ is obtained by applying the model's estimated coefficients to the corresponding explanatory variables in the event window, ensuring that return expectations remain consistent with historical risk-return relationships.

## 2.3 Abnormal Returns

In accordance with standard event study methodology, abnormal returns are estimated based on a comparison between observed stock returns and their expected values. This requires defining two distinct periods: the estimation window (1) and the event window (2), which form the basis for calculating abnormal returns.

1. This period precedes the event and is used to estimate the parameters of the expected return model. It comprises $L_1$ trading days, spanning from $t_0$ to $t_1 - 1$, where $t_0$ represents the start of the estimation window and $t_1 - 1$ marks its final day.

2. This period captures the market's response within the event window, encompassing $L_2$ trading days and extending from $t_1$, the first day of the event window, to $t_2$, the final day of the event window.

The calculation of the abnormal return (AR) strictly adheres to the methodology outlined by MacKinlay (1997), where, for stock $i$ on day $t$, AR is computed as the deviation of the observed return from its expected value:

$$AR_{i,t} = (R_{i,t} - Rf) - E(R_{i,t}) \tag{6}$$

where $E(R_{i,t})$ represents the expected return, obtained through the application of the Fama-French three-factor model. Since the expected return is inherently unobservable, it is estimated by applying the selected asset pricing model over the designated estimation window, spanning from $t_0$ to $t_1$-1 which precedes the event window. Subsequently, these estimated parameters are used to generate predicted values of expected returns for the event window by applying them to the observed realizations of the factor variables during this period. These model-derived predictions serve as the reference point for evaluating abnormal returns, ensuring that deviations reflect the impact of the event rather than systematic risk factors.

Specifically, the abnormal return for stock $i$ at time $t$ is obtained as the difference between its observed excess return and the expected return estimated from the Fama-French three-factor model. The excess return is computed as the stock's raw return minus the risk-free rate.

The average abnormal return (AAR) for stock $i$ over the event window is defined as:

$$AAR_i = \frac{1}{L_2} \sum_{t=t_1}^{t_2} AR_{i,t} \tag{7}$$

where $L_2$ denotes the number of days in the event window and $t_1$ and $t_2$ mark the beginning and end of the event window.

The cumulative abnormal return (CAR) over the event window is defined in accordance with MacKinlay (1997, Eq. 10) as:

$$CAR_i = \sum_{t=t_1}^{t_2} AR_{i,t} \tag{8}$$

## 2.4 Statistical Significance Testing

To evaluate the statistical significance of abnormal returns, the variance of residuals from the estimated model is computed. The residual variance, derived from the estimation window, serves as an empirical measure of the unexplained variability in stock returns after accounting for systematic risk factors. This variance is subsequently used to construct standard errors for hypothesis testing, ensuring robust inference regarding the impact of the event.

The variance of abnormal returns is defined in Eq. 8, (McKinley 1997 page 21). For large values of L1, that is for sufficiently many observations in the estimation window, the term that relates to uncertainty in the model parameters vanishes. Asymptotically, the variance of abnormal returns is therefore equal to the variance of the error term $\epsilon$ in Eq. 3. We use the variance of residuals $\hat{\sigma}_{\epsilon}^2$ as the best estimate for this variance. Therefore, $\hat{\sigma}_{AR}^2$ is:

(9) $$\hat{\sigma}_{AR}^2 = \frac{1}{L_1 - k} \sum_{t=t_0}^{t_1-1} \hat{\epsilon}_{i,t}^2$$

where: $L_1$ is the number of observations in the estimation window, $k$ is the number of estimated parameters and $\hat{\epsilon}_{i,t}$ represents the residuals from the return model.

Following McKinley (1997, Eq 14) the variance of the average abnormal return (AAR) over the event window consisting of $L_2$ days is defined as:

(10) $$\sigma_{AAR}^2 = \frac{\sigma_{AR}^2}{L_2}$$

Under the null hypothesis $H_0$ following MacKinlay (1997, Eq. 9), that the event has no impact on stock returns, abnormal returns are expected to be zero on average and follow a normal distribution with variance estimated from the estimation window:

(11) $$AR_{i,t} \sim N\left(0, \sigma^2(AR_{i,t})\right)$$

We standardize AAR to obtain the test statistic:

(12) $$t_{AAR_i} = \frac{AAR_i}{\hat{\sigma}_{AAR}} = \frac{AAR_i}{\sqrt{\frac{\hat{\sigma}_{AR}^2}{L_2}}}$$

Equivalently, following MacKinlay (1997), the null hypothesis $H_0$ states that the expected cumulative abnormal return $E(CAR_i)$ over the event window is zero:

(13) $$H_0: E(CAR_i) = 0$$

The variance of cumulative abnormal returns is given by:

(14) $$\sigma_{CAR}^2 = L_2 \cdot \sigma_{AAR}^2$$

Thus, the test statistic for cumulative abnormal returns is:

(15) $$t_{CAR_i} = \frac{CAR_i}{\hat{\sigma}_{CAR}}$$

Under the null hypothesis, the test statistic follows a t-distribution due to the estimation of model parameters, with degrees of freedom given by:

(16) $$df = L_1 - k$$

where $L_1$ represents the number of observations in the estimation window and $k$ denotes the number of estimated parameters in the return model.

# 3. Data

## 3.1 Data Sources and Sample Selection

This study utilizes financial market data to analyze stock price reactions to the 2024 U.S. presidential election. The primary research question examines how different industries, particularly the solar energy and oil & gas sectors, responded to the election outcome. The focus on these sectors is motivated by Donald Trump's declared U.S. energy emergency and his explicit "Drill, baby, drill" rhetoric (Sharma, 2025).

The renewable energy sector, particularly solar energy, has historically relied on government incentives, subsidies, and tax credits, whereas the fossil fuel industry is often influenced by deregulation, taxation policies, and geopolitical considerations. By comparing these two competing industries, this study seeks to provide insights into the impact of political events on market valuations.

To ensure a robust and meaningful comparison, companies from the solar energy sector were selected on the basis of market capitalisation and the availability of comprehensive public financial data. In addition, the companies must operate primarily in the US. Specifically, the five largest companies by market capitalisation were selected from all publicly traded companies on the NYSE that are classified as renewable energy companies, with a particular focus on solar energy companies. In addition, each company was required to have publicly available financial data dating back to at least 2020, ensuring at least four years of trading history (i.e., IPO prior to 2020) to provide a stable data basis for the entire estimation window. The selection was based on data from CompaniesMarketCap (n.d.).

Similarly, U.S. oil and gas companies were selected from all publicly traded firms in the S&P 500 classified under the oil & gas industry, ranked by market capitalization to capture the sector's largest and most influential players. Once a company met the inclusion criteria, it remained in the sample regardless of any subsequent changes in market capitalization.

Given the global nature of energy markets, the analysis further incorporates a selection of major European oil and gas firms. These companies were identified from all publicly traded firms classified under the oil and gas industry within the iShares STOXX Europe 600 Oil & Gas UCITS ETF (DE) (ISIN: DE000A0H08M3). The five largest European firms by market capitalization were included to assess whether the observed market reaction was unique to the U.S. sector or reflective of broader geopolitical and economic trends.

Beyond the energy sector, additional industries were included based on their potential exposure to political and economic shifts induced by the election. The electric vehicle (EV) battery sector was selected due to its strong connection to renewable energy policies, particularly government incentives for electrification and the transition to green energy. To ensure a comprehensive analysis, the three largest manufacturers in this sector were identified based on market capitalization, alongside emerging companies specializing exclusively in battery technology. This approach allows for a distinction between established industry leaders and firms with a specific focus on battery innovation, ensuring that the analysis captures the direct market impact on battery production.

The banking sector was included to assess the potential impact of deregulation, a policy area for which the first Trump administration from 2016 to 2020 is historically known (Crews, 2021). Deregulation can benefit financial institutions by reducing compliance costs and increasing lending flexibility, making this sector a relevant case for examination. Banks were selected based on market capitalization to focus on systemically important institutions.

Lastly, the technology sector was incorporated as a case study of an industry that could experience both positive and negative election-induced market effects. While deregulation and tax policies may be favorable for tech firms, international trade conflicts and potential regulatory scrutiny on data privacy, antitrust, and cybersecurity could have offsetting negative implications. As with other industries, the largest tech firms by market capitalization were selected to ensure an analysis of the most influential players.

Daily stock price data are sourced from Yahoo Finance via the quantmod package in R (Ryan & Ulrich, 2024). The dataset includes individual stock prices, market index returns, and key asset pricing factors necessary for estimating both expected and abnormal returns. A detailed overview of the selected firms is provided in Table 1.

**Table 1 - Selected Companies by industry and ticker symbols.**

| **Industry** | **Company** | **Ticker** |
|---|---|---|
| **Solar Energy (US)** | First Solar | FSLR |
| | Enphase Energy | ENPH |
| | NextEra Energy | NEE |
| | Sunrun | RUN |
| | SolarEdge Technologies | SEDG |
| **EV Battery Producers (US)** | Tesla | TSLA |
| | General Motors | GM |
| | Ford | F |
| | Microvast Holdings | MVST |
| | QuantumScape | QS |
| **U.S. Oil & Gas** | ExxonMobil | XOM |
| | Chevron | CVX |
| | ConocoPhillips | COP |
| | EOG Resources | EOG |
| | Occidental Petroleum | OXY |
| **European Oil & Gas** | BP | BP |
| | Shell | SHEL |
| | TotalEnergies | TTE |
| | Equinor | EQNR |
| | Eni | E |
| **Banking (US)** | JPMorgan Chase | JPM |
| | Bank of America | BAC |
| | Wells Fargo | WFC |
| | Morgan Stanley | MS |
| | Goldman Sachs | GS |
| **Technology (US)** | Apple | AAPL |
| | Nvidia | NVDA |
| | Microsoft | MSFT |
| | Alphabet | GOOGL |
| | Amazon | AMZN |

Beyond the primary sectoral analysis, this study examines firms that, due to their business models, regulatory exposure, or historical affiliations, were expected to be particularly sensitive to the policy direction under the Trump administration. The selection of these firms is based on their potential to be directly affected by anticipated policy changes in areas such as trade regulations, government contracts, subsidies, and tax policies.

Table 2 presents these firms, each of which is analyzed alongside two leading domestic competitors and two international counterparts. Given that certain companies may have closer political affiliations with the incoming Trump administration, this comparative approach aims to assess whether such ties influenced investor expectations and, consequently, stock price reactions. By incorporating both national and global benchmarks, the analysis seeks to distinguish between firm-specific characteristics, broader industry trends, and the potential impact of political alignment on market valuations.

**TABLE 2 - Companies selected for political alignment analysis with U.S. and international competitors.**

| **Potential political alignment** | **Largest U.S. Competitor** | **Major International Competitor** |
|---|---|---|
| **Tesla (TSLA)** | Ford (F) | BYD (BYDDY) |
| | General Motors (GM) | Volkswagen (VWAGY) |
| **Palantier (PLTR)** | IBM (IBM) | SAP (SAP) |
| | Snowflake (SNOW) | C3.ai (AI) |
| **UnitedHealth (UNH)** | Humana (HUM) | Allinaz (ALIZY) |
| | Elevance Health (ELV) | Cigna (CI) |

The S&P 500 Index (^GSPC) is included as a benchmark for market-wide movements, serving as the market return proxy in the Fama-French three-factor model. Additionally, Fama-French factor data are obtained from the Kenneth French Data Library at Dartmouth College (Fama & French, n.d.). This dataset provides essential asset pricing factors, including the risk-free rate, which is derived from U.S. Treasury Bill yields, the small-minus-big (SMB) factor, which captures the size premium, and the high-minus-low (HML) factor, which represents the value premium in stock returns. These factors extend the traditional CAPM framework by accounting for systematic deviations in asset pricing beyond the market risk premium.

To ensure the consistency and relevance of the dataset within the study period, the Fama-French factor data are processed and filtered using R (R Core Team, 2024). The dataset is retrieved from the Kenneth French Data Library (Fama & French, n.d.) and initially structured by converting the date format into a standardized representation. Subsequently, observations are restricted to those occurring on or before November 8, 2024, aligning with the timeframe of the analysis. The dataset is downloaded, extracted, and preprocessed to facilitate its integration into the asset pricing model. The complete workflow, including data handling and preprocessing steps, is documented in the Appendix, ensuring transparency and reproducibility of the analysis.

## 3.2 Temporal Structure of the Event Study

The estimation window, spanning 502 trading days from November 4, 2022, to November 4, 2024, is employed to estimate the parameters of the expected return models. Prior research emphasizes that an estimation window must be sufficiently long to accurately capture normal return behavior while mitigating the risk of excessive historical bias and over-sensitivity in model estimation. While Brown and Warner (1985) suggest that approximately 250 trading days are appropriate for estimation, long-horizon event studies often extend this period to one to five years (Kothari & Warner, 2007). MacKinlay (1997) identifies 100 to 250 trading days as a commonly used range, whereas Salinger (1992) argues that longer estimation windows offer additional advantages that have not been fully explored in previous research.

The selection of a 502-day estimation window reflects the different angles in the existing literature, balancing the need for robust parameter estimation with the necessity of minimizing distortions from outdated market conditions. This extended window is particularly relevant given the political context of the 2024 U.S. presidential election, as it encompasses the entire period since the 2022 midterm elections, thereby capturing potential shifts in market expectations influenced by evolving political dynamics. Empirical evidence suggests that election years are characterized by significantly lower investment levels due to heightened uncertainty regarding the electoral outcome (Julio & Yook, 2012). Consequently, an estimation window spanning two years provides a more resilient and reliable basis for return estimation compared to a shorter timeframe of less than one year (Julio & Yook, 2012). Furthermore, the length of the estimation window is consistent with the estimation approach of this study, which uses the three-factor model and an extended event window (Kothari & Warner, 2007).

The event window spans four trading days, from November 5, 2024, to November 8, 2024, designed to capture market reactions both immediately following and in the aftermath of the election outcome. The selection of this timeframe is informed by empirical research, which emphasizes that short event windows are most effective in isolating the immediate impact of political events on stock prices (Fama, 1998). However, to ensure robustness, the window must extend beyond a single day while also avoiding overlap with the estimation window (MacKinlay, 1997).

This temporal selection is particularly relevant given the extraordinary uncertainty surrounding the 2024 U.S. presidential election. Experts widely anticipated that determining the final outcome would take days or even weeks, citing potential delays in vote counting and legal disputes. Polymarket, a decentralized prediction platform that allows users to place wagers on the outcomes of various events, including elections, indicated since 5 October Donald Trump as the frontrunner (Polymarket, n.d.). In contrast, major media outlets such as CNN predicted a close race, further exacerbating market uncertainty (Agiesta & Edwards-Levy, 2024). Contrary to expectations, Trump was declared the winner on election night, a shock to both markets and the public, as it contradicted pre-election analyses.

Figure 1 provides a comprehensive overview of Tesla's stock price dynamics from December 31, 2020, to December 31, 2024, illustrating fluctuations over time and positioning both the estimation and event windows within broader market trends. The estimation window, spanning two years leading up to the election, is utilized to model expected returns by capturing long-term market behavior. The event window, in contrast, is specifically designed to assess short-term market reactions following the election outcome. The red dashed line highlights November 5, 2024, the day of the election, marking the beginning of the event window. The notable surge in Tesla's stock price following this date suggests that the observed movement reflects abnormal returns, likely driven by investor sentiment and recalibrated expectations regarding potential policy changes under the new administration.


Figure 1 - Tesla closing price from December 31, 2020, to December 31, 2024. The red dashed line marks November 5, 2024, the first trading day of the event window

### 3.3 Variable Definitions and Data Construction

The empirical analysis relies on a structured set of financial variables to quantify stock market reactions. The dependent variable is the logarithmic stock return, defined as the natural logarithm of the ratio of the adjusted closing price at time $t$ to its price at $t-1$. This approach ensures a continuous and time-consistent measure of price changes. Market returns are computed analogously using the S&P 500 Index, which serves as the market portfolio in the asset pricing model. To isolate excess returns, the risk-free rate is subtracted from both daily stock returns and market returns, ensuring that the estimated asset pricing relationships reflect systematic risk premia rather than compensation for the time value of money.

To assess the aggregate impact of the event, the average abnormal return (AAR) is calculated by taking the mean of abnormal returns for each stock in the sample for each day in the event window. This measure captures the systematic effect of the event on the market-adjusted stock performance of the selected firm. Additionally, the cumulative abnormal return (CAR) aggregates abnormal returns over the entire event window, providing a measure of the total price adjustment induced by the political event. The CAR quantifies the extent to which the event has led to sustained deviations from expected returns, thereby offering insights into the magnitude and persistence of market reactions.

# 4. Results

## 4.1 Empirical Findings

In this section, the previously formulated hypotheses and assumptions regarding market reactions to the election outcome are empirically tested. Specifically, the analysis examines six sectors: solar energy, electric vehicle (EV) battery production, U.S. oil and gas, European oil and gas, banking, and technology. The statistical tests conducted in this study assess whether the average abnormal returns (AAR) and cumulative abnormal returns (CAR) significantly deviate from zero. Formally, the null hypothesis $H_0$ states that $AAR = E(CAR) = 0$, implying that the election had no systematic impact on stock prices within each sector. This is tested using a two-tailed t-test, where the corresponding t-values and p-values indicate whether deviations from zero are statistically significant.

The results indicate significant abnormal returns within the solar energy sector with p-values well below the conventional 5% threshold. Companies such as First Solar (FSLR), Enphase Energy (ENPH), Sunrun (RUN) and SolarEdge (SEDG) experienced statistically significant negative cumulative abnormal returns (CAR). For example, Sunrun exhibited the largest reaction, with a CAR of -0.6301 (or -63%) ($p < 0.0001$), followed by SolarEdge (-0.4175, $p < 0.0001$) and Enphase Energy (-0.3659, $p < 0.0001$). These findings suggest that the election outcome led to a downward adjustment in investor expectations regarding the future regulatory and policy environment for renewable energy. Table 3 presents the complete set of results for the solar energy sector in decimal notation.

**TABLE 3 - Cumulative abnormal returns (CAR), t-values (t_CAR), and p-values (p_CAR) for the solar energy sector.**

| **Company** | **CAR** | **t_CAR** | **p_CAR** |
|---|---|---|---|
| **First Solar** | -0.16877 | -2.82562 | 0.00491 |
| **Enphase Energy** | -0.36591 | -5.32483 | 0.00000015 |
| **NextEra Energy** | -0.05223 | -1.60916 | 0.10822 |
| **Sunrun** | -0.63009 | -7.85320 | 0.000000000000025 |
| **SolarEdge** | -0.41749 | -5.17732 | 0.00000033 |

The results indicate notable abnormal returns in the electric vehicle battery sector. While Tesla (TSLA) exhibited a statistically significant positive cumulative abnormal return (CAR) of 18.4% ($p < 0.01$), smaller battery manufacturers such as Microvast Holdings (MVST) and QuantumScape (QS) experienced significantly negative abnormal returns. Specifically, MVST recorded a CAR of -24.5% ($p < 0.05$), and QS a CAR of -16.4% ($p = 0.0559$), suggesting that the election outcome led to a downward revision in investor expectations for these firms.

In contrast, legacy automakers General Motors (GM) and Ford (F) showed no statistically significant abnormal returns, with CARs of -0.36% ($p = 0.91$) and -1.57% ($p = 0.69$), respectively. This lack of significant reaction suggests that investors did not anticipate major policy shifts affecting their business models. The divergence in market responses within the sector highlights that Tesla benefited from the election result, whereas smaller, growth-oriented EV battery firms experienced adverse market reactions, likely due to increased uncertainty regarding government support. Table 4 presents the complete set of results for the electric vehicle battery sector.

**TABLE 4 - Cumulative abnormal returns (CAR), t-values (t_CAR), and p-values (p_CAR) for the EV battery production.**

| **Company** | **CAR** | **t_CAR** | **p_CAR** |
|---|---|---|---|
| **Tesla** | 0.18386 | 2.89055 | 0.00401 |
| **General Motors** | -0.00359 | -0.11000 | 0.91245 |
| **Ford** | -0.01568 | -0.39648 | 0.69192 |
| **Microvast Holdings** | -0.24512 | -2.05796 | 0.04011 |
| **QuantumScape** | -0.16410 | -1.91639 | 0.05589 |

The results reveal that the oil and gas sector showed no signs of significant abnormal returns in response to the election outcome. ExxonMobil (XOM), Chevron (CVX), and ConocoPhillips (COP) recorded cumulative abnormal returns (CAR) of -0.86%, -1.31%, and -0.68%, respectively, with p-values well above the conventional significance threshold, indicating that their stock prices were not meaningfully affected.

EOG Resources (EOG) was the only firm in this sector to show a marginally significant reaction, with a CAR of 4.89% and a p-value of 0.0993, suggesting a potential positive market adjustment. However, Occidental Petroleum (OXY) experienced a CAR of -3.80%, though its p-value of 0.1906 suggests that this reaction was not statistically significant.

Overall, the findings suggest that the election result did not lead to a substantial reassessment of investor expectations for the U.S. oil and gas industry. The complete results for this sector are presented in Table 5.

**TABLE 5 - Cumulative abnormal returns (CAR), t-values (t_CAR), and p-values (p_CAR) for the U.S. oil and gas industry.**

| Company | CAR | t_CAR | p_CAR |
|---|---|---|---|
| **ExxonMobil** | -0.00862 | -0.34959 | 0.72679 |
| **Chevron** | -0.01311 | -0.57268 | 0.56712 |
| **ConocoPhillips** | -0.00679 | -0.23334 | 0.81559 |
| **EOG Resources** | 0.04893 | 1.65143 | 0.09928 |
| **Occidental Petroleum** | -0.03801 | -1.31046 | 0.19064 |

In contrast to their U.S. counterparts, European oil companies exhibited more pronounced negative abnormal returns following the election. BP (BP), TotalEnergies (TTE), and Eni (E) all recorded statistically significant declines, with CAR values of -5.83% ($p < 0.05$), -5.79% ($p < 0.05$), and -5.07% ($p < 0.05$), respectively. These findings indicate a meaningful negative market reaction, suggesting that the election outcome led to a reassessment of expectations for these firms.

Shell (SHEL) and Equinor (EQNR) also experienced negative cumulative abnormal returns of -4.05% and -5.88%, though their p-values ($p = 0.0799$ and $p = 0.0967$, respectively) suggest only marginal statistical significance.

The contrast between U.S. and European oil companies may reflect differing investor perceptions regarding the geopolitical and regulatory implications of the election. While U.S. firms showed little reaction, the decline in European oil stocks suggests that investors may have anticipated greater political or economic shifts affecting global energy markets. Table 6 provides a complete overview of the results for the European oil sector.

**TABLE 6 - Cumulative abnormal returns (CAR), t-values (t_CAR), and p-values (p_CAR) for the European oil and gas industry.**

| Company | CAR | t_CAR | p_CAR |
|---|---|---|---|
| **BP** | -0.05832 | -2.20163 | 0.02816 |
| **Shell** | -0.04047 | -1.75492 | 0.07987 |
| **TotalEnergies** | -0.05793 | -2.35935 | 0.01869 |
| **Equinor** | -0.05876 | -1.66420 | 0.09670 |
| **Eni** | -0.05069 | -2.05737 | 0.04017 |

The results for the five largest U.S. banks reveal a generally positive reaction following the election, though the statistical significance varies across firms. Goldman Sachs (GS) exhibited the most pronounced response, with a cumulative abnormal return (CAR) of 8% ($p < 0.0001$), suggesting that investors perceived the election outcome as particularly favorable for the firm's future outlook. Morgan Stanley (MS) also recorded a positive CAR of 4.31%, though with a more moderate level of statistical significance ($p = 0.0551$).

JPMorgan Chase (JPM), Bank of America (BAC), and Wells Fargo (WFC) all showed positive but statistically insignificant CARs of 2.83% ($p = 0.1435$), 2.37% ($p = 0.2065$), and 3.34% ($p = 0.1601$), respectively. This indicates that while the broader banking sector experienced a modest upward adjustment in investor expectations, the response was not uniform across institutions.

The findings suggest that market participants viewed the election outcome as generally beneficial to the financial sector, potentially due to expectations of deregulation, tax policies, or interest rate adjustments favorable to banking institutions. However, the lack of significant abnormal returns for some banks implies that the reaction may have been more firm-specific rather than a sector-wide trend. Table 7 presents the complete set of results for the banking sector.

**TABLE 7 - Cumulative abnormal returns (CAR), t-values (t_CAR), and p-values (p_CAR) for the banking industry.**

| Company | CAR | t_CAR | p_CAR |
|---|---|---|---|
| **JPMorgan Chase** | 0.02834 | 1.46533 | 0.14346 |
| **Bank of America** | 0.02372 | 1.26483 | 0.20652 |
| **Wells Fargo** | 0.03339 | 1.40700 | 0.16005 |
| **Morgan Stanley** | 0.04313 | 1.92222 | 0.05515 |
| **Goldman Sachs** | 0.07985 | 4.00258 | 0.00007 |

The results for the five largest U.S. technology firms indicate a muted market response to the election outcome, with all firms exhibiting negative cumulative abnormal returns (CAR), though none reaching conventional levels of statistical significance. Apple (AAPL) recorded the largest decline, with a CAR of -2.94% ($p = 0.1529$), followed by Nvidia (NVDA) at -2.11% ($p = 0.6389$) and Microsoft (MSFT) at -1.49% ($p = 0.4249$).

Alphabet (GOOGL) and Amazon (AMZN) experienced the smallest movements, with CARs of -0.42% (p = 0.8809) and -0.82% (p = 0.7685), respectively, further supporting the conclusion that investors did not perceive the election as a major inflection point for the sector.

These findings suggest that the tech industry, unlike more politically sensitive sectors such as energy or finance, was relatively insulated from the election's immediate market impact. Given the sector's global nature, extensive regulatory considerations, and long-term growth drivers, investors may have anticipated little direct effect from the political transition. Table 8 presents the complete set of results for the technology sector.

**TABLE 8 - Cumulative abnormal returns (CAR), t-values (t_CAR), and p-values (p_CAR) for the technology industry.**

| Company | CAR | t_CAR | p_CAR |
|---|---|---|---|
| **Apple** | -0.02944 | -1.43145 | 0.15293 |
| **Nvidia** | -0.02111 | -0.46951 | 0.63891 |
| **Microsoft** | -0.01493 | -0.79849 | 0.42496 |
| **Alphabet** | -0.00417 | -0.14990 | 0.88091 |
| **Amazon** | -0.00816 | -0.29446 | 0.76853 |

Beyond sectoral trends, this study further investigates three firms: Tesla (TSLA), Palantir (PLTR), and UnitedHealth (UNH), which exhibited exceptionally strong cumulative abnormal returns (CAR). To assess whether these anomalies were firm-specific or reflective of broader market trends, each company was analyzed alongside two of its closest competitors within the U.S. market and two leading global counterparts. This comparative approach ensures a comprehensive evaluation of whether the observed abnormal returns were driven by firm-specific factors, sector-wide movements, or potential political affiliations influencing investor expectations.

As previously mentioned Tesla exhibited a statistically significant positive cumulative abnormal return (CAR) of 18.39% ($p < 0.01$), where the local competitors General Motors and Ford showed no statistically significant abnormal returns. In stark contrast, international competitors, specifically BYD (BYDDY) and Volkswagen (VWAGY), recorded significant and negative abnormal returns. BYD exhibited a CAR of -9.09% ($p < 0.05$), while Volkswagen experienced even stronger negative returns, with a CAR of -10.44% ($p < 0.001$), indicating a pronounced investor reaction against these firms, as illustrated in Figure 2.

This negative market reaction indicates that investors anticipated unfavorable consequences for non-U.S. manufacturers, likely driven by expectations of protectionist trade policies, heightened regulatory scrutiny of foreign competitors, or adjustments in government subsidies that disproportionately favor domestic firms. In contrast, domestic automakers, most notably Tesla, appear poised to benefit under the new administration, as investors recalibrated their expectations in light of potential policy shifts that could enhance the competitive positioning of Tesla. Tesla's strong positive reaction appears to be firm-specific, potentially reflecting investor expectations regarding its alignment with U.S. industrial policy, anticipated incentives for domestic electric vehicle manufacturers, and regulatory measures disadvantaging foreign competitors. Moreover, the close relationship between Elon Musk and Donald Trump may have reinforced investor confidence, as direct political influence could translate into favorable policies, tax breaks, or deregulation benefiting Tesla.

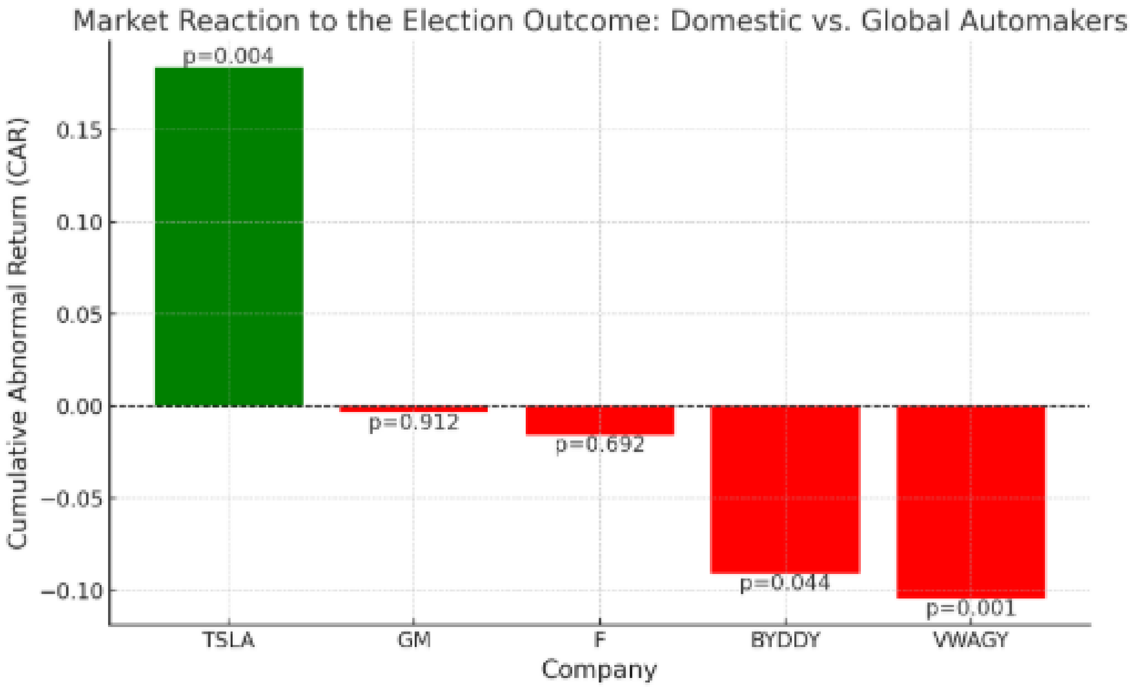

Figure 2 - Comparative visualization of Tesla's market reaction alongside domestic and global competitors.

Although Palantir (PLTR) was not previously examined in the sectoral analysis, its market reaction closely mirrors that of Tesla, exhibiting a stark contrast to its domestic and global competitors. Palantir recorded a significantly positive cumulative abnormal return (CAR) of 22.05% ($p < 0.01$), suggesting that investors perceived it as a likely beneficiary of the new political landscape. This reaction may be attributed to expectations of increased government contracts, particularly in the defense, intelligence, and data analytics sectors. In contrast, its U.S.-based competitor IBM exhibited no meaningful abnormal return (CAR = -0.04%, p =

0.9861), implying that the election outcome had little to no impact on its valuation. Similarly, Snowflake (SNOW) recorded a modest negative reaction (CAR = -2.21%, p = 0.6887), further reinforcing the notion that the election-induced effects were largely concentrated on Palantir rather than the broader data and cloud computing sector. Table 9 provides a comprehensive overview of the abnormal returns observed across these firms, illustrating the pronounced divergence between Palantir and its peers.

A comparable trend emerges when analyzing international competitors. C3.ai (AI), often associated with artificial intelligence-driven enterprise solutions, posted a negative CAR of -6.04% (p = 0.5141), while SAP, a dominant player in global enterprise software, also experienced a decline in market value (CAR = -3.60%, p = 0.1325). These results indicate that the election outcome did not generate a uniform effect across the broader technology sector. Instead, Palantir's strong positive reaction appears to be firm-specific, potentially reflecting investor expectations regarding its political affiliations, its role in national security-related contracts, or an anticipated regulatory environment favoring government-aligned technology firms.

**TABLE 9 - Cumulative abnormal returns (CAR), t-values (t_CAR), and p-values (p_CAR) for Palantir and its competitors.**

| **Company** | **CAR** | **t_CAR** | **p_CAR** |
|---|---|---|---|
| **Palantier** | 0.22050 | 3.28384 | 0.00110 |
| **IBM** | -0.00039 | -0.01738 | 0.98614 |
| **Snowflake** | -0.02213 | -0.40084 | 0.68871 |
| **C3.ai** | -0.06038 | -0.65298 | 0.51407 |
| **SAP** | -0.03603 | -1.50664 | 0.13254 |

Another company not previously examined that exhibited a significant cumulative abnormal return (CAR) is UnitedHealth (UNH). The firm recorded a notably positive CAR of 8.75% ($p < 0.01$), suggesting that investors anticipated favorable policy developments under the new administration, potentially in areas such as healthcare reimbursement, insurance regulation, or Medicare expansion. A similar pattern is observed for Humana (HUM), which also posted a substantial CAR of 11.2% ($p < 0.01$), reinforcing the hypothesis that major U.S. health insurers were perceived as beneficiaries of the political shift.

In contrast, Elevance Health (ELV) and Cigna (CI) displayed no statistically significant market reaction, with CAR values of -0.52% (p = 0.8606) and 0.60% (p = 0.8492), respectively. This divergence suggests that while some insurers were expected to gain from the new administration's policies, others were perceived as largely unaffected.

A stark contrast emerges when analyzing global competitors. Allianz (ALIZY), a European-based insurance company, experienced a pronounced negative CAR of -6.33% (p = 0.0020), indicating that the election-induced market reaction did not extend beyond U.S.-focused healthcare firms. This finding implies that investors expected the policy shifts to primarily influence the domestic private healthcare landscape, with limited implications for globally operating insurers. Table 10 presents the complete set of results, illustrating the differing market reactions among U.S. and international healthcare firms.

**TABLE 10 - Cumulative abnormal returns (CAR), t-values (t_CAR), and p-values (p_CAR) for UnitedHealth and its competitors.**

| **Company** | **CAR** | **t_CAR** | **p_CAR** |
|---|---|---|---|
| **UnitedHealth** | 0.08751 | 3.05980 | 0.00233 |
| **Humana** | 0.11197 | 2.66433 | 0.00796 |
| **Elevance Health** | -0.00515 | -0.17571 | 0.86060 |
| **Cigna** | 0.00598 | 0.19030 | 0.84915 |
| **Allianz** | -0.06327 | -3.10010 | 0.00204 |

## 4.2 Interpretation and Discussion

The empirical findings presented in this study illustrate a heterogeneous stock market reaction to the 2024 U.S. presidential election, with varying degrees of significance across sectors and individual firms. These results suggest that while political events can serve as catalysts for market adjustments, the extent of their influence is contingent upon firm- and industry-specific factors.

The pronounced negative abnormal returns observed in the renewable energy sector indicate that investors revised their expectations downward in response to the election outcome. This reaction is likely attributable to concerns over potential shifts in regulatory frameworks, subsidy structures, and tax incentives that could disadvantage renewable energy firms. Previous research has highlighted the importance of policy support for the renewable energy industry, particularly in relation to investment tax credits, carbon pricing mechanisms, and government-sponsored research and development programs (Henriques & Sadorsky, 2008; Bolton & Kacperczyk, 2021). The election result may have signaled a reduced likelihood of policy continuity in these areas, prompting a reassessment of firm valuations. In contrast, the traditional oil and gas sector exhibited largely insignificant abnormal returns, suggesting that investor expectations regarding this industry remained stable despite the political transition. This finding aligns with prior studies indicating that oil and gas firms are primarily influenced by global commodity prices, macroeconomic conditions, and supply-demand dynamics rather than short-term domestic political developments (Kilian, 2009; Kilian & Zhou, 2020). The muted market response of major U.S. oil companies suggests that investors anticipated minimal immediate policy changes affecting fossil fuel extraction, refining, and distribution. However, the statistically significant negative abnormal returns observed for certain European oil firms raise the possibility that global investors interpreted the election result as an indicator of potential shifts in U.S. foreign energy policy, trade agreements, or geopolitical relations.

The financial sector, by contrast, displayed a generally positive reaction to the election outcome, with some banks exhibiting statistically significant positive cumulative abnormal returns. This suggests that investors anticipated a favorable regulatory and economic environment under the new administration, potentially characterized by deregulatory measures, tax incentives, or accommodative monetary policies. Prior research has established a strong link between financial sector performance and expectations regarding financial regulation, capital requirements, and interest rate policies (Agénor, Alper & Silva, 2013). The significant positive response observed for Goldman Sachs and, to a lesser extent, Morgan Stanley, may reflect investor perceptions that investment banks would benefit more than commercial banks from the anticipated policy landscape. However, the lack of significant abnormal returns for JPMorgan Chase, Bank of America, and Wells Fargo suggests that broader sectoral trends were not uniformly distributed across all financial institutions.

The technology sector, unlike the energy and financial industries, exhibited minimal reaction to the election result. The absence of statistically significant abnormal returns across the five largest technology firms suggests that investors did not perceive the political transition as a major determinant of the sector’s valuation. This finding is consistent with the notion that technology firms operate within a globalized and highly diversified market, where firm-specific factors such as innovation cycles, competitive dynamics, and macroeconomic conditions play a pivotal role in shaping long-term performance (Petit & Teece, 2021). Given the sector’s dependence on long-term investment horizons, regulatory uncertainty, and global supply chains, the lack of significant market reaction may indicate that investors viewed the election as having only marginal implications for these firms' future profitability.

Beyond sectoral trends, the study identifies three firms - Tesla, Palantir, and UnitedHealth - as exhibiting particularly strong and statistically significant abnormal returns. The positive market response to Tesla, in contrast to the largely negative reactions within the broader EV battery sector, suggests that investors perceived the election outcome as uniquely beneficial to the firm. This divergence may be attributed not only to Tesla's established market position and brand strength but also to the close relationship between Elon Musk and Donald Trump, which could signal favorable policy treatment, regulatory advantages, or strategic collaboration between the administration and Tesla. The concurrent negative abnormal returns for Tesla's international competitors, particularly BYD and Volkswagen, further support this hypothesis, as they suggest that global investors anticipated a less favorable policy environment for non-U.S. automakers.

A similar pattern emerges in the case of Palantir, which recorded a significant positive abnormal return, while its domestic competitors, IBM and Snowflake, exhibited no meaningful market response. This suggests that Palantir's stock price reaction was not driven by general trends in the software and data analytics sector, but rather by firm-specific factors. Given Palantir's extensive government contracts and strategic alignment with U.S. defense and intelligence agencies, the election outcome may have reinforced investor expectations of continued or expanded government partnerships under the new administration. Previous research has demonstrated that firms with close political affiliations often benefit from preferential treatment in regulatory decisions, government procurement, and public-sector funding (Goldman, Rocholl, & So, 2009; Brown & Huang, 2017). The findings suggest that investors anticipated Palantir's political connections to translate into tangible financial benefits, thereby driving the positive market response.

The case of UnitedHealth also warrants attention, as the firm exhibited a significantly positive cumulative abnormal return, whereas some of its domestic and international competitors did not. The strong market reaction suggests that investors expected the election outcome to result in favorable policy developments for major U.S. health insurers, possibly in the form of deregulation for the private healthcare insurance field. However, the contrasting negative abnormal return observed for Allianz, a globally operating insurance firm, indicates that investors perceived the political shifts as primarily affecting the U.S. healthcare landscape rather than the broader international insurance market.

Taken together, these findings contribute to the growing body of literature on the intersection of financial markets and political events. They highlight that political transitions do not exert uniform effects across industries but instead generate asymmetric reactions shaped by firm-specific characteristics, sectoral dependencies, and investor expectations regarding regulatory and policy shifts. The results also underscore the complexity of disentangling political influences from broader macroeconomic and industry-specific drivers, reinforcing the importance of rigorous empirical approaches in event study analysis. While political developments can serve as catalysts for market adjustments, their impact remains contingent upon underlying economic structures, competitive dynamics, and investor sentiment, suggesting that financial markets react selectively rather than indiscriminately to electoral outcomes.

# 5. Conclusion

This study investigates stock market reactions to the 2024 U.S. presidential election using an event study methodology, focusing on six industries: solar energy, electric vehicle (EV) battery production, U.S. oil and gas, European oil and gas, banking, and technology. The results indicate that the solar energy sector experienced significant negative abnormal returns, indicating that investors reassessed the likelihood of sustained regulatory support and subsidy structures in the renewable energy sector. In contrast, U.S. oil and gas firms exhibited no significant market reaction, while major European oil firms recorded negative abnormal returns, potentially reflecting geopolitical risk pricing.

The financial sector responded positively, with investment banks experiencing stronger abnormal returns than commercial banks, which is consistent with expectations that deregulatory policies could favor capital markets. The technology sector remained largely unaffected, aligning with prior literature suggesting that firm-specific factors, such as innovation cycles and competitive dynamics, dominate short-term political effects in this sector (Petit & Teece, 2021).

At the firm level, Tesla's stock price experienced a notable increase following the election, while its international competitors, including BYD and Volkswagen, recorded negative abnormal returns. This contrast suggests that investors may have anticipated favorable trade or industrial policies benefiting U.S. automakers under the new administration. The divergence in abnormal returns between Tesla and its domestic competitors suggests that firm-specific political considerations, including public perceptions of executive-government relations, may have influenced market responses. Similarly, Palantir saw a substantial rise in stock value, whereas its domestic and international competitors showed no meaningful reaction, underscoring the role of firm-specific political exposure in shaping investor sentiment. In the healthcare sector, UnitedHealth exhibited positive abnormal returns, whereas Allianz, a European insurance firm, experienced a decline. This contrast further reinforces the notion that U.S.-centric policy shifts were a primary factor driving market reactions, particularly for companies that stood to benefit most from Trump-era policies or had openly aligned themselves with the administration.

These findings extend the literature on political uncertainty and asset pricing (Julio & Yook, 2012), reinforcing the notion that market responses to electoral outcomes are contingent upon industry-specific regulatory dependencies and firm-level political exposures. Future research should explore microfoundations of these market responses, particularly the interaction between firm-level political affiliations, lobbying activities, and industry-specific regulatory dependencies in election-induced asset pricing adjustments.

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# Appendix: R-code for reproduction

```
############################################################################
# Stock market dynamics and political information
# Event Study on the 2024 U.S. Presidential Election
# Estimating a Fama-French three-factor model
# by Noah Laufer, University of Applied Sciences Ludwigshafen
# February 2025
############################################################################
library(quantmod)
companies_df <- data.frame(
Industry = c(rep("Solar", 5), rep("EV Battery", 5), rep("US Oil & Gas", 5),
              rep("International Oil & Gas", 5), rep("Banking", 5), rep("Tech", 5),
              rep("Competitor Analysis", 15)),
Company = c("First Solar", "Enphase Energy", "NextEra Energy", "Sunrun", "SolarEdge",
            "Tesla", "General Motors", "Ford", "Microvast Holdings", "QuantumScape",
            "ExxonMobil", "Chevron", "ConocoPhillips", "EOG Resources", "Occidental Petroleum",
            "BP", "Shell", "TotalEnergies", "Equinor", "Eni",
            "JPMorgan Chase", "Bank of America", "Wells Fargo", "Morgan Stanley", "Goldman Sachs",
            "Apple", "Nvidia", "Microsoft", "Alphabet", "Amazon",
            "Tesla", "Tesla Competitor (US)", "Tesla Competitor (US)", "Tesla Competitor (Global)", "Tesla Competitor (Global)",
            "Palantir", "Palantir Competitor (US)", "Palantir Competitor (US)", "Palantir Competitor (Global)", "Palantir Competitor (Global)",
            "UnitedHealth", "UnitedHealth Competitor (US)", "UnitedHealth Competitor (US)", "UnitedHealth Competitor (Global)","UnitedHealth Competitor (Global)"),
Ticker = c("FSLR", "ENPH", "NEE", "RUN", "SEDG",
            "TSLA", "GM", "F", "MVST", "QS",
            "XOM", "CVX", "COP", "EOG", "OXY",
            "BP", "SHEL", "TTE", "EQNR", "E",
            "JPM", "BAC", "WFC", "MS", "GS",
            "AAPL", "NVDA", "MSFT", "GOOGL", "AMZN",
            "TSLA",
            "F", "GM","BYDDY", "VWAGY",
```

```
            "PLTR",
            "IBM","SNOW", "AI", "SAP",
            "UNH",
            "HUM","ELV", "CI" ,"ALIZY")
)
# List of ticker symbols
stock_tickers <- companies_df$Ticker
# Create a DataFrame for the results
myresults  <-  data.frame(Ticker  =  character(),  AAR  =  numeric(),  CAR  =
numeric(),
                        t_AAR = numeric(), p_AAR = numeric(),
                        t_CAR    =    numeric(),    p_CAR    =    numeric(),
stringsAsFactors = FALSE)
# Load S&P 500 data
cat("Lade S&P 500 Daten...\n")
getSymbols("^GSPC", from = "2020-12-31", to = "2024-12-31", auto.assign =
TRUE)
sp500_prices <- Cl(GSPC)
sp500_returns <- diff(log(sp500_prices))
# Load Fama-French data
cat("Lade Fama-French-Daten...\n")
zip_url  <-  "https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ftp/F-
F_Research_Data_Factors_daily_CSV.zip"
zip_file <- "F-F_Research_Data_Factors_daily_CSV.zip"
download.file(zip_url, zip_file, mode = "wb")
unzip(zip_file, exdir = "fama_french_data")
fama_french                <-                read.csv("fama_french_data/F-
F_Research_Data_Factors_daily.CSV", skip = 3)
# Prepare the data
colnames(fama_french)[1] <- "Date"
fama_french$Date <- as.Date(as.character(fama_french$Date), format="%Y%m%d")
cutoff_date <- as.Date("2024-11-09")
fama_french <- subset(fama_french, Date <= cutoff_date)
# Convert the factors used to extend the CAPM into decimal values
# RF = Risk-free rate (U.S. Treasury Bond), SMB = Small minus big (size
# factor), HML = Value factor (value vs. growth)
fama_french$RF <- fama_french$RF / 100
```

```r
fama_french$SMB <- fama_french$SMB / 100
fama_french$HML <- fama_french$HML / 100
# The market risk premium is calculated based on the S&P 500 (S&P 500 - RF)
fama_french <- subset(fama_french, select = -Mkt.RF)
# Loop through all tickers
for (ticker in stock_tickers) {
  cat("\nVerarbeite Ticker:", ticker, "...\n")
# Retrieve data
stock_data   <- getSymbols(ticker, from = "2020-12-31", to = "2024-12-31",
auto.assign = FALSE)
stock_prices <- Cl(stock_data)
# Calculate logarithmic returns
stock_returns <- diff(log(stock_prices))
# Create and merge DataFrame
df <- data.frame(
  Date = index(stock_returns),
  Stock_Returns = as.numeric(stock_returns),
  SP500_Returns = as.numeric(sp500_returns)
  )
df <- merge(df, fama_french, by = "Date", all.x = TRUE)
# Remove the first row containing NA values
df <- df[-1, ]
# Calculate excess returns
df$Stock_Excess <- df$Stock_Returns - df$RF
df$SP500_Excess <- df$SP500_Returns - df$RF
# Definition of the event periods
estimation_window <- (df$Date >= "2022-11-04" & df$Date <= "2024-11-04")
event_window <- (df$Date >= "2024-11-05" & df$Date <= "2024-11-08")

# Perform regression over the estimation window
capm_fama_model  <-  lm(Stock_Excess  ~  SP500_Excess  +  SMB  +  HML,  data  =
df[estimation_window, ])
# Calculate expected returns
df$Expected_Return <- predict(capm_fama_model, newdata = df)
# Calculate abnormal returns
df$Abnormal_Return <- df$Stock_Excess - df$Expected_Return
```

```
# Calculation of AAR and CAR

AAR <- mean(df$Abnormal_Return[event_window], na.rm = TRUE)

CAR <- sum(df$Abnormal_Return[event_window], na.rm = TRUE)

# Calculate the residual variance for the CAPM and the Fama-French three-
factor model over the estimation window

residual_variance_lm <- summary(capm_fama_model)$sigma^2

# T-test for AAR:

# The degrees of freedom for the t-test are determined by the estimation
window

L1 <- sum(estimation_window)

k <- length(coef(capm_fama_model))

df_AAR <- L1 - k

L2 <- sum(event_window)

# T-test for AAR:

std_err_AAR <- sqrt(residual_variance_lm / L2)

t_AAR <- AAR / std_err_AAR

p_AAR <- 2 * (1 - pt(abs(t_AAR), df = df_AAR))

# T-test for CAR:

# The degrees of freedom for the t-test are determined by the estimation
window

df_CAR <- L1 - k

std_AAR <- sqrt(residual_variance_lm)

t_CAR <- CAR / (sqrt(L2) * std_AAR)

p_CAR <- 2 * (1 - pt(abs(t_CAR), df = df_CAR))

# Save results

myresults <- rbind(myresults, data.frame(Ticker = ticker, AAR = AAR, CAR =
CAR,

                                           t_AAR = t_AAR, p_AAR = p_AAR,

                                           t_CAR = t_CAR, p_CAR = p_CAR))

}

# TSLA, F, and GM appear twice, once in the industry analysis and once among
the specially selected firms

myresults <- myresults[!duplicated(myresults$Ticker), ]

# Show final results

print(myresults)
```