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MARKET REACTION TO PAYMENT METHODS IN M&A TRANSACTIONS: EVIDENCE FROM THE U.S. ENERGY SECTOR

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MADRID | January 2026

ABSTRACT

This dissertation analyzes how the method of payment in mergers and acquisitions influences investor reactions, focusing on cash- and stock-financed transactions in the U.S. energy sector between 2004 and 2024. While M&A activity plays a central role in corporate strategy, financial markets often respond differently depending on how transactions are financed.

Using a sample of completed acquisitions, the study examines stock market behavior around announcement dates to assess whether investors systematically differentiate between payment structures when incorporating new information into prices. The empirical analysis combines a traditional event study with a panel event study framework, allowing both immediate and dynamic market responses to be evaluated.

The results reveal a clear asymmetry in market reactions. Cash-financed acquisitions are associated with neutral market responses, with no statistically significant abnormal returns around the announcement. In contrast, stock-financed acquisitions generate statistically significant negative abnormal returns for acquiring firms, which persist beyond the announcement date.

Overall, the findings indicate that payment method is a key determinant of how financial markets evaluate M&A transactions. The choice between cash and stock financing carries important short-term valuation implications, particularly in capital-intensive and volatile sectors such as energy, and is therefore a strategically relevant decision for both managers and investors.

KEYWORDS

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

RESUMEN

Este trabajo analiza cómo el método de pago en las operaciones de fusiones y adquisiciones influye en la reacción de los inversores, centrándose en transacciones financiadas en efectivo y mediante acciones en el sector energético estadounidense entre 2004 y 2024. Si bien la actividad de M&A desempeña un papel central en la estrategia corporativa, los mercados financieros suelen responder de forma diferente en función de cómo se financian las transacciones.

A partir de una muestra de adquisiciones completadas, el estudio examina el comportamiento del mercado bursátil en torno a las fechas de anuncio para evaluar si los inversores diferencian sistemáticamente entre estructuras de pago al incorporar nueva información a los precios. El análisis empírico combina un "event study" tradicional con un "event study" en panel, lo que permite evaluar tanto respuestas inmediatas como dinámicas del mercado.

Los resultados revelan una clara asimetría en las reacciones del mercado. Las adquisiciones financiadas en efectivo se asocian con respuestas neutras del mercado, sin rendimientos anormales estadísticamente significativos en torno al anuncio. En cambio, las adquisiciones financiadas mediante acciones generan rendimientos anormales negativos estadísticamente significativos para las empresas adquirentes, que persisten más allá de la fecha de anuncio.

En conjunto, los hallazgos indican que el método de pago es un determinante clave de cómo los mercados financieros valoran las operaciones de M&A. La elección entre financiación en efectivo y mediante acciones conlleva implicaciones relevantes para la valoración a corto plazo, especialmente en sectores intensivos en capital y volátiles como el energético, y constituye por tanto una decisión estratégicamente relevante tanto para directivos como para inversores.

PALABRAS CLAVE

Fusiones y Adquisiciones, Método de Pago, Financiación en Efectivo, Financiación mediante Acciones, Reacción del Mercado, Estudio de Eventos, Sector Energético de Estados Unidos

Table of Contents

Index of Figures

1. INTRODUCTION

1.1 Mergers and Acquisitions and Market Reactions

Mergers and acquisitions (M&A) are among the most significant strategic decisions undertaken by firms, allowing companies to grow, restructure, and adapt to changing competitive and technological environments. Beyond their long-term operational and strategic implications, M&A transactions are also closely scrutinized by financial markets, as investors rapidly reassess firm value in light of new information released at the time of the announcement. As a result, stock price reactions around M&A announcements have become a central focus of corporate finance research, offering insights into how markets interpret the expected consequences of these transactions.

One of the most consequential dimensions of an acquisition is the method of payment. Firms typically finance acquisitions using cash, stock, or a combination of both, and this choice affects not only the financial structure of the deal but also how it is perceived by investors. The method of payment can alter ownership structure, influence post-merger incentives, and shape expectations regarding risk, valuation, and managerial confidence. Importantly, payment structure may also function as a signal, conveying information about the acquiring firm's assessment of its own value and of the transaction itself.

A substantial body of academic literature suggests that markets respond differently to cash- and stock-financed acquisitions. Cash offers are often interpreted as a signal of confidence in the expected value of the deal, while stock-financed acquisitions may raise concerns related to dilution, overvaluation, or uncertainty. However, empirical evidence on acquiring firm returns remains mixed and highly context-dependent, varying across industries, time periods, and market conditions. This heterogeneity highlights the need for sector-specific analyses that account for the economic and structural characteristics shaping both M&A activity and investor behavior.

1.2 The U.S. Energy Sector as an Empirical Setting

The U.S. energy sector provides a particularly relevant setting in which to examine these issues. Over the past two decades, the sector has experienced profound transformation driven by technological innovation, commodity price volatility, regulatory change, and the global transition toward cleaner energy sources. Developments such as the shale revolution, periods of financial distress, and increasing ESG-related pressures have reshaped competitive dynamics and prompted waves of consolidation. As a result, M&A activity has played a central role in how energy firms adjust their asset portfolios, manage risk, and pursue strategic realignment.

These characteristics make the energy sector especially informative for analyzing the role of payment methods in M&A transactions. The capital-intensive nature of the industry, combined with cyclical cash flows and fluctuating valuations, places financing decisions at the core of acquisition strategy. Consequently, the choice between cash and stock may carry particularly strong informational content in this sector, influencing how investors interpret acquisition announcements under varying market conditions.

Against this backdrop, 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 between 2004 and 2024. By analyzing stock market behavior around M&A announcements, the study evaluates whether investors systematically differentiate between payment structures when incorporating new information into prices. The analysis draws on established empirical techniques to assess abnormal stock returns around announcement dates and to trace how market reactions evolve over time.

By focusing on payment method as a strategic and informational dimension of M&A activity, this dissertation seeks to contribute to a deeper understanding of how financial markets evaluate acquisition decisions. The findings aim to shed light on the role of financing choices in shaping investor perceptions and short-term valuation outcomes, offering insights that are relevant for corporate managers structuring M&A transactions as well as for investors interpreting acquisition announcements in a complex and evolving industry.

2. OBJECTIVE

The objective of this dissertation is to analyze how the choice of payment method in mergers and acquisitions influences investor reactions, with a particular focus on cash- and stock-financed transactions in the U.S. energy sector. Rather than treating payment structure as a purely technical financing decision, the study seeks to understand its role as a strategic element through which markets interpret the expected value, risk, and credibility of M&A transactions.

Payment method choice can convey relevant information about managerial expectations, firm valuation, and uncertainty surrounding an acquisition. This dissertation aims to assess whether financial markets systematically differentiate between cash- and stock-financed deals when incorporating M&A announcements into stock prices, and to what extent these differences are reflected in short-term valuation effects for acquiring firms.

The empirical analysis focuses on M&A transactions announced between 2004 and 2024, a period that encompasses multiple economic cycles and structural transformations in the U.S. energy industry, including the shale boom, periods of financial stress, the COVID-19 pandemic and the growing importance of the energy transition. This sector provides a particularly informative setting due to its capital intensity, exposure to commodity price volatility, and sustained levels of merger activity over time.

To address the research objective, the study evaluates stock market reactions around M&A announcements and compares the behavior of abnormal returns across different payment structures. By doing so, the dissertation aims to provide evidence on whether and how financing decisions in M&A transactions shape investor perceptions and market valuation.

Overall, the purpose of this thesis is to contribute to a better understanding of the strategic relevance of payment method choice in mergers and acquisitions, offering insights that are relevant both for corporate decision-makers involved in structuring transactions and for investors seeking to interpret the information conveyed by M&A announcements.

3. THEORETICAL FRAMEWORK

3.1 Mergers and Acquisitions: Concepts and Theoretical Foundations

3.1.1 Definition and Classification of Mergers and Acquisitions

Mergers and acquisitions (M&A) constitute one of the most significant strategic tools available to firms seeking to expand, restructure, or adapt to changing market conditions. Although often used interchangeably, the terms merger and acquisition have distinct legal and economic meanings. A merger typically refers to the combination of two companies into a single new entity, often through mutual agreement and with the aim of creating synergies or enhancing competitive advantage (DePamphilis, 2018). An acquisition, by contrast, involves one company purchasing a controlling stake in another, whereby the acquired firm may retain its legal identity as a subsidiary or be fully integrated into the acquiring entity (Gaughan, 2017). In practice, acquisitions are far more common than true mergers, though the term "mergers and acquisitions" is used broadly to describe the full range of corporate combination activities (Bruner, 2016).

M&A transactions can be classified according to several criteria, the most common being the nature of the relationship between the acquiring and target firms. A horizontal merger occurs when companies operating in the same industry and at the same stage of production combine, often with the objective of increasing market share or achieving economies of scale (Trautwein, 1990). A vertical merger involves firms operating at different stages of the value chain, such as a manufacturer acquiring a key supplier or distributor, which may lead to greater operational efficiency and reduced transaction costs (Gaughan, 2017). Finally, a conglomerate merger refers to the combination of firms from unrelated industries, typically motivated by diversification objectives or the pursuit of financial synergies (Bruner, 2016).

Another widely used classification concerns the degree of cooperation between the parties involved. In friendly takeovers, both the acquiring and target companies agree on the terms of the transaction and collaborate throughout the process. In contrast, hostile takeovers occur when the target firm's management opposes the acquisition, prompting the bidder to appeal directly to shareholders, often through a tender offer (DePamphilis, 2018). While hostile transactions represent a minority of deals, they attract considerable attention due to their complexity and potential governance implications.

M&A transactions can also be distinguished by their legal and structural form, which influences the post-deal integration process and governance outcomes. The most common forms include statutory mergers, in which one company absorbs another and assumes all its assets and liabilities; consolidations, where both firms dissolve to create a new entity; and tender offers, where the acquiring company offers to purchase shares directly from the target's shareholders (Gaughan, 2017). Each structure entails different regulatory, tax, and strategic considerations, shaping both the execution of the deal and its impact on shareholder value.

3.1.2 Strategic Motives Behind M&A Activity

Understanding the strategic motives behind mergers and acquisitions is essential to interpreting their market implications. One of the most widely cited explanations is the synergy hypothesis, which suggests that M&A create value by generating combined cash flows that exceed the sum of the standalone firms (Sirower, 1998). Synergies can be operational, arising from economies of scale, scope, or improved efficiency, financial, such as enhanced debt capacity or tax benefits, and managerial, including improved governance or superior management practices (Gaughan, 2017).

A second major driver is the pursuit of market power and competitive advantage. Horizontal mergers, in particular, allow firms to expand market share, reduce competition, and increase pricing power (Porter, 1998). Related to this is the motive of strategic diversification, where acquisitions enable firms to enter new product lines or geographic markets, reducing exposure to industry-specific risks (Bruner, 2016).

From a resource-based perspective, M&A serve as a mechanism to acquire strategic assets and capabilities that are difficult to develop internally, such as technology, intellectual property, or specialized human capital (Barney, 1991). In dynamic industries, acquisitions can also facilitate strategic realignment, allowing firms to adapt to regulatory shifts, technological disruptions, or energy transitions (Capron & Mitchell, 2012).

Finally, firms also may pursue acquisitions for financial restructuring or tax optimization, such as using accumulated losses of the target or redeploying free cash flows to avoid agency costs (Jensen, 1986). While these motives are not mutually exclusive, their relative importance varies across sectors, deal types, and market conditions. Together, they demonstrate the multifaceted rationale for M&A activity, shaping how investors interpret such transactions and anticipate their value implications.

3.1.3 Financial and Behavioural Theories of M&A

While strategic motives explain much of the rationale behind mergers and acquisitions, financial and behavioural theories provide additional insights into why firms engage in these transactions and why outcomes vary significantly across deals. A central explanation is offered by agency theory, which argues that managers may pursue acquisitions not solely to maximise shareholder value but to further their own interests, such as increasing their power, compensation, or job security (Jensen & Meckling, 1976). Such "empire-building" behaviour can lead to acquisitions that destroy shareholder value, particularly when managerial incentives are misaligned with those of investors.

Another influential framework is the market timing theory, which suggests that managers exploit periods when their firm's equity is overvalued to finance acquisitions using stock, thereby minimising the effective cost of the transaction (Shleifer & Vishny, 2003). This perspective implies that payment method choice is not purely a financial consideration but also reflects managerial beliefs about market conditions and firm valuation. Relatedly, information asymmetry plays a key role: managers typically have better information about their firm's intrinsic value than external investors, and their financing choices convey signals about that information (Myers & Majluf, 1984).

Behavioural explanations further expand the analysis. The hubris hypothesis (Roll, 1986) posits that managers often overestimate their ability to generate value from acquisitions, leading them to overpay for targets even when deals lack economic justification. Moreover, investor sentiment can influence both the timing and outcomes of M&A, as optimistic markets may reward acquisitions regardless of their fundamentals, while pessimistic markets may undervalue them (Baker et al., 2004).

3.1.4 Value Creation vs. Value Destruction: Empirical Evidence

The question of whether mergers and acquisitions create shareholder value has been one of the most extensively debated topics in corporate finance. A large body of empirical literature shows that, on average, target shareholders experience significant positive abnormal returns around the announcement date, often ranging between 20% and 30% (Andrade et al., 2001; Betton et al., 2007). These gains are generally attributed to acquisition premiums paid by bidders and reflect the market's expectation of value transfer from acquirers to targets.

The evidence for acquiring shareholders, however, is more mixed. Numerous studies report that acquirers earn returns close to zero or slightly negative around the announcement date (Bruner, 2002; Moeller et al., 2005). Several factors have been proposed to explain this outcome, including overpayment for targets, integration challenges, agency-driven acquisitions, and the dilution effects associated with stock-financed deals. These findings highlight that while M&A activity often redistributes value, it does not guarantee net wealth creation for the acquiring firm's shareholders.

The long-term performance of acquirers is even more contested. Some studies document positive abnormal returns over extended periods, particularly in deals driven by strategic fit or strong post-merger integration (Healy et al., 1992). Others, however, find evidence of value destruction in the years following acquisitions, especially in large, diversifying, or empire-building deals (Agrawal et al., 1992; Gregory & McCorriston, 2005). This divergence underscores the complexity of M&A outcomes and the importance of deal-specific and contextual factors.

3.2 Payment Methods in M&A Transactions

3.2.1 Overview of Payment Methods in M&A

The structure of payment is a central element of any merger or acquisition, shaping both the financial and strategic outcomes of the transaction. The two dominant payment methods are cash and stock (or share exchange), although hybrid deals that combine elements of both are also common (Gaughan, 2017). In a cash transaction, the acquirer pays the target's shareholders an amount of cash in exchange for their shares, resulting in an immediate transfer of ownership and no dilution of existing shareholders. In contrast, a stock transaction involves the exchange of the acquirer's shares for those of the target, thereby altering the ownership structure and aligning the future interests of both parties (Bruner, 2016).

The choice of payment method has implications beyond the mechanics of the transaction. It influences post-merger integration dynamics, capital structure, tax treatment, and shareholder control (DePamphilis, 2018). Empirically, cash deals have historically been more prevalent in transactions involving smaller targets or strong acquirers with substantial liquidity, while stock-financed acquisitions tend to dominate during periods of high market valuations and when strategic alignment between acquirer and target is prioritized (Faccio & Masulis, 2005).

3.2.2 Theoretical Foundations: Signalling, Asymmetry, and Managerial Intentions

The choice of payment method in mergers and acquisitions is not merely a financial decision but also a strategic signal that conveys information to the market about managerial expectations, firm valuation, and confidence. Central to this idea is signaling theory, which suggests that managers, possessing superior information about the true value and prospects of their firm, use payment decisions to communicate this information to investors (Myers & Majluf, 1984). When acquirers opt for cash financing, it is often interpreted as a signal of managerial confidence in the firm's intrinsic value and future performance, since managers would be reluctant to use internal funds or incur debt if they believed the acquisition would destroy value (Travlos, 1987).

Conversely, stock-financed acquisitions can signal potential overvaluation of the acquirer's equity. Managers who perceive their firm's shares as overpriced may prefer to use them as currency for acquisitions, thereby transferring part of the overvaluation risk to the target's shareholders (Shleifer & Vishny, 2003). This dynamic reflects the broader problem of information asymmetry between managers and investors, where financing choices provide indirect cues about private managerial assessments of firm value and deal quality (Fuller et al., 2002).

Agency theory also offers important insights into payment decisions. According to Jensen's (1986) free cash flow hypothesis, managers of firms with excess cash may be incentivized to undertake acquisitions even when value creation is uncertain, using cash resources to expand their influence or pursue personal goals. Similarly, the market timing theory suggests that managers exploit periods of equity overvaluation to finance acquisitions with stock, reducing financing costs but potentially diluting existing shareholders (Shleifer & Vishny, 2003). Together, these theories highlight that payment method decisions reflect not only financial constraints but also managerial intentions and private information, shaping how investors interpret and react to M&A announcements.

3.2.3 Implications of Payment Method for Market Reaction

The choice of payment method in M&A transactions carries significant implications for how investors interpret the deal and, consequently, how stock prices react around the announcement date. A substantial body of empirical research shows that cash-financed acquisitions tend to be associated with neutral or modestly positive short-term abnormal returns for acquiring firms, and consistently outperform stock-financed deals in relative terms (Travlos, 1987; Andrade et al., 2001). This pattern is consistent with signaling theory: cash offers are perceived as signals of managerial confidence in the expected synergies and future cash flows of the combined firm. Moreover, cash payments avoid share dilution, which is often viewed unfavorably by existing shareholders (Moeller et al., 2005).

In contrast, stock-financed acquisitions frequently generate weaker or negative announcement reactions. Investors may interpret the issuance of new equity as a signal that managers believe the firm's shares are overvalued (Myers & Majluf, 1984; Shleifer & Vishny, 2003). Stock deals also transfer part of the acquisition risk to target shareholders, which may be perceived as managerial caution or uncertainty about deal quality (Fuller et al., 2002). Additionally, the potential dilution of ownership and earnings per share can further dampen market enthusiasm.

These differences highlight that payment method choice functions not only as a financial mechanism but also as an informational signal. The market's interpretation of that signal influences short-term abnormal returns and plays a central role in understanding investor reactions to M&A announcements, particularly within sectors characterized by volatility and structural change, such as the U.S. energy industry.

3.2.4 Determinants of Payment Method Choice

The decision between cash and stock financing in M&A transactions is influenced by a range of firm-specific, deal-specific, and market-related factors. Among firm-level characteristics, liquidity and leverage play a central role: companies with substantial cash reserves or strong borrowing capacity are more likely to finance acquisitions with cash (Faccio & Masulis, 2005). Conversely, firms with limited internal funds or high leverage may prefer stock financing to avoid additional debt or liquidity constraints (Martin, 1996). Growth opportunities and valuation levels also matter, as firms with overvalued equity often choose to issue shares as an acquisition currency (Shleifer & Vishny, 2003).

Deal-specific features significantly shape payment decisions as well. Larger deals relative to the acquirer's size tend to involve stock financing to preserve financial flexibility (Officer, 2007). The nature of the target also matters: acquisitions of private firms or subsidiaries are more likely to be paid in cash, while public targets often involve stock consideration to align ownership interests (Faccio & Masulis, 2005).

Finally, macroeconomic and market conditions affect payment choices. Periods of high equity valuations or low interest rates encourage stock-financed transactions, whereas tighter credit markets increase reliance on cash or mixed payments (Harford et al., 2009).

3.2.5 Empirical Evidence from Prior Research

A substantial body of empirical research has examined how payment methods influence shareholder wealth around M&A announcements, showing that cash-financed deals tend to outperform stock-financed ones in relative terms, although the absolute abnormal returns for acquiring firms are often neutral or modest in magnitude. Travlos (1987) first documented this pattern in U.S. data, attributing it to the signaling effects of cash offers and the negative market interpretation of stock issuance. Subsequent studies have confirmed that stock-financed acquisitions are more likely to be associated with adverse market reactions, while cash payments are generally linked to more favorable or less negative announcement outcomes (Andrade et al., 2001; Bruner, 2002; Moeller et al., 2005).

Empirical evidence also reveals considerable heterogeneity in these effects depending on deal characteristics and market conditions. For example, Fuller et al. (2002) find that acquirers making multiple acquisitions tend to experience relatively better announcement returns when using cash, while stock offers are more sensitive to valuation levels and investor sentiment. Faccio and Masulis (2005) report that transactions involving private targets exhibit less pronounced differences between payment methods, suggesting that target type moderates market reactions.

3.3 Evolution of M&A Activity: Historical Perspective

3.3.1 M&A Waves and Historical Evolution

Mergers and acquisitions have historically occurred in distinct cyclical patterns known as M&A waves, periods marked by heightened deal activity followed by sharp declines. These waves are closely linked to macroeconomic conditions, regulatory changes, technological innovation, and financial market dynamics, reflecting broader shifts in the corporate and economic environment (Gaughan, 2017).

The first wave (1890s–1904) was driven by industrial consolidation in the United States, as firms sought economies of scale and market dominance in sectors such as steel, oil, and railroads (Nelson, 1959). The second wave (1916–1929) was characterised by vertical integration and the expansion of large corporations into supply chains, supported by improved capital markets. Following the Great Depression, the third wave (1960s) focused on conglomerate mergers, as firms pursued diversification strategies to mitigate risk and stabilise earnings (Weston & Mansinghka, 1971).

The fourth wave (1980s) saw the rise of hostile takeovers and leveraged buyouts, enabled by financial innovations such as junk bonds and deregulation of capital markets (Andrade et al., 2001). The fifth wave (1990s) shifted toward strategic and cross-border mergers, fuelled by globalisation, technological change, and shareholder value orientation (Martynova & Renneboog, 2008). Finally, the sixth wave (2003–present) reflects a more complex landscape, combining strategic consolidation, technology-driven deals, and increased private equity involvement, while also emphasising corporate governance, regulatory compliance, and ESG considerations (DePamphilis, 2021).

These historical patterns reveal several common features: waves tend to occur during periods of economic expansion, are supported by favourable financing conditions, and often coincide with structural shifts such as deregulation or technological disruption (Harford, 2005). They also tend to end abruptly with financial crises or market corrections. Understanding this cyclical nature is crucial, as it shapes not only the volume and type of M&A activity but also the financing decisions and market perceptions associated with them. These dynamics form the backdrop for analysing how payment methods influence market reactions in specific sectors and time periods.

3.3.2 Trends in Payment Methods Over Time

The prevalence of different payment methods in M&A transactions has evolved significantly over time, closely reflecting changes in financial markets, corporate strategies, and macroeconomic conditions. During early merger waves, particularly in the late 19th and early 20th centuries, cash was the dominant form of payment, reflecting limited development of equity markets and the reliance on internal financing and bank loans (Gaughan, 2017). As capital markets matured and equity issuance became more accessible, the use of stock financing increased, particularly during periods of high market valuations when firms could leverage elevated share prices as acquisition currency (Shleifer & Vishny, 2003).

Empirical evidence shows that payment method patterns often correlate with broader market cycles. For instance, stock-financed transactions were particularly prevalent during the conglomerate merger wave of the 1960s and the technology boom of the late 1990s, while cash-financed deals dominated during periods of tighter credit or undervalued equity markets (Faccio & Masulis, 2005; Harford, 2005). Hybrid structures combining cash and stock have also become more common, reflecting a balance between ownership alignment and financial flexibility. These historical trends underscore that payment method choice is dynamic and context-dependent, shaped by evolving corporate strategies and capital market conditions.

3.3.3 Evolution of M&A in the U.S. Energy Sector (2004–2024)

The U.S. energy sector has experienced substantial structural change over the past two decades, making it a particularly dynamic environment for merger and acquisition activity. Between 2004 and 2024, fluctuations in deal volume and deal value have closely followed shifts in technology, commodity prices, financial conditions, and regulatory and policy developments, resulting in recurring waves of consolidation and portfolio reallocation across the industry.

These cyclical patterns in M&A activity are consistent with the evolution of deal value and deal volume observed in the global energy industry over time, as illustrated in Figure 1.

The mid-2000s marked the start of the shale revolution, supported by advances in hydraulic fracturing and horizontal drilling that significantly increased domestic oil and gas production and reshaped global energy market dynamics (Kerr, 2010). This shift contributed to intensified deal activity as firms pursued acquisitions to secure high-quality acreage, expand reserves, and achieve greater operating scale, particularly in the years leading up to the mid-2010s.

The global financial crisis in 2008 temporarily reduced M&A activity, largely due to tighter credit conditions and increased uncertainty. As markets stabilized, transactions resumed with a stronger emphasis on balance sheet strength, cost discipline, and strategic portfolio optimization. Later, the sharp decline in oil prices starting in 2014 triggered another consolidation phase, as financially weaker firms faced greater pressure and larger players sought to streamline asset footprints, acquire distressed or high-quality resources, and improve capital efficiency.

From the late 2010s onward, the energy transition and the increasing relevance of environmental, social, and governance (ESG) considerations began to shape strategic priorities more directly. Alongside continued consolidation in traditional segments, M&A activity also reflected efforts to reposition portfolios toward lower-carbon technologies, including renewables and carbon management solutions, consistent with broader decarbonization trends (IEA, 2023). The COVID-19 shock in 2020 reinforced restructuring pressures, and subsequent policy initiatives, including the Inflation Reduction Act of 2022, further supported investment in clean energy and related corporate activity.

Across this period, financing conditions and valuation cycles also influenced the preferred method of payment in M&A transactions. Periods of strong cash generation tended to support a greater use of cash-financed acquisitions, whereas phases characterized by strong equity valuations made stock a more attractive acquisition currency. Overall, the U.S. energy sector's combination of cyclical volatility, technological disruption, and policy-driven change provides a particularly rich setting to examine how payment method choices shape market reactions over time.

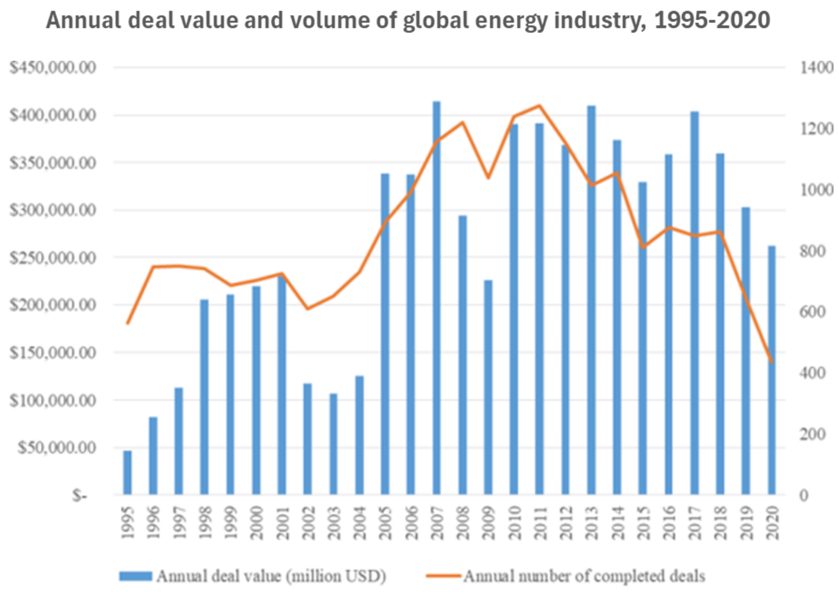

Figure 1 *- Annual deal value and volume of global energy industry, 1995-2020. (Source: Andriuškevičius & Štreimikienė, 2021)*

3.4 Structural Characteristics of the U.S. Energy Sector

3.4.1 Overview and Economic Importance of the Sector

The energy sector is one of the most strategically important components of the U.S. economy, underpinning industrial activity, transportation, and national security. It encompasses a diverse range of subsectors, including upstream exploration and production (E&P), midstream transportation and storage, downstream refining and distribution, and an increasingly prominent renewable energy segment (U.S. Department of Energy [DOE], 2023). Together, these activities account for a significant share of U.S. economic activity, representing 5.7% of U.S. gross domestic product in 2023 (Center for Sustainable Systems, University of Michigan, 2025).

Historically, the United States has been a global leader in energy production and consumption, maintaining one of the world's most integrated and competitive energy markets. The country's rise as a net exporter of energy since 2019 reflects the transformative impact of technological advances such as hydraulic fracturing, which dramatically increased domestic oil and gas output (IEA, 2023). The sector's capital intensity and reliance on long-term investments have made it a central player in U.S. financial markets, with energy companies representing a significant portion of equity and bond indices.

Beyond its economic weight, the energy industry holds profound geopolitical and environmental significance. U.S. energy independence has altered global trade flows and reduced vulnerability to supply disruptions, while the transition toward cleaner energy sources has positioned the sector at the forefront of the sustainability debate. The combination of strategic importance, exposure to macroeconomic cycles, and rapid technological change has made the U.S. energy sector a fertile ground for corporate restructuring and M&A activity. Understanding these dynamics is essential to contextualize how financial decisions, such as payment method choice, are interpreted by investors.

3.4.2 Market Structure, Technological Change, and Competitive Dynamics

The U.S. energy sector is characterized by a highly capital-intensive and cyclical market structure, in which profitability and investment decisions are closely linked to commodity price movements. Barriers to entry are substantial due to the need for specialized technologies, large-scale infrastructure, and compliance with complex regulatory requirements. As a result, the industry exhibits oligopolistic characteristics, with a limited number of large, vertically integrated firms, such as ExxonMobil, Chevron, and ConocoPhillips, playing a dominant role across exploration, production, and refining activities (IEA, 2023). Alongside these major players, a diverse set of independent exploration and production companies, midstream operators, and other specialized firms contribute to competition and flexibility across different segments of the value chain.

A defining transformation within the sector has been the shale revolution, driven by the adoption of hydraulic fracturing and horizontal drilling technologies in the early 2000s. These technological advances significantly expanded U.S. production capacity, lowered marginal extraction costs, and enabled access to previously uneconomic reserves (Kerr, 2010). The resulting increase in output reshaped global energy markets and altered competitive dynamics within the industry. In particular, smaller and more agile producers were able to scale operations more rapidly, challenging established incumbents and contributing to increased merger and acquisition activity as firms pursued economies of scale and operational efficiency.

These long-term structural changes are also reflected in the evolution of the U.S. electricity generation mix, which shows a sustained decline in coal alongside the rise of natural gas and renewable energy sources over the past two decades, as illustrated in Figure 2.

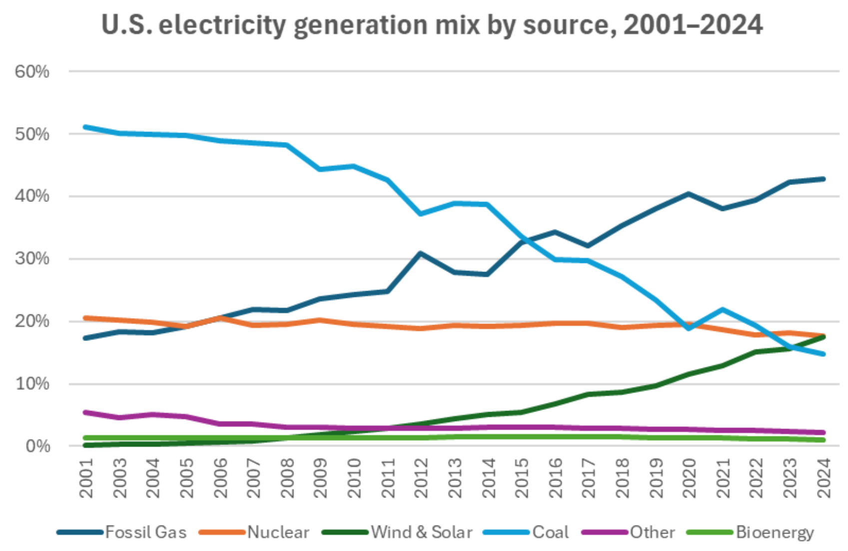

Figure 2 *- U.S. electricity generation mix by source, 2001–2024 (Source: Klein, 2024)*

Competitive behavior in the energy sector is further shaped by pronounced cyclical patterns. Periods of elevated commodity prices tend to encourage investment and acquisition activity as firms seek to expand reserves and production capacity. In contrast, market downturns are often associated with cost-cutting, asset divestitures, and consolidation, as companies adjust balance sheets and reallocate capital in response to declining prices and tighter financial conditions. These cyclical dynamics reinforce the role of mergers and acquisitions as a strategic mechanism through which firms adapt to changing market environments.

Finally, the increasing integration of digital technologies and data-driven tools has enhanced operational efficiency and decision-making across the sector. Advances in seismic imaging, predictive maintenance, and real-time production monitoring have improved cost control, asset utilization, and risk management, strengthening firms' competitive positions and further shaping industry structure.

3.4.3 Financial Characteristics, Investment Cycles, and M&A Behaviour

The financial structure of firms operating in the U.S. energy sector is heavily shaped by capital intensity, pronounced price volatility, and long investment horizons. Activities such as exploration, production, and infrastructure development require substantial upfront capital commitments, while expected returns are uncertain and closely tied to fluctuations in commodity prices. As a result, firms typically rely on a combination of internal cash flows, external debt financing, and asset sales, generating cyclical patterns in leverage, liquidity, and financial flexibility across the industry (IEA, 2023). Periods of high commodity prices and strong cash generation often allow firms to strengthen balance sheets and rebuild liquidity buffers, whereas downturns tend to prompt balance sheet adjustments, portfolio rebalancing, and consolidation efforts aimed at restoring financial stability.

These financial cycles have direct implications for merger and acquisition behavior. During expansionary phases, acquisitions are frequently driven by growth objectives and reserve accumulation, and are more likely to be financed with cash or debt given favorable liquidity conditions and strong firm valuations. In contrast, during periods of weaker cash flows or tighter credit conditions, firms may rely more heavily on equity financing in order to preserve liquidity, limit leverage, or maintain financial flexibility (Alexandridis et al., 2010). This variation in financing choices illustrates how payment method decisions reflect both managerial expectations and prevailing market conditions.

The volatility of operating cash flows further increases the sector's sensitivity to capital market dynamics. Access to external financing fluctuates with commodity price cycles, investor risk appetite, and broader monetary conditions, while the large scale of many energy-related transactions makes financing constraints particularly salient. In this context, mergers and acquisitions serve not only as a vehicle for growth but also as an important financial adjustment mechanism, enabling firms to restructure balance sheets, achieve economies of scale, and enhance resilience in a highly uncertain environment. These characteristics provide a compelling setting for examining how payment method choices convey information to investors and influence market reactions within the energy sector.

3.4.4 Implications for the Present Study

The structural and financial characteristics of the U.S. energy sector make it an ideal setting to examine how payment methods influence market reactions to M&A announcements. The industry's cyclicality, capital intensity, and exposure to commodity price volatility generate distinct financing behaviours that directly affect firms' choice between cash and stock. Moreover, the period 2004–2024 captures multiple structural transitions, such as the shale boom, the oil price collapse, and the energy transition, offering a unique opportunity to analyse how investors interpret these financing signals under varying market conditions. By applying both traditional and panel event study methodologies, this study aims to provide robust empirical evidence on how payment structure choices convey managerial expectations and shape investor valuation within one of the most strategically significant sectors of the U.S. economy.

4. METHODOLOGY

4.1 Event Study Methodology and Panel Event Studies

4.1.1 Event Studies: Definition, Purpose, and Theoretical Foundations

An event study is an empirical methodology used to measure how financial markets react to new information. By analyzing changes in stock prices around the announcement of a specific event, researchers can infer how investors perceive its expected impact on firm value (MacKinlay, 1997). The fundamental premise of this approach is grounded in the Efficient Market Hypothesis (EMH), which posits that asset prices incorporate all available information (Fama, 1970). Under the semi-strong form of market efficiency, any new information, such as a merger or acquisition announcement, should be rapidly reflected in stock prices, allowing the event study to isolate the market's immediate reaction.

The purpose of event studies is twofold. First, they allow researchers to test informational efficiency by evaluating how quickly and accurately markets assimilate new information. Second, they provide a quantitative framework to assess the value implications of corporate decisions or external shocks (Brown & Warner, 1985). In the context of M&A, stock price movements around announcement dates reveal investors' collective expectations about the potential synergies, risks, and strategic rationale behind a transaction.

Over time, event studies have become one of the most widely applied tools in empirical finance due to their conceptual simplicity, versatility, and interpretability. They serve as a powerful bridge between financial theory and market behavior, offering insights into how investors respond to managerial decisions and corporate events in real time.

4.1.2 Traditional Event Study: Concepts and Implementation

The traditional event study methodology provides a systematic framework to quantify the impact of a specific event on the market value of a firm. The process involves comparing a firm's actual stock returns during the event period with the returns that would have been expected had the event not occurred (MacKinlay, 1997). The difference between these two measures represents the abnormal return (AR), the market's reaction to new information.

The event date ($t = 0$) corresponds to the public announcement of the event, in this case, a merger or acquisition. To capture potential information leakage or delayed reactions, researchers define an event window, typically ranging from a few days before to a few days after the announcement (for example, [–1, +1], [–3, +3], or [–10, +10]). Surrounding the event window is an estimation window, a longer pre-event period (often 120–250 trading days) used to model normal returns and establish a performance benchmark.

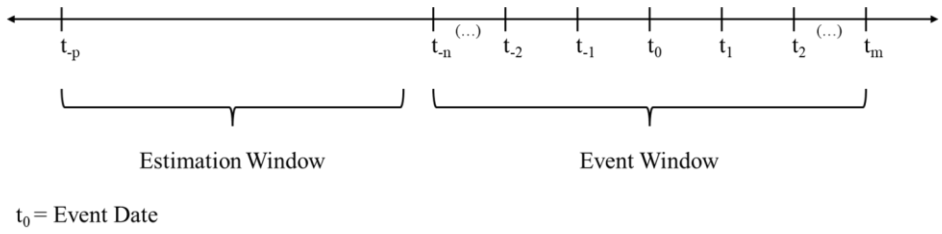

Figure 3 *- The Timeline of an Event Study (Source: Author's own elaboration)*

The expected or "normal" return of firm *i* at time *t* is generally estimated using one of several models:

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

where $R_{i,t}$ is the return of firm *i*, $R_{m,t}$ is the return on the market index, and α_i and β_i are firm-specific parameters estimated through ordinary least squares. This market model is the most widely used specification, as it controls for general market movements and firm-specific sensitivity (Brown & Warner, 1985). Simpler alternatives include the mean-adjusted model, which assumes constant expected returns, and the market-adjusted model, which assumes $\alpha_i = 0$ and $\beta_i = 1$.

The abnormal return (AR) for firm *i* on day *t* is calculated as:

$$AR_{i,t} = R_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i R_{m,t})$$

Cumulative abnormal returns (CAR) aggregate these effects over the event window:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t}$$

To account for differences in return volatility across firms and improve comparability, abnormal returns can also be standardized using the estimated standard deviation of abnormal returns from the estimation window. This yields standardized abnormal returns (SAAR) and standardized cumulative average abnormal returns (SCAAR), which adjust for heteroscedasticity and facilitate more reliable statistical inference, particularly when firms exhibit heterogeneous risk profiles.

The standardized abnormal return (SAAR) for firm i on day t is defined as:

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

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

Standardized cumulative average abnormal returns (SCAAR) are then obtained by aggregating standardized abnormal returns across firms and over the event window:

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

Statistical significance is typically assessed using t-tests based on cross-sectional averages of abnormal or cumulative abnormal returns across firms. To account for heteroscedasticity and event-induced variance, adjusted test statistics such as those proposed by Boehmer et al. (1991) are often employed.

4.1.3 Panel Event Studies: A Dynamic Extension of the Framework

While traditional event studies provide valuable insights into short-term market reactions, they face several methodological limitations when events are numerous, overlapping, or distributed over time. The panel event study (PES) framework extends the traditional model by incorporating both time-series and cross-sectional dimensions, allowing for a more dynamic and comprehensive analysis of how markets respond to events (Clarke & Schythe, 2021).

In a panel event study, the outcome variable, typically firm-level returns, is regressed on a series of event-time dummies that capture the temporal distance between each observation and the event date. This enables researchers to estimate the effect of the event at different points in time, both before and after the announcement, effectively modelling leads and lags. The general structure 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 $AR_{i,t}$ denotes the abnormal return of firm $i$on day t. The variables $Lag_{j,t}$ and $Lead_{k,t}$ are event-time indicator variables that equal one when a firm is observed $j$periods before or $k$periods after the event, respectively. Accordingly, the coefficients β_j and γ_k capture the time pattern of abnormal returns surrounding the event, making it possible to examine both pre-event dynamics (such as parallel trends or anticipation effects) and post-event responses. $X_{i,t}$ represents a set of control variables, $\mu_i$denote firm fixed effects, λ_t indicate time fixed effects, and $\varepsilon_{i,t}$ is the disturbance term.

Importantly, this panel event study specification can be interpreted within a difference-in-differences (DiD) framework. Firms that experience the event constitute the treated group, while firms that do not are used as a comparison group. Identification is achieved by comparing changes in abnormal returns for treated firms around the event to contemporaneous changes observed for control firms, thereby netting out common market-wide or time-specific shocks (Angrist & Pischke, 2009). This structure improves causal interpretation by isolating the component of stock price movements attributable to the event itself rather than to broader trend.

In this thesis, combining both approaches strengthens the empirical analysis: the traditional event study captures immediate market reactions through abnormal returns around announcement dates, while the panel event study provides a richer temporal perspective, tracing how investor responses evolve before and after M&A announcements. This dual methodology ensures robustness and allows for a deeper understanding of how payment method choices influence market valuation dynamics over time.

4.1.4 Limitations and Complementarities of Event Study Approaches

Event studies face several methodological challenges. A fundamental one is the joint hypothesis problem: tests of abnormal returns simultaneously test market efficiency and the chosen expected-return model, so rejections (or non-rejections) cannot be uniquely attributed to mispricing or to model misspecification (Fama, 1970; Fama, 1991; MacKinlay, 1997). This identification issue persists even with refined factor models and is particularly salient in crisis periods or sectoral samples.

Traditional designs are also vulnerable to event clustering, cross-sectional dependence, and event-induced variance, which can bias test statistics if not addressed (Campbell et al., 1996). Their static windowing limits detection of anticipatory or delayed market reactions.

Panel event studies mitigate some issues by exploiting time and cross-section variation, modeling leads and lags, and accommodating staggered events. Yet they introduce their own risks, including higher data demands, sensitivity to fixed-effects structure, potential functional-form misspecification, and exposure to the same joint-hypothesis critique when mapping residuals to "abnormal" performance.

Given these trade-offs, combining both approaches is advantageous. The traditional event study pinpoints immediate abnormal returns with transparent assumptions, while the panel framework traces dynamic adjustment paths and improves robustness to clustering. Using them jointly strengthens inference while remaining transparent about identification limits imposed by the joint hypothesis problem.

4.2 Data Sources

The empirical methodology employed in this dissertation is based on two primary data sources: detailed information on mergers and acquisitions obtained from FactSet, and financial market data sourced from Bloomberg. This section outlines the origin of the data and explains the selection and filtering criteria used to construct the final sample of M&A transactions analysed in the study.

4.2.1 M&A Transaction Data

Information on mergers and acquisitions was retrieved using the FactSet M&A Screening platform, which offers standardized and comprehensive coverage of corporate transactions at a global level. The initial dataset included all M&A announcements recorded between 1 January 2004 and 31 December 2024. This time frame was selected to encompass several distinct phases of activity in the U.S. energy sector, including periods of heightened commodity price volatility, industry consolidation, and the progressive shift toward cleaner energy sources.

To ensure the relevance and reliability of the sample, a set of screening criteria was applied, as illustrated in Figure 4. First, only transactions resulting in completed mergers or acquisitions involving the transfer of a controlling interest were retained, thereby excluding minority stakes and other non-control investments. Transactions that were cancelled, withdrawn, or merely rumoured were removed to focus exclusively on finalized deals with clear informational content for financial markets. Furthermore, a minimum deal value threshold of $500 million was imposed in order to concentrate on transactions of sufficient economic magnitude to plausibly trigger observable stock market reactions.

Additional restrictions were applied at the firm level. Both the acquiring company and the target firm were required to be domiciled in the United States and classified within the energy sector according to FactSet's industry taxonomy. Moreover, only transactions in which the acquiring firm was publicly listed at the time of the announcement were included, ensuring the availability of reliable stock price data for the event study analysis.

Finally, transactions were categorized according to their method of payment. Only acquisitions financed entirely with cash or entirely with stock were retained in the final dataset. Deals involving mixed forms of consideration were excluded to preserve a clear and transparent comparison between payment methods. After all filters were applied, the resulting sample comprised 135 cash-financed transactions and 96 stock-financed transactions.

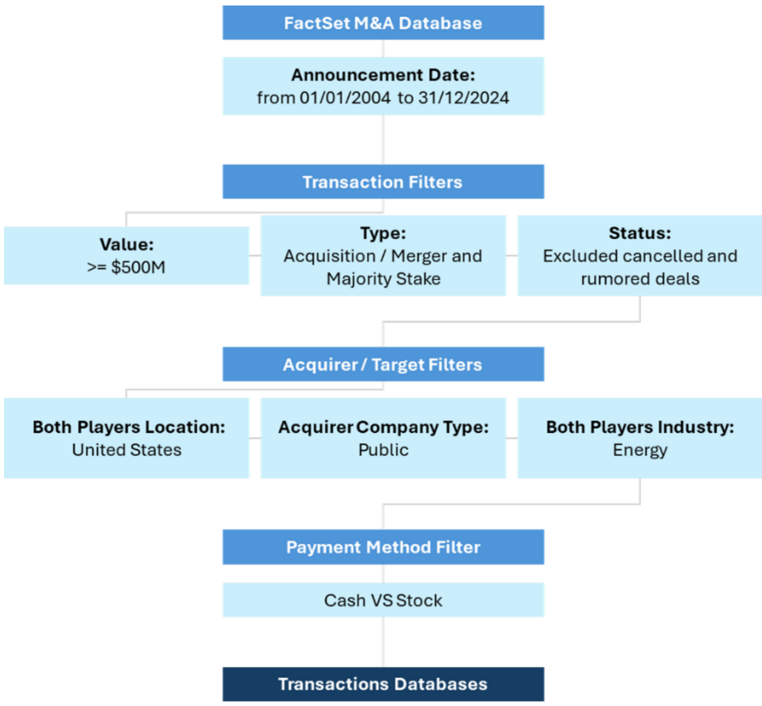

***Figure 4** – Filtering of M&A Transaction Data (Source:* Author's own elaboration*)*

4.2.2 Stock Price and Market Data

Daily stock price information for each acquiring firm was collected using the Bloomberg Excel Add-In. For every firm in the sample, adjusted closing prices were obtained for the period spanning 2004 to 2024, covering both the estimation window and the event window required for the empirical analysis. All price series were adjusted for corporate actions such as dividends and stock splits to ensure consistency and accuracy in return calculations.

In order to account for general market movements and isolate firm-specific performance, daily price data for a sector-representative benchmark index were also collected. The S&P Energy Select Sector Index (IXE) was selected as the market proxy, as it closely tracks the performance of major U.S. energy companies and constitutes an appropriate reference for sector-adjusted expected return estimation.

4.3 Sample Definition and Data Processing

After collecting the transaction-level information and stock price data, both datasets were systematically organized and processed to ensure internal consistency, methodological transparency, and full replicability of the empirical analysis.

As a first step, the data were segmented according to the method of payment. Two parallel data pipelines were established: one corresponding to acquisitions financed entirely with cash and another for transactions financed entirely with stock.

Within each payment category, the raw information was structured into three separate datasets:

1. A transaction dataset containing details related to M&A announcements.
2. A price dataset including daily stock price observations for acquiring firms.
3. A manually constructed matching dataset linking the names of acquiring firms in the transaction data to their corresponding stock market tickers used in the price data.

This matching dataset plays a central role in the empirical workflow, as it provides the unique identifier required to merge transaction-level information with firm-level price data and to construct a unified event-time panel in the subsequent Python-based analysis.

4.3.1 Preparation of M&A Transaction Data

Within the transaction datasets, all variables not directly required for the event study were removed. Only two key variables were retained for each observation:

- The M&A announcement date, labeled *EventDate*, which serves as the anchor point for all event-time calculations.
- The name of the acquiring firm, labeled *Name*, which is used to identify the firm and link the transaction to the corresponding stock price series.

During the data preparation stage, a limited number of transactions were identified as unsuitable for inclusion in the event study. In particular, some deals involved multiple acquirers where the primary acquirer was not publicly listed, despite the presence of at least one publicly traded co-acquirer. In such cases, the observed stock price movement of the listed firm could not be interpreted as a clean market reaction to the acquisition announcement, given that strategic control rested with a non-listed entity.

To maintain the interpretability and internal validity of the analysis, these observations were excluded from the sample. Specifically, 8 cash-financed transactions and 1 stock-financed transaction were removed on this basis. Following this additional filtering step, the final dataset comprised 127 cash-financed acquisitions and 95 stock-financed acquisitions, all involving a publicly listed lead acquirer with clearly identifiable market data.

4.3.2 Preparation of Stock Price and Market Data

The stock price datasets obtained from Bloomberg were cleaned and reduced to the variables strictly necessary for return calculation. All extraneous fields were removed, and only the following variables were retained:

- *Date*, indicating the trading day.
- *Ticker*, identifying the acquiring firm.
- *Price*, corresponding to the adjusted closing stock price.

To enable efficient merging across firms and facilitate time-series operations in Python, the price data were converted from wide format to long format using the Power Query functionality in Excel.

4.4 Event Study Implementation

4.4.1 Event Identification and Event Window Specification

The event analyzed in this study corresponds to the public announcement of a merger or acquisition, as recorded in the FactSet database. This announcement date marks the point at which information regarding the transaction, including the method of payment, becomes publicly available and can be incorporated into stock prices by market participants.

For both the traditional event study and the panel event study, the event window is defined as the period spanning from 10 trading days before to 10 trading days after the announcement date $[-10, +10]$. This window length is selected to capture potential price adjustments occurring prior to the official announcement due to information leakage, as well as any delayed market responses following the disclosure (Keown & Pinkerton, 1981; Brown & Warner, 1985). The use of a symmetric window of this magnitude is standard in the M&A literature, as it provides a balanced trade-off between capturing the full market reaction and limiting the influence of unrelated events (MacKinlay, 1997).

4.4.2 Estimation Window Definition

Normal, or expected, returns are estimated using an estimation window defined as the period extending from 365 trading days before the announcement to 30 trading days before the announcement, corresponding to the interval $[-365, -30]$. This window length is sufficiently long to generate stable parameter estimates while excluding observations close to the event date that may be affected by anticipation or early information release (MacKinlay, 1997; Kothari & Warner, 2007).

Maintaining a clear separation between the estimation window and the event window helps prevent event-related price movements from influencing the expected return model. This approach follows standard practice in event study methodology and contributes to the robustness of abnormal return estimates (Campbell, Lo, & MacKinlay, 1996; MacKinlay, 1997).

4.4.3 Model for Expected Return Estimation

Expected returns for each acquiring firm are estimated using the Capital Asset Pricing Model (CAPM). This model is chosen due to its strong theoretical foundations and its widespread application in empirical finance (Sharpe, 1964; Lintner, 1965). Relative to simpler alternatives, such as the constant mean return model, the CAPM explicitly incorporates exposure to systematic market risk, improving the precision of abnormal return estimates (Brown & Warner, 1985; MacKinlay, 1997).

At the same time, the CAPM avoids the increased data requirements and potential estimation noise associated with multifactor asset pricing models, which often provide limited additional explanatory power in short-horizon event studies. Market returns are proxied using the S&P Energy Select Sector Index (IXE), which serves as a sector-appropriate benchmark for U.S. energy firms. This index is also employed as the control group in the difference-in-differences specification of the panel event study.

4.4.4 Specification of the Risk-Free Rate

The risk-free rate used in the CAPM estimation is based on the yield of the 10-year U.S. Treasury bond, following standard practice in asset pricing research (Fama & French, 1993). Data on

Treasury yields are obtained from YCharts[1]. To align the risk-free rate with the daily frequency of stock returns, the annual yield is converted into a daily rate.

Specifically, the average annual yield over the 2004–2024 period, equal to 2.97%, is divided by 252 trading days, which is the conventional approximation for the number of trading days in a calendar year. The resulting daily rate is then used in the computation of expected returns under the CAPM framework.

4.4.5 Overview of the Empirical Implementation

Based on the methodological choices described above, abnormal returns are calculated for each firm over the event window and subsequently aggregated to obtain abnormal returns (AR), cumulative abnormal returns (CAR), average abnormal returns (AAR), and cumulative average abnormal returns (CAAR). In addition, standardized measures, SAAR and SCAAR, are computed to account for differences in return volatility across firms.

Standardization and statistical inference rely on the sample standard deviation of abnormal returns, rather than the population standard deviation, reflecting the finite nature of the estimation window. Within the panel event study framework, abnormal returns are further analyzed in event time to estimate dynamic effects both before and after the announcement.

All computations and estimations are implemented programmatically using Python, ensuring consistency, transparency, and full replicability across both the traditional event study and the panel event study analyses.

[1] The annual 10-year U.S. Treasury yield data are available on the YCharts website at: https://ycharts.com/indicators/10_year_treasury_rate_annual

5. RESULTS

5.1 Results from the Traditional Event Study

This section presents the findings of the traditional event study analysis for acquisitions financed with cash and with stock. The results are based on a final sample of 127 cash-financed and 95 stock-financed transactions. Market reactions are assessed using cumulative average abnormal returns (CAAR) and standardized cumulative average abnormal returns (SCAAR) computed over several event windows surrounding the announcement date.

5.1.1 Cash-Financed Acquisitions

For acquisitions financed entirely with cash, the analysis reveals no statistically significant abnormal performance for acquiring firms across any of the event windows considered. Although CAAR estimates are consistently negative, their magnitude remains small and none of the associated test statistics reach conventional significance levels. This conclusion holds for both raw and standardized measures, indicating that the results are not driven by firm-specific volatility effects, as illustrated 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 for Cash Financed Transactions (Source:* Author's own elaboration*)*

Over the widest event window $[-10, +10]$, the estimated CAAR is approximately –1.9%, with a p-value well above standard significance thresholds. The corresponding SCAAR is likewise statistically insignificant. These findings suggest that, on average, cash-financed acquisitions do not lead to a discernible short-term valuation impact for acquiring firms.

To examine whether prices adjust prior to the public announcement, the pre-event window $[-5, 0]$ is analyzed. While the estimated CAAR for this window is negative, it is not statistically significant, and the standardized results point to the same conclusion. This indicates an absence of systematic pre-announcement price movements, suggesting that the market does not anticipate cash-financed deals in a way that generates abnormal returns for acquirers. This interpretation is further supported by the daily AAR and SAAR plots, which show no meaningful accumulation of returns ahead of the announcement date.

The announcement-day window $[0, 0]$ and the immediate post-announcement window $[1, 1]$ are used to assess the timing of the market response. In both cases, CAAR and SCAAR values remain close to zero and statistically insignificant. The similarity of results across these windows indicates that the information is absorbed rapidly by the market, with no evidence of delayed adjustment or post-announcement drift. This pattern is consistent with an efficient and immediate processing of information related to cash-financed acquisitions.

Finally, the post-announcement window $[0, 5]$ is examined to test for any delayed market response. The results again show no statistically significant abnormal performance. Although CAAR remains slightly negative, its economic magnitude is limited, and the standardized results confirm the absence of a meaningful effect. This suggests that the announcement does not trigger any gradual reassessment of firm value in the days following disclosure.

Overall, the evidence indicates that cash-financed acquisitions do not elicit a statistically or economically significant market reaction for acquiring firms. The absence of abnormal returns before, on, or after the announcement implies that investors view cash payment as largely neutral. From the market's perspective, choosing cash as the method of payment neither conveys new information about firm valuation nor materially alters expectations regarding deal quality. These findings are consistent with the interpretation of cash financing as a transparent and well-understood payment mechanism whose implications are already incorporated into prices.

5.1.2 Stock-Financed Acquisitions

In contrast to cash-financed deals, acquisitions paid entirely with stock generate a pronounced and statistically significant negative market response. Across most event windows, CAAR estimates are both economically meaningful and statistically significant, indicating a reduction in shareholder value for acquiring firms following stock-financed M&A announcements. For the widest window $[-10, +10]$, the CAAR is approximately –4.1%, with a p-value below the 5 % level. The standardized measure reinforces this result, as the SCAAR is strongly negative and statistically significant. This confirms that the observed effect reflects a systematic market reaction rather than firm-specific volatility, as shown 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 for Stock Financed Transactions (Source:* Author's own elaboration*)*

The analysis of the pre-announcement window $[-5, 0]$ reveals a statistically significant negative CAAR, suggesting that part of the market response occurs before the official announcement. This pattern is also visible in the daily AAR and SAAR plots, where cumulative returns begin to decline prior to day 0. Such evidence is consistent with information leakage or anticipation effects in stock-financed transactions. Investors may partially infer the use of equity financing or obtain deal-related information ahead of the formal disclosure, leading to an early adjustment in stock prices.

On the announcement day itself $[0, 0]$, abnormal returns are negative and statistically significant, indicating an immediate adverse market reaction to the announcement of a stock-financed acquisition. The following window $[1, 1]$ remains negative, although with reduced magnitude and weaker statistical significance, suggesting that the bulk of the reaction is concentrated on the announcement date. The sharp decline in both AAR and SAAR at $t = 0$, clearly observable in the figures, supports the interpretation of a rapid and decisive market response.

Importantly, the negative reaction does not dissipate after the announcement. The post-event window $[0, 5]$ continues to exhibit a negative and statistically significant CAAR, indicating that abnormal returns persist in the days following the announcement. Rather than reversing, cumulative abnormal returns continue to deteriorate, implying that investors do not view the initial price drop as a temporary overreaction. This persistence is further confirmed by the standardized results, where SCAAR becomes increasingly negative in the post-announcement period.

Taken together, the findings provide strong and consistent evidence of an unfavorable market reaction to stock-financed acquisitions. The statistical significance observed across pre-announcement, announcement-day, and post-announcement windows suggests that equity-financed deals are systematically perceived as value-destroying by investors.

5.1.3 Comparison Across Payment Methods

A direct comparison between payment methods highlights a clear divergence in market responses. Cash-financed acquisitions show no statistically significant abnormal returns across any of the event windows examined. CAAR and SCAAR estimates 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.

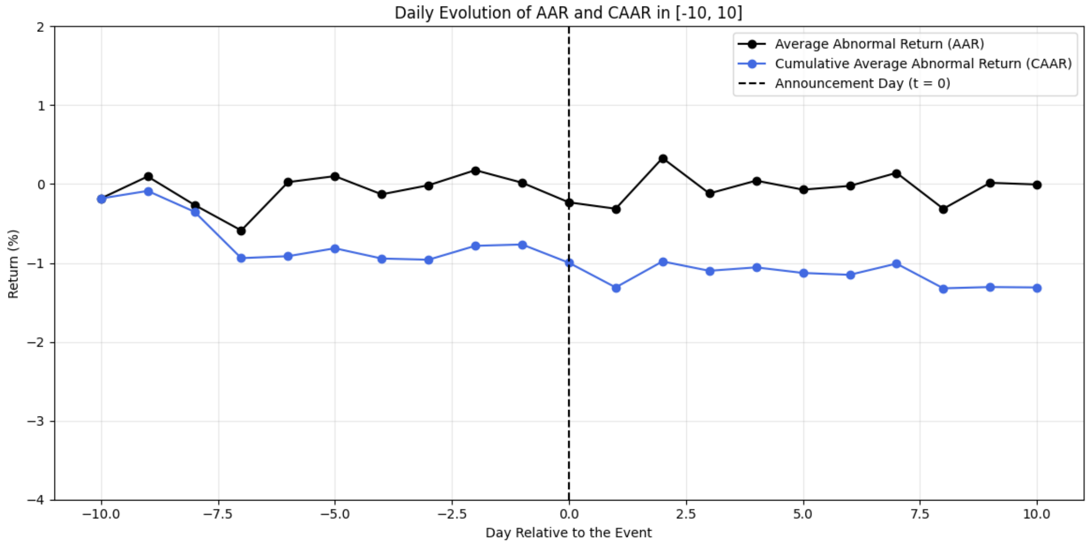

Figure 7 *- Daily Evolution of AAR and CAAR in [-10, 10] for Cash Financed Transactions (Source:* Author's own elaboration*)*

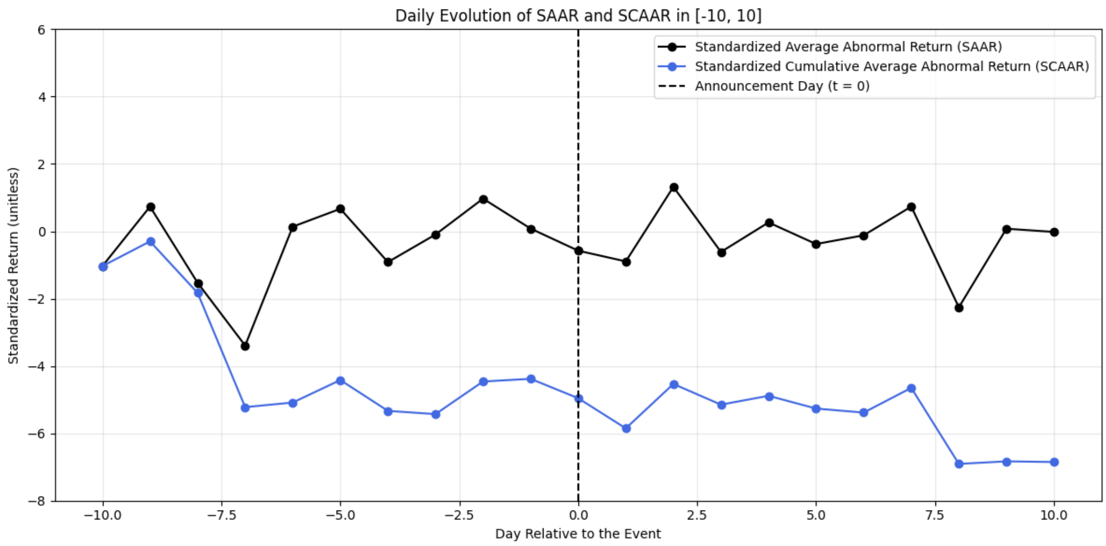

Figure 8 *- Daily Evolution of SAAR and SCAAR in [-10, 10] for Cash Financed Transactions (Source: Author's own elaboration)*

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

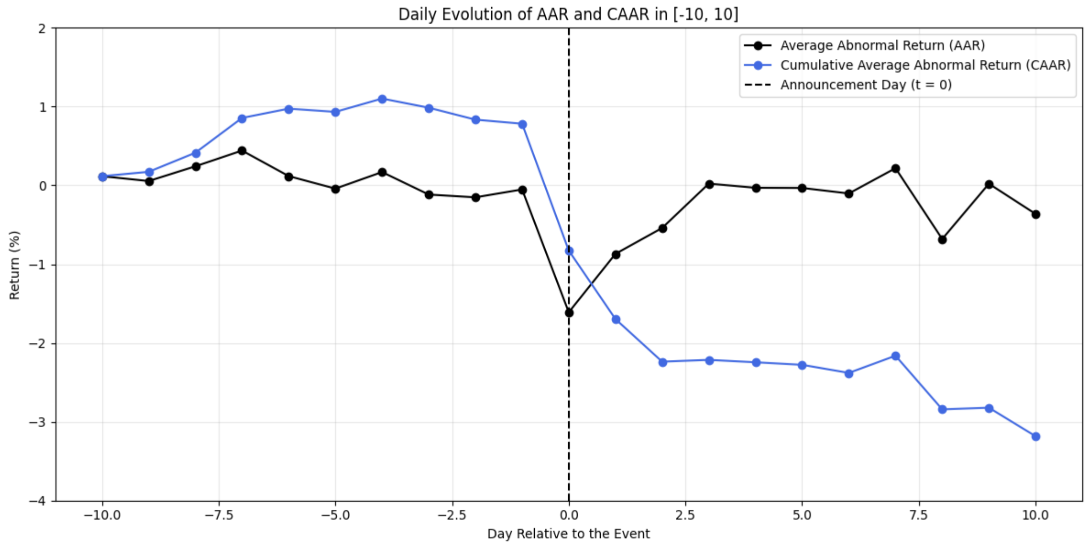

Figure 9 *- Daily Evolution of AAR and CAAR in [-10, 10] for Stock Financed Transactions (Source:* Author's own elaboration*)*

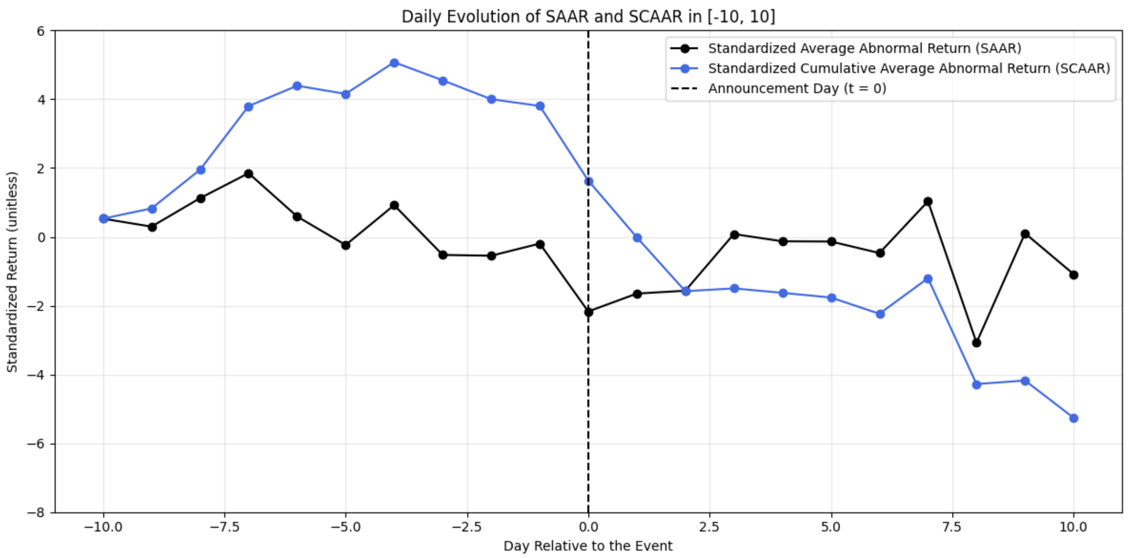

Figure 10 *- Daily Evolution of SAAR and SCAAR in [-10, 10] for Stock Financed Transactions (Source:* Author's own elaboration*)*

Differences between the two payment methods are also evident in the temporal dynamics of returns. Cash-financed acquisitions exhibit neither pre-announcement price movements nor post-announcement drift. Stock-financed acquisitions, on the other hand, display clear signs of both anticipation effects prior to the announcement and persistence of negative abnormal returns afterward.

Overall, the traditional event study results indicate that the method of payment plays a central role in shaping investor reactions to M&A announcements. Whereas 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 Results from the Panel Event Study

This section reports the findings obtained from the panel event study analysis for both cash- and stock-financed acquisitions. Unlike the traditional event study, this approach allows abnormal returns to be examined dynamically over time while explicitly controlling for firm-specific heterogeneity and common time effects. As a result, it provides a more detailed picture of how market reactions unfold around the announcement date.

5.2.1 Cash-Financed Acquisitions

The panel regression results indicate that acquisitions financed with cash do not give rise to statistically significant abnormal returns at any point surrounding the announcement. Event-time coefficients remain tightly clustered around zero throughout the event window from $t = -10$ to $t = +10$, and the associated confidence intervals consistently encompass zero, as shown in Figure 11.

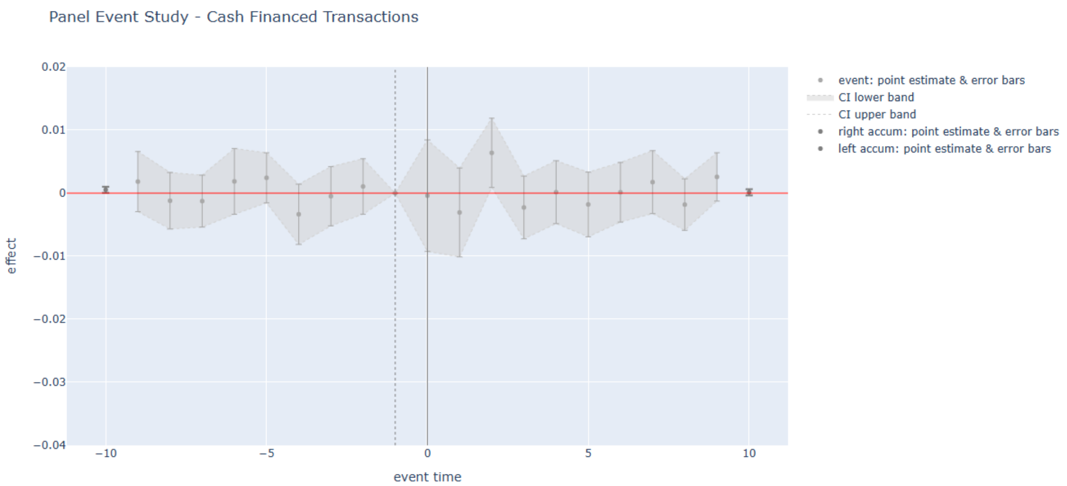

Figure 11 *- Panel Event Study Confidence Intervals for Cash Financed Transactions (Source:* Author's own elaboration*)*

At the announcement date ($t = 0$), the estimated coefficient is economically small and statistically insignificant, suggesting that the market does not respond immediately to the disclosure of a cash-financed acquisition. Likewise, coefficients in the pre-announcement period do not display systematic deviations from zero, providing no indication of anticipation effects or information leakage within the panel framework.

In the post-announcement period, estimated effects continue to hover around zero and do not follow a discernible trend. Although minor short-term fluctuations are observed in the point estimates, these variations are limited in magnitude and lack statistical significance. This pattern indicates the absence of delayed market adjustment or cumulative effects following the announcement.

The cumulative average abnormal return (CAAR) series derived from the panel estimates reinforces this interpretation. Cumulative effects remain close to zero across the entire event window, with no sustained upward or downward movement after the announcement date. The lack of persistence in the cumulative series suggests that investor perceptions of cash-financed acquisitions remain stable over time.

Overall, the panel event study results corroborate the conclusions drawn from the traditional event study. Both methodologies indicate that cash-financed acquisitions do not generate significant abnormal returns for acquiring firms, either at the time of announcement or in the subsequent period. The absence of dynamic effects further supports the view that cash payment does not transmit new or value-relevant information to the market in this sample.

5.2.2 Stock-Financed Acquisitions

In sharp contrast, the panel estimates for stock-financed acquisitions reveal a strong and statistically significant negative market reaction at the announcement date. The coefficient at $t = 0$ is clearly negative, and its confidence interval excludes zero, indicating a statistically significant immediate response to the announcement of an equity-financed deal, as illustrated in Figure 12.

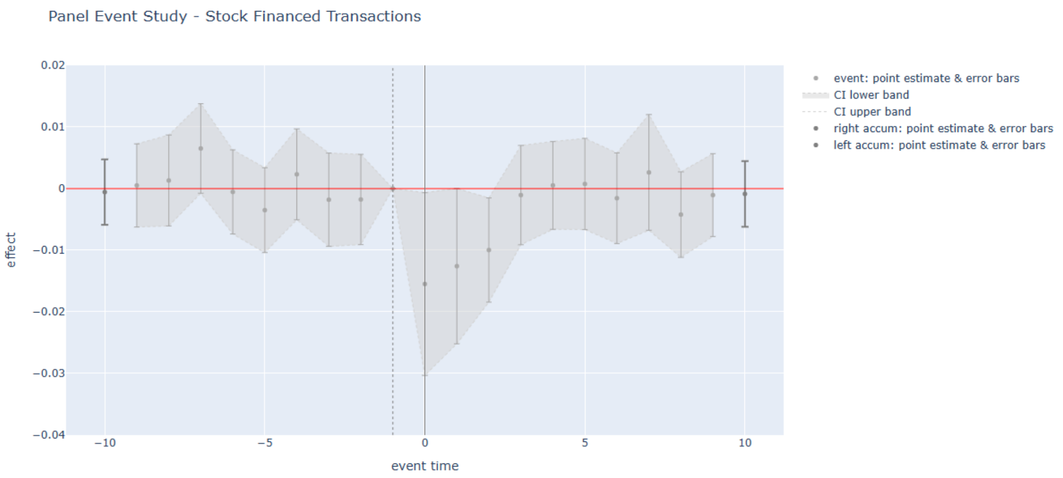

Figure 12 *- Panel Event Study Confidence Intervals for Stock Financed Transactions (Source:* Author's own elaboration*)*

This effect is particularly evident in the event-time plot, where the announcement-day coefficient represents the largest negative deviation observed within the event window. The magnitude of this estimate is economically meaningful and markedly larger than any fluctuations recorded in the pre-event period.

Before the announcement, event-time coefficients fluctuate around zero and are generally not statistically significant. While some minor movements appear in the days leading up to the announcement, the confidence intervals largely overlap with zero, suggesting limited evidence of systematic anticipation or information leakage once firm-level heterogeneity and time effects are taken into account. This stands in contrast to the traditional event study, where some pre-announcement accumulation was detected, indicating that controlling for these effects attenuates pre-event dynamics.

Following the announcement, abnormal returns remain negative over several subsequent days. Although the size of the daily effects gradually declines, cumulative abnormal average returns (CAAR) continue to decrease, indicating that the market does not reverse its initial assessment.

The cumulative series derived from the panel estimates displays a pronounced downward shift immediately after the announcement, followed by stabilization at a substantially negative level. This trajectory suggests that the valuation adjustment triggered by a stock-financed acquisition is both rapid and persistent, reflecting a lasting reassessment of firm value by investors.

Taken together, the panel event study provides strong evidence that stock-financed acquisitions are associated with significant value losses for acquiring firms. The combination of an immediate negative reaction at the announcement date and sustained post-announcement effects confirms that the adverse market response identified in the traditional event study remains robust in a dynamic panel setting. These findings reinforce the conclusion that the use of stock as a payment method is systematically linked to unfavorable market reactions.

5.2.3 Comparison Across Payment Methods

A direct comparison of panel results across payment methods reveals a clear divergence in dynamic market effects. Cash-financed acquisitions exhibit 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 persistent trend, as shown in Figure 13. This pattern indicates a neutral and stable market response over time.

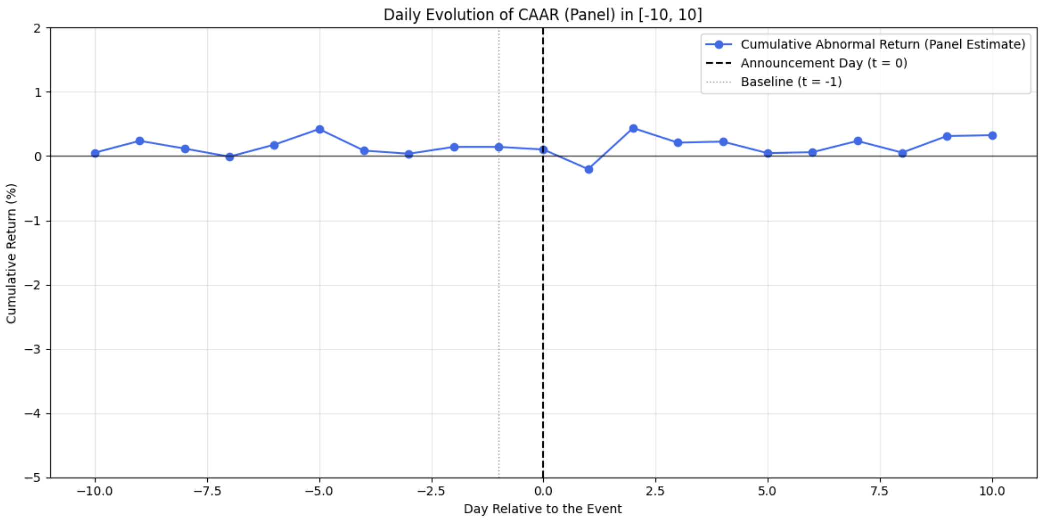

Figure 13 *- Daily Evolution of CAAR in [-10, 10] for Cash Financed Transactions (Source:* Author's own elaboration*)*

By contrast, stock-financed acquisitions show a pronounced and statistically significant negative effect at the announcement date, followed by persistently negative cumulative abnormal returns in the post-announcement period. As illustrated in Figure 14, the sharp decline at $t = 0$ and the subsequent stabilization at a lower cumulative level suggest that the market rapidly incorporates the information conveyed by equity payment and does not subsequently revise this evaluation.

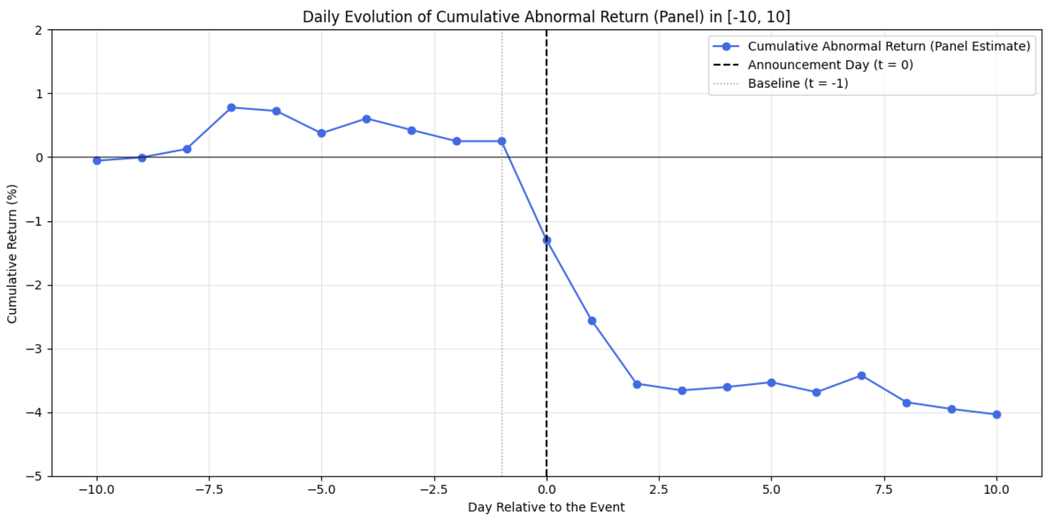

Figure 14 *- Daily Evolution of CAAR in [-10, 10] for Stock Financed Transactions (Source:* Author's own elaboration*)*

Overall, the panel event study confirms that the method of payment is a central determinant of market reaction. While cash-financed acquisitions are associated with negligible dynamic effects, stock-financed acquisitions trigger an immediate and lasting negative response. These results are fully consistent with the findings from the traditional event study and demonstrate that the differences across payment methods persist even when firm-level heterogeneity and dynamic adjustment processes are explicitly accounted for.

6. CONCLUSIONS

6.1 Interpretation of Market Reactions to M&A Payment Choices

This dissertation analyzes how financial markets respond to mergers and acquisitions depending on the chosen method of payment, focusing on cash- and stock-financed transactions in the U.S. energy sector over the period 2004–2024. Rather than viewing payment structure as a purely mechanical financing decision, the analysis highlights its role as a central element in how investors interpret and evaluate M&A announcements.

The empirical evidence reveals a clear asymmetry in investor reactions across payment methods. Acquisitions financed with cash are associated with a broadly neutral market response. Stock prices of acquiring firms do not exhibit statistically or economically meaningful abnormal returns before, at, or after the announcement. This stability suggests that cash payment is perceived as a familiar, transparent, and low-ambiguity transaction structure that does not materially alter investors' valuation of the acquiring firm at the time of the deal.

In contrast, stock-financed acquisitions generate a pronounced and negative market reaction. Acquiring firms experience significant declines in share prices around the announcement date, and these losses persist in the days that follow. The persistence of negative abnormal returns indicates that investors do not interpret the initial price drop as a short-lived overreaction, but rather as a reassessment of firm value triggered by the use of equity as acquisition currency.

These patterns are particularly relevant in the context of the U.S. energy sector, which is characterized by capital intensity, cyclical cash flows, and substantial valuation uncertainty. Across different market conditions captured in the 2004–2024 period, investors consistently appear to condition their responses to M&A announcements on how transactions are financed. Payment method therefore emerges as a meaningful signal that shapes market expectations regarding deal quality, valuation, and managerial confidence.

6.2 Strategic Implications for M&A Decision-Making

From a managerial and corporate finance perspective, the findings underline the strategic importance of payment method choice in mergers and acquisitions. Financing decisions are shown to have immediate valuation consequences, independent of any long-term operational or integration outcomes.

For acquiring firms, particularly in volatile and capital-intensive industries such as energy, the use of stock financing appears to be viewed unfavorably by investors. Equity-financed acquisitions may raise concerns related to dilution, potential overvaluation, or heightened uncertainty surrounding expected synergies. As a result, managers should be aware that opting for stock as a means of payment can entail short-term market penalties at the announcement stage.

Cash-financed acquisitions, by contrast, do not appear to trigger adverse market reactions. While they are not associated with positive abnormal returns, their neutrality suggests that cash payment is perceived as a credible and well-understood financing choice. In this sense, cash financing may help avoid negative signaling effects, even if it does not guarantee value creation.

For investors, the method of payment serves as a simple and observable indicator that aids in interpreting M&A announcements. The consistent underperformance of stock-financed deals relative to cash-financed ones suggests that payment structure can be used as an informative signal when assessing the likely short-term impact of acquisitions on shareholder value.

Taken together, these findings reinforce the idea that payment method is not a secondary detail in M&A transactions, but a central component of how such deals are evaluated by financial markets.

6.3 Limitations and Avenues for Further Research

Despite the insights provided, this study is subject to several limitations that point to opportunities for further research. First, the analysis concentrates on short-term market reactions and does not assess longer-term post-merger performance. Future research could examine whether the negative response to stock-financed acquisitions persists over extended horizons or is eventually offset by realized synergies.

Second, the study abstracts from deal-specific characteristics such as acquisition premiums, relative transaction size, strategic fit, or financing constraints. Incorporating these factors could help explain heterogeneity in market reactions and clarify the conditions under which stock financing is perceived less negatively.

Finally, the focus on purely cash- or stock-financed transactions, while analytically useful, excludes mixed-payment deals. Future work could extend the analysis to hybrid structures, explore differences across energy subsectors, or apply the framework to other industries or international markets to assess the broader applicability of the results.

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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 "Market Reaction to Payment Methods In M&A Transactions: Evidence from the U.S. Energy Sector", 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
```

```python
        # 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

```python
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

```python
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")
```

```
    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

```
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"})
    )
```

```
    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")
```

```
    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

```
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

```python
# --- 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})
```

```python
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))
```

```python
# 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)"
)
```

```python
# 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)
```

```python
# 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()
```