COMILLAS
UNIVERSIDAD PONTIFICIA

Facultad de Ciencias Económicas y Empresariales | ICADE

ANALYSIS ON PAYMENT METHOD EFFECTS IN U.S. ENERGY M&A: A PANEL EVENT STUDY APPROACH

Author: Carlos Méndez Cerdeira

Director: Alejandro Rodríguez Gallego

MADRID | January 2026

ABSTRACT

This dissertation examines how the method of payment in mergers and acquisitions (M&A) affects stock market reactions, focusing on the U.S. energy sector over the period 2004–2024. The choice between cash and stock financing is a central strategic decision in M&A transactions and may convey important information to investors regarding firm valuation and risk.

The analysis combines a traditional event study with a panel event study framework to capture both short-term abnormal returns around the announcement date and the dynamic evolution of market responses over time. Transaction data are obtained from FactSet, and stock price data are sourced from Bloomberg. The final sample includes 127 cash-financed and 95 stock-financed acquisitions involving publicly listed U.S. energy firms.

The results reveal a clear difference in market reactions across payment methods. Cash-financed acquisitions are associated with neutral market responses, showing no statistically significant abnormal returns before, on, or after the announcement. In contrast, stock-financed acquisitions generate statistically significant negative abnormal returns for acquiring firms. These adverse effects occur at the announcement date and persist in the post-announcement period, as confirmed by both methodological approaches.

Overall, the findings indicate that investors systematically differentiate between cash and stock payments when evaluating M&A announcements, highlighting the importance of payment structure as a determinant of short-term shareholder value in the U.S. energy sector.

KEYWORDS

Mergers and Acquisitions, Payment Method, Event Study, Panel Event Study, Stock Market Reaction, U.S. Energy Sector

RESUMEN

Este trabajo examina cómo el método de pago en las operaciones de fusiones y adquisiciones (M&A) afecta a las reacciones del mercado bursátil, centrándose en el sector energético de Estados Unidos durante el periodo 2004–2024. La elección entre financiación en efectivo y mediante acciones constituye una decisión estratégica central en las transacciones de M&A y puede transmitir información importante a los inversores sobre la valoración y el riesgo de la empresa.

El análisis combina un estudio de eventos tradicional con un marco de estudio de eventos en panel para captar tanto los rendimientos anormales de corto plazo en torno a la fecha de anuncio como la evolución dinámica de las respuestas del mercado a lo largo del tiempo. Los datos de transacciones se obtienen de FactSet y los datos de precios de las acciones proceden de Bloomberg. La muestra final incluye 127 adquisiciones financiadas en efectivo y 95 financiadas mediante acciones, en las que participan empresas energéticas estadounidenses cotizadas.

Los resultados muestran una clara diferencia en las reacciones del mercado según el método de pago. Las adquisiciones financiadas en efectivo se asocian con respuestas neutrales del mercado, sin rendimientos anormales estadísticamente significativos antes, durante o después del anuncio. En cambio, las adquisiciones financiadas mediante acciones generan rendimientos anormales negativos estadísticamente significativos para las empresas adquirentes. Estos efectos adversos se producen en la fecha del anuncio y persisten en el periodo posterior al anuncio, tal y como confirman ambos enfoques metodológicos.

En conjunto, los hallazgos indican que los inversores diferencian sistemáticamente entre pagos en efectivo y mediante acciones al evaluar anuncios de M&A, poniendo de manifiesto la importancia de la estructura de pago como determinante del valor para el accionista en el corto plazo en el sector energético de Estados Unidos.

PALABRAS CLAVE

Fusiones y Adquisiciones, Método de Pago, Estudio de Eventos, Estudio de Eventos en Panel, Reacción del Mercado Bursátil, Sector Energético de Estados Unidos

Table of Contents

Index of Figures

1. INTRODUCTION

Mergers and acquisitions (M&A) constitute one of the most important strategic tools available to firms seeking growth, diversification, or competitive advantage. Beyond their long-term operational and strategic implications, M&A transactions often trigger immediate reactions in financial markets, as investors reassess firm value in light of new information. Among the many dimensions of an acquisition, the method of payment plays a particularly central role, as it does not merely determine how the transaction is financed but also conveys signals about managerial expectations, valuation beliefs, and perceived risk.

This dissertation investigates how the choice of payment structure in M&A transactions affects stock market reactions, focusing on acquisitions within the U.S. energy sector. By examining market responses to cash- and stock-financed deals, the study aims to shed light on how investors interpret payment choices and incorporate the associated information into prices.

1.1 Introduction to Payment Methods in M&A

The method of payment in mergers and acquisitions is one of the most strategically significant decisions in corporate finance. Acquiring firms typically finance transactions using cash, stock, or a combination of both, and each option carries distinct informational implications. Prior research emphasizes that payment choice can influence investor perceptions regarding firm valuation, managerial confidence, and the expected quality of the transaction (Hansen, 1987; Travlos, 1987).

Cash offers involve the direct transfer of funds to target shareholders, either through internal resources or external borrowing. Such transactions are often interpreted as a signal of confidence by the acquiring firm's management, suggesting that the acquirer believes the transaction will generate sufficient value to justify the immediate outflow of cash (Myers & Majluf, 1984). In contrast, stock-financed acquisitions require the issuance of new shares to target shareholders. While this structure allows risk to be shared between both parties and preserves liquidity, it may also signal that management perceives its own shares to be overvalued or seeks to avoid the costs and scrutiny associated with external financing (Hansen, 1987).

Empirical evidence consistently documents differences in market reactions across payment methods. Cash-financed acquisitions tend to generate neutral or mildly positive reactions for acquiring firms, whereas stock-financed transactions are more frequently associated with negative abnormal returns (Travlos, 1987; Fuller et al., 2002; Moeller et al., 2004). These patterns highlight the informational content embedded in payment structure decisions and motivate a deeper examination of how markets respond to such signals.

1.2 The U.S. Energy Industry Context

1.2.1 Structural Characteristics of the U.S. Energy Sector

The U.S. energy sector is one of the largest and most strategically significant segments of the American economy, encompassing activities ranging from oil and gas exploration and refining to electricity generation and renewable energy production. The industry is characterized by high capital intensity, long investment horizons, and substantial exposure to regulatory, technological, and geopolitical forces (IEA, 2023). These features shape both corporate decision-making and investor behavior, increasing the informational content of major strategic announcements such as mergers and acquisitions.

Energy firms also operate in a highly cyclical environment, where commodity price fluctuations have a direct impact on profitability, valuation, and investment activity. Episodes of sharp price volatility, geopolitical tensions, and shifts in global demand have historically driven consolidation waves within the sector (Baumeister & Kilian, 2016). At the same time, extensive regulatory oversight and evolving environmental standards introduce additional uncertainty, making market reactions to strategic decisions particularly relevant to study.

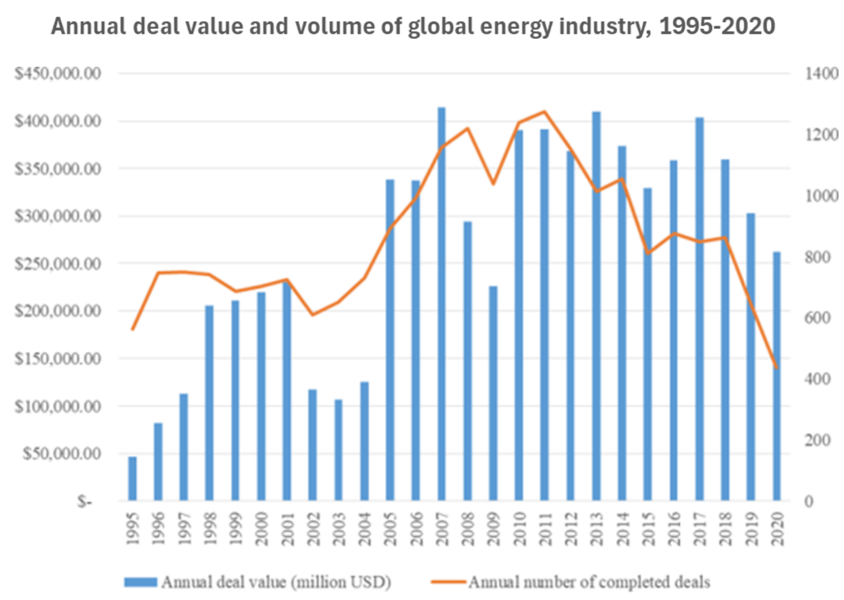

Figure 1 *- Annual deal value and volume of global energy industry, 1995-2020. (Source: Andriuškevičius & Štreimikienė, 2021)*

1.2.2 Sectoral Evolution and Structural Shifts (2004–2024)

The period from 2004 to 2024 has been marked by profound structural changes in the U.S. energy sector. One of the most significant developments has been the shale revolution, which substantially increased domestic oil and natural gas production through advances in hydraulic fracturing and horizontal drilling. This transformation altered industry dynamics and triggered extensive consolidation as firms sought scale, technological capabilities, and access to key resource basins (EIA, 2022).

Simultaneously, renewable energy has grown rapidly, driven by declining costs, policy incentives, and increasing environmental concerns. Many traditional energy companies have diversified into renewable and low-carbon technologies, reshaping strategic priorities and increasing uncertainty around long-term valuations. Regulatory initiatives and global shocks, including the 2014–2016 oil price collapse and the COVID-19 pandemic, further influenced deal-making behavior and investor expectations (IEA, 2023).

These structural transformations make the U.S. energy sector a particularly suitable context for analyzing how markets interpret and react to M&A announcements, especially with respect to the signals conveyed by payment structure choices.

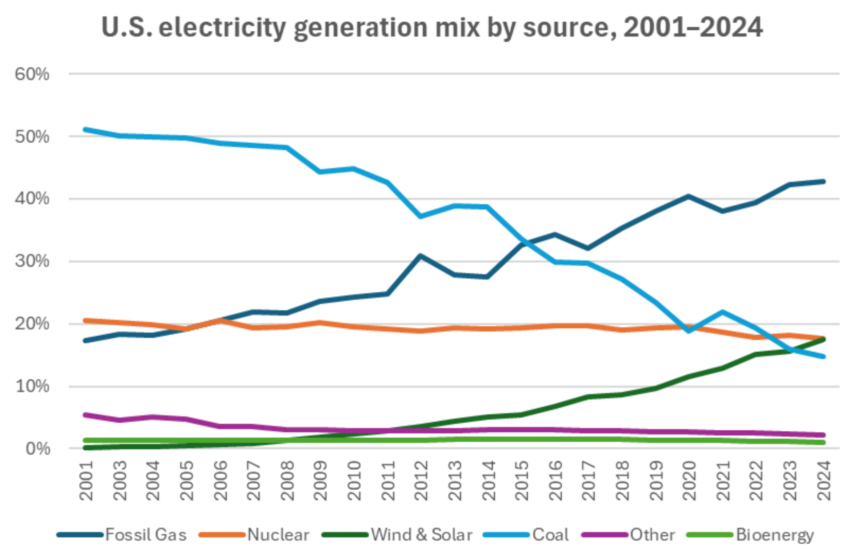

Figure 2 *- U.S. electricity generation mix by source, 2001–2024 (Source: Klein, 2024)*

2. OBJECTIVE

The objective of this thesis is to investigate how the choice of payment structure in mergers and acquisitions (M&A) transactions affects stock market reactions within the U.S. energy sector. By combining a traditional event study framework with a panel event study approach, the analysis aims to capture both the short-term abnormal returns generated around the announcement date and the dynamic effects of payment methods over time. In particular, the study examines whether acquisitions financed entirely with cash or entirely with stock are associated with systematically different market responses for acquiring firms. To maintain a clear identification strategy and ensure a clean comparison between payment methods, mixed-payment transactions were excluded from the sample, allowing the analysis to focus on the two most distinct and commonly studied financing structures.

The method of payment used in an acquisition often conveys important signals to investors regarding managerial expectations, perceived risk, and firm valuation, all of which can directly influence stock price behavior. Understanding how these signals are interpreted by the market is therefore essential for comprehending the dynamics surrounding M&A activity. Within this context, the analysis evaluates whether M&A announcements generate statistically significant abnormal returns, whether any such effects emerge prior to the public announcement, potentially indicating information leakage, and how rapidly markets incorporate new information once the transaction becomes public. Special attention is given to post-announcement return patterns, which provide insight into whether market reactions are immediate or display signs of delayed adjustment.

The U.S. energy sector offers a particularly relevant setting for this investigation due to its strategic importance and the substantial structural transformations it has undergone between 2004 and 2024. These include technological innovation, regulatory shifts, commodity price volatility, and the ongoing transition toward renewable energy sources, all of which have shaped corporate strategies and investor expectations. By examining M&A transactions over this 20-year period, the thesis seeks to contribute new empirical evidence on the relationship between payment methods and market behavior, offering insights relevant to both academic research and corporate decision-making in one of the most economically significant sectors of the United States.

3. THEORETICAL FRAMEWORK

3.1 Payment Methods in Mergers and Acquisitions

3.1.2 Theoretical Perspectives on Payment Structure

The choice between cash and stock in mergers and acquisitions is more than a financing decision, it reflects managerial beliefs, information conditions, and strategic incentives, all of which shape how investors interpret a transaction. Three main theoretical frameworks help explain why payment structure matters and how it influences market reactions: signalling theory, information asymmetry and market timing, and agency theory.

3.1.2.1 Signalling theory and managerial confidence

Signalling theory suggests that managers use financing choices to convey private information about firm value and future prospects to the market (Ross, 1977; Spence, 1973). A cash offer typically signals managerial confidence, as committing funds suggests that the acquirer expects the acquisition to generate returns sufficient to justify the expenditure. It also implies that managers view their own stock as fairly valued or undervalued (Myers & Majluf, 1984). In contrast, a stock offer may be interpreted as a signal that the acquirer's equity is overvalued, as managers may prefer to issue shares when they believe the market is overpricing them (Hansen, 1987). Managers who perceive their firm's shares as overpriced may therefore prefer to use them as currency for acquisitions, thereby transferring part of the overvaluation risk to the target's shareholders (Shleifer & Vishny, 2003). As a result, cash-financed deals are generally associated with more favourable or neutral market reactions compared to stock-financed ones, which are more often met with negative responses (Travlos, 1987; Moeller et al., 2004).

3.1.2.2 Information asymmetry and market timing

Information asymmetry theory extends this reasoning by emphasizing differences in knowledge between managers and investors. When managers know their firm is undervalued, they prefer to use cash to avoid issuing equity at a discount, if they believe it is overvalued, they may opt for stock to transfer some risk to new shareholders (Myers & Majluf, 1984). This logic aligns with the market timing hypothesis, which argues that managers exploit periods of high valuation by issuing stock and use cash when market conditions are less favourable (Baker & Wurgler, 2002). Investors are aware of this behaviour and often interpret payment choice as a proxy for management's private assessment of valuation.

3.1.2.3 Agency theory and ownership consideration

Agency theory highlights how conflicts of interest between managers and shareholders can shape payment decisions (Jensen & Meckling, 1976). Managers may prefer stock to avoid the scrutiny associated with raising external financing or to diversify their own wealth (Amihud et al., 1990). Conversely, cash financing imposes greater market discipline but may also enable inefficient acquisitions if managers have large free cash flows and pursue "empire building" strategies (Jensen, 1986; Harford, 1999). Ownership considerations also matter: firms wishing to avoid dilution may favour cash, while those seeking flexibility or risk-sharing may prefer stock.

3.1.3 Empirical Evidence on Market Reactions to Cash vs. Stock Deals

A substantial body of empirical research has examined how payment structure influences stock market reactions to mergers and acquisitions. Across decades of studies, one of the most robust findings is that cash-financed acquisitions are generally associated with more positive or neutral abnormal returns for acquiring firms than stock-financed ones.

One of the earliest and most influential contributions is Travlos (1987), who analyzed U.S. takeover bids and found that acquiring firms experience significantly higher abnormal returns when paying with cash compared to stock. Importantly, this result reflects that cash offers tend to avoid the negative reactions commonly observed in stock-financed deals, rather than consistently generating large positive gains for acquirers. Stock-financed transactions, by contrast, were often met with neutral or negative reactions, likely reflecting investor concerns about potential overvaluation of the acquiring firm's shares.

Subsequent research has reinforced this pattern. Fuller et al. (2002) examined a large sample of U.S. acquisitions and confirmed that stock-financed deals typically generate lower abnormal returns for acquiring firms, while cash-financed transactions are associated with returns closer to zero or mildly positive. Moeller et al. (2004) further demonstrated that acquirers in cash transactions tend to perform better relative to stock-financed acquirers, particularly in large deals, whereas stock-financed acquisitions are more likely to destroy value, especially when acquirer valuations are high. These findings are consistent with signaling and market timing explanations rather than the expectation of uniformly positive gains from cash offers.

Empirical evidence also shows that target shareholders almost always benefit from acquisitions, regardless of payment method, although the premiums paid are typically higher in cash deals (Andrade et al., 2001). At the same time, the magnitude and significance of acquirer returns vary across contexts. Industry characteristics, deal size, and market conditions can moderate the effect of payment choice, suggesting that the informational content of payment method is context-dependent rather than uniform (Faccio & Masulis, 2005).

3.2 Event Studies as a Tool to Analyse Market Reactions

3.2.1 Definition and Purpose of Event Studies

The Efficient Market Hypothesis (EMH) provides the theoretical foundation for event study methodology. First formalized by Fama (1970), the EMH posits that asset prices fully and instantaneously reflect all available information. Depending on its form (weak, semi-strong, or strong), the hypothesis distinguishes between markets that incorporate past prices, publicly available information, or even private information into prices.

Event studies are a widely used empirical method in finance for analyzing how markets respond to new information. They are based on the premise that, if markets are semi-strong form efficient, stock prices should rapidly incorporate all publicly available information once it becomes known (Fama, 1970). By examining stock price behavior around the announcement of a specific event, researchers can infer how investors interpret that information and assess its impact on firm value.

In the context of mergers and acquisitions, event studies are particularly useful for isolating the market reaction to transaction announcements and for testing how characteristics of those transactions, such as the payment method, influence investor response. The approach relies on identifying the precise moment when new information becomes public and then measuring the difference between actual stock returns and those expected in the absence of the event. This difference, known as the abnormal return, reflects the portion of price movement attributable to the new information.

The roots of event study methodology trace back to authors such as Ball and Brown (1968), who analyzed stock price reactions to earnings announcements, and were formalized by Fama et al. (1969), who provided a robust statistical framework for measuring abnormal returns around corporate events. Since then, event studies have been widely applied to a variety of corporate actions, including dividend announcements, earnings releases, stock splits, and, most prominently, mergers and acquisitions (MacKinlay, 1997).

In the study of payment methods, event studies allow researchers to quantify whether the market reacts differently to cash versus stock-financed deals and whether those reactions align with theoretical expectations. Empirical evidence suggests that cash offers are often interpreted as a signal of managerial confidence and potential undervaluation, and are therefore associated with neutral or mildly positive abnormal returns for acquiring firms around the announcement date (Myers & Majluf, 1984; Travlos, 1987). Conversely, stock-financed acquisitions, which may signal potential overvaluation or a desire to share risk with target shareholders, are more frequently associated with weaker or negative market reactions (Myers & Majluf, 1984; Travlos, 1987).

3.2.2 Key Components of a Traditional Event Study

3.2.2.1 Event Date, Event Window and Estimation Window

A fundamental step in designing an event study is identifying the event date and defining the event window and estimation window, as these choices directly affect the measurement and interpretation of abnormal returns.

The event date is the point at which new information is released to the market. In the context of this dissertation, it refers to the announcement date of the merger or acquisition and its payment method. Accurately identifying this date is crucial because abnormal returns are calculated relative to it. Using an incorrect date, such as the transaction completion date, can distort results and misrepresent the timing of the market's reaction (MacKinlay, 1997). Researchers must also consider potential information leakage, where stock prices begin to react before the official announcement due to rumors or insider activity (Keown & Pinkerton, 1981). To capture such effects, the event window is often extended to include days before the announcement.

The event window is the period surrounding the event date over which abnormal returns are measured. It is typically expressed in trading days relative to the announcement, such as $[-1, +1]$, $[-5, +5]$, or $[-10, +10]$. Although such windows are expressed in days, the number of observations within the window depends on data frequency. With intraday or high-frequency data, even a short window (e.g., $[-1, +1]$) can contain many data points, while daily data would produce only a few.

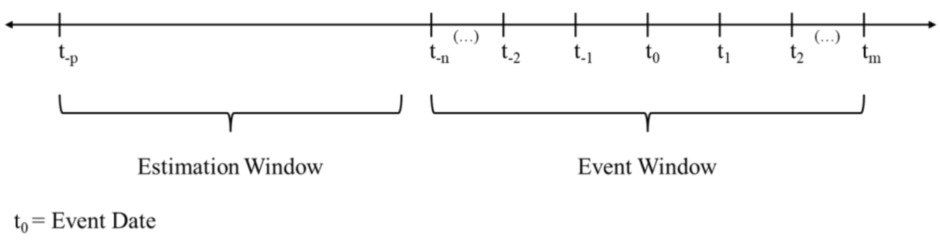

Figure 3 - The Timeline of an Event Study (Source: Author)

The choice of window length involves a trade-off. Shorter windows (e.g., three days) focus narrowly on the immediate market reaction and minimize the risk of capturing unrelated news, making them particularly suitable for testing how quickly and accurately payment method information is incorporated into prices (Brown & Warner, 1985). Longer windows may capture delayed adjustments or reactions to additional deal details, but they increase the risk of contamination from other market events (Corrado, 2011). The optimal window depends on the research question and the likelihood of information leakage or slow adjustment.

Equally important is the estimation window, which is used to calculate the expected or "normal" returns that would have occurred in the absence of the event. This baseline allows researchers to isolate the abnormal returns attributable to the payment method announcement. The estimation window is typically much longer than the event window, often ranging from 120 to 250 trading days prior to the event (MacKinlay, 1997). It usually ends several days before the event window begins to avoid contamination by early information effects (Campbell et al., 1996). The length of this window involves a similar trade-off: longer estimation periods improve the precision of return estimates but may capture changes in the firm's risk profile, while shorter periods reduce this risk but yield less precise estimates (Kothari & Warner, 2007).

3.2.2.2 Measuring Expected Returns

A central step in event study methodology is estimating the expected return of a firm's stock in the absence of the event. This expected return acts as a benchmark against which the abnormal return (AR) is calculated. The abnormal return represents the difference between the actual observed return and the return that would have been expected if the event had not occurred. The choice of model for expected returns influences the precision of abnormal return estimates and, therefore, the reliability of the conclusions drawn from the event study (Brown & Warner, 1985; MacKinlay, 1997).

Several models are commonly used to estimate expected returns, ranging from simple historical averages to multifactor asset pricing models. The most widely applied models in M&A event studies are summarized below.

A) Constant Mean Return Model

The simplest approach assumes that a firm's expected return is constant over the event window and equal to its average over the estimation window (Brown & Warner, 1980):

$$E[R_{i,t}] = \bar{R}_i$$

where $E\left[R_{i,t}\right]$ is the expected return of firm i at time t, and $\bar{R}_i$ is the mean return over the estimation period. Although easy to implement, this model ignores systematic market influences and is rarely used in isolation in modern studies.

B) Market Model

The market model, formalized by Brown and Warner (1985), improves upon the constant mean approach by explicitly accounting for the relationship between a firm's returns and overall market movements:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \epsilon_{i,t}$$

where $R_{i,t}$ is the return of firm i at time t, $R_{m,t}$ is the market return, α_i and β_i are firm-specific parameters, and $\epsilon_{i,t}$ is the error term.

The expected return is then:

$$E[R_{i,t}] = \hat{\alpha}_i + \hat{\beta}_i R_{m,t}$$

This model accounts for the portion of a firm's return that co-moves with the overall market but assumes a linear and stable relationship between firm and market returns.

C) Capital Asset Pricing Model (CAPM)

The CAPM, independently developed by Sharpe (1964) and Lintner (1965), builds on the market model by explicitly linking expected return to systematic risk:

$$E[R_{i,t}] = R_f + \beta_i(E[R_{m,t}] - R_f)$$

where R_f is the risk-free rate and $E[R_{m,t}] - R_f$ is the market risk premium. CAPM provides a theoretical foundation for the risk-return relationship and remains widely used in empirical finance, although it relies on simplifying assumptions such as a single risk factor and homogeneous expectations (Sharpe, 1964; Lintner, 1965).

D) Fama-French Three-Factor Model

Fama and French (1993) extended CAPM by adding two additional factors to capture size and value effects:

$$E[R_{i,t}] = \alpha_i + R_{f,t} + \beta_{i,M}(R_{M,t} - R_{f,t}) + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \varepsilon_{i,t}$$

Here, SMB represents the excess return of small over large firms, and HML represents the excess return of high book-to-market over low book-to-market firms. This model improves explanatory power, especially for cross-sectional return differences.

E) Carhart Four-Factor Model

Carhart (1997) further refined the model by adding a momentum factor:

$$E\left[R_{i,t}\right] = \alpha_i + R_{f,t} + \beta_{i,M}\left(R_{m,t} - R_{f,t}\right) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,MOM}MOM_t + \varepsilon_{i,t}$$

where MOM captures the return differential between recent winners and losers. Including momentum often improves model fit and abnormal return estimation.

F) Fama-French Five-Factor Model

Fama and French (2015) introduced two additional factors: profitability (RMW) and investment (CMA):

$$E[R_{i,t}] = \alpha_i + R_{f,t} + \beta_{i,M}(R_{m,t} - R_{f,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,RMW}RMW_t + \beta_{i,CMA}CMA_t + \varepsilon_{i,t}$$

This model provides a more comprehensive view of expected returns but increases data requirements and model complexity. In event studies, it is most useful when examining long-term post-announcement effects.

G) Model Choice

Each of these models involves a trade-off between simplicity and explanatory power. Simpler models, such as the constant mean or market model, require fewer assumptions and are well suited for short-term windows, which are common in M&A event studies. Multifactor models, while more complex, better capture systematic risk sources and are particularly valuable for longer-term analyses or when studying heterogeneous firm characteristics.

3.2.2.3 Measuring Abnormal Returns and Cumulative Abnormal Returns

The core objective of an event study is to measure how stock prices respond to new information. This is done by calculating abnormal returns (ARs), which represent the deviation of actual stock returns from those expected in the absence of the event. Abnormal returns capture the market's reaction to new information and are the key indicator of whether an event, such as an M&A announcement and its associated payment method, has created or destroyed shareholder value (MacKinlay, 1997).

For a given firm i on day t, the abnormal return is defined as:

$$AR_{i,t} = R_{i,t} - E[R_{i,t}]$$

where $R_{i,t}$ is the actual observed return of firm i on day t, and $E\left[R_{i,t}\right]$ is the expected return estimated using one of the models discussed in Section 3.2.2.2 Measuring Expected Returns (e.g., market model, CAPM). A statistically significant $AR_{i,t}$ indicates that the event has influenced the stock price beyond what would be expected based on normal market movements.

Since a single abnormal return provides only a snapshot of the market reaction on a particular day, researchers typically aggregate these effects across multiple days to capture the total market response over the event window. The cumulative abnormal return (CAR) over a period from day T_1 to T_2 is calculated as:

$$CAR_i(T_1, T_2) = \sum_{t=T_1}^{T_2} AR_{i,t}$$

The CAR reflects the total impact of the event on firm i's stock price over the specified window. This is particularly important in M&A studies, where market reactions may not be fully captured on the announcement day alone, as investors may take additional time to process the implications of payment method, deal structure, or expected synergies (Brown & Warner, 1985).

When analyzing a sample of multiple firms, researchers aggregate abnormal returns across all N firms to examine average market behavior. The average abnormal return (AAR) on day t is:

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t}$$

and the cumulative average abnormal return (CAAR) over the event window is:

$$CAAR(T_1, T_2) = \sum_{t=T_1}^{T_2} AAR_t$$

The CAAR provides a comprehensive view of how the market, on average, reacts to the event across the sample, and it is often the primary metric reported in empirical M&A research (Kothari & Warner, 2007).

In addition to the average-based measures, event studies often employ standardized abnormal returns to account for differences in return volatility across firms. The standardized abnormal return (SAAR) scales each firm's abnormal return by its estimated standard deviation from the estimation window, allowing for more comparable cross-sectional inference:

$$SAAR_{i,t} = \frac{AR_{i,t}}{\hat{\sigma}_i}$$

where $\hat{\sigma}_i$ denotes the standard deviation of abnormal returns for firm i, typically estimated over the estimation window.

Analogously, the standardized cumulative average abnormal return (SCAAR) aggregates standardized abnormal returns across firms and over the event window:

$$SCAAR(T_1, T_2) = \sum_{t=T_1}^{T_2} \frac{1}{N} \sum_{i=1}^{N} SAAR_{i,t}$$

The SCAAR provides a volatility-adjusted measure of the average market reaction, strengthening statistical inference when comparing market responses across different payment methods. In particular, raw CAR/CAAR measures can be sensitive to differences in share prices across firms, which may distort comparisons in a multi-firm sample. By using standardized metrics such as SAAR/SCAAR, abnormal performance is expressed in standard deviations, improving comparability across firms and ensuring that results are not driven by differences in scale or firm-specific volatility.

Abnormal and cumulative abnormal returns form the basis of the subsequent statistical analysis, where their significance is tested against the null hypothesis of no abnormal performance. The robustness of these measures depends on careful model selection, accurate identification of the event date and window, and appropriate handling of cross-sectional aggregation. Together, they provide a rigorous way to quantify how payment structure influences market reaction and shareholder value creation in M&A transactions.

3.2.2.4 Statistical Significance and Hypothesis Testing

Once abnormal returns (ARs), cumulative abnormal returns (CARs), and cumulative average abnormal returns (CAARs) are calculated, the next step in an event study is to assess whether these values are statistically different from zero. This step is crucial because it determines whether the observed market reactions can be attributed to the event, in this case, the announcement of an M&A transaction and its payment method, rather than random fluctuations in stock prices.

The standard approach is to apply parametric hypothesis tests, most commonly the Student's t-test, which compares the sample mean of abnormal returns to the null hypothesis of zero abnormal performance. This allows researchers to test whether investors react significantly to the event and whether the reaction differs depending on the payment structure.

A) Hypotheses Formulation

The hypotheses for a typical event study can be stated as:

Null hypothesis (H_0): The event has no effect on stock prices.

$$H_0: AR_{i,t} = 0 \text{ or } SCAR_i = 0$$

Alternative hypothesis (H_1): The event has a significant effect on stock prices.

$$H_1: AR_{i,t} \neq 0 \text{ or } SCAR_i \neq 0$$

A rejection of H_0 implies that the payment method announcement caused a statistically significant reaction in the market.

B) Testing Abnormal Returns

The one-sample t-test is widely used to assess whether the average abnormal return on a specific day differs significantly from zero. The general formula is:

$$t = \frac{\bar{X} - \mu^{H_0}}{\frac{s}{\sqrt{n}}}$$

where $\bar{X}$ is the sample mean of abnormal returns, μ^{H_0} is the hypothesized population mean under the null hypothesis (typically zero), s is the sample standard deviation, and n is the number of observations. This formulation follows standard statistical theory (Campbell et al., 1996) and is equivalent to the event-study-specific version often presented as:

$$t(AAR_t) = \frac{AAR_t}{S(AAR_t)}$$

where $S(AAR_t)$ is the standard error of the average abnormal return. A statistically significant t-statistic (typically at the 1%, 5%, or 10% levels) indicates that the abnormal return is unlikely to be zero by chance.

C) Testing Cumulative Abnormal Returns

To evaluate the overall effect of the event over a window of multiple days, the same logic is applied to cumulative measures. The test statistic for cumulative abnormal returns is calculated as:

$$t(CAR) = \frac{CAR}{S(CAR)}$$

where $S(CAR)$ is the standard error of the cumulative abnormal return, typically derived from the variance of the abnormal returns over the event window. When analyzing a sample of firms, the cumulative average abnormal return (CAAR) can be tested similarly.

D) Interpretation in the Context of Payment Methods

In this dissertation, hypothesis testing will be used to determine whether investors react significantly to M&A announcements and whether this reaction differs between cash- and stock-financed deals. A statistically significant positive or neutral AR or CAR following a cash announcement would support the view that cash offers are interpreted as a positive signal (Travlos, 1987; Moeller et al., 2004). Conversely, weak or negative reactions to stock offers would be consistent with theories of information asymmetry and overvaluation. These results provide the foundation for analysing how payment structure influences shareholder value in the U.S. energy sector.

3.2.3 Panel Event Studies

While traditional event studies are powerful tools for measuring short-term market reactions to corporate events, they are limited in their ability to capture dynamic effects over time or account for cross-sectional heterogeneity across firms and transactions. To address these limitations, researchers increasingly employ panel event study methodologies, which combine the event study framework with panel data econometrics to provide a richer and more nuanced understanding of market behavior (Clarke & Schythe, 2021).

A panel event study extends the standard approach by organizing data across both time and entities, enabling the estimation of abnormal returns or cumulative abnormal returns while controlling for firm-specific and time-specific factors. This is particularly valuable in M&A research, where transactions differ widely in size, structure, timing, and context. A panel structure allows the analysis to incorporate these variations, improving the precision and interpretability of the results.

Importantly, a panel event study can be implemented within a Difference-in-Differences (DiD) framework. In this setting, firms experiencing the event (the treated group) are compared against firms that do not (the control group). The DiD approach estimates the causal effect of the event by calculating the difference in abnormal returns before and after the event for the treated firms, and subtracting the corresponding difference for the control firms. This helps isolate the impact attributable to the event from broader market movements or temporal shocks (Angrist & Pischke, 2009). This study adopts precisely this DiD event study framework to identify the causal effect of payment method in M&A transactions on the acquiring firm's market reaction.

Formally, a panel event study can be expressed as:

$$R_{i,t} = \alpha + \sum_{j=2}^{J} \beta_j \,(Lag\ j)_{i,t} + \sum_{k=1}^{K} \gamma_k \,(\text{Lead k})_{i,t} + \mathrm{X}_{i,t}{}'\Gamma + \mu_i + \lambda_t + \epsilon_{i,t}$$

where $R_{i,t}$ represents the abnormal return for firm i on day t. The variables $(\text{Lag j})_{i,t}$ and $(\text{Lead k})_{i,t}$ are event-time dummy variables that take the value 1 when firm i is respectively j periods before the event or k periods after the event. Formally, following Clarke & Schythe (2021), these indicators are defined as:

$$\begin{aligned}
&(Lag\ J)_{i,t} = \mathbb{1}[t \leq Event_i - J],\\
&(Lag\ j)_{,i,t} = \mathbb{1}[t = Event_i - j] \text{ for } j \in \{1, \dots, J-1\},\\
&(Lead\ k)_{i,t} = \mathbb{1}[t = Event_i + k] \text{ for } k \in \{1, \dots, K-1\},\\
&(Lead\ K)_{i,t} = \mathbb{1}[t \geq Event_i + K].
\end{aligned}$$

Thus, the coefficients β_j and γ_k trace the dynamic evolution of abnormal returns around the event date, allowing the identification of any anticipatory effects in the pre-event period and the pattern of post-event adjustment. Under the difference-in-differences framework, the absence of statistically significant pre-event coefficients provides support for the parallel trends assumption. Importantly, the extreme event-time periods are collapsed into the marginal categories $Lag\ J$ and $Lead\ K$, which accumulate all observations occurring earlier than $-J$ and later than $+K$, respectively. $X_{i,t}$ is a vector of control variables, μ_i are firm fixed effects, λ_t are time fixed effects, and $\varepsilon_{i,t}$ is the error term.

One of the main advantages of this approach is its ability to model leads and lags explicitly. Traditional event studies typically aggregate returns over a short, predefined window, implicitly assuming that all market reactions occur within that period. However, in reality, investors may adjust their expectations before the official announcement due to information leakage or may continue to reassess the implications of the deal after it is announced (Salinger, 1992). By estimating coefficients for multiple event-time periods, panel models can detect such patterns and provide a more complete picture of how payment method information is incorporated into prices.

Panel event studies also help address issues of statistical power and inference. Because they pool data across both time and firms, they increase the number of observations and reduce the standard errors of estimated effects, improving the reliability of statistical tests (Clarke & Schythe, 2021). In addition, the inclusion of firm and time fixed effects helps control for unobserved heterogeneity and macroeconomic shocks, reducing omitted variable bias and enhancing causal interpretation.

This methodology is particularly useful in the context of this dissertation, which examines the relationship between payment method (cash vs. stock) and market reaction in the U.S. energy sector over a 20-year period. By combining a traditional event study approach to measure immediate abnormal returns with a panel framework to trace their evolution over time, the analysis can capture both short-term and dynamic market responses. This dual approach allows for a deeper investigation into how payment structure signals are processed by investors, whether their impact persists beyond the announcement day, and whether they vary across different market conditions or firm characteristics.

3.2.4 Limitations and Methodological Challenges

While event studies are among the most widely used tools in empirical finance, they are not without limitations. Understanding these methodological challenges is essential for interpreting results correctly and for designing a study that minimizes potential biases.

A fundamental limitation is the joint-hypothesis problem, which states that any test of market reaction simultaneously tests both market efficiency and the model used to estimate expected returns (Fama, 1991). If the chosen asset pricing model is miss specified, observed abnormal returns may reflect model error rather than a true market reaction. For example, using a simple market model in a period of structural change in the energy sector could lead to biased abnormal return estimates. This challenge cannot be fully resolved, but it can be mitigated by using well-established models such as the CAPM or Fama–French multifactor models and by conducting robustness checks with alternative specifications (Brown & Warner, 1985). In this thesis, this robustness strategy is implemented by combining the traditional MacKinlay (1997) event study with a panel Difference-in-Differences (DiD) specification.

Another key concern is event-induced variance, which occurs when the variance of stock returns increases around the event date due to heightened uncertainty (Salinger, 1992; Boehmer et al., 1991). Standard parametric tests assume constant variance, so a variance shift can lead to incorrect inferences about statistical significance. Techniques such as adjusting standard errors or applying non-parametric tests can help address this issue, though they introduce their own trade-offs in terms of power and interpretability.

Information leakage and confounding events also pose significant challenges. If information about the transaction or its payment method leaks before the official announcement, price adjustments may begin earlier, leading to underestimated abnormal returns on the announcement day (Keown & Pinkerton, 1981). Conversely, unrelated firm-specific or macroeconomic news released during the event window can contaminate results and attribute unrelated price movements to the event.

In the context of a panel event study within a difference-in-differences framework, this issue is closely related to the parallel trends assumption, which requires treated and control firms to exhibit similar return dynamics before the event. Evidence of significant pre-event effects may therefore indicate anticipation or violations of parallel trends, weakening the causal interpretation of post-announcement coefficients. Careful selection of the event window, examination of pre-event returns, and robustness checks using alternative windows can reduce these risks.

Finally, event studies are best suited for capturing short-term market reactions. They provide less insight into long-term performance or post-merger integration effects, which may also depend on the payment method. While extensions such as long-horizon event studies exist, they face additional challenges, including return autocorrelation and model misspecification (Barber & Lyon, 1997).

Despite these limitations, event studies remain a powerful and widely accepted empirical tool when applied carefully. By combining a traditional event study with a panel event study design, this dissertation addresses several of the issues discussed above, particularly those related to dynamic effects and unobserved heterogeneity. Nonetheless, interpreting abnormal returns must always account for the underlying assumptions and methodological constraints that shape the analysis.

4. METHODOLOGY

4.1 Data Sources and Data Collection

The empirical analysis in this dissertation relies on transaction-level data from FactSet and financial market data obtained via Bloomberg. This section describes the data sources used and the filtering process applied to construct the final sample of mergers and acquisitions.

4.1.1 Transaction Data

M&A transaction data were collected using the FactSet M&A Screening tool, which provides comprehensive and standardized information on corporate transactions worldwide. The initial universe consisted of all mergers and acquisitions announced between 1 January 2004 and 31 December 2024. This period was chosen to capture multiple industry cycles in the U.S. energy sector, including commodity price shocks, consolidation waves, and the energy transition.

A series of filters was applied to ensure consistency, relevance, and data quality, as summarized in Figure 4. First, transactions were restricted to completed acquisitions or mergers involving a majority stake, thereby excluding minority investments and non-control transactions. Cancelled and rumored deals were excluded to ensure that only finalized announcements with clear market implications were retained. In addition, a minimum transaction value of $500 million was imposed to focus on economically meaningful deals that are more likely to generate observable market reactions.

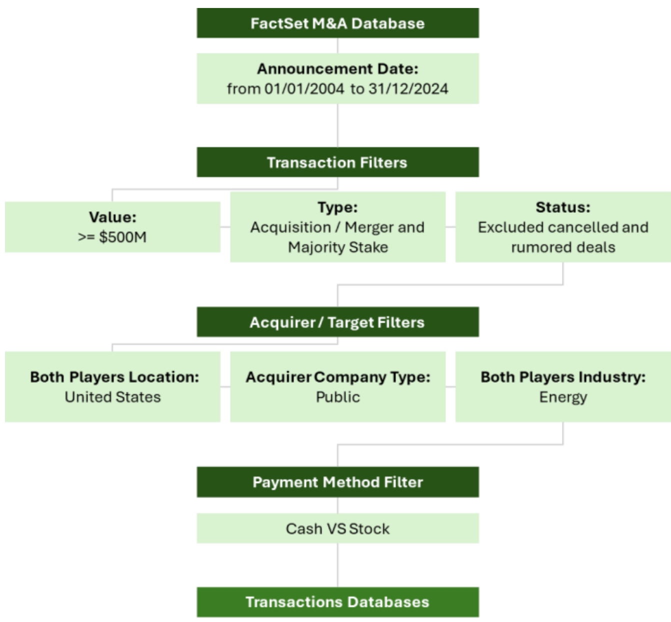

Figure 4 *- Transaction Data Filtering (Source: Author)*

Further filters were applied at the firm level. Both the acquirer and the target were required to be located in the United States, and both firms had to operate within the energy sector, as defined by FactSet's industry classification. To ensure the availability of stock price data, the acquirer firm was required to be publicly listed at the time of the transaction.

Finally, transactions were classified based on their payment method. Only deals that were 100% paid in cash or 100% paid in stock were retained. Mixed-payment transactions were excluded to maintain a clear and unambiguous comparison between payment structures. After applying all filters, the final transaction sample consisted of 135 cash-financed acquisitions and 96 stock-financed acquisitions.

4.1.2 Price Data

Daily stock price data for all acquiring firms were obtained using the Bloomberg Excel Add-In. For each acquirer, daily adjusted closing prices were collected over the period 2004–2024, covering both the estimation and event windows required for the event study analysis. Prices were adjusted for corporate actions such as stock splits and dividends to ensure consistency in return calculations.

To control for overall market movements, daily price data for a sector-specific benchmark were also collected. In the absence of a natural untreated control group, the S&P Energy Select Sector Index (IXE) is used as a market proxy to capture common shocks affecting U.S. energy stocks. This allows expected returns to be estimated net of broad sector-wide fluctuations, so abnormal returns reflect the firm-specific component associated with the M&A announcement.

4.2 Sample Construction and Data Preparation

Once the raw transaction and price data were collected, the datasets were organized and prepared to ensure consistency, transparency, and replicability of the empirical analysis.

The initial step consisted of separating the data by payment method. Two parallel data structures were created: one for cash-financed transactions and one for stock-financed transactions.

For each payment method, the raw data were divided into three distinct files:

1. A transactions file, containing information on M&A announcements.
2. A price file, containing daily stock price data for acquiring firms.
3. A linking file, created manually, which mapped the acquiring firm names from the transaction data to their corresponding stock market tickers in the price data.

The linking file plays a crucial role in the empirical workflow, as it provides the key identifier used later to merge transaction-level and price-level data into a single event-time dataset in Python.

4.2.1 Transaction Data Preparation

In the transactions files, all variables not required for the event study were removed. Only two columns were retained:

- The announcement date, renamed *EventDate*, which serves as the reference point for event-time calculations.
- The acquirer company name, renamed *Name*, used to identify firms and link transactions to stock price data.

During the sample construction process, a small number of transactions were identified as problematic for the purposes of the event study. Specifically, some deals involved multiple acquiring firms, where the leading acquirer was not a publicly listed company, even though at least one co-acquirer was public. In these cases, the stock price reaction of the publicly listed firm could not be reliably interpreted as the market response to the transaction announcement, as the public firm was not the primary decision-maker.

To preserve the validity and interpretability of the event study, these transactions were excluded from the sample. In total, 8 cash-financed transactions and 1 stock-financed transaction were removed based on this criterion. After this additional cleaning step, the final sample consisted of 127 cash transactions and 95 stock transactions, all involving a publicly listed lead acquirer with clearly identifiable stock price data.

4.2.2 Price Data Preparation

In the price files, the raw Bloomberg output was cleaned and reduced to the essential variables required for return computation. All columns were removed except:

- *Date*, representing the trading day.
- *Ticker*, identifying the firm.
- *Price*, corresponding to the daily adjusted closing price.

To facilitate merging and time-series manipulation, the price data were transformed from wide format to long format using the Power Query tool in Excel.

4.3 Event Study Design and Implementation

4.3.1 Event Definition and Event Window

The event of interest is defined as the public announcement date of the merger or acquisition, as reported by FactSet. This date represents the moment at which information about the transaction and its payment method becomes publicly available to investors.

For both the traditional and panel event study, the event window is set to [-10, +10] trading days relative to the announcement date. This window length is chosen to capture potential information leakage prior to the announcement as well as delayed market reactions following the disclosure (Keown & Pinkerton, 1981; Brown & Warner, 1985). A symmetric window of this length is commonly used in M&A studies, as it balances the need to capture the full market response while limiting contamination from unrelated events (MacKinlay, 1997).

4.3.2 Estimation Window

To estimate normal returns, an estimation window is defined as the period from 365 trading days before the event to 30 trading days before the event, that is [-365, -30] relative to the announcement date. This window is sufficiently long to obtain reliable parameter estimates while excluding observations close to the event that could be affected by information leakage or anticipation effects (MacKinlay, 1997; Kothari & Warner, 2007).

The separation between the estimation window and the event window helps ensure that the expected return model is not contaminated by event-related price movements, in line with standard event study methodology (Campbell et al., 1996; MacKinlay, 1997).

4.3.3 Expected Return Model

The expected return for each acquiring firm is estimated using the Capital Asset Pricing Model (CAPM). The CAPM was selected as it provides a well-established and theoretically grounded framework while maintaining a reasonable level of complexity (Sharpe, 1964; Lintner, 1965). Compared to simpler models, such as the constant mean return model, CAPM explicitly accounts for systematic market risk (Brown & Warner, 1985; MacKinlay, 1997). At the same time, it avoids the additional data requirements and estimation noise associated with multifactor models, which may offer limited incremental benefits in short-horizon event studies. Market returns are proxied using the S&P Energy Select Sector Index (IXE), which provides a sector-relevant benchmark for U.S. energy firms and is also used as the control group in the difference-in-differences specification of the panel event study.

4.3.4 Risk-Free Rate Specification

The risk-free rate is based on the 10-year U.S. Treasury yield (Fama & French, 1993), obtained from YCharts[1]. To ensure consistency with the daily frequency of stock returns, the annual risk-free rate is converted into a daily rate. Specifically, the average annual yield over the period 2004–2024, equal to 2.97%, is divided by 252 trading days, which is the standard assumption for the number of trading days in a year. This yields the daily risk-free rate used in the CAPM estimation.

4.3.5 Implementation Overview

Using the parameters described above, abnormal returns are computed for each firm over the event window, and subsequently aggregated to obtain AR, CAR, AAR, CAAR, as well as their standardized counterparts SAAR and SCAAR. Standardization and statistical inference are based on the sample standard deviation of abnormal returns, rather than the population standard deviation, reflecting the fact that the estimation window provides a finite sample of observations. In the panel event study, abnormal returns are further analyzed in an event-time framework to estimate dynamic effects before and after the announcement. All calculations and estimations are implemented programmatically in Python, ensuring reproducibility and consistency across both the traditional and panel event study analyses.

[1] YCharts 10 Year Treasury Rate page can be accessed at: https://ycharts.com/indicators/10_year_treasury_rate_annual

5. RESULTS

5.1 Traditional Event Study Results

This section reports the results of the traditional event study for cash and stock financed acquisitions, based on a sample of 127 cash-financed and 95 stock-financed transactions. Market reactions are evaluated using cumulative average abnormal returns (CAAR) and standardized cumulative average abnormal returns (SCAAR) across multiple event windows around the announcement date.

5.1.1 Cash-Financed Transactions

Across all examined windows, no statistically significant abnormal performance is observed for acquiring firms involved in cash-financed transactions. CAAR values are consistently negative but small in magnitude, and none of the corresponding t-statistics or p-values indicate statistical significance at conventional levels. This pattern holds for both raw and standardized measures, suggesting that the results are not driven by firm-specific volatility, as summarized in Figure 5.

Window	CAAR	Std_CAR	SE_CAAR	SCAAR	p_value
[-1,1]	-0.008054	0.067697	0.009479	-0.849631	0.39958
[-3,3]	-0.002491	0.076295	0.010683	-0.23315	0.816597
[-5,5]	-0.003362	0.087237	0.012216	-0.27525	0.784258
[-10,10]	-0.019114	0.125905	0.01763	-1.084174	0.283488
[0,5]	-0.005466	0.07529	0.010543	-0.518489	0.606405
[-5,0]	-0.001351	0.061435	0.008603	-0.156989	0.875886
[-2,0]	-0.000652	0.052475	0.007348	-0.088739	0.929644
[0,0]	-0.003595	0.049428	0.007061	-0.509187	0.612954
[1,1]	-0.004845	0.03851	0.005392	-0.898547	0.373201

Figure 5 - *CAAR and SCAAR Results - Cash Financed Transactions (Source: Author)*

For the widest window, [-10, +10], the CAAR is approximately -1.9 percent, with a p-value well above standard significance thresholds. Similarly, the SCAAR for this window remains statistically insignificant. These results indicate that, on average, cash-financed acquisitions do not generate a measurable short-term valuation effect for acquiring firms.

To assess the presence of information leakage or insider trading, the window [-5, 0] is examined. The CAAR in this window is negative but statistically insignificant, and the standardized results lead to the same conclusion. This suggests that there is no evidence of systematic price adjustment prior to the announcement, implying that the market does not anticipate cash-financed deals in a way that generates abnormal returns for acquirers. The absence of significant pre-event abnormal returns is also visible in the daily AAR and SAAR plots, where no clear trend or accumulation of returns emerges before the announcement date.

The [0, 0] and [1, 1] windows are used to evaluate whether the market reacts immediately to the announcement and whether any delayed adjustment occurs. In both cases, the CAAR and SCAAR are close to zero and statistically insignificant. It is important to note that these single-day windows rely on a single abnormal return observation per event, so they are intended to capture the immediate announcement effect rather than a broader cumulative market adjustment. The similarity of results between these two windows indicates that the market incorporates the information quickly and without delay, with no evidence of post-announcement drift. This pattern is consistent with a rapid and efficient processing of information related to cash-financed acquisitions.

The window [0, 5] is used to test whether a delayed reaction exists following the announcement. The results again show no statistically significant abnormal performance. The CAAR remains negative but economically small, and the standardized measure confirms the absence of a meaningful effect. This indicates that there is no event effect in the days following the announcement.

Taken together, the results provide no evidence of a statistically or economically significant market reaction to cash-financed acquisitions for acquiring firms. The lack of abnormal returns before, on, or after the announcement suggests that cash payment is perceived as neutral by investors. The market neither rewards nor penalizes acquirers for choosing cash as the method of payment. These findings are consistent with the view that cash offers do not convey new or surprising information about firm valuation or deal quality from the perspective of investors. They also align with the notion that cash financing is a well-understood and transparent payment method, whose implications are already reflected in market expectations.

5.1.2 Stock-Financed Transactions

In contrast to cash-financed transactions, stock-financed acquisitions exhibit a clear and statistically significant negative market reaction. Across most event windows, CAAR values are economically large and statistically significant, indicating that acquiring firms experience a decline in shareholder value following stock-financed M&A announcements. For the widest window, [-10, +10], the CAAR is approximately -4.1 percent, with a p-value below 5 percent. The standardized measure confirms this result, with a strongly negative SCAAR that is statistically significant. This indicates that the negative reaction is not driven by firm-specific volatility and reflects a systematic market response, as reported in Figure 6.

Window	CAAR	Std_CAR	SE_CAAR	SCAAR	p_value
[-1,1]	-0.033087	0.089155	0.012246	-2.701813	0.00929
[-3,3]	-0.043164	0.109428	0.015031	-2.871668	0.005895
[-5,5]	-0.042371	0.116408	0.01599	-2.649857	0.010642
[-10,10]	-0.040821	0.126908	0.017432	-2.341719	0.023061
[0,5]	-0.039911	0.112809	0.015496	-2.575645	0.012887
[-5,0]	-0.023119	0.072716	0.009988	-2.314573	0.024619
[-2,0]	-0.023195	0.072648	0.009979	-2.324403	0.024044
[0,0]	-0.021469	0.069265	0.009699	-2.213491	0.031455
[1,1]	-0.011806	0.054908	0.007542	-1.565372	0.123562

Figure 6 *- CAAR and SCAAR Results - Stock Financed Transactions (Source: Author)*

The pre-announcement window [-5, 0] reveals a statistically significant negative CAAR, suggesting that part of the market reaction occurs before the official announcement date. This pattern is also evident in the daily AAR and SAAR plots, where cumulative returns begin to decline prior to day 0. This evidence is consistent with the presence of information leakage or anticipation effects in stock-financed transactions. Investors may partially anticipate the use of equity financing or infer deal-related information in advance, leading to a gradual price adjustment before the announcement becomes public.

The [0, 0] window shows a negative and statistically significant abnormal return, indicating that the announcement itself triggers an immediate adverse reaction from the market. The [1, 1] window also remains negative, although the magnitude and statistical significance are weaker, suggesting that most of the reaction is concentrated on the announcement day. The sharp drop in both AAR and SAAR at t = 0, clearly visible in the figures, supports the view that the market reacts swiftly to the disclosure of a stock-financed acquisition.

The post-announcement window [0, 5] continues to display a negative and statistically significant CAAR, indicating that the adverse market reaction persists beyond the announcement day. Rather than reversing, cumulative abnormal returns continue to deteriorate over the days following the event. This persistence is further confirmed by the standardized results, where SCAAR becomes increasingly negative in the post-event period. The absence of a rebound suggests that the market does not view the initial reaction as an overreaction but rather as a reassessment of firm value following the announcement.

Overall, the results provide strong evidence of a negative market reaction to stock-financed acquisitions by acquiring firms. The statistical significance observed across multiple windows, including pre-announcement, announcement-day, and post-announcement periods, indicates that equity-financed deals are perceived unfavorably by investors.

5.1.3 Comparison by Payment Method

The comparison reveals a clear divergence in market response. Cash-financed transactions exhibit no statistically significant abnormal returns across any of the examined event windows. CAAR and SCAAR values for cash deals remain small in magnitude and statistically insignificant before, on, and after the announcement date, indicating the absence of a measurable market reaction for acquiring firms, as illustrated in Figure 7 and Figure 8.

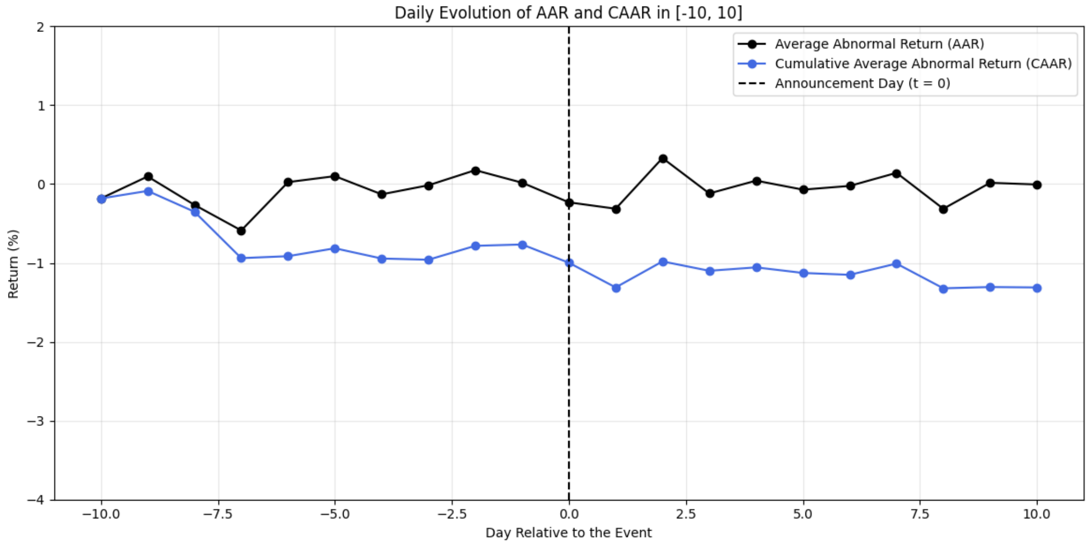

Figure 7 *- Daily Evolution of AAR and CAAR in [-10, 10] - Cash Financed Transactions (Source: Author)*

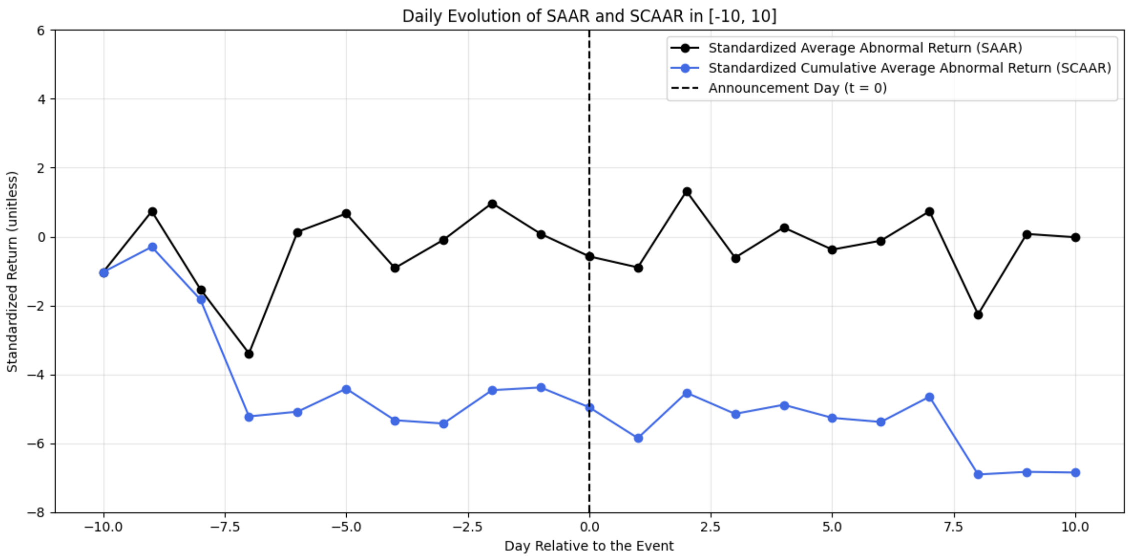

Figure 8 *- Daily Evolution of SAAR and SCAAR in [-10, 10] - Cash Financed Transactions (Source: Author)*

In contrast, stock-financed transactions display consistently negative and statistically significant abnormal returns across multiple windows. The difference is particularly pronounced around the announcement date and in the post-announcement period. While cash deals show stable cumulative returns close to zero, stock-financed deals experience a sharp decline in CAAR and SCAAR that persists beyond the event date, as shown in Figure 9 and Figure 10.

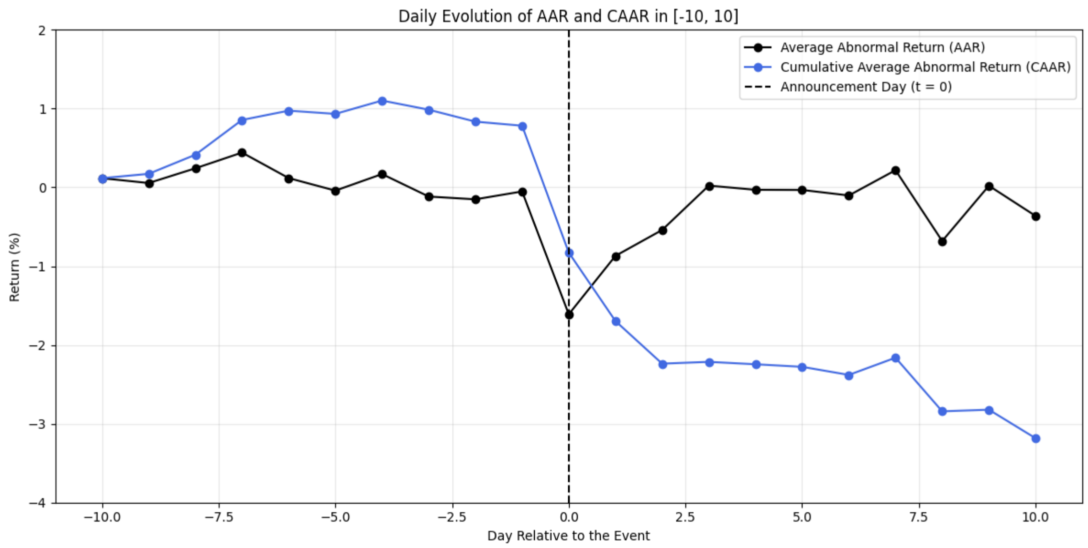

Figure 9 *- Daily Evolution of AAR and CAAR in [-10, 10] - Stock Financed Transactions (Source: Author)*

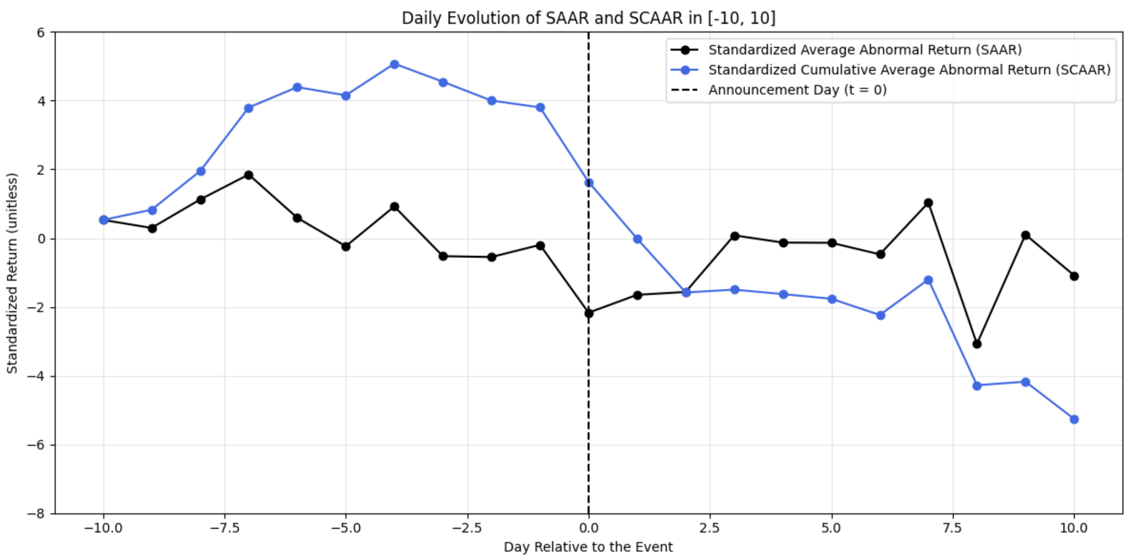

Figure 10 *- Daily Evolution of SAAR and SCAAR in [-10, 10] - Stock Financed Transactions (Source: Author)*

The contrast is also evident in the temporal patterns. Cash-financed acquisitions show no signs of pre-announcement price adjustment or post-announcement drift, whereas stock-financed acquisitions exhibit both pre-announcement deterioration and post-announcement persistence in cumulative abnormal returns.

Overall, the traditional event study results indicate that payment method is a key dimension along which market reactions differ. While cash-financed acquisitions are met with a neutral response, stock-financed acquisitions are associated with economically and statistically significant negative abnormal returns for acquiring firms.

5.2 Panel Event Study Results

This section presents the results of the panel event study for cash and stock financed acquisitions, which allows for the analysis of the dynamic evolution of abnormal returns around the announcement date while accounting for firm-level heterogeneity and time effects.

5.2.1 Cash-Financed Transactions

The panel estimates indicate that cash-financed transactions do not generate statistically significant abnormal returns at any point around the announcement date. The estimated lead and lag (event-time) coefficients fluctuate closely around zero throughout the event window from t = −10 to t = +10, and their corresponding confidence intervals consistently include zero, as illustrated in Figure 11.

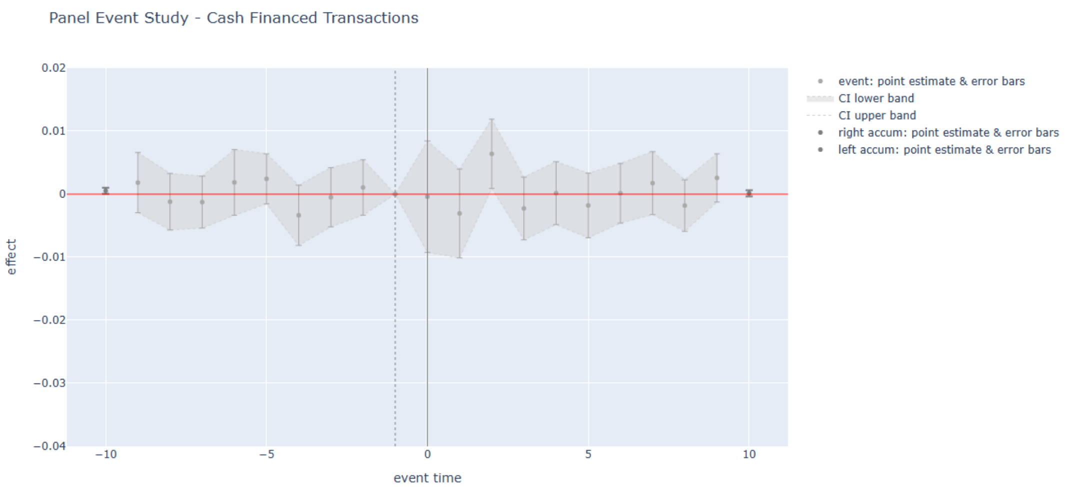

Figure 11 *- Panel Event Study Confidence Intervals - Cash Financed Transactions (Source: Author)*

In particular, the coefficient at the announcement date (t = 0) is small in magnitude and statistically insignificant, suggesting that the market does not exhibit an immediate reaction to the announcement of a cash-financed acquisition. Similarly, no significant effects are observed in the lead coefficients (pre-event periods), providing no evidence of anticipation or information leakage.

The lag coefficients (post-announcement periods) remain close to zero and do not display a systematic trend. While minor short-term fluctuations are visible in the point estimates, these movements are economically small and statistically insignificant. This indicates that there is no delayed adjustment or cumulative effect following the announcement of cash-financed transactions.

The cumulative effect (cumulative abnormal return, CAAR) derived from the panel estimates further supports this conclusion. Cumulative effects remain near zero throughout the event window, with no sustained increase or decrease after the announcement date. The absence of a persistent post-event pattern suggests that the market response to cash-financed acquisitions is neutral and stable over time.

Overall, the panel event study results are fully consistent with the findings from the traditional event study. Both approaches indicate that cash-financed acquisitions are not associated with significant abnormal returns for acquiring firms, either immediately or over time. The lack of statistically significant dynamic effects reinforces the conclusion that cash payment does not convey new or value-relevant information to the market in this sample.

5.3.2 Stock-Financed Transactions

In contrast to cash-financed transactions, the panel estimates for stock-financed acquisitions reveal a pronounced and statistically significant negative reaction at the announcement date. The coefficient at t = 0 is strongly negative, and the corresponding confidence interval does not include zero, indicating a statistically significant immediate market response to the announcement of a stock-financed deal, as shown in Figure 12.

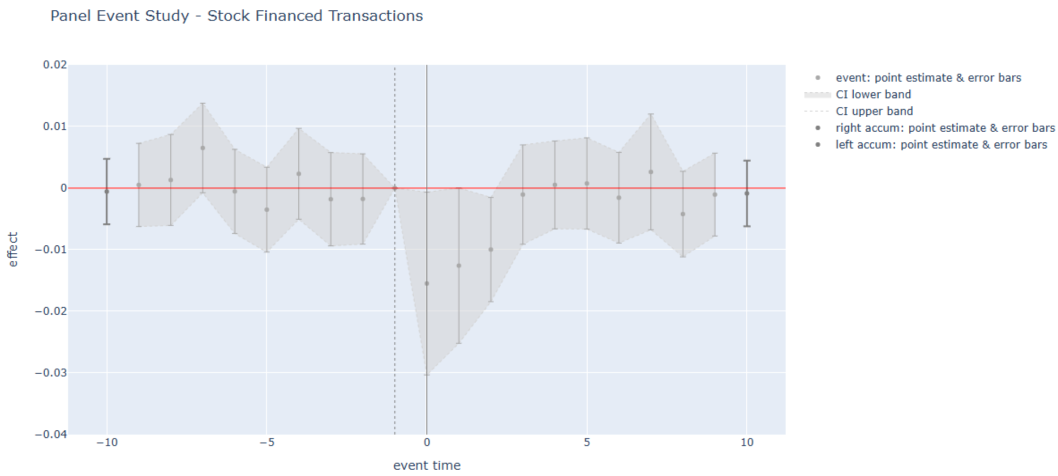

Figure 12 *- Panel Event Study Confidence Intervals - Stock Financed Transactions (Source: Author)*

This sharp decline is visually evident in the event-time plot, where the point estimate at the announcement date represents the largest negative effect observed within the event window. The magnitude of this effect is economically meaningful and substantially larger than any pre-event fluctuations.

Prior to the announcement, estimated coefficients fluctuate around zero and are generally statistically insignificant. While minor movements are visible in the days leading up to the event, the confidence intervals largely overlap with zero, suggesting limited evidence of systematic anticipation or information leakage in the panel framework.

This contrasts with the traditional event study results, where some pre-announcement accumulation was observed, indicating that once firm-level heterogeneity and time effects are accounted for, pre-event dynamics become less pronounced.

Following the announcement, abnormal returns remain persistently negative over several days. Although the magnitude of the daily effects gradually diminishes, cumulative abnormal average returns (CAAR) continue to decline, indicating that the market does not reverse its initial reaction.

The cumulative average abnormal return (CAAR) series derived from the panel estimates shows a sharp downward shift immediately after the announcement, followed by a stabilization at a significantly negative level. This pattern suggests that the market reassessment triggered by a stock-financed acquisition is both immediate and durable.

Overall, the panel event study provides strong evidence that stock-financed acquisitions are associated with significant value losses for acquiring firms. The immediate negative reaction at the announcement date, combined with persistent post-announcement effects, confirms that the adverse market response observed in the traditional event study is robust to a dynamic panel specification. These findings reinforce the conclusion that the choice of stock as a payment method is systematically linked to negative market reactions, a result that stands in clear contrast to the neutral response observed for cash-financed transactions.

5.4.3 Comparison by Payment Method

The comparison reveals a clear divergence in dynamic effects. Cash-financed transactions show no statistically significant abnormal returns at any point within the event window. Event-time coefficients remain close to zero both before and after the announcement, and cumulative abnormal average returns (CAAR) derived from the panel estimates do not display a sustained trend, as illustrated in Figure 13. This indicates that the market response to cash-financed acquisitions is neutral and stable over time.

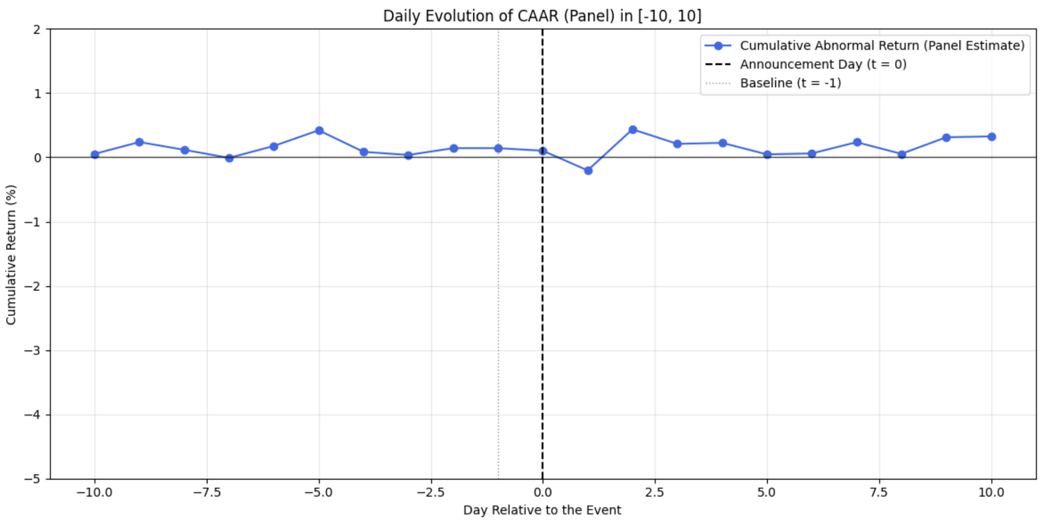

Figure 13 *- Daily Evolution of CAAR in [-10, 10] - Cash Financed Transactions (Source: Author)*

In contrast, stock-financed transactions exhibit a strong and statistically significant negative reaction at the announcement date, followed by persistent negative cumulative abnormal average returns (CAAR) in the post-announcement period. As shown in Figure 14, the immediate drop at $t = 0$ and the subsequent stabilization at a lower cumulative level suggest that the market rapidly incorporates the information conveyed by stock payment and does not subsequently revise this assessment.

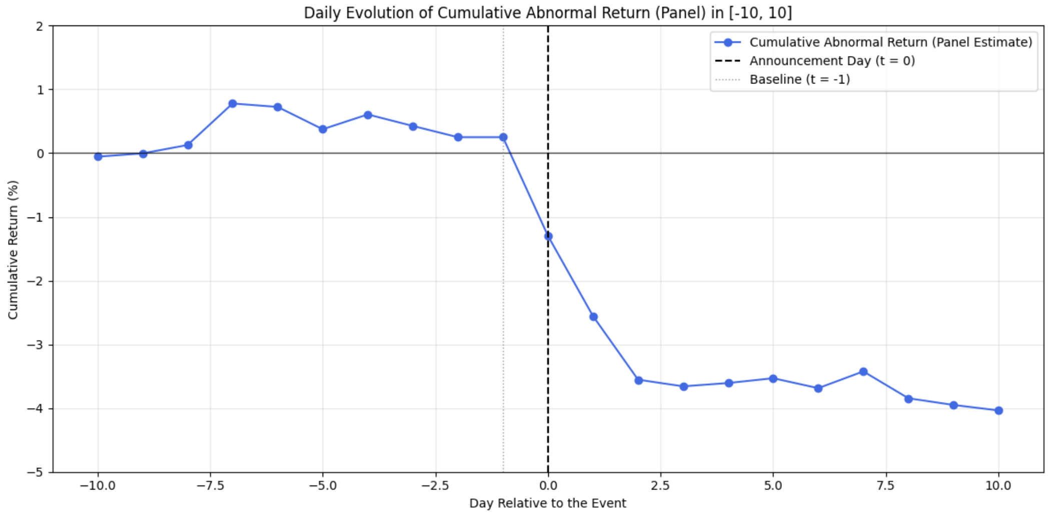

Figure 14 *- Daily Evolution of CAAR in [-10, 10] - Stock Financed Transactions (Source: Author)*

Taken together, the panel results confirm that payment method is a key determinant of market reaction. While cash-financed acquisitions are associated with negligible dynamic effects, stock-financed acquisitions trigger a sharp and lasting negative response. These findings are consistent with the traditional event study results and demonstrate that the observed differences across payment methods persist when firm-level heterogeneity and dynamic adjustment are explicitly accounted for.

6. CONCLUSIONS

6.1 Main Findings and Contributions

This dissertation examines how the method of payment in mergers and acquisitions influences market reactions, focusing on cash- and stock-financed transactions in the U.S. energy sector over the period 2004–2024. By combining a traditional event study with a panel event study framework, the analysis captures both short-term abnormal returns around the announcement date and the dynamic evolution of market responses over time.

The empirical results provide clear and consistent evidence that payment method is a key determinant of market reaction. Cash-financed acquisitions are associated with neutral market responses for acquiring firms. Across all event windows and in both methodological approaches, abnormal returns remain small and statistically insignificant before, on, and after the announcement date. These findings suggest that cash payments are perceived as a transparent and well-understood financing choice, conveying limited new information to investors.

In contrast, stock-financed acquisitions generate economically and statistically significant negative abnormal returns for acquiring firms. The traditional event study reveals negative cumulative average abnormal returns across multiple windows, including pre-announcement, announcement-day, and post-announcement periods. These results are reinforced by the panel event study, which identifies a sharp negative reaction at the announcement date followed by persistent negative cumulative average abnormal returns. The consistency of results across both methodologies indicates that the adverse market response to stock-financed deals is robust and not driven by model specification or short-term noise.

Taken together, the findings support theoretical predictions derived from signaling theory, information asymmetry, and market timing arguments, according to which stock payments may be interpreted as signals of overvaluation or increased uncertainty (Myers & Majluf, 1984; Travlos, 1987). While this dissertation does not seek to test these mechanisms directly, the empirical evidence strongly suggests that investors systematically differentiate between payment structures when evaluating M&A announcements.

From a practical perspective, the results highlight the importance of payment structure as a strategic decision in M&A transactions. For managers in the U.S. energy sector, the choice between cash and stock financing has clear implications for shareholder value at the time of announcement. For investors, payment method provides a valuable signal for interpreting the expected impact of acquisition announcements.

6.1 Limitations and Future Research

Despite its contributions, this study has several limitations that point to avenues for future research. First, the analysis focuses exclusively on short-term market reactions. Future studies could extend the framework to examine long-term post-merger performance, although such analyses face additional methodological challenges (Barber & Lyon, 1997).

Second, while the panel event study controls for firm and time fixed effects, it does not incorporate additional deal-level control variables such as acquisition premiums, relative deal size, or measures of strategic fit, which may further shape investor responses and help explain cross-sectional variation in abnormal returns. Including these characteristics as controls in the panel framework could strengthen the analysis by isolating the effect of the payment method from other transaction-specific determinants of market reactions.

Additionally, future research could explore mixed-payment transactions, which were excluded in this dissertation to maintain a clean comparison, or investigate whether the observed effects vary across subsectors within energy, such as oil and gas versus renewables. Finally, extending the analysis to other industries or international settings would help assess the generalizability of the findings.

7. BIBLIOGRAPHY

Alexandridis, G., Petmezas, D., & Travlos, N. G. (2010). Gains from Mergers and Acquisitions Around the World: New Evidence. *Financial Management*, *39*(4), 1671–1695. https://doi.org/10.1111/j.1755-053X.2010.01126.x

Amihud, Y., Lev, B., & Travlos, N. G. (1990). Corporate Control and the Choice of Investment Financing: The Case of Corporate Acquisitions. *The Journal of Finance (New York)*, *45*(2), 603–616. https://doi.org/10.1111/j.1540-6261.1990.tb03706.x

Andrade, G., Mitchell, M., & Stafford, E. (2001). New Evidence and Perspectives on Mergers. *The Journal of Economic Perspectives*, *15*(2), 103–120. https://doi.org/10.1257/jep.15.2.103

Andriuškevičius, K., & Štreimikienė, D. (2021). Developments and Trends of Mergers and Acquisitions in the Energy Industry. *Energies (Basel)*, *14*(8), 2158. https://doi.org/10.3390/en14082158

Angrist, J. D., & Pischke, J. S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Baker, M., & Wurgler, J. (2002). Market Timing and Capital Structure. *The Journal of Finance (New York)*, *57*(1), 1–32. https://doi.org/10.1111/1540-6261.00414

Ball, R., & Brown, P. (1968). An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research*, *6*(2), 159–178. https://doi.org/10.2307/2490232

Barber, B. M., & Lyon, J. D. (1997). Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. *Journal of Financial Economics*, *43*(3), 341–372. https://doi.org/10.1016/S0304-405X(96)00890-2

Boehmer, E., Masumeci, J., & Poulsen, A. B. (1991). Event-study methodology under conditions of event-induced variance. *Journal of Financial Economics*, *30*(2), 253–272. https://doi.org/10.1016/0304-405X(91)90032-F

Brown, S. J., & Warner, J. B. (1980). Measuring security price performance. *Journal of Financial Economics*, *8*(3), 205–258. https://doi.org/10.1016/0304-405X(80)90002-1

Brown, S. J., & Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of Financial Economics*, *14*(1), 3–31. https://doi.org/10.1016/0304-405X(85)90042-X

Campbell, J. Y., Lo, A. W., & Mackinlay, A. C. (1996). *The Econometrics of Financial Markets* (2. printing, with corrections). Princeton University Press.

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance (New York)*, *52*(1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Clarke, D., & Tapia-Schythe, K. (2021). Implementing the panel event study. *The Stata Journal*, *21*(4), 853–884. https://doi.org/10.1177/1536867X211063144

Corrado, C. J. (1989). A nonparametric test for abnormal security-price performance in event studies. *Journal of Financial Economics*, *23*(2), 385–395. https://doi.org/10.1016/0304-405X(89)90064-0

Corrado, C. J. (2011). Event studies: A methodology review. *Accounting and Finance (Parkville)*, *51*(1), 207–234. https://doi.org/10.1111/j.1467-629X.2010.00375.x

Faccio, M., & Masulis, R. W. (2005). The Choice of Payment Method in European Mergers and Acquisitions. *The Journal of Finance (New York)*, *60*(3), 1345–1388. https://doi.org/10.1111/j.1540-6261.2005.00764.x

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance (New York)*, *25*(2), 383–417. https://doi.org/10.1111/j.1540-6261.1970.tb00518.x

Fama, E. F. (1991). Efficient Capital Markets: II. *The Journal of Finance (New York)*, *46*(5), 1575–1617. https://doi.org/10.1111/j.1540-6261.1991.tb04636.x

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010

Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The Adjustment of Stock Prices to New Information. *International Economic Review (Philadelphia)*, *10*(1), 1–21. https://doi.org/10.2307/2525569

Fuller, K., Netter, J., & Stegemoller, M. (2002). What Do Returns to Acquiring Firms Tell Us? Evidence from Firms That Make Many Acquisitions. *The Journal of Finance (New York)*, *57*(4), 1763–1793. https://doi.org/10.1111/1540-6261.00477

Hansen, R. G. (1987). A Theory for the Choice of Exchange Medium in Mergers and Acquisitions. *The Journal of Business (Chicago, Ill.)*, *60*(1), 75–95. https://doi.org/10.1086/296386

Harford, J. (1999). Corporate Cash Reserves and Acquisitions. *The Journal of Finance (New York)*, *54*(6), 1969–1997. https://doi.org/10.1111/0022-1082.00179

Jaffe, J. F. (1974). Special information and insider trading. *The Journal of Business (Chicago, Ill.)*, *47*(3), 410–428.

Jensen, M. C. (1986). Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers. *The American Economic Review*, *76*(2), 323–329.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, *3*(4), 305–360. https://doi.org/10.1016/0304-405X(76)90026-X

Keown, A. J., & Pinkerton, J. M. (1981). Merger Announcements and Insider Trading Activity: An Empirical Investigation. *The Journal of Finance (New York)*, *36*(4), 855–869. https://doi.org/10.1111/j.1540-6261.1981.tb04888.x

Klein, C. (2024, December 20). *Wind and solar overtook coal on the US grid in 2024*. Canary Media. https://www.canarymedia.com/articles/clean-energy/wind-and-solar-overtook-coal-on-the-us-grid-in-2024

Kothari, S. P., & Warner, J. B. (2007). Chapter 1 - Econometrics of Event Studies. In *Handbook of Empirical Corporate Finance SET* (pp. 3–36). Elsevier B.V. https://doi.org/10.1016/B978-0-444-53265-7.50015-9

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, *47*(1), 13–37. https://doi.org/10.2307/1924119

MacKinlay, A. C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature*, *35*(1), 13–39.

Moeller, S. B., Schlingemann, F. P., & Stulz, R. M. (2004). Firm size and the gains from acquisitions. *Journal of Financial Economics*, *73*(2), 201–228. https://doi.org/10.1016/j.jfineco.2003.07.002

Mossin, J. (1966). Equilibrium in a Capital Asset Market. *Econometrica*, *34*(4), 768–783. https://doi.org/10.2307/1910098

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, *13*(2), 187–221. https://doi.org/10.1016/0304-405X(84)90023-0

Pástor, Ľ., & Stambaugh, R. F. (2003). Liquidity Risk and Expected Stock Returns. *The Journal of Political Economy*, *111*(3), 642–685. https://doi.org/10.1086/374184

Patell, J. M. (1976). Corporate Forecasts of Earnings Per Share and Stock Price Behavior: Empirical Test. *Journal of Accounting Research*, *14*(2), 246–276. https://doi.org/10.2307/2490543

Roll, R. (1977). A critique of the asset pricing theory's tests. *Journal of Financial Economics*, *4*(2), 129–176.

Ross, S. A. (1977). The Determination of Financial Structure: The Incentive-Signalling Approach. *Bell Journal of Economics*, *8*(1), 23–40. https://doi.org/10.2307/3003485

Samuelson, P. A. (1965). Proof That Properly Anticipated Prices Fluctuate Randomly. *Industrial Management Review*, *6*(2), 41.

Salinger, M. (1992). Standard Errors in Event Studies. *Journal of Financial and Quantitative Analysis*, *27*(1), 39–53. https://doi.org/10.2307/2331297

Spence, M. (1973). Job Market Signaling. *The Quarterly Journal of Economics*, *87*(3), 355–374. https://doi.org/10.2307/1882010

Seyhun, H. N. (1986). Insiders' profits, costs of trading, and market efficiency. *Journal of Financial Economics*, *16*(2), 189–212. https://doi.org/10.1016/0304-405X(86)90060-7

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance (New York)*, *19*(3), 425. https://doi.org/10.2307/2977928

Shiller, R. J. (1981). Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends? *The American Economic Review*, *71*(3), 421–436.

Shiller, R. J. (2003). From Efficient Markets Theory to Behavioral Finance. *The Journal of Economic Perspectives*, *17*(1), 83–104. https://doi.org/10.1257/089533003321164967

Shleifer, A., & Vishny, R. W. (1997). The Limits of Arbitrage. *The Journal of Finance (New York)*, *52*(1), 35–55. https://doi.org/10.1111/j.1540-6261.1997.tb03807.x

Travlos, N. G. (1987). Corporate Takeover Bids, Methods of Payment, and Bidding Firms' Stock Returns. *The Journal of Finance (New York)*, *42*(4), 943–963. https://doi.org/10.1111/j.1540-6261.1987.tb03921.x

7.1 Declaration on the Use of Generative Artificial Intelligence Tools in Bachelor's Final Degree Projects

WARNING: The University considers that ChatGPT and other similar tools are very useful in academic life; however, their use is always under the responsibility of the student, since the answers they provide may not be accurate. In this regard, their use is NOT permitted in the preparation of the Final Degree Project to generate code, as these tools are not reliable for this task. Even if the code works, there is no guarantee that it is methodologically correct, and it is highly likely that it is not.

I hereby declare that I, Carlos Méndez Cerdeira, a student of Dual Degree Program in Business Administration and Management [ADE] and Business Analytics (E-2 +Analytics) at Universidad Pontificia Comillas, upon submitting my Final Degree Project entitled "Analysis On Payment Method Effects In U.S. Energy M&A: A Panel Event Study Approach", have used the Generative Artificial Intelligence tool ChatGPT or other similar generative AI tools only in the context of the activities described below:

1. **Research idea brainstorming:** Used to generate and outline possible research areas.
2. **Critical analysis:** Used to identify counter-arguments to a specific thesis I intend to defend.
3. **References:** Used together with other tools, such as Science, to identify preliminary references, which were later verified and validated.
4. **Methodological support:** Used to identify applicable methods for specific research problems.
5. **Code interpreter:** Used to carry out preliminary data analysis.
6. **Multidisciplinary studies:** Used to understand perspectives from other academic communities on multidisciplinary topics.
7. **Template builder:** Used to design specific formats for sections of the project.
8. **Language and style editor:** Used to improve the linguistic and stylistic quality of the text.
9. **Preliminary flowchart and content generator:** Used to outline initial diagrams.
10. **Synthesizer and explainer of complex books:** Used to summarize and understand complex literature.
11. **Example problem generator:** Used to illustrate concepts and techniques.

12. **Reviewer:** Used to receive suggestions on how to improve and refine the project at different levels of rigor.

13. **Translator:** Used to translate texts from one language to another.

I affirm that all the information and content presented in this project are the result of my own individual research and effort, except where otherwise indicated and where appropriate credit has been given (I have included the relevant references in the Final Degree Project and explicitly stated the purposes for which ChatGPT or similar tools were used). I am aware of the academic and ethical implications of submitting non-original work and accept the consequences of any violation of this declaration.

Date: 24/01/2026

Signature:

8. ANNEXES

8.1 Datasets for Cash-Financed Transactions

8.1.1 Transaction-Level Data

EventDate	Name
12/05/2024	CNX Resources Corp.
11/13/2024	Coterra Energy, Inc.
08/28/2024	ONEOK, Inc.
08/21/2024	Enterprise Products Partners LP
07/29/2024	Permian Resources Corp.
07/28/2024	Northern Oil & Gas, Inc.
06/27/2024	SM Energy Co.
06/12/2024	Matador Resources Co.
05/20/2024	Phillips 66
03/19/2024	Diversified Energy Co. Plc
12/27/2023	The Williams Cos., Inc.
11/13/2023	Mach Natural Resources LP
11/06/2023	Kinder Morgan, Inc.
11/01/2023	The Williams Cos., Inc.
09/05/2023	Western Midstream Partners LP
06/20/2023	Civitas Resources, Inc.
06/15/2023	Earthstone Energy, Inc.
05/12/2023	Forge Energy Ii Delaware LLC /Private Group/; Northern Oil & Gas, Inc.; Vital Energy, Inc.
12/15/2022	The Williams Cos., Inc.
11/02/2022	Marathon Oil Corp.
09/29/2022	DT Midstream, Inc.
08/17/2022	Phillips 66
08/09/2022	Devon Energy Corp.
06/08/2022	Devon Energy Corp.
03/14/2022	The Williams Cos., Inc.
02/16/2022	Crescent Energy Co.
01/10/2022	Enterprise Products Partners LP
11/03/2021	Continental Resources, Inc.
10/05/2021	Southwest Gas Holdings, Inc.
09/20/2021	ConocoPhillips

06/01/2021	Kinder Morgan, Inc.
05/03/2021	Oasis Petroleum, Inc.
10/27/2020	EQT Corp.
05/04/2020	National Fuel Gas Co.
03/18/2019	The Williams Cos., Inc.
03/14/2019	EQM Midstream Partners LP
10/18/2018	Valero Energy Corp.
07/30/2018	Discovery Midstream Partners LLC /Private Group/; Kohlberg Kravis Roberts & Co. LP; The Williams Cos., Inc.
06/29/2018	Diversified Energy Co. Plc
05/10/2018	Shell Midstream Partners LP
06/19/2017	Occidental Petroleum Corp.
03/21/2017	Marathon Oil Corp.
03/09/2017	Marathon Oil Corp.
02/16/2017	Petrolia Energy Corp.
01/24/2017	Plains All American Pipeline LP
01/12/2017	Mesquite Energy, Inc.
01/12/2017	WPX Energy, Inc.
11/28/2016	Permian Resources Corp.
09/26/2016	Energy Transfer Operating LP
09/26/2016	RM Partners LP
08/15/2016	Concho Resources, Inc.
08/08/2016	SM Energy Co.
07/13/2016	Diamondback Energy, Inc.
06/20/2016	Marathon Oil Corp.
05/03/2016	SRC Energy, Inc.
02/24/2016	Western Midstream Operating LP
12/07/2015	Devon Energy Corp.
06/01/2015	Enterprise Products Partners LP
04/06/2015	M3 Ohio Gathering LLC; The Williams Cos., Inc.; Williams Partners LP; Utica Gas Services LLC; Utica East Ohio Midstream LLC /Private Group/; M3 Midstream LLC
03/02/2015	Tallgrass Energy Partners LP
10/28/2014	Western Midstream Operating LP
10/27/2014	ONEOK Partners LP
10/16/2014	Southwestern Energy Co.

09/25/2014	Ultra Petroleum Corp.
09/02/2014	Buckeye Partners LP
06/30/2014	Linn Energy LLC
06/15/2014	The Williams Cos., Inc.
05/21/2014	Mesquite Energy, Inc.
04/01/2014	Range Resources - Louisiana, Inc.
02/28/2014	Midcon Compression LLC /Midstream Compression Bus/ /Pvt Grp/; Williams Partners LP; Archrock Partners LP; Williams Compression LLC; Archrock Partners Operating LLC
10/24/2013	Schlumberger Ltd.
10/21/2013	Ultra Petroleum Corp.
10/09/2013	Buckeye Partners LP
10/01/2013	Memorial Production Partners LP
09/05/2013	Oasis Petroleum, Inc.
07/31/2013	EXCO Resources, Inc.
06/24/2013	Maverick Natural Resources LLC
06/10/2013	Atlas Resource Partners LP
06/03/2013	Kodiak Oil & Gas Corp.
04/16/2013	Atlas Pipeline Partners LP
04/04/2013	Midstates Petroleum Co., Inc.
03/28/2013	Denbury, Inc.
03/15/2013	Rosetta Resources, Inc.
12/11/2012	Williams Partners LP
12/03/2012	Atlas Pipeline Partners LP
09/20/2012	Exxon Mobil Corp.
09/17/2012	Epl Oil & Gas LLC
09/10/2012	Plains Exploration & Production Co.
08/16/2012	Boardwalk Pipelines Holding Corp.; Boardwalk Pipeline Partners LP
05/13/2012	Concho Resources, Inc.
05/09/2012	Marathon Oil Corp.
03/10/2012	Legacy Reserves LP
02/27/2012	Linn Energy LLC
11/04/2011	Linn Energy LLC
11/02/2011	CVR Energy, Inc.

10/17/2011	Boardwalk Pipeline Partners LP
09/08/2011	Hess Corp.
09/01/2011	Valero Energy Corp.
06/01/2011	Marathon Oil Corp.
05/05/2011	Kinder Morgan Energy Partners LP
05/02/2011	Arch Resources, Inc.
03/22/2011	ETP Legacy LP
11/15/2010	The Williams Cos., Inc.
11/09/2010	Chevron Corp.
10/05/2010	Plains Exploration & Production Co.
07/28/2010	Enbridge Energy Partners LP
07/20/2010	Apache Corp.
07/20/2010	Exxon Mobil Corp.
04/12/2010	Apache Corp.
03/21/2010	CNX Resources Corp.
03/15/2010	CNX Resources Corp.
01/19/2010	Williams Partners LP /Old/
03/09/2009	Arch Resources, Inc.
07/28/2008	Sempra
06/05/2008	Concho Resources, Inc.
07/02/2007	Linn Energy LLC
06/04/2007	XTO Energy, Inc.
05/21/2007	Spectra Energy LLC
01/29/2007	Shell Oil Products Co. LLC; The Shell Transport & Trading Co. Ltd.; Shell Oil Co.; Andeavor LLC
11/16/2006	Williams Partners LP /Old/
09/15/2006	Florida Gas Transmission Co. LLC; ETP Legacy LP
08/28/2006	Western Refining, Inc.
06/29/2006	Devon Energy Corp.
06/23/2006	Anadarko Petroleum Corp.
06/23/2006	Anadarko Petroleum Corp.
04/17/2006	PXP Producing Co. LLC
01/23/2006	W&T Offshore, Inc.
10/03/2005	Chesapeake Energy Corp.
07/19/2005	EP Energy Corp.; El Paso Interim Corp.

05/09/2005	ONEOK, Inc.
02/24/2005	ConocoPhillips
01/26/2005	ETP Legacy LP
11/01/2004	NuStar Energy LP
08/06/2004	Ovintiv Exploration, Inc.
04/26/2004	ETP Legacy LP

8.1.2 Firm–Ticker Matching File

Name	**Ticker**
CNX Resources Corp.	CNX US Equity
Coterra Energy, Inc.	CTRA US Equity
ONEOK, Inc.	OKE US Equity
Enterprise Products Partners LP	EPD US Equity
Permian Resources Corp.	PR US Equity
Northern Oil & Gas, Inc.	NOG US Equity
SM Energy Co.	SM 7 08/01/32 Equity
Matador Resources Co.	MTDR US Equity
Phillips 66	PSX US Equity
Diversified Energy Co. Plc	DEC US Equity
The Williams Cos., Inc.	WMB US Equity
Mach Natural Resources LP	MNR US Equity
Kinder Morgan, Inc.	KMI US Equity
Western Midstream Partners LP	WES US Equity
Civitas Resources, Inc.	CIVI US Equity
Earthstone Energy, Inc.	ESTE US Equity
Forge Energy Ii Delaware LLC /Private Group/; Northern Oil & Gas, Inc.; Vital Energy, Inc.	Forge Energy Ii Delaware LLC /Private Group/; Northern Oil & Gas, Inc.; Vital Energy, Inc. Equity
Marathon Oil Corp.	MRO US Equity
DT Midstream, Inc.	DTM US Equity
Devon Energy Corp.	DVN US Equity
Crescent Energy Co.	CRGY US Equity
Continental Resources, Inc.	CLR 4.9 06/01/44 Equity
Southwest Gas Holdings, Inc.	SWX US Equity
ConocoPhillips	COP US Equity

Oasis Petroleum, Inc.	0559002D US Equity
EQT Corp.	EQT US Equity
National Fuel Gas Co.	NFG US Equity
EQM Midstream Partners LP	EQM 5 1/2 07/15/28 Equity
Valero Energy Corp.	VLO US Equity
Discovery Midstream Partners LLC /Private Group/; Kohlberg Kravis Roberts & Co. LP; The Williams Cos., Inc.	Discovery Midstream Partners LLC /Private Group/; Kohlberg Kravis Roberts & Co. LP; The Williams Cos., Inc. Equity
Shell Midstream Partners LP	SHLX US Equity
Occidental Petroleum Corp.	OXY US Equity
Petrolia Energy Corp.	PETROLIA ENERGY Equity
Plains All American Pipeline LP	PAA US Equity
Mesquite Energy, Inc.	SNEC 6 1/8 01/15/23 Equity
WPX Energy, Inc.	WPX US Equity
Energy Transfer Operating LP	ETP US Equity
RM Partners LP	RMP US Equity
Concho Resources, Inc.	CXO US Equity
Diamondback Energy, Inc.	FANG US Equity
SRC Energy, Inc.	SRCI US Equity
Western Midstream Operating LP	WES 7 1/4 04/01/30 Equity
M3 Ohio Gathering LLC; The Williams Cos., Inc.; Williams Partners LP; Utica Gas Services LLC; Utica East Ohio Midstream LLC /Private Group/; M3 Midstream LLC	M3 Ohio Gathering LLC; The Williams Cos., Inc.; Williams Partners LP; Utica Gas Services LLC; Utica East Ohio Midstream LLC /Private Group/; M3 Midstream LLC Equity
Tallgrass Energy Partners LP	TEP 6 3/4 03/15/34 Equity
ONEOK Partners LP	OKE 6 1/8 02/01/41 Equity
Southwestern Energy Co.	SWN US Equity
Ultra Petroleum Corp.	ULTRA PETROLEUM Equity
Buckeye Partners LP	BPL 3.95 12/01/26 Equity
Linn Energy LLC	1087405D US Equity
Range Resources - Louisiana, Inc.	RRC US Equity
Midcon Compression LLC /Midstream Compression Bus/ /Pvt Grp/; Williams Partners LP; Archrock Partners LP; Williams	Midcon Compression LLC /Midstream Compression Bus/ /Pvt Grp/; Williams Partners LP; Archrock Partners LP; Williams

Compression LLC; Archrock Partners Operating LLC	Compression LLC; Archrock Partners Operating LLC Equity
Schlumberger Ltd.	SLB 1.4 09/17/25 Equity
Memorial Production Partners LP	0618562D US Equity
EXCO Resources, Inc.	EXCE US Equity
Maverick Natural Resources LLC	1677830D US Equity
Atlas Resource Partners LP	ARPJ 10 3/4 PERP Equity
Kodiak Oil & Gas Corp.	0751520D US Equity
Atlas Pipeline Partners LP	APL US Equity
Midstates Petroleum Co., Inc.	AMPY US Equity
Denbury, Inc.	DEN US Equity
Rosetta Resources, Inc.	1477069D US Equity
Williams Partners LP	WPZ US Equity
Exxon Mobil Corp.	XOM US Equity
Epl Oil & Gas LLC	EPL US Equity
Plains Exploration & Production Co.	PXP US Equity
Boardwalk Pipelines Holding Corp.; Boardwalk Pipeline Partners LP	Boardwalk Pipelines Holding Corp.; Boardwalk Pipeline Partners LP Equity
Legacy Reserves LP	0812354D US Equity
CVR Energy, Inc.	CVI US Equity
Boardwalk Pipeline Partners LP	BWP US Equity
Hess Corp.	HES US Equity
Kinder Morgan Energy Partners LP	KMI 6 1/2 09/01/39 Equity
Arch Resources, Inc.	ARCH US Equity
ETP Legacy LP	ENERGY TRANSFER CDS USD SR 5Y Equity
Chevron Corp.	CVX US Equity
Enbridge Energy Partners LP	ENBCN 5 1/2 09/15/40 Equity
Apache Corp.	APA US Equity
Sempra	SRE US Equity
XTO Energy, Inc.	XTO US Equity
Spectra Energy LLC	SE 6 3/4 02/15/32 Equity
Shell Oil Products Co. LLC; The Shell Transport & Trading Co. Ltd.; Shell Oil Co.; Andeavor LLC	Shell Oil Products Co. LLC; The Shell Transport & Trading Co. Ltd.; Shell Oil Co.; Andeavor LLC Equity

Florida Gas Transmission Co. LLC; ETP Legacy LP	Florida Gas Transmission Co. LLC; ETP Legacy LP Equity
Western Refining, Inc.	WNR US Equity
Anadarko Petroleum Corp.	APC US Equity
PXP Producing Co. LLC	FCX 5 1/2 06/15/06 Equity
W&T Offshore, Inc.	WTI US Equity
Chesapeake Energy Corp.	EXE US Equity
EP Energy Corp.; El Paso Interim Corp.	EP ENERGY CORP.; EL PASO INTERIM Equity
ConocoPhillips; EPCO, Inc.	COP US Equity2
NuStar Energy LP	NS US Equity
Ovintiv Exploration, Inc.	NFX US Equity

8.2 Datasets for Stock-Financed Transactions

8.2.1 Transaction-Level Data

EventDate	Name
11/24/2024	ONEOK, Inc.
08/21/2024	CONSOL Energy, Inc.
05/29/2024	ConocoPhillips
03/18/2024	Dril-Quip, Inc.
03/11/2024	EQT Corp.
02/07/2024	California Resources Corp.
01/22/2024	Sunoco LP
01/11/2024	Chesapeake Energy Corp.
01/04/2024	APA Corp.
12/19/2023	Kodiak Gas Services, Inc.
10/23/2023	Chevron Corp.
10/11/2023	Exxon Mobil Corp.
08/21/2023	Permian Resources Corp.
08/16/2023	Energy Transfer LP
07/13/2023	Exxon Mobil Corp.
06/15/2023	Patterson-UTI Energy, Inc.
05/22/2023	Chevron Corp.
05/16/2022	Diamondback Energy, Inc.
10/27/2021	Phillips 66

10/21/2021	Altus Midstream Co.
07/12/2021	Ranger Oil Corp.
06/07/2021	Bonanza Creek Energy, Inc.
05/24/2021	Coterra Energy, Inc.
05/10/2021	Bonanza Creek Energy, Inc.
12/21/2020	Diamondback Energy, Inc.
11/09/2020	Bonanza Creek Energy, Inc.
10/20/2020	Pioneer Natural Resources Co.
10/19/2020	ConocoPhillips
09/28/2020	Devon Energy Corp.
08/12/2020	Southwestern Energy Co.
07/20/2020	Chevron Corp.
02/27/2020	Equitrans Midstream Corp.
12/19/2019	Apergy Corp.
10/14/2019	Parsley Energy, Inc.
08/26/2019	PDC Energy, Inc.
07/15/2019	Callon Petroleum Co.
06/17/2019	Keane Group, Inc.
05/08/2019	MPLX LP
05/06/2019	Midstates Petroleum Co., Inc.
11/08/2018	Western Midstream Partners LP
10/22/2018	EnLink Midstream LLC
08/14/2018	Diamondback Energy, Inc.
08/01/2018	Energy Transfer LP
05/17/2018	Cheniere Energy, Inc.
05/17/2018	The Williams Cos., Inc.
04/26/2018	EQM Midstream Partners LP
03/28/2018	Concho Resources, Inc.
03/27/2018	Tallgrass Energy LP
02/23/2018	Alliance Resource Partners LP
02/08/2018	NuStar Energy LP
01/02/2018	Archrock, Inc.
12/05/2017	HighPoint Operating Corp.
11/21/2017	Stone Energy Corp.
07/21/2017	Andeavor Logistics LP

02/01/2017	ONEOK, Inc.
01/04/2017	DCP Midstream LP
12/12/2016	Patterson-UTI Energy, Inc.
11/21/2016	Energy Transfer Operating LP
10/14/2016	Delek US Energy, Inc.
05/16/2016	Range Resources Corp.
05/04/2016	Phillips 66 Partners GP LLC; Phillips 66 Partners LP
05/27/2015	EnLink Midstream Partners LP
05/11/2015	Noble Energy, Inc.
05/06/2015	Crestwood Equity Partners LP
02/17/2015	Devon Energy Corp.
10/01/2014	Enterprise Products Partners LP
09/17/2014	Enbridge Energy Partners LP
08/10/2014	Kinder Morgan, Inc.
07/24/2014	Maverick Natural Resources LLC
07/13/2014	Whiting Petroleum Corp.
06/15/2014	Williams Partners LP
11/19/2013	Energy Transfer LP
05/07/2013	Pioneer Natural Resources Co.
05/06/2013	Crestwood Equity Partners LP
02/21/2013	Linn Energy LLC
03/25/2011	Vanguard Natural Resources LLC
02/23/2011	Enterprise Products Partners LP
02/22/2011	Holly Corp.
09/21/2010	PVR Partners LP
09/07/2010	Enterprise Products Partners LP
08/09/2010	Crestwood Equity Partners LP
06/11/2010	Buckeye Partners LP
02/21/2010	Schlumberger Ltd.
12/14/2009	Exxon Mobil Corp.
06/01/2009	Cameron International Corp.
04/29/2009	Enterprise Products Partners LP
04/27/2009	Atlas America, Inc.
04/02/2008	Patriot Coal Corp.
05/07/2007	Enterprise GP Holdings LP

07/10/2006	WPS Resources Corp.
06/12/2006	Plains All American Pipeline LP
01/26/2005	Coterra Energy Operating Co.
11/02/2004	NuStar Energy LP
08/12/2004	National-Oilwell, Inc.
04/07/2004	Kerr-McGee Corp.
02/12/2004	Plains Exploration & Production Co.
	S&P Energy Select Sector (IXE)

8.2.2 Firm–Ticker Matching File

Name	**Ticker**
ONEOK, Inc.	OKE US Equity
CONSOL Energy, Inc.	242935Z US Equity
ConocoPhillips	COP US Equity
Dril-Quip, Inc.	INVX US Equity
EQT Corp.	EQT US Equity
California Resources Corp.	CRC US Equity
Sunoco LP	SUN US Equity
Chesapeake Energy Corp.	EXE US Equity
APA Corp.	APA US Equity
Kodiak Gas Services, Inc.	KGS US Equity
Chevron Corp.	CVX US Equity
Exxon Mobil Corp.	XOM US Equity
Permian Resources Corp.	PR US Equity
Energy Transfer LP	ET US Equity
Patterson-UTI Energy, Inc.	PTEN US Equity
Diamondback Energy, Inc.	FANG US Equity
Phillips 66	PSX US Equity
Altus Midstream Co.	KNTK US Equity
Ranger Oil Corp.	ROCC US Equity
Bonanza Creek Energy, Inc.	CIVI US Equity
Coterra Energy, Inc.	CTRA US Equity
Pioneer Natural Resources Co.	PXD 2.15 01/15/31 Equity
Devon Energy Corp.	DVN US Equity
Southwestern Energy Co.	SWN US Equity

Equitrans Midstream Corp.	ETRN US Equity
Apergy Corp.	CHX US Equity
Parsley Energy, Inc.	PE US Equity
PDC Energy, Inc.	PDCE US Equity
Callon Petroleum Co.	CPE US Equity
Keane Group, Inc.	0856629D US Equity
MPLX LP	MPLX US Equity
Midstates Petroleum Co., Inc.	0812183D US Equity
Western Midstream Partners LP	WES US Equity
EnLink Midstream LLC	ENLC US Equity
Cheniere Energy, Inc.	LNG US Equity
The Williams Cos., Inc.	WMB US Equity
EQM Midstream Partners LP	EQM 5 1/2 07/15/28 Equity
Concho Resources, Inc.	CXO US Equity
Tallgrass Energy LP	TEP 6 3/4 03/15/34 Equity
Alliance Resource Partners LP	ARLP US Equity
NuStar Energy LP	NS US Equity
Archrock, Inc.	AROC US Equity
HighPoint Operating Corp.	BBG US Equity
Stone Energy Corp.	STONE ENERGY Equity
Andeavor Logistics LP	ANDV US Equity
DCP Midstream LP	DCP US Equity
Energy Transfer Operating LP	ETP US Equity
Delek US Energy, Inc.	9876533D US Equity
Range Resources Corp.	RRC US Equity
Phillips 66 Partners GP LLC; Phillips 66 Partners LP	Phillips 66 Partners GP LLC; Phillips 66 Partners LP Equity
EnLink Midstream Partners LP	ENLK US Equity
Noble Energy, Inc.	NBL US Equity
Crestwood Equity Partners LP	CEQP US Equity
Enterprise Products Partners LP	EPD US Equity
Enbridge Energy Partners LP	ENBCN 5 1/2 09/15/40 Equity
Kinder Morgan, Inc.	KMI US Equity
Maverick Natural Resources LLC	1677830D US Equity
Whiting Petroleum Corp.	WLL US Equity

Williams Partners LP	WPZ US Equity
Linn Energy LLC	1087405D US Equity
Vanguard Natural Resources LLC	0121796D US Equity
Holly Corp.	HFC US Equity
PVR Partners LP	0811881D US Equity
Buckeye Partners LP	BPL 3.95 12/01/26 Equity
Schlumberger Ltd.	SLB 1.4 09/17/25 Equity
Cameron International Corp.	2596482D US Equity
Atlas America, Inc.	0003196D US Equity
Patriot Coal Corp.	0197374D US Equity
Enterprise GP Holdings LP	0296328Q GR Equity
WPS Resources Corp.	TEG US Equity
Plains All American Pipeline LP	PAA US Equity
Coterra Energy Operating Co.	XEC 4 3/8 03/15/29 Equity
National-Oilwell, Inc.	NOV US Equity
Kerr-McGee Corp.	0544749D US Equity
Plains Exploration & Production Co.	PXP US Equity

8.3 Python Scripts

To avoid unnecessary repetition while preserving transparency, the annexes include one Python script for each methodological approach. The traditional event study script corresponds to cash-financed transactions, while the panel event study script corresponds to stock-financed transactions. The underlying computational logic, estimation procedures, and statistical tests are identical across payment methods. Differences are limited to the data-loading and problematic deals filtering, which can be directly observed in the respective scripts.

8.3.1 Traditional Event Study Python Script

0. Libraries

```
import pandas as pd
import numpy as np
import statsmodels.api as sm
from scipy import stats
import matplotlib.pyplot as plt
```

1. Loading and Cleaning Excel Dataset

1.1 Prices Data

```
data = pd.read_excel('Prices_Cash_DataSet_Clean_V4.xlsx', na_values=["#N/A"])
data
data.columns
```

Check that data is numeric

```
data['Price'] = pd.to_numeric(data['Price'], errors='coerce')


print(data.dtypes.head())
```

Compute Cumulative Logaritmic Returns

```
if True:
    df_prices = data.pivot(index='Date', columns='Ticker', values='Price')
    df_returns = np.log(df_prices / df_prices.shift(1))  # df_prices.pct_change()
    df_panel = df_returns.reset_index().melt(id_vars='Date')
    data = df_panel.rename(columns={'value':'log_return'})

data
```

1.2 Transactions Data

```
transactions = pd.read_excel('Transactions_Cash_DataSet_Clean_V3.xlsx')
transactions
```

Delete problematic deals

```
# Drop Forge Energy
transactions = transactions[transactions["Name"] !=
    "Forge Energy Ii Delaware LLC /Private Group/; Northern Oil & Gas, Inc.; Vital Energy, Inc."]

# Drop Discovery Midstream
transactions = transactions[transactions["Name"] !=
    "Discovery Midstream Partners LLC /Private Group/; Kohlberg Kravis Roberts & Co. LP; The Williams Cos., Inc."]

# Drop M3 Ohio Gathering
transactions = transactions[transactions["Name"] !=
    "M3 Ohio Gathering LLC; The Williams Cos., Inc.; Williams Partners LP; Utica Gas Services LLC; Utica East Ohio Midstream LLC /Private Group/; M3 Midstream LLC"]

# Drop Midcon Compression
transactions = transactions[transactions["Name"] !=
    "Midcon Compression LLC /Midstream Compression Bus/ /Pvt Grp/; Williams Partners LP; Archrock Partners LP; Williams Compression LLC; Archrock Partners Operating LLC"]

# Drop Boardwalk Pipelines
transactions = transactions[transactions["Name"] !=
    "Boardwalk Pipelines Holding Corp.; Boardwalk Pipeline Partners LP"]
```

```
# Drop Shell Oil Products
transactions = transactions[transactions["Name"] !=
    "Shell Oil Products Co. LLC; The Shell Transport & Trading Co. Ltd.; Shell Oil Co.; Andeavor LLC"]

# Drop Florida Gas Transmission
transactions = transactions[transactions["Name"] !=
    "Florida Gas Transmission Co. LLC; ETP Legacy LP"]

# Drop EP Energy
transactions = transactions[transactions["Name"] !=
    "EP Energy Corp.; El Paso Interim Corp."]

# Check how many rows remain
print(f"Remaining rows: {len(transactions)}")

transactions
```

Add Tickers to Transactions Table

```
# Load Ticker/Name table
ticker_map = pd.read_excel("Ticker_Name_Cash_Clean_V1.xlsx")

# Merge transactions with ticker_map first (to add tickers to each transaction)
transactions = pd.merge(transactions, ticker_map, on="Name", how="left")

transactions
```

1.3 Dates Indexing

Create Date Index Table

```
# Create master trading day index (based on all unique dates in prices)
date_index_table = (
    data[['Date']]
    .drop_duplicates()
    .sort_values('Date')
    .reset_index(drop=True)
)

date_index_table['date_index'] = date_index_table.index + 1

date_index_table = date_index_table[['date_index', 'Date']]

print(date_index_table.head())
print(date_index_table.tail())
```

Add index to returns table

```
# Merge date_index into price/returns data
data = data.merge(date_index_table, on='Date', how='left')

# Keep only relevant columns
data = data[['Ticker', 'date_index', 'log_return']]

print(data.head())
```

Add index to transactions table

```
# Add index to events
transactions = transactions.merge(
    date_index_table,
    left_on='EventDate',
    right_on='Date',
    how='left'
)

transactions = transactions.rename(columns={'date_index': 'event_date_index'})
transactions = transactions[['Name', 'Ticker', 'event_date_index']]

print(transactions.head())

transactions = transactions.sort_values("event_date_index").reset_index(drop=True)
transactions["Event_id"] = transactions.index + 1
```

2. Event and Estimation Windows Definition

2.1 Event Window

```
PREWINDOW = -10
POSTWINDOW = +10
```

2.2 Estimation Window

```
ESTIMATION_START = -365
ESTIMATION_END   = -30
```

3. Abnormal Return (AR) Computation

3.1 CAPM Model Inputs

```python
MARKET_TICKER = "S&P Energy Select Sector (IXE)"

# Market daily returns with date_index
market_returns = (
    data[data['Ticker'] == MARKET_TICKER]
    [['date_index', 'log_return']]
    .rename(columns={'log_return': 'ret_mkt'})
)

market_returns

rf_daily = 0.0297 / 252 # Assuming 252 trading days
```

3.2 CAPM Estimation and AR Computation Loop

```python
rows_AR = []   # will store Ticker | Time_to_Event | AR

for _, ev in transactions.iterrows():
    # 1) Basic event info
    firm_ticker = ev["Ticker"]
    event_idx   = ev["event_date_index"]

    # Skip if no event index or if the firm IS the market
    if pd.isna(event_idx) or firm_ticker == MARKET_TICKER:
        continue

    # 2) Firm returns for this ticker
    firm_returns = (
        data[data["Ticker"] == firm_ticker]
        [["date_index", "log_return"]]
        .rename(columns={"log_return": "ret_firm"})
    )


    # 3) Merge firm + market returns on date_index
    df_ev = firm_returns.merge(market_returns, on="date_index", how="inner")
    df_ev["Ticker"] = firm_ticker

    # Drop missing returns
    df_ev = df_ev.dropna(subset=["ret_firm", "ret_mkt"])
    if df_ev.empty:
        continue

    # 4) Time to event
    df_ev["Time_to_Event"] = df_ev["date_index"] - event_idx

    # 5) Estimation window for CAPM
    df_est = df_ev[
        (df_ev["Time_to_Event"] >= ESTIMATION_START) &
        (df_ev["Time_to_Event"] <= ESTIMATION_END)
    ].copy()

    # Not enough data → skip event
    if len(df_est) < 30:
        continue


    # 6) CAPM on excess returns: (Ri - Rf) = α + β (Rm - Rf)
    df_est["excess_firm"] = df_est["ret_firm"] - rf_daily
    df_est["excess_mkt"]  = df_est["ret_mkt"]  - rf_daily

    X = sm.add_constant(df_est["excess_mkt"])
    y = df_est["excess_firm"]
    model = sm.OLS(y, X).fit()

    alpha = model.params["const"]
    beta  = model.params["excess_mkt"]

    # 7) Event window where we compute AR
    df_evt_window = df_ev[
        (df_ev["Time_to_Event"] >= PREWINDOW) &
        (df_ev["Time_to_Event"] <= POSTWINDOW)
    ].copy()

    if df_evt_window.empty:
        continue
```

```
        # 8) Expected return: ER = Rf + α + β (Rm - Rf)
        df_evt_window["ER"] = (
            rf_daily + alpha + beta * (df_evt_window["ret_mkt"] - rf_daily)
        )

        # 9) Abnormal return: AR = R - ER
        df_evt_window["AR"] = df_evt_window["ret_firm"] - df_evt_window["ER"]

        # 10) Store only the final structure
        rows_AR.append(
            df_evt_window[["Ticker", "Time_to_Event", "AR"]]
        )

    # 11) Final AR table for all events
    final_AR_table = pd.concat(rows_AR, ignore_index=True)

    print(final_AR_table.head())
    print(final_AR_table.tail())
```

4. Statistical Inference

4.1 ARR

```
aar_rows = []

for tau, group in final_AR_table.groupby("Time_to_Event"):
    ars = group["AR"].dropna()
    N   = len(ars)
    if N == 0:
        continue

    mean_ar = ars.mean()
    std_ar  = ars.std(ddof=1)

    # t-test against 0 (H0: mean = 0)
    t_stat, p_val = stats.ttest_1samp(ars, 0.0, nan_policy="omit")


    aar_rows.append({
        "Time_to_Event": tau,
        "N_events": N,
        "AAR": mean_ar,
        "Std_AR": std_ar,
        "t_stat": t_stat,
        "p_value": p_val
    })

AAR_stats = (
    pd.DataFrame(aar_rows)
    .sort_values("Time_to_Event")
    .reset_index(drop=True)
)

print(AAR_stats.head())
print(AAR_stats.tail())
```

4.2 CAR & CAAR

```
CAR_WINDOWS = [
    (-1, 1),
    (-3, 3),
    (-5, 5),
    (-10, 10),
    (0, 5),
    (-5, 0),
    (-2, 0),
    (0, 0),
    (1, 1),
]
```

```python
car_results = []

for (start, end) in CAR_WINDOWS:
    # 1) restrict to this window
    mask = (
        (final_AR_table["Time_to_Event"] >= start) &
        (final_AR_table["Time_to_Event"] <= end)
    )
    window_data = final_AR_table.loc[mask].copy()

    # 2) CAR per ticker (or per Event_id if you stored it)
    CAR_per_ticker = (
        window_data
        .groupby("Ticker")["AR"]
        .sum()
        .reset_index()
        .rename(columns={"AR": "CAR"})
    )
```

```python
    cars = CAR_per_ticker["CAR"].dropna()
    N    = len(cars)
    if N == 0:
        continue

    mean_car = cars.mean()        # CAAR for this window
    std_car  = cars.std(ddof=1)

    # t-test against 0: H0: mean CAR = 0
    t_stat, p_val = stats.ttest_1samp(cars, 0.0, nan_policy="omit")

    car_results.append({
        "Window": f"[{start},{end}]",
        "N_events": N,
        "CAAR": mean_car,
        "Std_CAR": std_car,
        "t_stat": t_stat,
        "p_value": p_val
    })

CAR_CAAR_stats = pd.DataFrame(car_results)
```

```python
print(CAR_CAAR_stats)
```

4.3 SAAR

```python
saar_rows = []

for tau, group in final_AR_table.groupby("Time_to_Event"):
    ars = group["AR"].dropna()
    N = len(ars)
    if N == 0:
        continue

    AAR = ars.mean()
    std_AR = ars.std(ddof=1)

    # Standard error of AAR
    se_AAR = std_AR / np.sqrt(N) if std_AR > 0 else np.nan

    # SAAR = AAR / SE(AAR)  (normalized)
    SAAR = AAR / se_AAR if (se_AAR is not None and se_AAR > 0) else np.nan

    # Same t-test you already do (should match SAAR numerically)
    t_stat, p_val = stats.ttest_1samp(ars, 0.0, nan_policy="omit")
```

```python
    saar_rows.append({
        "Time_to_Event": tau,
        "N_events": N,
        "AAR": AAR,
        "Std_AR": std_AR,
        "SE_AAR": se_AAR,
        "SAAR": SAAR,
        "p_value": p_val
    })

SAAR_stats = (
    pd.DataFrame(saar_rows)
    .sort_values("Time_to_Event")
    .reset_index(drop=True)
)

print(SAAR_stats.head())
print(SAAR_stats.tail())
```

4.4 SCAAR

```python
scaar_results = []

for (start, end) in CAR_WINDOWS:
    # 1) restrict to this window
    mask = (
        (final_AR_table["Time_to_Event"] >= start) &
        (final_AR_table["Time_to_Event"] <= end)
    )
    window_data = final_AR_table.loc[mask].copy()

    # 2) CAR per ticker (or per Event_id if you stored it)
    CAR_per_ticker = (
        window_data
        .groupby("Ticker")["AR"]
        .sum()
        .reset_index()
        .rename(columns={"AR": "CAR"})
    )
```

```python
    cars = CAR_per_ticker["CAR"].dropna()
    N = len(cars)
    if N == 0:
        continue

    CAAR = cars.mean()
    std_CAR = cars.std(ddof=1)

    # Standard error of CAAR (mean of CARs)
    se_CAAR = std_CAR / np.sqrt(N) if std_CAR > 0 else np.nan

    # SCAAR = CAAR / SE(CAAR)  (normalized)
    SCAAR = CAAR / se_CAAR if (se_CAAR is not None and se_CAAR > 0) else np.nan

    # Same t-test you already do (should match SCAAR numerically)
    t_stat, p_val = stats.ttest_1samp(cars, 0.0, nan_policy="omit")
```

```python
    scaar_results.append({
        "Window": f"[{start},{end}]",
        "N_events": N,
        "CAAR": CAAR,
        "Std_CAR": std_CAR,
        "SE_CAAR": se_CAAR,
        "SCAAR": SCAAR,
        "p_value": p_val
    })

SCAAR_stats = pd.DataFrame(scaar_results)

print(SCAAR_stats)
```

5. Visualization of Results

```python
YMIN_GLOBAL = -8
YMAX_GLOBAL = 6

YMIN_CAAR = -4
YMAX_CAAR = 2
```

5.1 CAAR Curve

```python
import matplotlib.pyplot as plt

# 1. Compute Average Abnormal Return (AAR) by day
AAR_curve = (
    final_AR_table
    .groupby("Time_to_Event")["AR"]
    .mean()
    .sort_index()
)

# 2. Convert to cumulative (CAAR)
CAAR_curve = AAR_curve.cumsum()

# 3. Plot CAAR
plt.figure(figsize=(10,6))
plt.plot(CAAR_curve.index, CAAR_curve.values)
plt.axvline(0, linestyle='--')  # Event day reference
plt.xlabel("Time to Event")

plt.ylabel("Cumulative Abnormal Return (CAAR)")
plt.title("Cumulative Abnormal Returns around Event Window")
plt.grid(True)
plt.show()
```

5.2 AR + CAAR

```python
# --- 1. Compute AAR ---
AAR_curve = (
    final_AR_table
    .groupby("Time_to_Event")["AR"]
    .mean()
    .sort_index()
)

# --- 2. Compute CAAR (cumulative AAR) ---
CAAR_curve = AAR_curve.cumsum()

# --- 3. Plot ---
plt.figure(figsize=(12,6))

# AAR line
plt.plot(
    AAR_curve.index,
    AAR_curve.values * 100,   # convert to %
    marker="o",
    color="black",
    label="Average Abnormal Return (AAR)"
)


# CAAR line
plt.plot(
    CAAR_curve.index,
    CAAR_curve.values * 100,  # convert to %
    marker="o",
    color="royalblue",
    label="Cumulative Average Abnormal Return (CAAR)"
)

# Vertical event line at t = 0
plt.axvline(0, color="black", linestyle="--", label="Announcement Day (t = 0)")

# Title
plt.title("Daily Evolution of AAR and CAAR in [-10, 10]")

# Axis labels
plt.xlabel("Day Relative to the Event")
plt.ylabel("Return (%)")


# Grid
plt.grid(True, alpha=0.3)

# Legend
plt.legend()

plt.tight_layout()

plt.ylim(YMIN_CAAR, YMAX_CAAR)

plt.show()
```

5.3 SAAR + SCAAR

```
# --- 1. Compute SAAR by day (tau) ---
# SAAR_tau = AAR_tau / (Std_AR_tau / sqrt(N_tau))  (i.e., normalized)
saar_rows = []

for tau, group in final_AR_table.groupby("Time_to_Event"):
    ars = group["AR"].dropna()
    N = len(ars)
    if N == 0:
        continue

    AAR = ars.mean()
    std_AR = ars.std(ddof=1)
    se_AAR = std_AR / np.sqrt(N) if std_AR > 0 else np.nan
    SAAR = AAR / se_AAR if (se_AAR is not None and se_AAR > 0) else np.nan

    saar_rows.append({"Time_to_Event": int(tau), "SAAR": SAAR})
```

```
SAAR_curve = (
    pd.DataFrame(saar_rows)
    .dropna()
    .set_index("Time_to_Event")["SAAR"]
    .sort_index()
)

# --- 2. Compute SCAAR (cumulative SAAR) ---
SCAAR_curve = SAAR_curve.cumsum()

# --- 3. Plot ---
plt.figure(figsize=(12,6))
```

```
# SAAR line
plt.plot(
    SAAR_curve.index,
    SAAR_curve.values,
    marker="o",
    color="black",
    label="Standardized Average Abnormal Return (SAAR)"
)

# SCAAR line
plt.plot(
    SCAAR_curve.index,
    SCAAR_curve.values,
    marker="o",
    color="royalblue",
    label="Standardized Cumulative Average Abnormal Return (SCAAR)"
)
```

```
# Vertical event line at t = 0
plt.axvline(0, color="black", linestyle="--", label="Announcement Day (t = 0)")

# Title
plt.title("Daily Evolution of SAAR and SCAAR in [-10, 10]")

# Axis labels
plt.xlabel("Day Relative to the Event")
plt.ylabel("Standardized Return (unitless)")

# Grid
plt.grid(True, alpha=0.3)
```

```
# Legend
plt.legend()

plt.tight_layout()

plt.ylim(YMIN_GLOBAL, YMAX_GLOBAL)

plt.show()
```

8.3.2 Panel Event Study Python Script

0. Libraries

```
from linearmodels import PanelOLS, OLS
import numpy as np
import pandas as pd
import plotly.express as px
import plotly.graph_objs as go
```

1. Loading and Cleaning Excel Dataset

1.1 Prices Data

```
data = pd.read_excel('Prices_Stock_DataSet_Clean_V4.xlsx', na_values=["#N/A"])
data
data.columns
```

Check that data is numeric

```
data['Price'] = pd.to_numeric(data['Price'], errors='coerce')


print(data.dtypes.head())
```

Compute Cumulative Logaritmic Returns

```
if True:
    df_prices = data.pivot(index='Date', columns='Ticker', values='Price')
    df_returns = np.log(df_prices / df_prices.shift(1))  # df_prices.pct_change()
    df_panel = df_returns.reset_index().melt(id_vars='Date')
    data = df_panel.rename(columns={'value':'log_return'})

data
```

1.2 Transactions data

```
transactions = pd.read_excel('Transactions_Stock_DataSet_Clean_V2.xlsx')
transactions
```

Delete problematic deals

```
# Drop Forge Energy
transactions = transactions[transactions["Name"] !=
    "Phillips 66 Partners GP LLC; Phillips 66 Partners LP"]

# Check how many rows remain
print(f"Remaining rows: {len(transactions)}")

transactions
```

Add Tickers to Transactions Table and merge Transactions and Prices tables

```
#data = pd.merge(data, transactions, on='Ticker')

# Load Ticker/Name table
ticker_map = pd.read_excel("Ticker_Name_Stock_Clean_V1.xlsx")

# Merge transactions with ticker_map first (to add tickers to each transaction)
transactions = pd.merge(transactions, ticker_map, on="Name", how="left")

# Merge that with your price-return data on 'Ticker'
data = pd.merge(data, transactions, on="Ticker", how="inner")

# Drop missing log returns if needed
data = data.dropna(subset=["log_return"])

data
```

2. Calculate "time to event"

Some configuration parameters

```
BASELINE_LAG = -1
PREWINDOW = -10
POSTWINDOW = +10
CUT_LEFT = -120
CUT_RIGHT = +120
```

Time to event calculation

```
if True:
  # Ensure datetime type
  data['Date'] = pd.to_datetime(data['Date'])
  data['EventDate'] = pd.to_datetime(data['EventDate'])

  # Compute business days safely
  data['TimeToEvent'] = np.busday_count(
      data['EventDate'].values.astype('datetime64[D]'),
      data['Date'].values.astype('datetime64[D]')
  )
```

```
  data = data.loc[data.TimeToEvent < CUT_RIGHT]
  data = data.loc[data.TimeToEvent > CUT_LEFT]
  data['TimeToEvent'] = data['TimeToEvent'].clip(PREWINDOW, POSTWINDOW)
```

Create dummies (variables that are set to 0 or 1) if the observation happens at a specific time to event.

```
dummies = pd.get_dummies(data['TimeToEvent']).astype(int)
data = data.join(dummies)
data = data.set_index(['Ticker', 'Date'])
data
```

```
data[['TimeToEvent', 'log_return']].groupby('TimeToEvent').mean()
```

3. Solve fixed-effects panel

```
dependent = data['log_return']
exog = data.drop(columns=['log_return', 'Name', 'EventDate', 'TimeToEvent', BASELINE_LAG])

if False:
    # add constant?
    exog['const'] = 1.0

fe_model = PanelOLS(dependent,
                    exog,
                    time_effects=True,  # Toqueteable
                    entity_effects=True, # Toqueteable
                    drop_absorbed=False)
```

```
fe_result = fe_model.fit(cov_type='robust')

print(fe_result)
fe_result.estimated_effects
```

4. Plot the event

```
YMIN_GLOBAL = -5
YMAX_GLOBAL = 2

YMIN_CI = -0.04
YMAX_CI = 0.02
```

4.1 Plot with CI Bands

```
result = fe_result

# get confidence interval for given level
alpha = 0.05
data = result.conf_int(level = 1 - alpha)

# calculate middle of interval (the actual values)
data['value'] = data.mean(axis=1)
data.loc[BASELINE_LAG, 'value'] = 0.0
data.loc[BASELINE_LAG, 'upper'] = 0.0
data.loc[BASELINE_LAG, 'lower'] = 0.0

# add constant ??
if 'const' in result.params:
    #data = data + result.params['const']
    data = data.drop(index=['const'])
```

```
data = data.sort_index()

data
```

```
def plotly_event_study(data, baseline, plot_ends, title, filename=None):

    fig = go.Figure()

    # Add a horizontal line at y=0 (or any other y-value you need)
    fig.add_hline(y=0, line={'dash': 'solid', 'width': 1, 'color': 'red'})
    fig.add_vline(x=0, line={'dash': 'solid', 'width': 1, 'color': 'gray'})
    if baseline != 0:
        fig.add_vline(x=baseline, line={'dash': 'dot', 'width': 1, 'color': 'gray'})

    if plot_ends:
        left_end = data.iloc[:1]
        right_end = data.iloc[-1:]
        data = data.iloc[1:-1]
```

```python
# point estimate and error bars of left accumulation
fig.add_trace(
    go.Scatter(
        x=left_end.index,  # or another column if your DataFrame has a specific column for the x-axis
        y=left_end['value'],
        error_y=dict(
            type='data',  # indicates that the values for the error bars are given explicitly
            symmetric=False,  # indicates that the error bars are not symmetric
            array=left_end['upper'] - left_end['value'],
            # specifies the length of the portion of the error bar above the value
            arrayminus=left_end['value'] - left_end['lower'],
            # specifies the length of the portion of the error bar below the value
            color='gray',
            thickness=2,
            width=4
        ),
```

```python
        name='left accum: point estimate & error bars',
        marker=dict(
            color='gray',
            size=5
            # symbol='diamond'
        ),
        mode='markers')  # you can change to 'lines' or 'lines+markers' if that's more appropriate for your data
)
```

```python
# point estimate and error bars of right accumulation
fig.add_trace(
    go.Scatter(
        x=right_end.index,  # or another column if your DataFrame has a specific column for the x-axis
        y=right_end['value'],
        error_y=dict(
            type='data',  # indicates that the values for the error bars are given explicitly
            symmetric=False,  # indicates that the error bars are not symmetric
            array=right_end['upper'] - right_end['value'],
            # specifies the length of the portion of the error bar above the value
            arrayminus=right_end['value'] - right_end['lower'],
            # specifies the length of the portion of the error bar below the value
            color='gray',
            thickness=2,
            width=4
        ),
```

```python
        name='right accum: point estimate & error bars',
        marker=dict(
            color='gray',
            size=5
            # symbol='diamond'
        ),
        mode='markers')  # you can change to 'lines' or 'lines+markers' if that's more appropriate for your data
)
```

```python
# Upper Bound
fig.add_trace(
    go.Scatter(x=data.index,
               y=data['upper'],
               line_color='lightgray',
               line={'dash': 'dot', 'width': 1},
               name='CI upper band',
               mode='lines',
               opacity=0.15)
)
```

```python
# Lower Bound fill in between with parameter 'fill': 'tonexty'
fig.add_trace(
    go.Scatter(x=data.index,
               y=data['lower'],
               line_color='lightgray',
               line={'dash': 'dot', 'width': 1},
               fill='tonexty',
               name='CI lower band',
               mode='lines',
               opacity=0.15)
)
```

```python
    # event point estimate and error bars
    fig.add_trace(
        go.Scatter(
            x=data.index,  # or another column if your DataFrame has a specific column for the x-axis
            y=data['value'],
            error_y=dict(
                type='data',  # indicates that the values for the error bars are given explicitly
                symmetric=False,  # indicates that the error bars are not symmetric
                array=data['upper'] - data['value'],
                # specifies the length of the portion of the error bar above the value
                arrayminus=data['value'] - data['lower'],
                # specifies the length of the portion of the error bar below the value
                color='darkgray',
                thickness=1,
                width=3
            ),
```

```python
            name='event: point estimate & error bars',
            marker=dict(
                color='darkgray',
                size=5
                # symbol='diamond'
            ),
            mode='markers')  # you can change to 'lines' or 'lines+markers' if that's more appropriate for your data
    )
```

```python
    # use percentages in axes
    fig.update_layout(
        width=1200,
        height=600,
        title=title,
        xaxis_title='event time',
        yaxis_title=r'effect',
    )

    fig.update_yaxes(range=[YMIN_CI, YMAX_CI])

    fig.show()
```

```python
    if filename:
        fig.write_image(filename)
```

```python
plotly_event_study(data, BASELINE_LAG, (PREWINDOW, POSTWINDOW), 'Panel Event Study - Stock Financed Transactions')
```

4.2 Cumulative Return Plot

```python
data['cum_ret'] = data['value'].cumsum()
data
```

```python
# ---- Safety: ensure the index is numeric event time and sorted ----
panel_plot_df = data.copy()
panel_plot_df.index = panel_plot_df.index.astype(int)
panel_plot_df = panel_plot_df.sort_index()

# Optional: restrict exactly to [-10, 10] if your "plot_ends" logic kept more points
panel_plot_df = panel_plot_df.loc[(panel_plot_df.index >= PREWINDOW) & (panel_plot_df.index <= POSTWINDOW)].copy()

# ---- Build the plot ----
plt.figure(figsize=(12, 6))
```

```python
# Main line: cumulative effect
plt.plot(
    panel_plot_df.index,
    panel_plot_df["cum_ret"] * 100,   # convert to %
    marker="o",
    color="royalblue",
    label="Cumulative Abnormal Return (Panel Estimate)"
)

# Horizontal zero line
plt.axhline(0, color="black", linewidth=1, alpha=0.7)

# Vertical event line at t=0
plt.axvline(0, color="black", linestyle="--", label="Announcement Day (t = 0)")
```

```python
    # (Optional) baseline marker line if you want it visible (your baseline is -1)
    # Comment out if you prefer only the t=0 line like in the traditional plot
    if BASELINE_LAG is not None:
        plt.axvline(BASELINE_LAG, color="gray", linestyle=":", linewidth=1, alpha=0.8, label=f"Baseline (t = {BASELINE_LAG})")

    # Titles and labels (English)
    plt.title(f"Daily Evolution of CAAR (Panel) in [{PREWINDOW}, {POSTWINDOW}]")
    plt.xlabel("Day Relative to the Event")
    plt.ylabel("Cumulative Return (%)")

    # Grid + legend (same vibe as your traditional plot)
    plt.grid(True, alpha=0.3)
    plt.legend()
```

```python
    plt.tight_layout()

    plt.ylim(YMIN_GLOBAL, YMAX_GLOBAL)

    plt.show()
```