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UNIVERSITY OF VAASA

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**Target Firm Tobin's Q and Acquirer Announcement
Returns: Evidence from U.S. Mergers and
Acquisitions, 2009–2024**

Testing the Predictive Power of Tobin's Q in the Post-Financial Crisis Period

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ABSTRACT:

The Q hypothesis of corporate takeovers proposes that higher acquirer announcement returns are connected to the acquisition of undervalued target firms. However, the generalizability of the relationship between target firm Tobin's Q and acquirer stock returns has been increasingly contested in modern M&A market conditions. This thesis investigates whether target firm Tobin's Q has retained predictive power for acquirer cumulative abnormal returns in the post-financial-crisis United States M&A market.

The study derives from the Q-theory of takeovers as its central theoretical benchmark, supplemented by market efficiency, signalling theory, agency theory and managerial hubris, and behavioral finance perspectives. The approximate Tobin's Q is applied as the primary measure of target firm valuation, with payment method incorporated as the main control variable based on information asymmetry theory.

The sample consists of 344 completed public-to-public M&A transactions in the United States announced between 2009 and 2024, with stock prices obtained from the Polygon.io API and financial statements data extracted from SEC EDGAR database. Event-study methodology is applied across five event windows using mean- and market adjusted benchmark models, complemented by cross-sectional OLS regressions with industry and year fixed effects and heteroskedasticity-robust standard-errors.

The null hypothesis is not rejected: target firm Tobin's Q does not significantly predict acquirer cumulative abnormal returns in any specifications. Payment method occurs as the dominant cross-sectional predictor of acquirer stock returns, with stock-paid acquisitions generating significantly more negative returns than cash-paid deals in all specifications.

The findings are interpreted through a regime-conditional framework: the null finding on Tobin's Q is consistent with elevated equity market valuations, growth-versus-value stock cycle, and managerial miscalibration on the firm valuation which all characterise the sample period of 2009-2024, rather than a disconfirmation of the Q hypothesis itself. The Tobin's Q-CAR relationship is expected to reimpose itself in future market environments closer to historical fundamental benchmarks. Conversely, the robustness of the payment method effect, confirms that adverse selection remains a solid cross-sectional driver of acquirer wealth effects across decades.

KEYWORDS: Q hypothesis, Tobin's Q, macroeconomic regime, cumulative abnormal return, event study, payment method, stock-financed acquisitions, adverse selection, mergers and acquisitions

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ABSTRACT:

Yrityskauppoihin liittyvä Q-hypoteesi esittää, että ostajayhtiön korkeammat osaketuotot yrityskaupan julkistushetkellä liittyvät aliarvostettujen kohdeyhtiöiden hankintaan. Kohdeyhtiön Tobinin Q:n ja ostajayhtiön osaketuottojen välinen yhteys on kuitenkin modernilla M&A-markkinalla kiistanalainen. Tämä pro gradu -tutkielma tarkastelee, onko kohdeyhtiön Tobinin Q säilyttänyt kykynsä ennustaa ostajayhtiön kumulatiivisia osaketuottoja yrityskaupan julkistuksen yhteydessä finanssikriisin jälkeisessä Yhdysvalloissa vuosina 2009–2024.

Tutkimuksen teoreettisena viitekehyksenä toimii yrityskauppojen Q-hypoteesi, jota täydennetään markkinatehokkuuden, signalointiteorian, agenttiteorian ja käyttäytymistieteellisen rahoituksen näkökulmilla. Tobinin Q toimii kohdeyhtiön markkina-arvostuksen mittarina, ja transaktion maksutapa sisällytetään analyysiin keskeisenä kontrollimuuttujana informaation epäsymmetriaan liittyvien teorioiden pohjalta.

Aineisto koostuu 344 julkisten yhtiöiden välisestä yrityskaupasta Yhdysvalloissa. Osakekurssi-data on kerätty Polygon.io-rajapinnasta ja tilinpäätöstiedot SEC EDGAR -tietokannasta. Tutkimuksessa hyödynnetään tapahtumatutkimusmenetelmää viidessä tapahtumaikkunassa sekä keskiarvo- ja markkinakorjattuja malleja. Lisäksi analyysia täydennetään lineaarisella OLS-regressiomallilla, jossa huomioidaan toimiala- ja vuosikohtaiset kiinteät vaikutukset sekä heteroskedastisuuden kestävä testaus (HC3, VIF ja Breusch–Pagan).

Tulosten perusteella nollahypoteesia ei voida hylätä, sillä kohdeyhtiön Tobinin Q ei ennusta luotettavasti ostajayhtiön kumulatiivisia osaketuottoja missään tapahtumaikkunassa. Sen sijaan transaktion maksutapa osoittautuu merkittäväksi selittäjäksi: omilla osakkeilla rahoitetut yrityskaupat tuottavat systemaattisesti negatiivisempia osaketuottoja kuin käteisellä toteutetut transaktiot.

Tuloksia tulkitaan regiimiriippuvaisessa viitekehyksessä. Q-hypoteesin heikko toimivuus on yhdenmukainen tutkimusjakson korkeiden osakemarkkina-arvostusten, kasvuosakkeiden korostuneen suosion ja johdon mahdollisten arvostusvirheiden kanssa. Tulokset eivät siten välttämättä kumoja Q-hypoteesia, vaan viittaavat siihen, että Tobinin Q:n ja ostajayhtiön osaketuottojen välinen yhteys voi palautua markkinaolosuhteiden normalisoituessa. Samalla maksutavan vahva vaikutus tukee näkemystä siitä, että haitallinen valikoituminen säilyy keskeisenä ostajayhtiön arvonsiirtoa selittävänä tekijänä yrityskaupoissa.

KEYWORDS: Q hypothesis, Tobin's Q, macroeconomic regime, cumulative abnormal return, event study, payment method, stock-financed acquisitions, adverse selection, mergers and acquisitions

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1 Introduction

In the corporate world and financial markets, mergers and acquisitions (M&A) have been used as a strategic tool to shift corporate control, reallocate resources, navigate strategic direction, and enable growth prospects of a firm. Compared to general capital expenditure or investment projects, M&A transactions include significant scale of irreversible capital commitments that usually exceed the scale of organic internal investment projects of firms. These corporate events involve multiple stakeholders, including acquired and acquiring firms, their shareholders, advisory firms, regulators, and creditors, making these transactions most pivotal economic transaction for a firm in today's business world. (Cumming, Jindal & Kumar, 2023)

The broader economic significance and magnitude of M&A is substantial. Since the post-dot-com bubble period, the global M&A market has averaged around 43 000 deals per year with the total annual transactions value close to 3.2 trillion US dollars, representing an average deal size around 75 million US dollars over the period of 2000 to 2025. (IMAA, n.d.) Figure 1 visualizes that the M&A activity does not occur at steady linear pace but aggregates in separate merger waves, where each wave is driven by specific combination of macroeconomic conditions, shifts in regulatory environment, and developments in technology. The currently ongoing merger wave could be characterized by acquisitions in artificial intelligence and digital infrastructure, continuing to restructure the competitive landscape across industries. (PwC, 2026).

Contrary to the scale and economic significance of the M&A market, fundamental long-term empirical puzzle persists: why do shareholders of the acquiring firm repeatedly fail to benefit from M&A? Decades of research have evidenced that the acquirer's announcement date returns have been averaging near zero or marginally negative in M&A transactions, even that targets shareholders capture the notable premiums (Andrade, Mitchell, & Stafford, 2001; Moeller, Schlingemann, & Stulz 2004). The skewed distribution of returns, where wealth transfers from acquirers' shareholders to targets' shareholders raises a principal question about the factors in cross-sectional variation of

acquirer stock returns, whether a specific property in the target firm can consistently predict market's assessment on the quality of the deal.

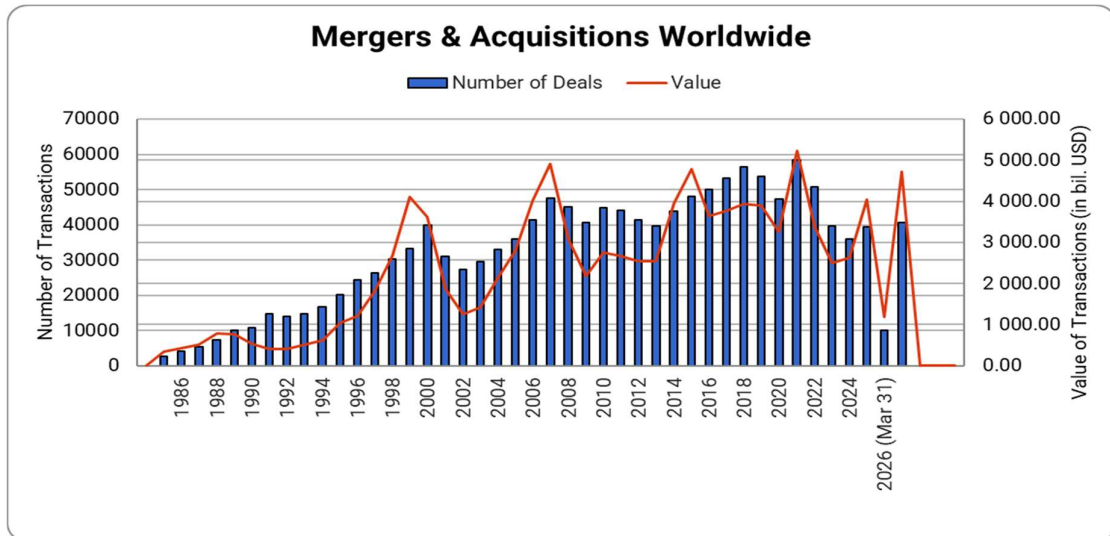


Figure 1 Global M&A Statistics (IMAA, n.d.).

A core prospect to explain the cross-sectional variation is the target firm's relative market valuation to its fundamental value of assets, captured closely by Tobin's Q ratio. The Q hypothesis of corporate takeovers, originally established by Lang, Stulz, and Walkling (1989) and moreover extended by Servaes (1991), estimates that acquirers gain higher returns at the announcement when acquiring low Tobin's Q targets, in other words trading at or below replacement cost of its assets. In this view, Tobin's Q is a proxy for target firms' management quality, where the value is created through efficiently managed acquirers taking over underperforming targets to utilize their assets more productively. The predictive power of Tobin's Q has been increasingly challenged in post-1990 samples, with concrete evidence, indicating that the relationship might have diminished or completely vanished in the modern-day M&A market. (Dong et al., 2006; Moeller et al., 2005)

This thesis investigates whether target firms' Tobin's Q can predict the short-term stock market reactions of the acquiring firm around M&A announcements during 2009-2024 sample period. The sample consists of 344 completed M&A deals between two publicly listed U.S. firms, with cumulative abnormal returns (CAR) computed through an event study framework. The announcement-window CARs are then regressed to target Tobin's

Q and selected deal-level control variables through cross-sectional OLS analysis. By examining the post-financial crisis period, this thesis contributes to the ongoing debate on the time-dependent generalizability of the Q hypothesis in a macroeconomic environment defined by low interest rates, heightened equity market valuations, and dominance of intangible asset-intensive industries.

1.1 Purpose of the Study

The purpose of this study is to analyze whether the current market valuation of target firm, measured by approximate Tobin's Q (Tobin's Q), provides measurable proxy of value creation or conversely a signal of mispricing that explains acquirers' short-term stock market reaction around the M&A announcement. Although prior empirical research has provided compelling arguments about why the quality of target Tobin's Q should predict acquirers' stock returns, today's M&A and financial markets present challenges for those predictions, therefore motivating for a fresh empirical analysis of the topic.

From corporate finance standpoint, M&A should at least in theory create value for the acquiring firms' shareholders as they enable an opportunity to integrate and restructure target firm's assets, utilizing them more efficiently than what target firm could use individually. High market valuation of a target firm, relative to its assets, implies market's perception on strong growth expectations. If the acquiring firm's management holds a high level of human capital to execute the growth options efficiently, the market should react positively to the announcement of the M&A. However, prior research underscores how market valuations can deviate from the fundamental value of the firm through market psychology and behavior (Barberis and Thaler, 2003). Under these circumstances, high Tobin's Q of a target may reflect a behavioral premium excessively above the intrinsic value of assets. Accordingly, market should be expected to "punish" the acquirer for overpaying for growth opportunities which have low probability to be realized.

In summary, this thesis seeks to connect the corporate and behavioral finance dimensions of M&A by evaluating whether market valuation of target firm reflects markets' perception of genuine economic opportunity or mispricing, and how it interacts with

short-term stock price movements of the acquirer. This study contributes to existing literature by producing an up-to-date test of the Q hypothesis in a period not covered by the foundational empirical studies supporting the hypothesis.

Additionally, a foundational limitation shapes the entire investigation of this thesis. The fundamental, intrinsic value of any firm's equity is not directly observable, only the market price is. Whether the market prices mirror the true underlying economic value or systematic deviation from that value, is itself an empirical question, and one that becomes difficult to answer particularly in periods of macroeconomic regime changes, sustained market value extremes, or behavioral distortion of the price discovery process. The post-financial-crisis sample period what this thesis examines falls within an environment in which several such conditions appear to exist simultaneously. The implications are that any finding on the predictive power of Tobin's Q in this period must be interpreted not as a context-neutral conclusion on the Q hypothesis itself, but as a verdict conditional to the broader valuation environment where the test is conducted. This direct framing motivates the analytical structure of the thesis, in which the empirical results are interpreted explicitly against the macroeconomic and behavioral conditions defining the post-financial-crisis U.S. equity market.

1.2 Research Objectives and Hypotheses

This study examines the relationship between target firms' market valuation and acquirers' short-term returns around the M&A announcements in U.S market for public-to-public transactions between 2009 and 2024. Specifically, the thesis tests whether target firms' Tobin's Q predicts the cumulative abnormal returns for acquiring firms' stock around the announcement date. Based on the theoretical framework of the Q hypothesis on corporate takeovers, the following hypothesis is tested:

***H¹ (Alternative)** = Target firms' Tobin's Q predicts acquiring firms' cumulative abnormal returns around the announcement date of M&A transaction, where higher Tobin's Q is connected to more negative returns.*

H^0 (null) = Target firms' Tobin's Q does not significantly predict acquirers' cumulative abnormal returns around the announcement date of the M&A transaction

The alternative hypothesis follows the findings of the initial Q hypothesis combined with the argument for overpayment: high Tobin's Q targets equal high deal premiums and the market penalize acquirers for paying excessive premiums for the non-realistic growth options. Testing the hypothesis in period of 2009 to 2024 provides an insight into whether predictive relationship of target's quality and acquirers stock returns can hold in today's market. Or if the relationship has disappeared due to unexplained deal-, firm-, or market-level factors which have not been discussed in prior literature.

1.3 Structure of the Thesis

The structure of this study is constructed as follows. Chapter 1 provides the background, motivation, research objectives and hypothesis of the study. Chapter 2 establishes the theoretical foundation covering principal forms of M&A transactions, payment methods, classical theories, M&A theories, and the history of merger waves, and corporate as well behavioral finance theories. Chapter 3 reviews the existing empirical literature on acquirer announcement returns, the Q hypothesis, and the role of payment method, completing the theoretical and empirical framework of this thesis. Chapter 4 describes the sample data and methodology used in this study, including the data sources, sample construction criteria, event study framework, cross-sectional regression specifications, and robustness check procedures. Chapter 5 provides empirical results from the event study and cross-sectional regression analysis. Chapter 6 discusses the implications of the results, addresses the limitations of the analysis, and identifies directions for future research. Chapter 7 concludes the thesis with a summary of the key findings and contributions.

2 Theoretical Framework

This chapter constitutes the theoretical framework against which the empirical results of this thesis are partly interpreted. The discussion proceeds in seven sections. Section 2.1 provides the forms of M&A transactions. Section 2.2 describes the main payment methods used in M&A. Section 2.3 reviews classical theories connected to M&A activity. Section 2.4 walks through the history of merger waves in U.S. and positions the present sample within that broader trajectory. Section 2.5 discusses how information flows shape investor responses to corporate transactions. Section 2.6 provides normative financial theories on firm valuation. Section 2.7 introduces behavioral finance framework, discussing how cognitive biases show limitations to normative financial theory. Together, these sections provide the lens which the relationship between Tobin's Q and acquirer stock returns around announcement is analyzed in the empirical chapter of this thesis.

2.1 Mergers and Acquisitions

M&A among other similar transactions are in theory a synonym for a large-scale transaction which fundamentally is intended to change the nature and structure of the firm. Despite the transactions may differ technically, they are commonly described as strategic transactions which include the change or transition in the control of a firm which correlates with the shifts in the strategic direction of the firm. (Frankel et al., 2017)

In past decades these strategic transactions have increasingly gained a significant position in corporate world and have served firms as an alternative option for a capital investment or when strategic partnerships have not provided the essential control and economic value to boost the organic growth of a corporation. (Frankel et al., 2017; Andrade, Mitchell & Stafford, 2001) M&A can be natured as a synthetic growth due to non-organic expansions of business via acquiring an existing firm leading to rapid business expansion. Prior research has implied similarly to Frankel et al. (2017) that M&As fuel more rapid growth for firms compared to the firms relying on the organic growth generated through fundamental business operations.

Horizontal mergers occur when two or several companies existing in the same industry producing same products or services merge into a single entity. Expressed in another way, it can be called a merger between direct competitors within an industry. Motivation behind this form of merger is power-driven, where the primary goal is to gain more market share subsequently strengthening the acquirers' position and power in the market. Horizontal mergers may also aim to reduce the amount of competition, which inherently can lead to increase operational profitability due to new market environment with less competition. This enables the new entity and rest of the competitors to increase prices of products and potentially lead to cost savings for the acquirer depending on if the economy of scale is achieved. (Gaughan, 2015) The profitability gains from horizontal mergers are not guaranteed, as economic outcomes depend on how effectively the acquirer is able to combine their assets and operations with the target firm.

Compared to horizontal mergers, **vertical mergers** occur when companies still operate in the same industry but in different parts of the supply chain of producing the products or services. The merging firms usually have more buyer-seller types of relationship rather than direct rivalry. The acquiring firm's usually focuses on increasing operational efficiency by stabilizing the supply chain of the business and gaining more control over the production line. (Gaughan, 2015) Fan and Goyal (2006) discussed that vertical mergers do not focus on certain industries but across time have been found to occur broadly across different sectors, demonstrating universal strategic rationale to secure supply chains and lower transaction costs through vertical integration.

Mergers which occur when the merging firms operate in unrelated industries with no connection in the supply chain of the product or service are called **conglomerate mergers** (Gaughan, 2015). While some theories on conglomerate mergers have emphasized the potential benefits of internal capital market efficiencies, diversification of unrelated cash flows, and transfer of managerial human capital, the empirical findings have been consistent in revealing that the operational benefits from conglomerate mergers are constrained and frequently overstated (Shleifer & Vishny, 1991). Since investors can diversify the portfolio-level risk, logic behind conglomerate mergers has leaned more towards

financial motives. The empirical findings suggest that the combination of low-correlated firms and their cashflows can improve the acquiring firm's credit profile, which naturally connects to the default probability of a firm that widens its total borrowing capacity (Lewellen, 1971). The financial motives produce more robust rationale for these mergers as the operational synergies of two firms in unrelated industries are non-existent.

Congeneric mergers involve firms operating in the same industry but selling distinct products or services (Gaughan, 2015). Conversely to conglomerate mergers, firms in congeneric mergers normally share mutual operational functions such as distribution networks, enabling extensions in product-line and broader utilization of distribution channels, potentially generating better operational synergies (Damodaran, 2005). These mergers have been empirically found to distribute more systematic operational synergies compared to the conglomerates, distinctively through increased market reach of the products and cumulative growth of revenue. The prior findings have also shown that acquirers in the congeneric mergers demonstrate modest efficiency gains upon the merger, although the gains tend to be relatively small compared to the synergy opportunities from horizontal mergers. The partial relatedness characteristic of congeneric mergers suggests lower integration risk in contrast to horizontal mergers, as the combining firms hold greater operational independence throughout the process. (Gaughan, 2015)

Compared to mergers, **acquisitions** take place when acquirer takes controlling stake of ownership in target firm. Acquisitions are defined as an explicit buyer-seller relationship instead of a combination of firms. The acquirer usually obtains the capacity to control strategic and operational decisions by buying either the controlling stake of shares or assets of the target firm. Generally, there are two forms of acquisitions; friendly and hostile, where in hostile acquisition the acquirer attempts to obtain control of the target firm against the management and board's preferences. Conversely, in friendly acquisition the target firm's management and board are in favor of the offer. (Gaughan, 2015) A recent example of a hostile acquisition is Paramount's competing tender offer to acquire Warner Bros Discovery over Netflix's initial offer which was originally preferred by the Warner Bros management and the board of directors. (PwC, 2026) Acquisitions, like

mergers, are real options to pursue rapid synthetic growth through the access to new markets and technology, achieve economies of scale, or remove direct competitors from the market. Compared to mergers, acquisitions involve more asymmetric integration process and put greater emphasis on the valuation, negotiation, and planning of post-acquisition integration, as the acquiring firm has overall responsibility for the economic outcomes of the combined new entity. (Gaughan, 2015)

2.2 Payment Methods

In M&A, **cash** is the most straightforward method of payment as the acquirer pays the determined consideration in cash to target's shareholders. Cash offers are seen more attractive to the sell-side of the transaction due to the clarity of payment and diminished exposure to post-deal market fluctuations of the share price. On the buy-side, cash-only deals require adequate liquidity from the acquirer, often funded through cash reserves or debt. Use of debt can yield elevated financial leverage and therefore affect the future financial flexibility of the new entity. Cash-paid M&As are normal in situations where acquiring firm aims to attain full control of the target, avoids diluting the ownership of existing shareholders, or communicates strong internal confidence on the value of transaction. As cash deals diminish some level of uncertainty around internal share valuation, they might mitigate the frictions in deal negotiations and pace up completion of the deal. (Myers & Majluf, 1984)

Acquirer firm can, instead of using internal funding, issue **debt** or borrow capital to generate cash for the transaction. M&A financed with debt can improve the surviving entities' return to equity because of the increased financial leverage, simultaneously increasing the financial risk of the new entity unless cash flows are well above the borrowing costs. Debt-financed acquisitions are most common in private equity sector, where the transaction is defined as a leveraged buy-out, a structure where debt forms majority portion of total transaction value. Despite potential tax advantages from interest deductibility, leverage can limit managerial discretion through the disciplining effect of mandatory debt service (Jensen, 1986) and make the firm more vulnerable to economic

downturns. Based on the capital structure theory, debt financing is used when internal financing is not sufficient. (Myers & Majluf, 1984; Frank & Goyal, 2008)

In **stock**-paid M&A, the acquirer offers their own shares to the targets' shareholders in exchange for the shares of target firm. Stock payment is typically used by acquirers who aim to sustain liquidity, avoid increasing financial leverage, or share risk exposures with the target shareholders, distributing the post-deal entity's future cash flows and underlying risks among the existing and new shareholders. One of the main characteristics of stock-paid deals is the influence of the acquirers' market valuation on the target shareholders perceived value of the transaction, as the consideration received is strictly linked to the acquirers' current valuation. Stock payments commonly occur when the acquirer's stock is relatively overvalued, reducing the effective financing cost of share-based consideration in contrast to cash or debt. (Myers & Majluf, 1984; Baker & Wurgler, 2002) This dynamic is particularly observable during the periods of broader market overvaluation, where acquiring firms strategically exploit inflated equity valuations as a financing currency to complete transactions that would otherwise be expensive (Rhodes-Kropf & Viswanathan, 2004).

Recent survey evidence by Graham (2022) provides a behavioral foundation for the adverse selection mechanism by documenting how managers systematically misperceive their own firm's equity valuation. Surveying CFOs of large U.S. firms, Graham records that managers systematically perceive their firm's equity to be undervalued relative to their internal valuation estimates, even in periods when objective market evidence suggests the opposite. This managerial miscalibration creates a structural condition under which stock-paid deals occur precisely when managers believe their stock is most undervalued, which from an outside investor's perspective corresponds with period when broader market evidence suggests prices are most elevated. The Graham (2022) findings therefore link the classical adverse-selection prediction (Myers & Majluf, 1984) to a present-day behavioral mechanism: managerial overconfidence about firm's valuation operates as a selection device biasing stock-paid deals towards periods of bilateral overvaluation.

Acquirers can also utilize a combination of **cash and stock** payments, which offers an opportunity to benefit from advantages of both payment methods. Mixed payment allows the acquirer to control effectively the firm's liquidity and leverage on balance sheet, while exposing the target firm shareholders to future performance up and downsides for the new entity. This approach assists reconciling valuation issues during negotiations, the cash component offers a certain payment, while the stock component provides risk exposure and potential upside tied to future cash flows. The mixed method is commonly used in "strategic" acquisitions, where acquirer and target seek to attain financial flexibility, diversify risk, and ensure smoother integration dynamics. This financing method can diminish the excessive dilution of shareholders' equity or reliance on debt, making it flexible financing structure for M&As. (Andrade, Mitchell & Stafford, 2001)

2.3 M&A Theories

In the M&A literature a single theory cannot entirely explain observed deal behavior, because the transactions occur under heterogeneous conditions – including divergent strategic objectives and governance structures, shifting information environments, and distinctions in market timing. Accordingly, empirical research interprets M&A through various complementary theoretical frameworks, where each one emphasizes different drivers – everything from synergy creation to behavioral biases. Empirical reviews of M&A typically gather these explanations into recurring theoretical categories and confirm that several motives often coexist within the same transaction. (Andrade, Mitchell & Stafford, 2001; Martynova & Renneboog, 2008)

In this thesis, the theoretical overview serves two key functions. First, it identifies the established motives behind the transactions, why acquirers pursue M&A and why targets agree to them. Second, it provides testable implications for how target market valuations affect M&A outcomes — for example, some theories suggest that acquiring overvalued firms increases the risk of overpayment and weak post-deal performance, while others argue that undervalued targets provide robust synergy potential and superior long-term value creation for the acquirer (Martynova & Renneboog, 2008).

Efficiency theory is one of the most common explanations for M&A, proposing that the transactions are primarily driven by prospective synergies, which enhance the total value of the new combined entity (Damodaran, 2005). At the core of the theory is the concept that the value of the new combined entity (V_{AB}) exceeds the sum of the individual values of the acquirer (V_A) and the target (V_B):

$$V_{AB} > V_A + V_B$$

Equation 1 Synergy Condition (Damodaran, 2005)

Distinct from theories that consider M&A as a tool for restructuring the market, efficiency theory suggests that the principal motive resides in the creating economic value through the optimization of operational and financial resources, and cost and management restructuring. The gains typically can be divided into operating and financial. (Damodaran, 2005; Seth, 1990)

Operational synergies originate from economies of scale and the economies of scope (Damodaran, 2005). Economies of scale enable the acquirer to lower unit costs by spreading fixed costs over a higher volume of production — a typical driver in horizontal mergers (Eckbo, 1983). Economies of scope emerge when the shared resources, like distribution channels or R&D, generate efficiencies that neither one of the firms could have achieved independently (Damodaran, 2005). Financial synergies emerge from an optimized capital structure and reduced cost of capital for the new entity. A larger and more diversified new entity might benefit from the lower borrowing costs due to the diminished bankruptcy risk through the coinsurance effect (Lewellen, 1971), or increased access to internal capital markets. Additionally, tax benefits can also occur if the acquirer is able to utilize the target's tax losses to shield its own earnings.

Efficiency theory also includes the differential managerial efficiency hypothesis, that views the market for corporate control as governance mechanism where efficiently managed firms aim to acquire underperforming ones. Through the mechanism value is created by replacing the targets' inefficient management and governance structures with acquirers' internal controls and strategic expertise. The reallocation of human capital

ensures that resources are transferred from poor utilization to those who can maximize the assets productive capacity. (Jensen & Ruback, 1983).

Market power theory proposes that M&As are driven by the objective of enhancing the acquirers' influence over the market, established through dominant market position. In contrast to theories which focus on benefits through synergies, market power theory implies that value creation does not result from streamlining firms' internal operations but from changing the external competitive landscape. For example, through horizontal mergers, a firm can decrease the level of competition in the market, thereby gaining market share and obtaining more monopolistic power — enabling the acquirer to raise prices above marginal cost without losing significant volume of customers (Stigler, 1950). In vertical mergers, acquirers can improve their market position through the control of essential segments within the value chain, like distribution channels, and therefore potentially eliminating competition from the market (Tirole, 1988). An illustrative example case is Microsoft's 69 billion USD acquisition of Activision Blizzard in 2023, where the U.S. Federal Trade Commission and the U.K. Competition and Markets Authority blocked the deal on the grounds that combining Microsoft's Xbox platform with Activision's gaming portfolio would foreclose competition in the cloud-gaming and console markets. The regulatory scrutiny itself underlines how other market participants and regulatory bodies sometimes recognize the competitive concentration mechanisms in market.

If the market sees the deal as an economically successful option resulting in higher industry concentration, the stock price should rise based on the expectations of higher future cash flow. That said, stock movement can be also affected by regulatory concerns, as potential competition-law interventions can result in negative short-term returns on the acquirer's stock. (Eckbo, 1983) The market power gained through the transactions should also materialize in improved profit margins and returns on invested capital. If the market power hypothesis holds, acquirers' post-transaction fundamental performance should exhibit an increase in operating profit and cash flow because of the improved ability to influence prices or supply chain advantages. However, prior research has

pointed out a paradox within this theory (Eckbo, 1983): if a merger increases industry-level market power, consequently the stock prices of competitors should also rise.

Hubris hypothesis delivers a behavioral explanation for M&A activity, challenging the classical efficiency theory that assumes the decision-making is driven by operational and financial synergies. Richard Roll (1986) argued that the acquirers' management often falls into overconfidence ("hubris") by accepting their internal valuation more accurate than market's, therefore overestimating their capabilities to generate value from the transaction. Hence, the management's pride and bias can yield the acquirer to pay premiums for the target that exceeds any realistic economic outcomes, leading wealth transfer from the acquirers' shareholders to target's shareholders. (Roll, 1986)

The principle of the hubris hypothesis is that, although there is no conscious intent to harm the acquiring firm, managerial overconfidence leads to winner's curse effect, especially in a competitive bidding acquisition. In this setting, the valuation and Tobin's Q of target play a key role. From the acquirers' standpoint, successfully bidding on overvalued target calls for offering a further premium on top of the existing high market valuation. The hubris hypothesis therefore proposes that the acquirers' management inaccurately thinks they are capable to generate more value from the target than what the target's high valuation already reflects. This creates the winner's curse: the acquirer wins the deal itself but pays a price which exceeds the target's fundamental value and its realistic capacity to create economic value. Accordingly, the hubris hypothesis predicts that the new entities' value remains either stagnant or declines following the deal announcement, since the premium is paid based on the management's stubbornness rather than economic rationality. (Roll, 1986; Malmendier & Tate, 2008; Hayward & Hambrick, 1997) A frequently cited modern-day example is AOL's 165 billion USD acquisition of Time Warner in the beginning of 2000, completed at the peak of the dot-com bubble market environment. Despite paying a premium based on the assumption that AOL's already elevated stock valuation reflected a genuine internet-era value creation potential, the combined after all destroyed 200 billion USD in shareholder wealth in the years upon

transaction, with AOL Time Warner's CEO later admitting that the management's confidence in extracting synergies from the merger reflected overconfidence.

In short-term, the hubris hypothesis anticipates a negative stock market reaction for the acquirer. If the market is rational, the rational investors should recognize the overpayment for the target and adjust the acquirer's share price down at the announcement of the deal. In long-term, the acquirers' fundamental performance and value creation are expected to be either insignificant or negative, because the high initial cost of the investment in the target sets a high hurdle rate that the realized operating synergies cannot realistically exceed. (Roll, 1986; Malmendier & Tate, 2008; Hayward & Hambrick, 1997)

Agency theory, introduced by Jensen and Meckling (1976), addresses the key conflicts of interest between the firm's shareholders and its management. Under the frictionless market assumption by normative financial theory, management should pursue decisions on M&A based on maximization of shareholders' wealth. However, the agency theory proposes that managers, as the utility-maximizers, might undertake self-serving objectives that deviate from shareholders' interests. This deviation emerges in the market for corporate control, where the benefits — like increased power, compensation, or prestige — can often override the economic costs of a M&A for the acquiring firm. (Jensen & Meckling, 1976; Jensen, 1986)

The agency theory interprets that the targets' valuation can be a secondary motive when management pursues M&A. For example, management may commit to managerial entrenchment by acquiring target firms that require specific expertise despite the target would have inferior fundamental prospects; the situation where the management holding certain expertise is hard to replace (Shleifer & Vishny, 1989). In contrast, managers can pursue diversifying M&A to diminish the firm-specific risk connected to their undiversified human capital, although the shareholders are able to diversify at the portfolio level (Amihud & Lev, 1981). Hence, the agency theory estimates that when M&A decisions are driven by the management benefits at the expense of the shareholders' wealth, the acquirers' stock should face a negative short-term reaction as the market expects the agency costs linked with deal (Morck, Shleifer & Vishny, 1990).

The third agency mechanism in the agency theory framework is the free cash flow hypothesis by Jensen (1986), proposes that firms with considerable free cash flow are more prone to pursue value-destroying M&As rather than returning the excess capital to the shareholders. According to this, retaining and mobilizing excess cash through M&A expands the resources under managerial control and reinforces managerial discretion, even when the investments produce returns below the firm's cost of capital. The free cash flow hypothesis therefore predicts that acquirers with high free cash flow and limited growth opportunities — low Tobin's Q firms — are most probable to partake in such value-destroying transactions, and that the stock price reaction to the deal announcement should be correspondingly negative (Jensen, 1986).

Real options theory provides a nuanced framework for understanding M&A by going beyond the constraints of traditional valuation methods. Net present value (NPV) analysis presumes that investment decisions are one-shot and have fixed future cash flows. Conversely, the real options theory holds that M&A is not an action to purchase target firms' existing assets, but to purchase a portfolio of strategic options for future investment opportunities (Dixit & Pindyck, 1994). The real options enable the acquirer to proceed with certain future actions on the operational side — for example, expansion into a new market, scaling up well-performing operations, or scaling down the underperforming units. Exercising such real options depends on how the market opportunities or uncertainty unfold over time. When the paid premium for the target equals effectively paying an option premium for the flexibility to make future operational investments that would be unavailable without the acquisition (Smit & Trigeorgis, 2004).

In the post-deal phase, value creation depends on the effective exercise of the real options. Options remain in-the-money if the management succeeds actively responding to market conditions and opportunities; if the acquiring firm fails to effectively integrate the high valuation target or overlooks the follow-on investments that the M&A has enabled, the paid premium becomes a sunk cost consequently leading to value destruction. In contrast, successful long-term performance in the post-transaction represents the realization of the upside potential from target's growth options. Real options theory

therefore provides a functional interpretation of understanding why acquirers might pay high premiums for targets' that have high market valuation: they are not only buying the targets' existing operations and assets, but also the strategic flexibility to potentially stabilize the future uncertainty in the market. (Smit & Trigeorgis 2004)

2.4 History of Merger Waves

Empirical research shows that M&As do not occur regularly but rather in distinct clusters known as waves (Mitchell & Mulherin, 1996). Literature links these waves mainly to macroeconomic shocks that destabilize the industry-level equilibrium — such as deregulation, technological innovations, or capital market volatilities — alongside with sufficient capital market liquidity to finance the resulting reallocation of corporate assets (Harford, 2005). Since the late nineteenth century, six merger waves have been empirically recorded in the U.S., each evidently driven by different mixture of regulatory, technological, and financial conditions (Martynova & Renneboog, 2008). Understanding the historical merger waves is relevant to this thesis as the sample period starts from the end of the sixth merger wave, and spans through longer time horizon as well different macroeconomic conditions compared to the merger waves prior to the 21st century.

The first merger (1893-1904) wave was defined by a massive-scale horizontal integration which fundamentally restructured the industrial landscape of the United States. Expansion of the U.S. railroad system and telegraph network pushed the local markets to consolidate into a single competitive national market. Accordingly, firms aggressively seek to acquire firms from the same industry to gain a dominant market position in the new national market. The wave resulted in creating industrial mega corporations such as U.S. Steel and Standard Oil. Stigler (1950) identified this period as the era of merger for monopoly, where acquirers' main objective was to remove competition and establish monopolistic market power. The wave ended with the stock market crash of 1904, and thereafter the antitrust law of the Sherman Antitrust Act of 1890 was reinforced by the Clayton Antitrust Act and the Federal Trade Commission Act in 1914 to prevent any further monopolistic concentration in the market. (Stigler, 1950)

The fundamental driver of the first wave's M&A activity was the firms striving for monopoly rents (Stigler, 1950) rather than the operational or managerial synergies often highlighted in modern M&A literature. Therefore, the acquirers' anticipated value creation was based on the target's capacity to contribute to the dominant market position that enabled pricing power. Whereas the modern empirical research uses Tobin's Q to distinguish under- and overvalued firms, the first merger wave was marked by capital watering, in which the issued stock was significantly exceeded to true intrinsic value of firm's assets, accumulating into a speculative overvaluation (Nelson, 1959) which led to inflated stock market valuations that eventually collapsed in 1904.

The second wave (1916-1929) was characterized by what Stigler (1950) referred as 'merger for oligopoly'. The wave emerged in the period following the World War I, when the U.S. economy grew rapidly and the automobile and radio industries matured at a fast pace. Resulting from the tightened antitrust legislation after the first wave — which made pursuing a monopoly position risky — the market structure moved towards oligopolistic consolidation defined by a small number of dominant firms competing in concentrated industries. This period pivoted the market towards vertical integration, as firms aimed to create value by safeguarding their supply chains and controlling the distribution channels to secure operational stability. (Chandler, 1977)

The second wave was strongly connected to the Roaring Twenties stock market boom, where the stock market valuations detached from its intrinsic book value. The 1920s was distinguished by valuations driven by heightened financial speculation and by the perceived efficiency of the new managerial enterprise. (Chandler 1977) In contrast to the capital watering of the first wave, the value creation was increasingly associated with economies of scale and scope. Even so, the high valuations paid for targets at the peak of the speculative bubble failed to converge into fundamental value, as the market crash in 1929, followed by the Great Depression that exposed many of these industrial giants either overleveraged, overvalued, or both (Gaughan, 2015).

The third wave (1965-1969) represents a major departure from the industrial consolidation of the previous waves. This era was driven by rigorous implementation of the Celler-

Kefauver Act, an amendment to the Clayton Antitrust Act, which was initially implemented to reinforce the Sherman Antitrust Act. The Celler-Kefauver Act ended the so-called asset loopholes, therefore effectively preventing anti-competitive horizontal and vertical mergers that would limit industry competition. As a result, firms were compelled to seek growth through diversification into unrelated industries and business segments. This period presented a rise of managerialist philosophy, in which it was believed that management could apply universal administrative procedures to assets in any industry to increase firms' performance. (Shleifer & Vishny, 1991)

The third wave was defined by the pursuit of synergy through financial engineering at the financial statement level, rather than operational integration or synergies. Many acquirers in the conglomerate mergers achieved artificially high valuations around 1965 by acquiring low-growth firms with relatively low valuations, creating the illusion of a high-growth conglomerate. The financial engineering — also known as EPS magic — was created through the bootstrapping technique where high-valued firms acquired low-valued firms via stock-for-stock exchanges to create immediate growth in acquirers' earnings per share that was unrelated to operational profitability. The illusion was contingent on the valuation asymmetry between the acquirer and target, successfully concealing the lack of organic operational growth through an ongoing and aggressive cycle of M&A. (Shleifer & Vishny, 1991; Jensen, 1986)

In the early 1970s, the emergence of oil crisis and increasing interest rates directly exposed the inefficiencies of artificially overvalued conglomerates. Consequently, the market value of these 'diversified' firms fell below the combined book value of the assets, directly demonstrating that inflated equity valuations achieved through M&A failed to generate fundamental economic value for the acquirers. The third wave ultimately initiated the de-conglomeration and divestiture wave in the 1980s. (Shleifer & Vishny, 1991; Mitchell & Mulherin, 1996)

The fourth wave (1981-1989) demonstrated a fundamental shift in the corporate strategic approach to M&As, transitioning from the previous waves diversification era to a period defined by hostile takeovers, leveraged buyouts (LBO) and private equity activity,

and intensive revert back to corporate specialization. Unlike the financial illusion that fueled the third merger wave, the fourth was driven by a rise in the high-yield bond market and the acceleration of private equity which utilized LBOs. In this period, external corporate raiders — investors acquiring large stakes in undervalued or underperforming firms — took control against the wishes of target's management. Acquirers' also utilized substantial amounts of debt to take over these targets', with a key motivation of breaking them apart and unlocking the hidden value. (Shleifer & Vishny, 1991)

The period attempted to address the agency costs and "conglomerate discount" that burdened firms in the previous wave. Deriving from the free cash flow hypothesis (Jensen, 1986), the management of mature corporations often wasted cash on the value-destroying mechanism of empire building rather than returning it to shareholders. This wave functioned as a disciplinary mechanism against that behavior; the extensive debt loads connected to LBO's pushed the management to reinstate operational efficiencies and divest non-core operations and assets to cover the interest payments. Similarly to the third wave, the fourth was less about the synergies in a conventional sense; it focused instead on breaking down the conglomerates created in the 1960s, restoring firms to their core competencies. Shleifer and Vishny (1991) described this as a process of reversing the previous wave's business "diversifications".

Moreover, the fourth wave was triggered by the neoclassical drivers, consisting of large-scale deregulation in the financial, energy, and telecommunications sectors. Mitchell and Mulherin (1996) argued that the M&A activity in the 1980s was a rational response to the industry-level shocks, as M&A delivered most efficient way to rapidly reallocate assets in the shifting macroeconomic environment. By the end of the decade, the mix of tax advantages for debt, loosening of antitrust regulation under the Reagan administration, and the maturation of the private equity and LBOs fundamentally transformed the corporate landscape in the U.S., targeting to prioritize shareholder value over managerial empire-building. The wave ended in the collapse of the high-yield bond market, triggered by bankruptcy of investment bank Drexel Burnham Lambert, which removed the principal source of financing for takeovers. Liquidity constraints together with tightened

state anti-takeover legislation and recession ended the era of hostile corporate raids and leveraged divestiture-driven acquisitions. (Gaughan, 2015; Jensen, 1989)

The fifth merger wave (1993–2000) occurred in late 1990s and was defined by a shift towards strategic mega-mergers and the emergence of the globalized market for corporate control. Transitioning away from the previous wave's hostile M&A environment, this era focused more on friendly M&A financed widely through stock payments that aimed to achieve economies of scale and scope in response to rapid advancements in technology and deregulation. Andrade, Mitchell, and Stafford (2001) record that the wave of deregulation in the financial, telecommunications, and energy sectors accounted for nearly half of the decade's M&A activity, making the 1990s a decade in which the M&As were used as a primary tool to restructure industries.

This wave also marked an extraordinary acceleration in cross-border transactions and growth of multinational giant corporations, as globalization and the emerging internet economies drove firms to expand internationally. Whereas the previous wave concentrated on debt financing, the fifth wave leveraged the high equity valuations to finance large-scale consolidations. Holmstrom and Kaplan (2001) argued that corporate governance was subject to major professionalization during the period, as executive stock options and active board members aligned managerial incentives with shareholder value. Even so, the reliance on overvalued equity also presented a significant behavioral bias; stock-financed mergers were driven by the market misvaluation, in which acquirers used their inflated equity value to acquire tangible assets (Shleifer & Vishny, 2003). The wave ended in 2000 shortly after the burst of the dot-com bubble and sharp decline of the global equity markets. This period and the subsequent market crash exposed most of the firms — especially in technology and media mergers — that failed to converge the transaction into real economic value, resulting in a brief but sharp decline in the M&A transaction volume and a shift to more cautious, value-based transaction structures (Andrade, Mitchell & Stafford, 2001).

The sixth merger wave (2003-2008) surfaced in the direct aftermath of the dot-com bubble collapse and the Enron fraud scandal in the early 2000s. This period was strongly

influenced by quantitative easing from central banks, which fueled abundant liquidity in the market and cheap debt, and by the institutionalization of private equity as the dominant force in the global market for corporate control. The favorable debt market environment and low interest rates enabled private equity firms to pursue highly leveraged buyout deals, in which the targets were often undervalued public companies that the private equity firms converted to private. (Alexandridis, Mavrovitis, & Travlos, 2012)

Like the previous wave, this one continued to enhance globalization and cross-border M&A activity. The wave extended beyond the Western market to include acquisitions involving firms from BRIC nations. In addition, this period saw a rise of shareholder activism, as hedge funds began pressuring firms to divest non-core operational assets or merge to maximize short-term shareholder returns. (Brav, Jiang, Partnoy & Thomas, 2008) The wave continued until late 2007, when the subprime mortgage crisis in the U.S. triggered global credit constraints and diminished the market liquidity. By mid-2008, the collapses of the major financial institutions and the subsequent lack of available debt financing brought the sixth wave to an end. (Alexandridis et al., 2012) The post-crisis institutional and monetary environment that followed shaped the M&A landscape examined in this thesis, as discussed in the next section.

The “seventh” wave (2011-current) began to build up around 2014, when an extended period of low interest rates combined with economic shifts towards digitalization played a crucial role in shaping M&A activity. There is no official empirical evidence of an end to this wave, and technological innovation has continued to expand in quantum computing and artificial intelligence (AI); for the purpose of this thesis, the wave is therefore treated as ongoing. The current wave focuses on strategic survival in the face of technological disruptions. M&A has been used as the primary tool for firms to acquire digital capabilities and intangible assets that could not have been developed internally. The phenomenon has shifted the market dynamics and concentration towards mega corporations in the technology industry — such as Google and Meta — with firms of this scale using horizontal mergers to consolidate the dominance of their platforms. (Alexandridis, Antypas, & Travlos, 2017)

The wave's sharp acceleration due to the COVID-19 pandemic and the subsequent 'deal frenzy' period of 2021, during which the M&A activity was booming. The late-stage boost was characterized by the rise of Special Purpose Acquisition Companies (SPAC), a shell company merging with private target providing an alternative fast-track public-listing route to the traditional IPO process, although SPAC-listed firms typically experience greater post-listing volatility (Klausner, Ohlrogge & Ruan, 2022). Vertical business model integrations re-emerged as firms aimed to establish stable supply chains in technology and have direct access to consumer data. Year 2022 was marked as the inflection point, as central banks increased interest rates to battle against elevated inflation, which further increased the cost of capital and lowered equity valuations (Goldman Sachs, 2026). However, since the high inflation and its consequences were unrelated to the M&A-specific dynamics, this thesis treats the seventh wave still ongoing.

A critical distinction lies between the seventh wave and previous waves. Whereas the fifth wave was driven by rising valuations linked to technological advancement, the current AI-driven market is supported by significant hyperscale investments into data centers and semiconductors. As of 2026, analysts have suggested that the current M&A environment represents a fundamental structural transition to an era of artificial intelligence rather than a temporary trend (Goldman Sachs, 2026; PwC, 2026). Whether recent years represent the final speculative stage of the seventh wave or the rise of a distinct next wave remains an open question. The resilience of the market will depend on whether AI can convert from a capital-intensive experiment into a productivity-enhancing tool across the global corporate landscape. If the transition fails, the seventh wave will likely end similarly to its predecessors.

2.5 Market Efficiency and Corporate Finance Theory

The efficient market hypothesis (EMH) was formalized by Fama (1970), assumes that all asset prices in financial markets reflect all available information. More specifically, EMH assumes that because all investors act rationally and have access to the same information, an individual investor cannot systematically achieve excess risk-adjusted returns over the market average. EMH is defined by three forms of information efficiency. Under

the weak form, the assets' market price reflects all past information and does not include any information beyond historical data. Under semi-strong form, the asset prices reflect all historical information and current publicly available information; in other words, the prices do not incorporate private or insider information. Under the strong form of the efficient market, the prices reflect all public and private information, in which case the superior returns over market are, at least in theory, impossible. In semi-strong and strong forms, the asset prices should be adjusted immediately to new information published in the market (Fama, 1970), such as earnings or acquisition announcements. EMH provides a normative benchmark to test market efficiency in the context of M&As, and a justification for analyzing the short-term market perception of these events. If the market is truly efficient, the acquirers' share price should instantaneously adjust upon the announcement of the deal to reflect the market's unbiased estimate of the deal's NPV.

However, empirical literature has documented post-announcement drift, where stock prices continue to adjust to public information after its release, suggesting that market do not incorporate instantaneously new information (Ball & Brown, 1968). Despite such phenomenon, defined as anomalies in normative theory, the EMH framework remains the dominant baseline in event study research, including M&A, because the announcement-window deviations from theoretical efficiency are typically small relative to the substantial wealth effects observed at announcement (Andrade, Mitchell, & Stafford, 2001).

Due to the empirical evidence against EMH it should not be treated as an established empirical fact but as a normative theoretical benchmark. Beyond post-announcement drift, additional normative anomalies —including the value premium, momentum effects (Jegadeesh & Titman, 1993), and equity premium puzzle — have repeatedly contradicted the EMH's strongest form, and behavioral finance has emerged precisely to explain such persistent deviations (Barberis & Thaler, 2003). The behavioral perspective argues that systematic cognitive biases and limits to arbitrage create sustained mispricing that cannot be eliminated by rational arbitrageurs alone (Shleifer & Vishny, 1997). This thesis adopts a dual-perspective approach, where the EMH framework is used to

motivate the empirical methodology, while the behavioral finance literature reviewed in subsequent sections provides the interpretation of results when they appear inconsistent with strict pricing predictions. This dual posture is essential because the sample period of this study features consistent valuation extremes and proven misalignment between observable market valuations and managerial valuation perceptions, conditions under which the behavioral frameworks are most likely to interpret results of analysis produced by normative financial models.

Related to market efficiency, **information asymmetry** occurs in a transaction — such as M&A — when the other party holds superior information relative to the other party (Akerlof, 1970). This results in an imbalance of power that can lead to inefficiency in the market information flow. One solution to address this inefficiency is signaling theory, introduced by Michael Spence (1973), which proposes that the more informed party might send signals to the uninformed party through observable actions, expressing the underlying quality or motivation behind the specific transaction.

M&As are prime examples of asymmetric information in large-scale transactions. Acquirer typically perform due diligence on targets and will hold a greater quantity and quality of information about the potential M&A transaction compared to the market. However, the targets' management knows full details of the underlying business, which makes target the ultimate superior information holder relative to the acquirer and market. In M&A, the choices made — for example the payment method or selection of target — function as a signal to the rest of the market (Ross, 1977). On the payment method, Myers and Majluf (1984) argue that equity issuing can signal overvaluation of the firm's current stock price, which leads to negative market reaction. In contrast to financial signals, the target selection acts more as a strategic signal to the other stakeholders. Jovanovic and Rousseau (2002) suggest that when a firm seeks to acquire highly valued targets, it signals a transition toward a growth- and intangible-heavy strategy. However, the high information asymmetry concerning the actual fundamental value of the intangible assets and their growth potential can culminate in valuation errors.

Adverse selection derives from information asymmetry and arises when one party — typically the buyer — cannot differentiate between high- and low-quality assets, potentially leading to market failure in which only the low-quality assets are traded (Akerlof, 1970). In such situations, the counterparty holding superior information can benefit at the expense of the less-informed counterparty. Originally formalized in auction theory (Thaler, 1988), the winner's curse describes the systematic tendency for the winning bidder in a competitive auction to overpay, since the act of winning itself signals that the bidder valued the asset more highly than all other competitors. In M&A the adverse selection emerges in the winner's curse through acquirer overestimating the target's value and the potential upside it could bring to the acquirers' operations. The risk of overestimation is especially severe on targets with considerable intangible value, since their true economic value cannot be easily computed like with physical assets. In prior studies on winner's curse, Varaiya (1988) revealed that when the number of bidders in a takeover increase, so does the probability of overpayment. Furthermore, Rhodes-Kropf and Viswanathan (2004) propose that during the periods of market overvaluation, the adverse selection becomes more common as management uses their overvalued stocks to acquire the targets. Firm Valuation

The principle of value maximization holds that the main objective of management is to maximize shareholders' wealth, typically measured by the firm's share price. This normative goal furthermore assumes that the investors and shareholders are rational, risk-averse participants who prefer more wealth rather than less and prefer the wealth to be received earlier rather than later. Management can achieve this objective only by implementing a corporate strategy that selects portfolio of projects and investments that generate the highest expected NPV while minimizing costs. (Brealey, Myers, & Allen, 2020).

An extension to this principle is rational market timing, in which the firm and its management actively manage the finances to respond to the stochastic financing conditions in the market. Under this framework, firms do not act based on their current cash needs but rather time the equity market rationally to build a buffer of cash when external financing costs are relatively low. This behavior is driven by the expectation that favorable

windows of cheap equity funding are limited and can disappear during financial crisis and severe market stress. (Bolton, Chen & Wang, 2011). When market timing extends from financing decisions to corporate acquisitions, overvalued firms have been documented to use inflated equity as acquisition currency, with implications for deal structure and acquirer announcement returns (Shleifer & Vishny, 2003).

Empirical findings suggest that market timing is coherent with firms who prepare for future financial distress, as most of the firms issuing equity appear to be constrained by liquidity needs rather than by attractive investment opportunities. Moreover, the interaction between market timing and fixed issuance cost can culminate into non-monotonic investment behavior, in which a firm increases capital expenditures as it approaches the equity issuance threshold to exploit favorable terms before they expire. This strategic response to volatile capital market conditions is vital for protecting the firm's value in both short and long term. (Bolton et al. 2011).

Pecking order theory proposes that firms adhere to a certain order of preferences in financing to diminish the costs associated with information asymmetry (Myers & Majluf, 1984). Under this framework, internal funding is the most preferred source of funding followed by debt funding. Equity funding places as the last resort, since the costs of equity issuance under information asymmetry are typically the highest (Myers & Majluf, 1984; Frank & Goyal, 2008). This is fundamentally driven by the fact that management holds informational advantage over the firms' true value relative to investors and other stakeholders. Hence, the market sees equity issuance as a signal that the firm's share price is overvalued, which leads to negative stock price reaction (Myers & Majluf, 1984).

In M&A, pecking order theory implies that the acquirer's financing choice serves as an essential signal to the market regarding the value of acquirer and target. An acquirer with a significant cash reserve can avoid the trap of issuing undervalued equity, thus preventing capital misallocation and value-destructive financing in the acquisition (Myers & Majluf, 1984). The theory therefore suggests that the stock price reaction to M&A depends on the financing option being used to pay for the transaction, particularly, if a

high-valued target represents prospective growth opportunities that the acquirer wants to secure without diluting its equity. (Myers & Majluf, 1984).

2.6 Behavioral Finance

Today's financial economics rests on the assumption of rational decision-making, formally defined through the expected utility framework of Von Neumann and Morgenstern (1944). Under this framework, individuals are assumed to hold complete and transitive preferences, evaluate uncertain outcomes by their expected utility, and consistently choose the option which maximizes this expected utility. This axiomatic conception of rationality underpins the EMH, the capital asset pricing model, and the broader normative architecture of modern finance theory, including the standard valuation models. Behavioral finance has emerged over the past decades as a framework which systematically documents and theorizes the empirical deviations from the foundation of rationality. (Shiller, 2003; Barberis & Thaler, 2003). Rooted in cognitive psychology, behavioral finance argues that investors and managers operate under cognitive limitations, emotional influences, and systematic biases that produce decisions inconsistent with the predictions of classical rational agent models.

Bounded rationality denotes a shift from the normative financial economics assumptions of rationality to a more realistic paradigm where individuals function under cognitive limitations and information asymmetry (Simon, 1955; Kahneman, 2003). Rather than optimizing every outcome, individuals apply satisficing strategies by choosing options that meet an acceptable threshold rather than pursuing the theoretical maximum utility, because the cognitive cost of full optimization exceeds its practical benefit in most real-world decision contexts (Simon, 1955). Experimental research in asset markets has provided support for this view, showing that most participants systematically deviate from fundamental value-based decision-making, instead relying on simple heuristics and coordination on trend-following behavior (Hommes et al., 2005).

Empirical findings have shown that cognitive limitations have significant implications for practical financial decision-making. Kahneman (2003) showed that individuals

consistently rely on heuristic shortcuts rather than comprehensive analysis when they face complex decisions under uncertainty — a pattern particularly relevant in the field of M&A, in which the intrinsic value of target's intangible assets and growth prospects is inherently hard to assess. Bounded rationality has direct implications for corporate decision-making contexts where information is incomplete and outcomes are uncertain — conditions that characterize most of the M&A transactions, especially when evaluating intangible assets, market environments and synergy potential.

Anchoring bias occurs when individuals form estimations by relying heavily on the first piece of information available and make decisions based on that reference. This cognitive heuristic typically results in systematically skewed outcomes since the anchor, even if irrelevant, continues to exert disproportionate influence on the final judgement. (Kahneman & Tversky, 1974) For example, prior research has discovered the industry median forecasted earnings per share (FEPS) as one of the main anchors in financial markets, finding that analysts produce more optimistic forecasts for firms whose FEPS is low relative to their industry peers (Cen, Hilary, & Wei, 2013).

Empirical evidence further suggests that anchoring bias has significant implications for market efficiency. Analysts are averse to publish forecasts that deviate significantly from the industry average, even when fundamental information would support a more substantial revision. This leads to predictable stock return patterns — although normative theory implies that markets are not predictable — as firms with high FEPS relative to the industry median tend to experience high abnormal stock returns once their true profitability is revealed. (Cen et al., 2013) Anchoring effects have also been recorded in corporate acquisitions, where reference price points such as 52-week-high stock prices systematically influence bid prices and acquirer announcement returns (Baker, Pan & Wurgler, 2012).

Over- and underreaction further challenges the fundamental assumption of EMH by evidencing how stock prices systematically deviate from their fundamental values (DeBondt & Thaler, 1985; Barberis et al., 1998). Overreaction is often observed in the long-term, in which stocks that have performed poorly tend to outperform the 'winners'

from the same period due to the mean-reversion effect. This mean-reversion is often attributed to investors excessively emphasizing recent performance patterns and downplaying long-term statistical evidence (DeBondt & Thaler, 1985). In contrast, underreaction is linked to the momentum effect in the short to medium term, in which stock prices respond slowly to new available information — such as M&A announcement — causing winning stocks to remain winners despite the new data (Jegadeesh & Titman, 1993).

Behavioral models attempt to explain these patterns through specific judgement biases, such as conservatism and representativeness, whereby individuals give too much weight to the recent patterns in decision-making (Barberis et al., 1998). Empirical evidence shows that although large-cap stocks react more efficiently to new information, underreactions are more common in mid- and small-cap stocks (Hong, Lim & Stein, 2000). Over- and underreaction dynamics imply that, in M&As, the acquirers' stock price movement around the announcement may reflect either an initial underreaction to underlying synergy potential or an overreaction to the growth opportunities.

Overconfidence is one of the most systematic biases in corporate management, defined by an exaggerated assessment of one's own abilities, knowledge, and likelihood of success. Moore and Healy (2008, p.502) identify three distinct dimensions: overestimation (overestimating one's own performance), overplacement (better-than-average), and overprecision (excessive certainty in one's beliefs). While overconfidence sometimes yields positive outcomes, such as increased investments in R&D and innovation (Hirshleifer et al., 2012; Malmendier & Tate, 2005), it is more commonly linked to negative financial outcomes, including manipulation of cash flows and systematic forecasting errors (Malmendier & Tate, 2005; Moore & Healy, 2008).

In M&A, overconfidence emerges as managerial hubris, which is discussed in detail in Section 2.3.3 as a theoretical explanation for value-destroying M&A transactions. From the behavioral finance perspective, the underlying mechanism is the cognitive distortion through which management systematically overestimate their capabilities to extract economic value from targets and underestimate the risks of integration. (Malmendier & Tate, 2008)

Herding behavior refers to a systematic tendency of investors to copy actions of others rather than justify their decision-making through independent analysis (Hwang & Salmon, 2004). This behavior is driven by reputational concerns, as managers might fear that deviating views from the market consensus can jeopardize their career opportunities or performance evaluations. (Scharfstein & Stein, 1990; Chevalier & Ellison, 1999). Empirical findings show that herding is significantly stronger in periods of high uncertainty and market instability, when fear-driven decision-making escalates investors' tendency to follow others. This dynamic often leads to financial bubbles where asset prices deviate significantly from their true intrinsic values (Bikhchandani & Sharma, 2000; Lo, Repin, & Steenbarger, 2005).

Investment strategies alone can trigger herding behavior, as fund managers perform momentum investing or engage in window dressing by buying stocks that have recently performed well. (Grinblatt et al., 1995; Lakonishok et al., 1992). In M&A, herding can lead to merger wave behavior, in which firms within an industry feel obliged to acquire other firms merely because their competitors are doing so. While merger waves have been attributed to industry-level shocks (Mitchell & Mulherin, 1996), peer-driven limitations among CEOs have been also identified as a contributing mechanism (Goel & Thakor, 2010). This dynamic can result in artificial demand and poor decision-making, as acquirers' management defers to peer behavior and popular trends rather than conducting rigorous fundamental analysis of the target.

Market timing theory proposes that firms issue equity when the market value of the firm is high relative to the historical values, and conversely, repurchase shares when valuations are low (Baker & Wurgler, 2002; Frank & Goyal, 2008). The theory suggests that a firm's capital structure is the cumulative outcome of past attempts to time the market, which implies that financing decisions are not directly driven by optimal capital structure considerations but the management's assessment of relative valuation (Baker & Wurgler, 2002). Under this paradigm, managers are assumed to be rational market agents who exploit temporary misvaluation of their firms' equity to maximize the firm's value. Empirical evidence has generated mixed support for the rational version of market timing.

While equity issuers tend to have low subsequent idiosyncratic returns and repurchasing firms' yield to higher returns — patterns aligning with market timing — the findings are also consistent with mispricing-correction explanations instead of actual market timing skills. Loughran and Ritter (1995) showed that managers consistently fail to time the market successfully, as the abnormal returns associated with the stock repurchases reflect the correction of prior undervaluation rather than active timing ability.

More recent survey-based evidence challenges this rational interpretation. Graham (2022) demonstrates that CFOs persistently believe their own equity is undervalued across market conditions and over time. This conflicts with the mechanics of market timing theory: if managers consistently think their stock price is undervalued, the rational response would be to repurchase shares and avoid equity issuance, yet firms continue to use their stock as a financing method. Graham's evidence therefore reframes market timing as fundamentally a behavioral phenomenon based in managerial miscalibration, overconfidence and bounded rationality, rather than pure exploitation of mispricing.

When applied to M&A, this behavioral framing of market timing produces a notable paradox. If managers persistently perceive their own firm's equity as overvalued (Graham, 2022), the rational expectation is that they avoid using stock as acquisition currency. Yet stock-paid M&A of high Tobin's Q targets — highly valued by the market — remain a substantial share of M&A activity. This combination of perceived acquirer undervaluation with bilateral high-valuation deals raises a meaningful empirical question: whether such transactions reflect behavioral inconsistency, miscalibrated forecasts, or strategic considerations beyond the rational market timing framework.

3 Literature review

Prior empirical literature on M&A has developed over decades, providing at times conflicting body of evidence on the wealth effects. This chapter reviews the prior research directly relevant to this thesis, structured around three main themes: short-term stock market reactions to M&A announcements, the explanatory power of target Tobin's Q for acquirer stock returns, and the payment method effect on acquirer negative abnormal returns. Building on the theoretical framework in the previous chapters, these threads of empirical literature complete the foundation which against results are reflected.

3.1 Short-term Stock Price Reaction to M&A Announcement

Acquirer's short-term stock price reaction around the M&A announcement is one of the most broadly studied topics in corporate finance. The consensus is that target firms' shareholders generate significant positive returns following the announcement, whereas acquirers' shareholders gain average returns of near-zero or slightly negative. Andrade, Mitchell, and Stafford (2001) deliver a review of M&A activity from 1973 to 1998, finding that the announcement-period combined returns for the merging parties are approximately two percent of the total combined value, suggesting that mergers create value. However, the combined gain is distributed asymmetrically, where targets' shareholders earn most of the gains, while acquirers' shareholders gain returns that are statistically not distinct from zero. These findings are consistent in all three decades in their sample period, implying a stable pattern of M&A wealth effects over time.

The findings of Andrade et al. (2001) deserve a critical examination based on the sample period. The aggregate stability of returns through three decades conceals substantial differences in the underlying merger waves of the period — the de-conglomeration of the 1970s, the hostile takeover wave of 1980s, and the 1990s emphasis on stock-paid M&A activity — each of which generated acquirer-target return distributions through different economic mechanisms. Furthermore, the asymmetric distribution of returns likely indicates structural attributes of the M&A market rather than inefficient pricing: in competitive bidding environment where acquirers' pursue market power, the winner's

course mechanism pushes them to transfer the synergy gains to targets' shareholders through paid premiums in order to win the deal, while targets superior information about themselves allows them to extract the upper bound of negotiating range (Roll, 1986; Akerlof, 1970). The finding that acquirer shareholders gain near-zero returns is therefore consistent with behavioral interpretation of M&A activity (Malmendier & Tate, 2008), and the key empirical question is not whether M&As create value, but what macroeconomic conditions and managerial motives drive M&A activity, and why such transactions are pursued despite the evident wealth transfer from acquirer to target shareholders.

Moeller, Schlingemann, and Stulz (2004) examine a sample of 12,023 acquisitions by U.S. public firms from 1980 to 2001 and found a significant deviation between equally weighted and value-weighted acquirer stock returns. While equally weighted abnormal returns at the announcement were 1.1 percent, acquirers' shareholders lost on average 25.2 million USD per announcement on a dollar-weighted basis. This divergence reveals a significant size effect in acquisition returns: returns for shareholders of small-cap acquirers are around two percent higher than for large-cap acquirers, regardless of the payment method or whether the target is public or private. In a follow-up study, Moeller, Schlingemann, and Stulz (2005) showed that during the merger wave of 1998-2001, acquirers' shareholders lost 12 cents for each dollar paid on transactions, resulting in a total loss of 240 billion USD. The authors attribute this exceptional destruction of wealth to a small number of acquisitions involving extremely high-valued acquirers, emphasizing the danger of overvalued acquirers pursuing large-scale deals.

The robustness of this size effects across firm characteristics, deal types, time periods present noteworthy puzzle, and several mechanisms have been proposed in the literature to rationalize the result. Large acquirers tend to undertake larger and more complex deals that are more difficult to integrate successfully, generating greater post-merger execution risk that the market discounts at the announcement. Large acquirers are also more likely to suffer from agency problems associated with managerial empire-building (Jensen, 1986), in which CEOs of large firms pursue acquisitions for reasons of size and scope rather than fundamental value creation. Furthermore, large acquirers tend to pay

higher acquisition premiums (Alexandridis, Fuller, Terhaar & Travlos, 2013), and the disciplining effect of internal capital constraints is weaker, allowing large firms to undertake value-destroying transactions that smaller firms could not finance. Together, these mechanisms suggest empirically that the acquirer size effect reflects systematic differences in deal quality, governance discipline, and integration risk between small and large acquirers rather than a structural advantage of small firms.

3.2 Tobin's Q and Corporate Takeovers

The relationship between Tobin's Q and merger gains was initially investigated by Lang, Stulz, and Walkling (1989) in a foundational study of successful tender offers. The findings interpreted that shareholders of high Tobin's Q acquirers gained notably more than shareholders of low Tobin's Q acquirers, while shareholders of low Tobin's Q targets gained more than shareholders of high Tobin's Q targets. The interaction effect was compelling: takeovers in which well-managed acquirers — proxied by high Tobin's Q — took over poorly managed targets generated the highest overall gains. These findings established what became known as the Q hypothesis of takeovers — that Tobin's Q proxies' managerial efficiency, and that value is created through managerial efficiency.

Servaes (1991) extended the analysis of Lang et al. (1989) to a comprehensive sample of 704 M&A over the period 1972 to 1987. He confirmed that target, acquirer, and total announcement returns are higher when the target has a low Tobin's Q and the acquirer has a high Tobin's Q. Accordingly, the findings of the initial study were confirmed to hold and remain significant after controlling for other determinants of M&A gains, such as payment method and whether the offer was contested. By the early 1990s, the consistency of these findings across larger samples consolidated the view that Tobin's Q is an economically significant predictor for the M&A outcomes. The Q hypothesis recognized by these foundational studies had two key assumptions: Tobin's Q is a reliable proxy for managerial quality, and that the patterns seen in the 1970-1980 sample data generalize to subsequent market environments.

The assumptions motivate for critical scrutiny. First, that Tobin's Q would robustly proxy managerial quality, assumes that the visible market valuations capture management's true contribution to firm value, distinguishable from industry conditions, sector-wide growth dynamics, and macroeconomic regime effects. Second, that sample of 1970-1980 patterns generalize to subsequent market environments — assumes persistent relationship between target valuation and acquirer wealth effects across distinctly different macroeconomic conditions, including monetary policy regimes, interest rates, and equity premium levels, which are tightly connected to each other. The empirical research reviewed in the next section implies that both assumptions have been increasingly challenged, motivating this thesis to interpret in regime-conditional context any null finding on Tobin's Q in the post-financial-crisis period.

Regardless of the compelling evidence from the initial studies, recent studies have increasingly challenged whether the Q hypothesis holds its predictive power in recent time frames. Dong, Hirshleifer, Richardson, and Teoh (2006) examined whether market misvaluation, in addition to managerial quality, drives takeover activity. Built on the framework of Shleifer and Vishny (2003), they presented an alternative misvaluation hypothesis, suggesting that stock-paid transactions are driven by overvalued acquirers seeking relatively less overvalued targets to use as currency for the acquisition. Under this alternative hypothesis, a high Q acquirer signals overvaluation rather than managerial quality, and stock return patterns from the prior samples might partially reflect the market's reaction to misvaluation rather than expected synergies from improved management. Dong et al. (2006) found that the Q hypothesis evidence is stronger in the pre-1990 samples than in the 1990-2000 sample, while evidence for the misvaluation hypothesis follows the opposite pattern. Both hypotheses are not jointly exclusive, but their explanatory power has shifted over time, suggesting more structural changes in the relationship between target's market valuation and acquirers' stock returns.

The supplementary evidence from Moeller et al. (2005) further diminishes the Q hypothesis. If the Q hypothesis holds, acquirers' announcement returns should have been driven primarily by the quality differential between high-Q acquirers and low-Q targets.

Conversely, what drove the returns in the period of 1998-2001, was acquirer's overvaluation itself — high-valued acquirers systematically destroyed shareholder value regardless of target features. This implies that the high Tobin's Q on the acquirers did not capture managerial efficiency — as in the initial Q hypothesis — but stock overvaluation, which is directly the alternative measure of Tobin's Q proposed by Dong et al. (2006). Therefore, the Q hypothesis, as initially formulated, cannot explain why high Tobin's Q acquirers — allegedly the well-managed firms — would consistently destroy shareholder value at scale. The structural shift in this evidence motivates a modern-day test of the Q hypothesis in a sample period characterized by sustained valuation extremes and structurally different macroeconomic conditions.

Table 1 Summary Table of Empirical Findings on Acquirer Announcement Returns.

Authors & Publishing Year	Sample Period	Geographic Area	Sample size	Methodology	Acquirer Abnormal Returns Finding
<i>Lang, Stulz, & Walkling (1989)</i>	1968 – 1986	U.S.	87 tender offers	Event study, OLS cross-sectional regression	Significantly positive for high-Q acquirers acquiring low-Q targets
<i>Servaes (1991)</i>	1972 – 1987	U.S.	704 mergers and tender offers	Event study, OLS cross-sectional regression	Positive total gains; higher when high-Q acquirer meets low-Q target
<i>Andrade, Mitchell, & Stafford (2001)</i>	1973 – 1998	U.S.	4,256 deals	Event study	Combined merging parties earn positive announcement returns; near-zero or slightly negative for acquirers, positive for targets
<i>Moeller, Schlingemann, & Stulz (2004)</i>	1980 – 2001	U.S.	12,023 acquisitions	Event study, OLS cross-sectional regression	Equally weighted return +1.1%; aggregate dollar loss across the sample; significant size effect (small acquirers gain ~2% more)
<i>Moeller, Schlingemann, & Stulz (2005)</i>	1998 – 2001	U.S.	4,136 deals	Event study	Significant aggregate wealth destruction; \$240bn loss attributable to overvalued large acquirers
<i>Dong, Hirshleifer, Richardson, & Teoh (2006)</i>	1978 – 2000	U.S.	3,705 deals	Event study, OLS cross-sectional regression (uses P/B and P/V ratios as misvaluation proxies)	Q hypothesis evidence stronger pre-1990; misvaluation hypothesis stronger 1990–2000
<i>Travlos (1987)</i>	1972 – 1981	U.S.	167 deals	Event study	Significantly negative for stock-financed deals; near-zero for cash-financed
<i>Alexandridis, Antypas, & Travlos (2017)</i>	1990 – 2015	U.S.	26,078 deals	Event study	Positive acquirer returns post-2009; stock-financed deals no longer destroy value
<i>This thesis</i>	2009 – 2024	U.S.	344 completed public-to-public deals	Event study, OLS cross-sectional regression with HC3 robust Ses	Null on Tobin's Q; significantly negative for stock-financed deals

3.3 Event Study and Cross-Sectional Regression

The event study methodology used in this thesis adheres the framework established by Brown and Warner (1985), who provided a method to systematically evaluate the statistical properties of daily stock return data and their implications for event study structure. They demonstrated empirically that simple approaches to computing abnormal returns perform well in terms of test specification and power, even when the special characteristics of daily returns are not explicitly controlled. They found that simple benchmark models perform similarly to the complex market model approaches, justifying the use of simple abnormal return measures in event studies.

The mean-adjusted returns model, which computes the abnormal return as a deviation between the realized return of an asset and the historical average return during the estimation window, traces back to the original event study papers of Ball and Brown (1968) and Fama, Fisher, Jensen, and Roll (1969). Brown and Warner (1985) confirmed that the mean-adjusted model generated well-specified test statistics under a wide range of conditions. The market-adjusted model, in which the abnormal return is computed as a difference between the assets realized return and benchmarks' return, provides specific control for broader market movements around the event day. Using one model as a primary and other model as robustness check is standard practice in empirical M&A event study research, as demonstrated by MacKinlay (1997, pp. 17-20), who gave a comprehensive review of event study methodologies and their application in corporate finance.

The rejection of equilibrium-based asset pricing models — such as Capital Asset Pricing Model and its multifactor extensions — as the benchmark in this study is justified by well-documented empirical failures of the CAPM and its extensions in explaining the cross-section of stock returns (Roll, 1977; Fama and French, 2004). The joint-hypothesis problem associated with these asset pricing models makes it infeasible to differentiate the abnormal returns traceable to the event itself from those attributable to the model.

3.4 Payment Method Effect

While the primary interest of this thesis is to examine the relationship between the target's Tobin's Q and acquirers' announcement returns, the payment method must be controlled for any credible empirical test of the relationship. Prior literature has recognized payment methods as one of the most significant variables for acquirer announcement returns. Its exclusion from the cross-sectional regression would introduce a significant omitted variable bias that could alter the estimated effects of targets' Tobin's Q.

The theoretical foundation for payment method effects is derived from the information asymmetry from Myers and Majluf (1984, p.195), who showed that under asymmetric information, managers acting in the interest of the existing shareholders will tend to issue equity when they believe the firm's equity is overvalued relative to its fundamental value. A rational investor anticipates this behavior and views stock-paid M&As as a negative signal for the intrinsic value of the acquirers' stock, which drives down the acquirers' stock price upon the announcement. Cash-paid transactions carry no such adverse selection signal and are associated with neutral or positive stock price reactions.

Travlos (1987) provided foundational empirical evidence for this mechanism, showing significant negative abnormal acquirer returns for stock-financed deals, and insignificant positive returns for all-cash transactions in the sample covering period 1972 to 1981. The asymmetry has been shown to be exceptionally enduring across different samples, time periods, and geographies, and was confirmed by Andrade et al. (2001), who found that acquisitions paid at least partially with the acquirer's equity generated combined announcement returns near-zero, while acquisitions covered with cash-only accumulated positive combined returns.

While the findings on non-existent or negative stock returns associated with stock-paid deals are one of the most robust consistencies in the M&A literature, recent evidence suggests this pattern has diminished in the post-2009 period. The Myers and Majluf (1984) EMH-based rational-agents framework underlying the prior empirical findings explaining the payment method effect has been complicated further by the survey-based

evidence from Graham (2022), who proved that CFOs regularly believe their own equity is undervalued despite the market environment being characterized by overvaluation. This evidence sits in direct tension with the Myers and Majluf assumption that management issues equity only when they believe the firm's stock is overvalued, suggesting that the true mechanism connecting payment method to acquirers' returns is less consistent with rational-agents framework than the foundational literature suggests. These dynamics hold implications for this thesis: although the payment method remains a crucial control variable, the expected effects on the acquirers' returns might differ in magnitude, character, or underlying mechanism in the 2009-2024 sample period compared to historical findings.

4 Data and Methodology

This chapter discusses the data sources, sample construction, and empirical methodology of the thesis. The analysis combines an event study measuring acquirer short-term CARs around the M&A announcement date with cross-sectional OLS regression connecting CARs to target Tobin's Q and selected deal- and firm-level controls. The chapter concludes with a discussion of the limitations of empirical analysis and the overall study.

4.1 Data

The sample is built using the Bloomberg Terminal M&A database, covering completed M&A transactions announced between January 1, 2009, and December 31, 2024. This period captures the post-financial crisis era, through the COVID-19 pandemic and its aftermath, providing a broad range of market conditions against which to assess the Tobin's Q-CAR relationship. Any shorter sample period would provide only a snapshot prone to transient macroeconomic conditions and market shocks rather than a generalizable cross-sectional observation.

The sample is restricted to public-to-public U.S. M&A transactions for two reasons. First, calculating targets Tobin's Q requires continuous market price and financial statement data, both primarily available for listed firms. Second, restricting to listed target firms to ensure CARs are computed in a liquid and, to a certain extent, informationally efficient market with theoretically a rapid price discovery, and the U.S.-only restriction eliminates variation in institutional environments, accounting standards, and regulatory frameworks that would complicate cross-border comparisons (Erel, Liao & Weisbach, 2012). Aligning with the standard practice in prior M&A research (Fama & French, 1992; Loughran & Ritter, 1995). Firms in the financial sector (SIC codes 6000-6999) and utilities sectors (SIC codes 4900-4999) are excluded from the sample. Financial firms face discrete capital adequacy requirements and regulatory accounting frameworks that distort Tobin's Q measurement, and utility firms operate under regulated rate-based pricing that influences asset valuations independently of market dynamics.

Following the Fuller, Netter and Stegemoller (2002, p.1768) framework, a 5 percent materiality threshold is applied: the announced transaction value must constitute at least 5 percent of the acquirer’s market capitalization 30 trading days before announcement. This excludes deals unlikely to generate observable stock price responses and ensures the event study captures transactions that are strategically and financially material for the acquirer.

Daily stock prices for acquirers, targets, and the S&P500 index are sourced from the Polygon.io API. Fundamental financial statement data — total assets, total debt, shares outstanding, and additional variables to compute Tobin’s Q — are extracted mainly for target firms from SEC EDGAR 10-K filings using the XBRL data infrastructure, with the most recent filing prior to each M&A deal announcement. The complete data retrieval, processing, and analysis pipeline was developed in Python, encompassing API integration with Polygon.io, XBRL parsing of SEC filings, cross-sectional regression with HC3 robust standard errors, and robustness checks. The full code base is provided in Appendix 2. Table 2 summarizes the sample filtering process, deriving the final sample of 344 transactions from the initial Bloomberg dataset.

Table 2 Sample Selection Breakdown.

Sample Selection Criterion	Deal count
Initial Bloomberg deal universe (completed, public-to-public, U.S. M&A transactions, from 2009–2024)	1,297
Less: Non-US acquirer firms	(3)
Less: Cross-border transactions (non-US target firms)	(344)
Less: Financial sector firms excluded (SIC 6000–6999)	(87)
Less: Utility sector firms excluded (SIC 4900–4999)	(4)
Less: Below materiality threshold, insufficient stock price data, or missing Tobin's Q data	(515)
Final sample	344

4.2 Event Study Methodology

To analyze the short-term stock price reaction of acquirers to M&A announcements, this thesis applies an event study framework followed by the foundational methodology of Brown and Warner (1985, pp. 6-8). The event study framework computes abnormal stock returns by comparing the actual realized returns of acquirers' stock in the event window to a benchmark expected return estimated from a pre-event estimation window. In this study, the estimation window is set to 180 trading days prior to the M&A announcement date ($T = 0$). For each acquirer, the arithmetic average daily return over the 180-day estimation window serves as the benchmark expected normal return in the mean-adjusted event study model. The six-month window provides a sufficient number of observations to establish a stable benchmark daily return and is close enough in time to the announcement date to capture the prevailing return environment of the acquirer. For every acquirer (i), the average daily return in the estimation window is calculated:

$$\bar{R}_i = \left(\frac{1}{T}\right) \times \sum R_{i,t} \quad \text{for } t \in \text{estimation } 180 - \text{day window}$$

Equation 2 Daily Average Return

where the $R_{i,t}$ is the daily log return of the acquirer i on day t , and T is the number of trading days in the estimation window. If an acquirer has fewer than 180 trading days available prior to the announcement date, the maximum number of trading days is used.

This study utilizes two supplementary benchmark event study models to measure the daily abnormal returns of the acquirer's stock, following Brown and Warner's (1985) recommendation to use several simple models as a robustness check on event study results. The principal benchmark is the mean-adjusted returns model, in which the acquirer's (i) abnormal return on the day (t) is determined as the difference between the actual daily return and the historical average daily return in the estimation window:

$$AR_{i,t}(Mean) = R_{i,t} - \bar{R}_i$$

Equation 3 Daily Abnormal Return (Mean-Adjusted)

The model does not require assumptions about the relationship between the stock returns and market returns, which makes it resistant to the model misspecification concerns that affect equilibrium-based asset pricing models. Brown and Warner (1985) showed that the mean-adjusted returns approach provides well-specified test statistics under a broad range of conditions. The approach tracks back to the primal event study papers of Ball and Brown (1968) and Fama, Fisher, Jensen, and Roll (1969). The market-adjusted returns model serves as the secondary benchmark and robustness check, in which the abnormal return equals the difference between the daily return of acquirers' stock and the coexistent return of the S&P500 benchmark index:

$$AR_{i,t}(Market) = R_{i,t} - R_{m,t}$$

Equation 4 Abnormal Return (Market-Adjusted)

where $R_{m,t}$ is the daily return of the S&P500 index on day t . The market-adjusted approach implicitly assumes a beta coefficient of one for all stocks but, unlike the mean-adjusted model, does not require an estimation window to calculate average daily returns, as it uses the simultaneous return of the benchmark index of each event day. This model controls broader market movements that influence all the stocks on the announcement day, partly addressing a limitation of the mean-adjusted model, which does not incorporate stock market-wide shocks.

As discussed in the literature review about the event study methodology (Section 3.3), equilibrium-based asset pricing models —such as CAPM and multifactor extensions to it — are rejected as the benchmark for this study due to the well-documented joint hypothesis problem and the instability of factor loadings over time (Roll, 1977; Fama & French, 2004). The mean- and market-adjusted models adopted in this study avoid these complications while maintaining statistical validity for short-term event windows, in which the expected daily return under any reasonable pricing model is near zero (Brown & Warner, 1985)

CARs for acquirer (i) over the event window (t_1, t_2) is defined as the sum of daily abnormal returns within the window:

$$CAR_i(\tau_1, \tau_2) = \sum AR_{i,t} \quad \text{for } t = \tau_1 \text{ to } \tau_2$$

Equation 5 Cumulative Abnormal Return

Following the multi-window approach recommended by MacKinlay (1997), CARs are calculated for five separate windows to capture both the immediate stock price reactions and the wider information absorption process around the M&A deal announcement. Event windows extending beyond 20 trading days are not used in this study. Longer windows accumulate noise in daily stock returns and substantially increase the likelihood of confounding events — such as earnings announcements, industry-wide news, or other firm-specific developments — that would obscure the M&A announcement effect and reduce the statistical power of the test (MacKinlay, 1997).

CAR (T-0): The announcement day, capturing the direct price impact of the public announcement.

CAR (-1, +1): The three-day window around the announcement date, capturing information spillover immediately before the announcement and the preliminary market adjustment one day after.

CAR (-2, +2): A five-day window providing a marginally wider view of the stock price reaction, capturing slightly delayed information processing

CAR (-5, +5): An eleven-day window capturing the full price discovery process in the days immediately surrounding the announcement.

CAR (-20, +5): An extended but asymmetric window starting from $t = -20$ trading days prior to the announcement, capturing possible information leakage in the pre-announcement window when the deal is still under negotiated and the due diligence is in progress.

The statistical significance of the mean CAR is evaluated using a one-sample t-test against the null hypothesis of zero mean abnormal return. The statistical significance is reported at the 1%, 5%, and 10% levels, with $N-1 = 343$ degrees of freedom.

4.3 Cross-Sectional Regression Analysis

To assess whether the target firm's market valuation, measured by Tobin's Q, explains cross-sectional variation in the acquirer's stock returns around the announcement, a cross-sectional Ordinary Least Square (OLS) regression is estimated for each five abnormal return windows across both event study models. The dependent variable is the deal-level CAR, and the main independent variable is the target firm's Tobin's Q. The regression specification is as follows:

$$CAR_i = \alpha + \beta_1 Q_i + \beta_2 \ln(DealSize_i) + \beta_3 PayStock_i + \beta_4 PayMixed_i + \beta_5 PayOther_i + \sum_j \gamma_j IndustryFE_j + \sum_k \delta_k YearFE_k + \varepsilon_i$$

Equation 6 Cross-Sectional OLS Regression Formula

where CAR_i is the CAR for the deal (i); Q_i is the target firm's Tobin's Q; $\ln(DealSize_i)$ is the natural logarithm of the announced transaction value in US dollars; $PayStock_i$, $PayMixed_i$, and $PayOther_i$ are dummy variables for the payment method with all-cash paid deals as the reference category; $IndustryFE_j$ is two-digit SIC code for the industry fixed effects grounded in the acquirers primary industry; $YearFE_k$ is the announcement year controlling for the year fixed effects; and ε_i is the error term.

All regression specifications are estimated using heteroskedasticity-robust standard errors (HC3), following the suggestions of MacKinnon and White (1985). Robust standard errors are specifically crucial in cross-sectional regression of the abnormal returns, where the deal-level residual variance is likely to fluctuate systematically with the deal size, acquirer size, and industry parameters. The HC3 variant offers a conclusion even when the substantial heteroskedasticity is present without mandating specification of the heteroskedastic structure.

4.4 Tobin's Q

Tobin's Q is the main independent variable in this study. Tobin's Q is a financial ratio that measures a firm's market capitalization relative to its replacement cost of assets (Tobin, 1969), serving in prior research as a market-based proxy for managerial efficiency, capital

productivity, and the firm's intangible asset base. Theoretically correct formulation, established by Lindenberg and Ross (1981, p.4), defines Tobin's Q as the ratio of the market value of the assets — equity plus the market value of debt — to the replacement cost of those same assets:

$$Tobin's\ Q = \frac{Market\ Capitalization_i}{Replacement\ Cost\ of\ Assets_i}$$

Equation 7 Tobin's Q (Lindenberg & Ross, 1981)

The foundational formulation of Tobin's Q requires asset-level data on the age and composition of physical assets, which is highly infeasible to obtain in large-sample empirical studies, including this one. To address this practical limitation, Chung and Pruitt (1994) developed a simplified approximation of Tobin's Q using available financial statement data:

$$Approximate\ Tobin's\ Q = \frac{(Market\ Capitalization_i + Total\ Debt_i)}{Total\ Assets}$$

Equation 8 Approximate Tobin's Q (Chung and Pruitt, 1994)

Chung and Pruitt (1994, p. 73) demonstrated that this approximation measure explains a minimum of 96.6 percent of the variability in the initial Lindenberg and Ross (1981) operationalization of Tobin's Q. Ever since, the Chung and Pruitt approximation has become the standard measure of Tobin's Q in the empirical corporate finance research and is the formulation adopted in this thesis.

For each target in the sample, Tobin's Q is computed as the sum of the target's market capitalization and total debt, divided by the book of total assets. Market capitalization is computed using the closing stock price of 30 trading days prior to the M&A announcement, multiplied by shares outstanding from the most recent 10-K filing prior to the announcement. The 30-day pre-announcement measurement window for market capitalization is used to avoid deal-related stock price noise immediately preceding the announcement, following the framework suggested in the M&A literature (Schwert, 1996). Total Debt_{*i*} is the sum of short-term and long-term debt from the same 10-K filing before, and Total Assets is the book value of total assets from the same filing.

4.5 Control Variables

Deal size is calculated as the natural logarithm of the announced transaction value in USD, following the standard used by Moeller, Schlingemann, and Stulz (2004). The natural logarithm transformation addresses the right-skewed distribution of deal values and allows the coefficient to be interpreted as the change in CAR associated with a one percentage change in deal size.

The payment method is captured by a set of dummy variables corresponding to each deal. Following the classifications in the Bloomberg Terminal M&A deals list, deals are classified as: Cash (reference category), Stock (PayStock), Cash and Stock (PayMixed), and Cash or Stock (PayOther). Cash is used as the reference category because established literature shows that cash-financed deals are typically associated with announcement returns than stock-financed deals. (Travlos, 1987; Myers & Majluf, 1984).

Industry fixed effects are captured using the two-digit SIC code of the acquirer's primary industry, the standard approach in cross-sectional M&A regressions (Moeller et al., 2004; Servaes, 1991). Two-digit codes provide appropriate industry specification while avoiding the over-fragmentation that can emerge from four-digit SIC codes given the sample of 344 deals. Year fixed effects are captured by the announcement year to control for time-varying macroeconomic conditions, merger wave dynamics, and possible variations in market sentiment that can affect the acquirer CARs systematically across deals announced in the same year.

4.6 Robustness Checks

The use of two distinct event study benchmark models — a mean-adjusted approach serving as the primary and a market-adjusted approach as an additional robust check — it provides cross-model validation of the CAR estimates and regression results. Together with the winsorization checks, the consistency of results across both models and across robustness specifications strengthens the credibility of the empirical results.

Two sets of robustness checks are applied to assess the sensitivity of the key findings to distributional assumptions and the measurement of Tobin's Q. In the first robustness check, the target's Tobin's Q is winsorized at 5th and 95th percentiles of the cross-sectional distribution, in which the values below the 5th percentile are replaced by the 5th percentile value, and conversely, values above the 95th percentile with the 95th percentile value. This method engages with the issue of extreme right-skewness of Tobin's Q, which may allow a small number of outlier observations to exert excessive influence on the regression estimates. The winsorized regression is applied to both event study approaches across all five CAR windows. To further assess the robustness of the results, the second robustness check applies winsorization at the 1st and 99th percentiles to all continuous independent variables — the Tobin's Q and log deal size — and tests whether the results are robust to extreme values in continuous regressors, not just the main independent variable of interest. The second robustness check is also applied to both models across all CAR windows.

Beyond the winsorisation checks, variance inflation factors (VIF) test is computed and computed on the cross-sectional regression specification to verify the absence of high intercorrelation of main variables and to formally test for heteroskedasticity. Diagnostic results are reported in Section 5.4.

4.7 Scope and Limitations

Despite theoretical justification for the data and methodology, several limitations are acknowledged. The sample is limited to U.S. public-to-public M&A deals, which constrains the broader applicability of the findings to other markets or deal structures. Excluding private-sector targets extracts a substantial M&A activity segment for which the relationship between target valuation and acquirer stock returns may differ, given the distinct liquidity and information dynamics of public-to-private acquisitions.

The event study methodology, despite its broad adoption, faces two documented limitations. First, Boehmer, Musumeci, and Poulsen (1991) show that even small event-induced increases in stock return variance results in standard event-study test statistics to

over-reject the null of zero abnormal returns, potentially misinterpreting volatility shifts for genuine wealth effects. The event-induced variance is endogenous to the event itself, since the announcement can increase information flow, trading activity, and stock price uncertainty in ways that the estimation window cannot capture. Second, the event study's framework is anchored in the semi-strong form of EMH (Fama, 1998), under which announcement-window prices unbiasedly capture the market's valuation of the event. This underlying assumption sits tentatively with the behavioral finance evidence reviewed in previous chapters, where investors systematically over- and underreact to new information, exhibit cognitive biases, and managerial decisions reflect bounded rather than fully rational optimization. Therefore, acquirer CARs capture the market's immediate incomplete reaction to the event under conditions of imperfect rationality and elevated variance, rather than conclusive measures of economic value creation.

The OLS cross-sectional regression framework warrants similar discussion of three documented methodological limitations. First, OLS assumes that the explanatory variables are uncorrelated with the error term, but normative corporate finance applications consistently violate this assumption through omitted variable bias, synchronicity between the firm characteristics and the outcome variable, and the measurement error in proxies such as approximate Tobin's Q (Roberts & Whited, 2013). Strategic motivations and other unobserved deal-, firm-, and market-specific variables can simultaneously influence target's valuation and acquirer's returns at announcement, producing coefficient estimates on Tobin's Q that partially reflect omitted dynamics rather than the causal effect of target valuation. Second, the M&A transactions analyzed in any cross-sectional regression are not randomly drawn from the universe of potential deals but present self-selected, successfully completed transactions; Heckman (1979) shows that this selection produces biased coefficient estimates whenever the unobserved factors driving deal selection are correlated with those driving the outcomes. Third, cross-sectional regression captures the average linear relationship between target Tobin's Q and acquirers' CARs across the sample but cannot identify if this relationship is causal, operates through different mechanisms across deal contexts, or varies non-linearly across the distribution of target valuations (Roberts & Whited, 2013). These limitations do not invalidate the use of OLS — it

remains the standard methodological approach in M&A event-study research — but they constrain the interpretive scope of findings: estimated coefficients should be understood as conditional connections within the observed sample rather than as definitive measures of how target valuations casually determine acquirer stockholders' wealth effects.

Two further limitations concern the computation of Tobin's Q and the interpretive scope of CARs. Approximate Tobin's Q (Chung and Pruitt, 1994) depends on book values as a proxy for replacement cost for assets. For firms holding significant intangible assets, such as in the technology and pharmaceutical sectors, book values systematically downplay the true economic value of the asset base, introducing existent measurement error that weakens the estimated relationship between target valuation and acquirer returns. Peters and Taylor (2017) suggest an intangible-adjusted Tobin's Q that embeds estimates of internally generated intangible assets, though its data requirements limit application in large-sample studies. Finally, the event study as a method measures the market's ex-ante perception of the deal value rather than the actual economic value generated upon the transaction. Announcement-window CARs reflect markets expectations that can subsequently prove incorrect, for example due to the challenges in integration challenges, regulatory hurdles, or the shifts in the market might change the deal's economic outcome. This thesis therefore characterizes the market's initial assessment of target quality at announcement rather than whether high Tobin's Q target ultimately produces superior fundamental performance and creates value for the acquirer.

5 Empirical Results

This chapter presents empirical results of the thesis in four sections. The first section provides the descriptive statistics for the sample and key variables used in the regression. The second section reports the results from the event study, including the distribution of CARs across all event windows and the statistical tests used to measure their significance. The third section presents the results of the cross-sectional regression, in which the findings on whether the target firm's Tobin's Q and deal-level control variables can explain the variation in the acquirers CARs are reported. The fourth section discusses the results of the robustness checks and validates reliability of the empirical results.

5.1 Descriptive Statistics

Tables 2 and 3 show the descriptive statistics for the key variables used in the empirical analysis. The overall sample includes 344 completed public-to-public firms M&A transactions in the United States, announced between 2009 and 2024.

Table 3 Descriptive Statistics, Mean-Adjusted Model.

	N	Mean	Median	Skewness	Kurtosis	Std Dev	Std Error
CAR (T-0)	344	-0.47%	-0.20%	-0.74	5.64	6.40%	0.34%
CAR (-1, +1)	344	-0.58%	-0.40%	-1.19	5.35	8.55%	0.46%
CAR (-2, +2)	344	-0.86%	-0.25%	-1.17	4.81	9.16%	0.49%
CAR (-5, +5)	344	-1.23%	-0.92%	-0.71	2.38	10.23%	0.55%
CAR (-20, +5)	344	-0.43%	-0.18%	-0.18	1.32	13.11%	0.71%
Tobin's Q	344	1.81	1.29	5.17	39.4	2.02	0.11
Deal Size (ln)	344	20.60	20.62	0.07	-0.34	1.68	0.09

Note. This table presents descriptive statistics for the key variables. CARs are expressed as percentages. Table 2 reports statistics based on the mean-adjusted model and Table 3 based on the market-adjusted model. Tobin's Q is the Chung and Pruitt (1994) approximation. Deal Size is the natural logarithm of the announced transaction value in USD. Skewness and kurtosis statistics are discussed in the text. N = 344 completed U.S. public-to-public M&A transactions, 2009–2024.

Several observations can be drawn from the dataset. In both models the mean CARs are negative across all event windows, with the lowest mean return of -0.47 percentage at

T-0 to -1.23 percentage at the -5, +5 window in the mean-adjusted model. This trend aligns with the existing empirical literature that have recorded close to zero or slightly negative returns for the acquirer in public-to-public M&A transactions (Andrade et al., 2001; Moeller et al., 2004) The median CARs are likewise negative, but with modest magnitude than the mean returns, demonstrating a return distribution where a small number of significant negative outliers pull the mean return below the median.

Table 4 Descriptive Statistics, Market-Adjusted Model.

	N	Mean	Median	Skewness	Kurtosis	Std Dev	Std Error
CAR (T-0)	344	-0.53%	-0.28%	-0.70	5.84	6.34%	0.34%
CAR (-1, +1)	344	-0.50%	-0.13%	-1.26	5.98	8.36%	0.45%
CAR (-2, +2)	344	-0.80%	-0.53%	-1.28	5.62	9.03%	0.49%
CAR (-5, +5)	344	-1.18%	-0.59%	-0.63	1.94	9.52%	0.51%
CAR (-20, +5)	344	-0.63%	-0.17%	-0.35	2.13	11.86%	0.64%
Tobin's Q	344	1.81	1.29	5.17	39.40	2.02	0.11
Deal Size (ln)	344	20.60	20.62	0.07	-0.34	1.68	0.09

Note. This table presents descriptive statistics for the key variables. CARs are expressed as percentages. Table 2 reports statistics based on the mean-adjusted model and Table 3 based on the market-adjusted model. Tobin's Q is the Chung and Pruitt (1994) approximation. Deal Size is the natural logarithm of the announced transaction value in USD. Skewness and kurtosis statistics are discussed in the text. N = 344 completed U.S. public-to-public M&A transactions, 2009–2024.

The distribution of target Tobin's Q presents significant right-skewness and excess kurtosis. The mean Q of 1.81 exceeds the median Tobin's Q of 1.29, verifying the right-skewness of the distribution. The maximum positive Q of 21.12 shows the existence of high-valuation target, Celator Pharmaceuticals, which had market cap of 523 million USD relatively to its total assets of 26 million; the total debt was only 15 million meaning that the high market value of equity explains the high Tobin's Q value for this firm. The excess kurtosis of 39.41 is far above the value of zero expected under a normal distribution, confirming the presence of extreme observations in the upper tail of distribution. This distributional attribute motivates the winsorization-based robustness checks discussed in Section 5.4. The standard deviation of 2.02 and standard error of 0.11 indicates a right-skewed but tractable distribution.

The deal sizes are approximately normally distributed on the log scale, mean of 20.60 and standard deviation of 1.68, corresponding a transaction value of close to 880 million USD at the mean. The small deviation between mean of 20.60 and median of 20.62 confirms that the log transformation effectively corrects the right-skewness present in raw transaction values.

Table 5 Distribution of Payment Methods.

Payment Method	N	% of Sample
Cash	189	54.94%
Stock	65	18.90%
Cash and Stock	68	19.77%
Cash or Stock	22	6.40%
Total	344	100.00%

Note. This table presents the distribution of the 344 sample transactions by payment method as recorded in the Bloomberg Terminal M&A database. Cash or Stock reflects transactions where the payment structure was not conclusively classified.

Table 3 shows the distribution of deals by payment method in the sample. Cash-only deals prevail over the entire at 54.94 percent, consistent with the post-financial-crisis transition toward cash-financed acquisitions reported in the prior literature (Andrade et al. 2001). Stock-paid deals account for 18.90 percent of the sample, while cash-stock mixed deals form the second-largest payment method at 19.77 percent. The cash-or-stock category, representing transactions where the payment structure was not conclusively classified, accounts for the remaining 6.40 percent.

5.2 Event Study

Table 5 presents mean and median CARs across all event windows, together with one-sample t-tests of the null hypothesis that the mean CAR equals to zero. CARs are presented as percentages; while the statistical figures, t-stat and p-value, are computed from decimal returns. As specified in Section 4.2, the mean-adjusted model uses the acquirers' average daily return over the 180-day estimation window prior to the announcement, while the market-adjusted model applies the contemporaneous S&P500 returns as the benchmark.

Table 6 Event Study Results.

<i>Panel A: Mean-Adjusted Model</i>					
	T-0	-1, +1	-2, +2	-5, +5	-20, +5
Mean CAR	-0.47%	-0.58%	-0.86%	-1.23%	-0.43%
Median CAR	-0.20%	-0.40%	-0.25%	-0.92%	-0.18%
Standard deviation	6.40%	8.55%	9.16%	10.23%	13.11%
N	344	344	344	344	344
t-statistic	-1.35	-1.26	-1.75	-2.24	-0.60
p-value	0.18	0.21	0.08	0.03	0.55
<i>Panel B: Market-Adjusted Model</i>					
	T-0	-1, +1	-2, +2	-5, +5	-20, +5
Mean CAR	-0.53%	-0.50%	-0.80%	-1.18%	-0.63%
Median CAR	-0.28%	-0.13%	-0.53%	-0.59%	-0.17%
Standard deviation	6.34%	8.36%	9.03%	9.52%	11.86%
N	344	344	344	344	344
t-statistic	-1.54	-1.10	-1.64	-2.30	-0.99
p-value	0.13	0.27	0.10	0.02	0.33

Note. This table presents mean and median CARs for acquiring firms across five event windows around the M&A announcement date (T=0). Panel A reports results from the mean-adjusted model using a 180-day estimation window. Panel B reports results from the market-adjusted model using the S&P 500 index as the benchmark. Standard deviations are expressed as percentages. t-statistics are from one-sample t-tests of the null hypothesis that mean CAR equals zero. p-values are two-tailed. N = 344 completed U.S. public-to-public M&A transactions, 2009–2024. Bold values indicate statistical significance at the 5% level ($p < 0.05$).

The results in Table 5 show consistent pattern of negative announcement returns across all event windows in both models, although the mean CARs do not achieve statistical significance in most specifications. In the mean-adjusted model, mean CARs vary from -0.47 at T-0 to -1.23 in the (-5, +5) window. The (-5, +5) window yields the strongest result, with a t-stat value of -2.24, and p-value of 0.03, implying significance level at the 5 percent level. The 5-day window (-2, +2) provides -0.86 percent mean and -0.92 percent median CARs at 10 percent level. All other windows show are statistically insignificant, implying that the null hypothesis of zero mean abnormal returns cannot be rejected at conventional significance levels.

The market-adjusted model yields generally similar results relative to the mean-adjusted model. Mean CARs span from -0.50 percent at the (-1, +1) window to -1.18 percent in the (-5, +5) window, with the (-5, +5) window again generating the most extreme t-stat -2.30 and a p-value of 0.02. The consistency between the models' results provides initial empirical evidence that the event study findings are robust to the choice of benchmark model. In summary, the event study yields statistically significant negative CARs in the (-2, +2) and (-5, +5) windows under both models, while the announcement day (T-0) and (-1, +1) windows are statistically insignificant.

5.3 Cross-Sectional Regression

Tables 5 and 6 present the results from the OLS cross-sectional regressions for the mean-adjusted (Table 5) and market-adjusted (Table 6) CAR models. The dependent variable is the acquirer's CAR for each of the five event windows defined in the event study. Industry fixed effects, based on two digit SIC-codes of the acquirer, and year fixed effects, based on the announcement year of the M&A deal, are included in all specifications. HC3 heteroskedasticity-robust standard errors are applied to ensure valid statistical inference in the presence of non-constant error variance.

The coefficient on target Tobin's Q, the main independent variable, is negative across all event windows in both models, ranging from -0.0067 to -0.0009 in the mean-adjusted model (Table 6) and from -0.0044 to -0.0008 in the market-adjusted model (Table 7). None of the coefficients reach statistical significance at conventional levels, with all p-values exceeding 0.10. The results demonstrate a failure to reject the null hypothesis of this thesis: target firm Tobin's Q does not significantly predict acquirers' CARs around the M&A announcement date.

Table 7 Cross-Sectional Regression Results, Mean-Adjusted Model.

Variable	T-0	-1, +1	-2, +2	-5, +5	-20, +5
Tobin's Q (target)	-0.0026	-0.0015	-0.0009	-0.0029	-0.0067
	(0.0021)	(0.0027)	(0.0027)	(0.0033)	(0.0045)
Deal Size (ln)	0.0007	0.0076**	0.0078**	0.0010	0.0038
	(0.0022)	(0.0033)	(0.0036)	(0.0037)	(0.0056)
Payment: Stock	-0.0186	-0.0421**	-0.0463**	-0.0455**	-0.0197
	(0.0134)	(0.0175)	(0.0182)	(0.0208)	(0.0305)
Payment: Cash&Stock	-0.0371***	-0.0629***	-0.0583***	-0.0544***	-0.0188
	(0.0118)	(0.0168)	(0.0166)	(0.0194)	(0.0239)
Payment: Cash or Stock	-0.0068	0.0011	-0.0032	0.0018	0.0211
	(0.0124)	(0.0227)	(0.0271)	(0.0244)	(0.0265)
Intercept	-0.0897	-0.1264*	-0.1653**	0.0460	-0.0958
	(0.0689)	(0.0766)	(0.0790)	(0.1063)	(0.1598)
Observations	344	344	344	344	344
R-squared	0.2453	0.2406	0.2424	0.2252	0.2135
Adj. R-squared	0.0655	0.0597	0.0619	0.0406	0.0261
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Note. This table presents OLS cross-sectional regression results where the dependent variable is the acquirer's CAR across five event windows. Table 6 uses mean-adjusted CARs and Table 7 uses market-adjusted CARs as dependent variable. The reference payment category is cash. Standard errors (in parentheses) are HC3 heteroskedasticity-robust. Industry fixed effects use two-digit SIC codes of the acquirer. Year fixed effects are based on announcement year. $N = 344$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Theoretically, the null finding has two competing interpretations. Under the initial Q hypothesis (Servaes, 1991), the absence of a significant Tobin's Q effect would suggest that the managerial quality signal incorporated to Tobin's Q no longer functions as it did in the sample of 1970-1980. Alternatively, under the misvaluation framework (Dong et al., 2006), the null result aligns with target's Tobin's Q losing predictive power as the post-2000 environment increasingly mixes managerial-quality signals with valuation-regime signals. These interpretations converge on the same practical implication: target Tobin's Q, has lost its predictive role in modern U.S. M&A market.

Table 8 Cross-Sectional Regression results, Market-Adjusted Model.

Variable	T-0	-1, +1	-2, +2	-5, +5	-20, +5
Tobin's Q (target)	-0.0026	-0.0012	-0.0008	-0.0023	-0.0044
	(0.0022)	(0.0025)	(0.0025)	(0.0026)	(0.0034)
Deal Size (ln)	0.0009	0.0076**	0.0088***	0.0038	0.0065
	(0.0022)	(0.0030)	(0.0033)	(0.0034)	(0.0051)
Payment: Stock	-0.0190	-0.0415**	-0.0500***	-0.0448**	-0.0255
	(0.0130)	(0.0166)	(0.0175)	(0.0180)	(0.0251)
Payment: Cash & Stock	-0.0374***	-0.0622***	-0.0575***	-0.0475**	-0.0270
	(0.0118)	(0.0165)	(0.0163)	(0.0185)	(0.0220)
Payment: Cash or Stock	-0.0083	-0.0057	-0.0073	-0.0009	0.0038
	(0.0119)	(0.0224)	(0.0259)	(0.0229)	(0.0262)
Intercept	-0.0763	-0.0881	-0.1265	0.0582	0.0138
	(0.0555)	(0.0835)	(0.0872)	(0.1370)	(0.2091)
Observations	344	344	344	344	344
R-squared	0.2506	0.2484	0.2537	0.2375	0.2360
Adj. R-squared	0.0720	0.0693	0.0758	0.0559	0.0539
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Note. This table presents OLS cross-sectional regression results where the dependent variable is the acquirer's CAR across five event windows. Table 6 uses mean-adjusted CARs and Table 7 uses market-adjusted CARs as dependent variable. The reference payment category is cash. Standard errors (in parentheses) are HC3 heteroskedasticity-robust. Industry fixed effects use two-digit SIC codes of the acquirer. Year fixed effects are based on announcement year. $N = 344$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The most significant factor affecting the acquirer's announcement-date stock returns, both economically and statistically, is the payment method of the M&A transaction. In the mean-adjusted model, acquirer's using stock as the payment method produce significantly negative CARs at the 5 percent level, -0.0421 in the (-1, +1) window, -0.063 percent in the (-2, +2) window, and -0.0455 percent in the (-5, +5) window. The mixed cash-and-stock-payment produces also negative coefficients that are significant at 1 percent level in most event windows, with the largest negative coefficient of -0.0629 in the (-1, +1) window. The market-adjusted model validates these findings by producing closely identical results: stock-paid deals producing significantly negative Cars at the 1 and 5 percent levels in three event windows, and cash-and-stock payments produce significantly negative CARs in four event windows out of five, with the largest negative

coefficient of -0.0622 again in the (-1, +1) window. The cash-or-stock dummy generates statistically insignificant results for both models and in all windows, which is consistent with the small sample size of only 22 deals and the uncertainty of the financing structure of the deal.

The negative payment-method coefficients are consistent with the predictions of the adverse-selection framework (Myers & Majluf, 1984), under which acquirers issue stock when they consider their equity to be overvalued, and rational investors respond by discounting the announcement return. The magnitude of minus 4 to 6 percent penalty for stock-paid deals is consistent with prior empirical findings (Travlos, 1987; Andrade et al., 2001) and indicates that the signaling content of payment method has remained stable across decades, even as other M&A wealth effect predictors have weakened. The mixed payment penalty, of same magnitude, suggests that the partial use of equity is sufficient to trigger the same discount effect from the market.

The deal size variable shows a positive connection with CARs that is statistically significant at the 5 percent level in two windows of the mean-adjusted model: coefficient of 0.0076 in (-1, +1) window and 0.0078 in (-2, +2) window. The market-adjusted results are consistent with these findings generating 0.0076 and 0.0088 for the same windows at the 5 and 1 percent levels respectively. The positive coefficients imply that, holding payment method, industry and year fixed effects constant, larger M&A transactions are associated with marginally more favorable short-term acquirer stock price reactions.

The positive effects of deal size reflect with the size-discount finding of Moeller et al. (2004), who documented that small acquirers earn around 2 percentage points higher returns than larger acquirers in the 1980-2001 sample. The reversal of the size effect warrants cautious interpretation. One possibility is that the post-2009 sample is dominated by scale-driven horizontal consolidation, where bigger M&A deals offer greater scope for possible synergy realization through economies of scale. (Chatterjee, 1986). However, this is pure speculation, and identifying the mechanism behind this size-effect reversal lies beyond the scope of the present study and is left for future research.

5.4 Robustness Checks

Two sets of robustness checks are performed to assess the robustness of the main findings. The first robustness check winsorizes target Tobin's Q at the 5th and 95th percentiles in both benchmark models. The second check winsorizes Tobin's Q and the log deal size jointly at the 1st and 99th percentiles in both models. Each robustness check is applied across all five event windows in both the mean-adjusted and market-adjusted models, yielding a total of twenty additional regression specifications.

Table 9 Winsorized Tobin's Q (5th–95th pct), Mean-Adjusted Model.

Variable	T-0	-1, +1	-2, +2	-5, +5	-20, +5
Tobin's Q (target)	-0.0068*	-0.0062	-0.0044	-0.0074	-0.0149*
	(0.0041)	(0.0053)	(0.0052)	(0.0058)	(0.0078)
Deal Size (ln)	0.0012	0.0081**	0.0082**	0.0014	0.0046
	(0.0023)	(0.0033)	(0.0036)	(0.0037)	(0.0057)
Payment: Stock	-0.0193	-0.0430**	-0.0469***	-0.0463**	-0.0210
	(0.0134)	(0.0175)	(0.0181)	(0.0207)	(0.0304)
Payment: Cash & Stock	-0.0368***	-0.0626***	-0.0581***	-0.0541***	-0.0180
	(0.0117)	(0.0166)	(0.0165)	(0.0194)	(0.0237)
Payment: Cash or Stock	-0.0079	0.0001	-0.0039	0.0007	0.0189
	(0.0124)	(0.0226)	(0.0269)	(0.0245)	(0.0267)
Observations	344	344	344	344	344
R-squared	0.2520	0.2453	0.2445	0.2281	0.2185
Adj. R-squared	0.0738	0.0655	0.0645	0.0441	0.0323
Winsorization	5th–95th pct	5th–95th pct	5th–95th pct	5th–95th pct	5th–95th pct
Industry & Year FE	Yes	Yes	Yes	Yes	Yes

Note. This table presents robustness check results for the cross-sectional OLS regression where target Tobin's Q is winsorized at the 5th and 95th percentiles (RC1). Table 8 uses mean-adjusted CARs and Table 9 uses market-adjusted CARs as dependent variable. The reference payment category is cash. Standard errors (in parentheses) are HC3 heteroskedasticity-robust. Industry fixed effects use two-digit SIC codes of the acquirer. Year fixed effects are based on announcement year. N = 344. *p<0.10, **p<0.05, ***p<0.01

The results of the robustness checks support the main findings of this study. The coefficients on Tobin's Q remains negative through both robustness check and benchmark models with all 20 coefficient estimates being negative. In the first robustness check, the coefficient on Tobin's Q achieves statistical significance at the 10 percent level in the T-0 window in both models, with coefficient estimates of -0.0068 in the mean-adjusted

model and -0.0070 in the market-adjusted model. For the (-20, +5) window also yields a marginally significant Tobin's Q coefficient of -0.0149 in the mean-adjusted model at the 10 percent level. In the second robustness check, the (-20, +5) window generates similarly a marginally significant Tobin's Q coefficient of -0.0115 at the 10 percent level. Across all other event windows, the coefficients of Tobin's Q prevails statistically insignificant at conventional levels, being consistent with the main regression findings.

Table 10 Winsorized Tobin's Q (5th–95th pct), Market-Adjusted Model.

Variable	T-0	-1, +1	-2, +2	-5, +5	-20, +5
Tobin's Q (target)	-0.0070*	-0.0051	-0.0035	-0.0051	-0.0089
	(0.0041)	(0.0051)	(0.0052)	(0.0055)	(0.0069)
Deal Size (ln)	0.0013	0.0081***	0.0092***	0.0041	0.0070
	(0.0022)	(0.0031)	(0.0033)	(0.0034)	(0.0052)
Payment: Stock	-0.0198	-0.0423**	-0.0505***	-0.0453**	-0.0261
	(0.0130)	(0.0166)	(0.0175)	(0.0180)	(0.0252)
Payment: Cash & Stock	-0.0370***	-0.0619***	-0.0573***	-0.0473**	-0.0266
	(0.0117)	(0.0163)	(0.0162)	(0.0184)	(0.0219)
Payment: Cash or Stock	-0.0093	-0.0065	-0.0079	-0.0016	0.0026
	(0.0119)	(0.0222)	(0.0258)	(0.0230)	(0.0264)
Observations	344	344	344	344	344
R-squared	0.2581	0.2517	0.2550	0.2387	0.2375
Adj. R-squared	0.0813	0.0734	0.0775	0.0573	0.0558
Winsorization	5th–95th pct	5th–95th pct	5th–95th pct	5th–95th pct	5th–95th pct
Industry & Year FE	Yes	Yes	Yes	Yes	Yes

Note. This table presents robustness check results for the cross-sectional OLS regression where target Tobin's Q is winsorized at the 5th and 95th percentiles (RC1). Table 8 uses mean-adjusted CARs and Table 9 uses market-adjusted CARs as dependent variable. The reference payment category is cash. Standard errors (in parentheses) are HC3 heteroskedasticity-robust. Industry fixed effects use two-digit SIC codes of the acquirer. Year fixed effects are based on announcement year. N = 344. *p<0.10, **p<0.05, ***p<0.01.

The marginal significance at the T-0 and (-20, +5) windows suggests that there is a weak negative tendency between the target Tobin's Q and acquirer CARs that becomes more apparent after winsorizing extreme Tobin's Q values. Tobin's Q coefficient does not reach statistical significance at conventional levels in any of the shorter event windows. Since the marginally significant Tobin's Q effects emerge in only a few windows, the robustness

check do not alter the initial conclusion from the study: target Tobin's Q is not a robust predictor for acquirer CARs around the M&A announcement date in this sample.

Table 11 Winsorized All Variables (1st–99th pct), Mean-Adjusted Model.

Variable	T-0	-1, +1	-2, +2	-5, +5	-20, +5
Tobin's Q (target)	-0.0044	-0.0034	-0.0025	-0.0053	-0.0115*
	(0.0032)	(0.0042)	(0.0043)	(0.0046)	(0.0059)
Deal Size (ln)	0.0008	0.0077**	0.0079**	0.0011	0.0043
	(0.0023)	(0.0033)	(0.0037)	(0.0037)	(0.0057)
Payment: Stock	-0.0188	-0.0424**	-0.0465**	-0.0458**	-0.0204
	(0.0134)	(0.0176)	(0.0182)	(0.0207)	(0.0304)
Payment: Cash & Stock	-0.0366***	-0.0624***	-0.0580***	-0.0538***	-0.0177
	(0.0118)	(0.0167)	(0.0166)	(0.0194)	(0.0238)
Payment: Cash or Stock	-0.0067	0.0016	-0.0027	0.0020	0.0215
	(0.0125)	(0.0226)	(0.0270)	(0.0242)	(0.0264)
Observations	344	344	344	344	344
R-squared	0.2486	0.2420	0.2430	0.2274	0.2188
Adj. R-squared	0.0696	0.0614	0.0627	0.0433	0.0327
Winsorization	1st–99th pct	1st–99th pct	1st–99th pct	1st–99th pct	1st–99th pct
Industry & Year FE	Yes	Yes	Yes	Yes	Yes

Note. This table presents robustness check results for the cross-sectional OLS regression where both Tobin's Q and log deal size are jointly winsorized at the 1st and 99th percentiles (RC2). Table 10 uses mean-adjusted CARs and Table 11 uses market-adjusted CARs as dependent variable. The reference payment category is cash. Standard errors (in parentheses) are HC3 heteroskedasticity-robust. Industry fixed effects use two-digit SIC codes of the acquirer. Year fixed effects are based on announcement year. N = 344. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The findings on the payment method dummies are robust across four out of five event windows; only the window (-20, +5) does not show statistical significance for stock and cash-and-stock dummies. The stock and cash-and-stock dummies remain negative, economically meaningful, and statistically significant at the 1 and 5 percent levels across the four shorter event windows in both robustness checks. The magnitude of the coefficients is nearly identical to those in the initial regressions of Section 5.3: in the (-1, +1), (-2, +2), and (-5, +5) windows, the stock payment ranges between estimates of -0.0418 to -0.0505, and the cash-and-stock coefficient ranges between -0.0471 and -0.0626. The log deal size upholds the positive coefficient and significance on the acquirer's CARs in the (-1,

+1) and (-2, +2) windows, within the range of 0.0077 to 0.0081 in the (-1, +1) window and in the range of 0.0079 and 0.0092 in the (-2, +2) window across both robustness check and both benchmark models.

Table 12 Winsorized All Variables (1st–99th pct), Market-Adjusted Model.

Variable	T-0	-1, +1	-2, +2	-5, +5	-20, +5
Tobin's Q (target)	-0.0044	-0.0027	-0.0018	-0.0036	-0.0072
	(0.0033)	(0.0041)	(0.0042)	(0.0044)	(0.0052)
Deal Size (ln)	0.0010	0.0078**	0.0089***	0.0039	0.0068
	(0.0022)	(0.0031)	(0.0034)	(0.0034)	(0.0052)
Payment: Stock	-0.0193	-0.0418**	-0.0501***	-0.0449**	-0.0258
	(0.0130)	(0.0167)	(0.0176)	(0.0180)	(0.0252)
Payment: Cash & Stock	-0.0369***	-0.0618***	-0.0573***	-0.0471**	-0.0263
	(0.0117)	(0.0164)	(0.0163)	(0.0185)	(0.0220)
Payment: Cash or Stock	-0.0081	-0.0052	-0.0068	-0.0006	0.0043
	(0.0120)	(0.0223)	(0.0259)	(0.0228)	(0.0259)
Observations	344	344	344	344	344
R-squared	0.2542	0.2491	0.2537	0.2381	0.2381
Adj. R-squared	0.0765	0.0702	0.0759	0.0565	0.0565
Winsorization	1st–99th pct	1st–99th pct	1st–99th pct	1st–99th pct	1st–99th pct
Industry & Year FE	Yes	Yes	Yes	Yes	Yes

Note. This table presents robustness check results for the cross-sectional OLS regression where both Tobin's Q and log deal size are jointly winsorized at the 1st and 99th percentiles (RC2). Table 10 uses mean-adjusted CARs and Table 11 uses market-adjusted CARs as dependent variable. The reference payment category is cash. Standard errors (in parentheses) are HC3 heteroskedasticity-robust. Industry fixed effects use two-digit SIC codes of the acquirer. Year fixed effects are based on announcement year. N = 344. *p<0.10, **p<0.05, ***p<0.01.

In summary, the robustness checks confirm that the null finding on target Tobin's Q is not driven by the outliers in the data, and that the payment method effect is the dominant and robust cross-sectional factor, among the selected factors, for acquirer's announcement CARs in this sample. The consistency of findings across the event study results, the cross-sectional regressions, and the robustness checks underscores the reliability of the empirical conclusions of this study. Diagnostic tests verify statistical reliability of the cross-sectional regression specification. The variance inflation factors confirm the absence of high intercorrelation with maximum VIF value of 1.137 across all variables and event windows — well below the conventional threshold of 5. The Breusch-Pagan

tests reject the null of homoskedasticity at the 5 percent level in 7 of the 10 specifications, validating the use of HC3 heteroskedasticity-robust standard errors throughout the analysis. Full diagnostic results across both benchmark models and all five event windows are reported in Appendix 3.

6 Discussion

This chapter interprets the empirical findings documented in the previous chapter in the context of prior literature, considers their theoretical and practical implications, and identifies the limitations of the analysis. The interpretation is structured around two key findings of this study: first, the null findings on Q hypothesis, and second, the strong negative effect of the stock and stock-and-cash payment method on acquirers returns at the M&A announcement. Finally, this chapter concludes by outlining further directions for future research around the topic.

6.1 Null Findings on Tobin's Q: Implications and Interpretations

The core hypothesis of this thesis — that target firm Tobin's Q predicts negative acquirer CARs — is not supported by the empirical findings of the study. Through all event windows, in both benchmark models, and in all robustness specifications, the coefficient on Tobin's Q is statistically insignificant at conventional levels. This finding is robust to winsorization of extreme Tobin's Q values and to the choice of benchmark model, offering additional confidence that the failure to reject the null hypothesis is not a direct consequence of the methodological choices made in this thesis.

The null finding aligns with the evolution of evidence of the Q hypothesis since its initial formulation. Foundational studies by Lang, Stulz, and Walkling (1989) and Servaes (1991) documented a significant negative relationship between the target firm Tobin's Q and acquirer stock return at the announcement, using the samples prior 1990s. However, the later research has questioned whether these findings can be generalized in more recent periods. Dong, et al. (2006) report that evidence underpinning the Q hypothesis is notably amplified in the pre-1990 samples than in more recent samples, pointing out structural shifts in the relationship between target valuation and acquirer returns across time. Similarly, Moeller et al. (2005) found essentially no meaningful relationship between the target's Tobin's Q and the bidder returns in the more recent sample. This study, examining the post-financial-crisis period from 2009 to 2024, extends the evidence to a more

recent merger wave, confirming that target Tobin's Q has not retained any significant predictive power for acquirer announcement returns in today's M&A market.

6.2 Alternative Interpretation for the Null Finding

Several plausible dynamics can explain why target Tobin's Q lacks predictive power for acquirers' announcement returns in the modern-day M&A activity. One compelling explanation might reside in the interplay of behavioral biases on both sides of the transaction. From the target firm's perspective, higher Tobin's Q firms — typically growth companies in high-growth sectors such as technology and healthcare during the sample period — can carry systematically inflated valuations driven by investor overconfidence, over-optimism, anchoring, herding behavior, and forecasts based on historical growth, rather than rational fundamental analysis alone. (Barberis & Thaler, 2003).

The behavioral mechanisms outlined above do not operate in sole isolation: they unfold against sustained market condition of elevated market-wide valuations during the 2009-2024 sample period. The Shiller cyclically adjusted price-to-earnings ratio (CAPE), which divides the current real S&P 500 prices by the ten-year average of real earnings, remained well above its long-term historical mean of 17 throughout most of the sample, varying between 20 and 38 (Shiller, 2015; Figure 2). The Buffett indicator, defined as the ratio of total U.S. stock market capitalization to U.S. gross domestic product (Buffett, 2001), similarly remained at historically elevated levels, exceeding the 100 percent throughout the majority of sample period and furthermore reaching to record high levels at the end of the sample period (Figure 3). This high-valuation environment was supported by a sustained period of historically low interest rates and abundant liquidity, with loose fiscal and monetary policy across most of the sample period contributing to elevated equity valuations across the broader U.S. market.

These indicators, together with sustained accommodative monetary environment suggest that the 2009-2024 sample falls within the extended high-valuation regimes in which market-wide practice levels were systematically elevated relative to historical norms of corporate fundamental earnings and aggregate economic output.

Compounding this aggregate signal, Graham (2022) documents that CFOs across the same period persistently report believing their own firm's equity is undervalued, indicating a clear misalignment between observable market-level valuations and managerial valuation perceptions.

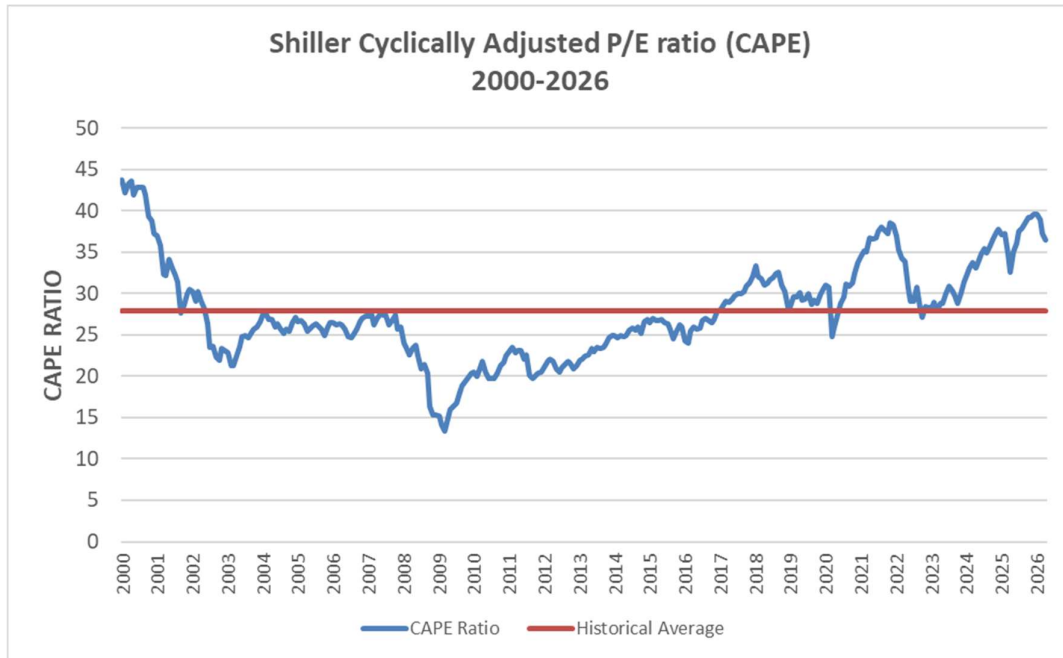


Figure 2 Shiller Cyclically Adjusted Price-To-Earnings Ratio (CAPE), 2000–2026.

Note: Adapted from Online data Robert Shiller, by R. J. Shiller, n.d., Yale University (<http://www.econ.yale.edu/~shiller/data.htm>)

For this thesis, the market conditions matter because target Tobin's Q is a relative measure of market valuation against the book-value replacement cost, interpreting that when market-wide valuation levels are systematically high, cross-sectional differences in target Tobin's Q absorb a greater portion of market-level noise and simultaneously diminishes the share of fundamental firm-quality variation, weakening the role of Tobin's Q as a cross-sectional signal of target's quality and attractiveness for acquirers. This dynamic is a strong rationale to explain the null finding resulted from this thesis and provides a strong macroeconomic condition against which acquirer-side behavioral biases compound the challenge of translating target valuation into predictable announcement returns.

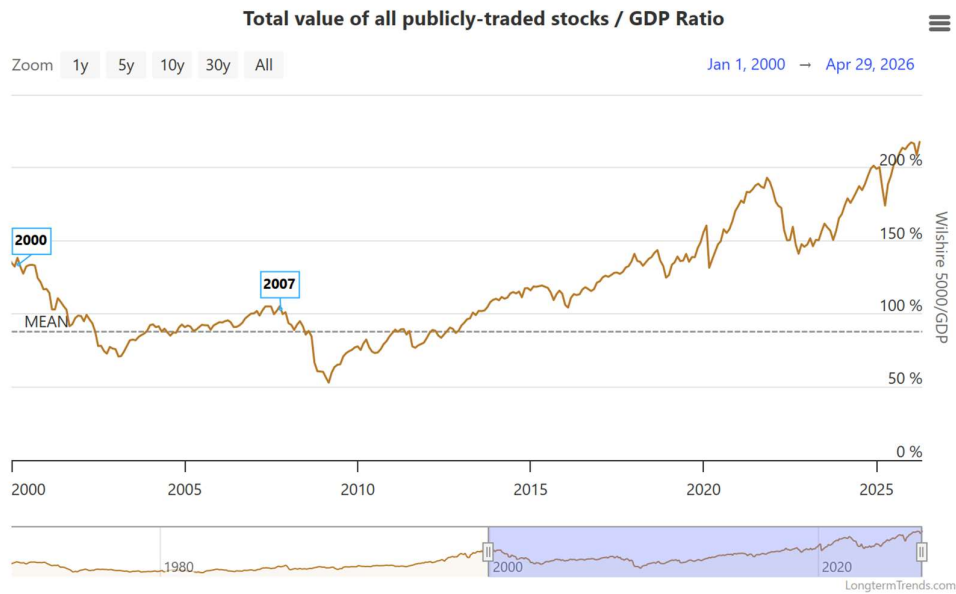


Figure 3 Buffett indicator, 2000-2026

Note: Ratio of total U.S. stock market capitalization to nominal gross domestic product, 2000–2026. The indicator concept was introduced by Buffett (2001) as a measure of aggregate market valuation relative to economic output. Reproduced from LongTermTrends (n.d.).

Further dynamic specific to the 2009-2004 sample period reinforces the difficulty of using Tobin's Q as a clean predictor of acquirer announcement returns: this period was characterized by sustained outperformance of U.S. growth stocks over U.S. value stocks, deviating sharply from the long-term historical pattern where value stocks earned a premium over growth stocks (Fama & French, 1992; Lakonishok, Shleifer, & Vishny, 1994). The MSCI USA Growth Index captures U.S. large- and mid-cap firms with growth style characteristics, while the MSCI USA Value Index captures U.S. large- and mid-cap firms with value-style characteristics. Figure 4 shows the cumulative price performance of the MSCI USA Growth Index and the MSCI USA Value Index between 1997 and 2026, with both indices rebased to 100 in January 1997. The two indices tracked closely from 1997 through approximately 2009, with Growth Index temporarily peaking during the dot-com bubble between 2000 and 2001 before reverting to similar levels. From the start of this study's sample period in January 2009, these two indices diverge distinctly and by April 2026, the Growth Index reaches to a level of approximately 1,590 while the Value Index reaches only to 460, indicating that U.S. growth stocks have delivered cumulative price

returns roughly three to four times those of U.S. value stocks across the sample period (MSCI Inc., n.d.-a, n.d.-b).

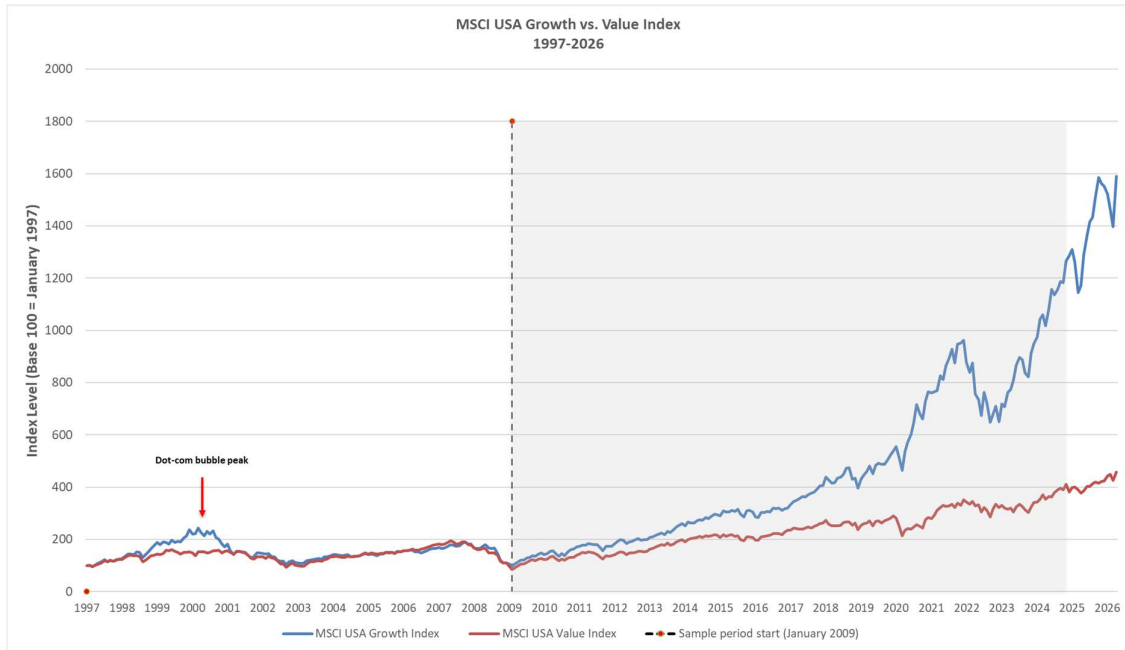


Figure 4 MSCI USA Growth Index and MSCI USA Value Index, 1997–2026

Note: Data retrieved from MSCI Inc. The shaded area marks the sample period of this study (January 2009 to December 2024). The two indices tracked closely from 1997 through approximately 2009, after which U.S. growth stocks substantially outperformed U.S. value stocks across the remainder of the period. (Price returns, base value = 100 at January 1997)

This type of regime asymmetry has direct implications for the interpretive role of Tobin's Q in cross-sectional M&A analysis. Because target Tobin's Q in this study is, by construction, a measure of relative market valuation against book-value replacement cost, high Q-targets in this sample are clustered among the same growth-style firms that the U.S. market was systematically rewarding throughout the period. In a regime where growth-firm returns consistently dominate value-firm returns, the cross-sectional information that Tobin's Q would normally carry about target quality becomes influenced with a market-wide bias preferencing for growth firms. The signal that the foundational Q-hypothesis literature attributed to target Tobin's Q — that high-Q targets reflect overvaluation and therefore predict negative acquirer returns at announcement (Lang, Stulz, & Walkling, 1989; Servaes, 1991) — has eroded completely in this environment, because the same high-Q firms are also the firms whose stock prices have been driven up by

sustained behavioral-level demand rather than by firm-specific fundamentals alone. This dynamic, alongside the elevated macro valuations and behavioral mechanisms discussed in this section, contributes interpretive rationale to the null finding observed in this thesis.

On the acquirer side, the hubris hypothesis (Roll 1986) suggests that acquirer management systematically overestimates its ability to generate synergies from the transaction, leading to overpayment for target firms regardless of the target's quality. When this overconfidence interacts with the inflated target valuations driven by behavioral, macro, and extended period of growth stocks outperformance outlined previously, the premiums paid for the target may meet or exceed the present value of expected synergies. As a result, shareholders of the acquirer earn close to zero or negative announcement returns — not because of the market efficiency prices the assets involved, but because these compounding behavioral and structural frictions ultimately erode the equity value of the acquirer. This interpretation aligns with Malmendier and Tate (2008), who find that overconfident CEOs are more likely to undertake acquisitions, and that the market reacts more negatively to their announcements. The acquirer-side miscalibration is reinforced by the broader survey-based evidence from Graham (2022), who show that CFOs consistently perceive their firms equity as undervalued even in visible regimes of historically elevated market valuations such as those seen for this study's sample period — implying that managerial valuation perceptions does systematically deviate from observable market-level evidence in ways that distort acquisition decisions.

In summary, the layered dynamics discussed in this section — target-side behavioral biases inflating the high-Q-valuations, an elevated macro valuation environment, a sustained outperformance of growth stock over value stocks rewarding the same firms identified as high-Q targets, and acquirer-side managerial overconfidence and miscalibration — provide an interpretive framework consistent with the broader behavioral-finance challenge against the EMH discussed in the theoretical framework and literature review of this thesis, and therefore suggest that the interpretive role of target Tobin's Q as a clean cross-sectional signal of acquirer return is correspondingly disappeared in the modern-day M&A market, examined in the sample period of this thesis, where the

fundamental performance or value of the firm does not drive the demand or price of the stock.

6.3 Payment Method Effect

In contrast to the null finding on Tobin's Q, the payment method shows one of the most robust findings in this study. Stock payment, either alone or mixed with cash, produces notably more negative returns at the announcement compared to cash-paid deals throughout most event windows, in both models, and all four robustness specifications. The economic magnitude of the payment method is considerable, with stock-paid deals generating around -4.2 to -5.1 percent lower CARs than cash-paid deals, and mixed payments of cash and stock generate roughly -3.7 to -6.3 percent lower returns. The payment method effects are statistically significant between at the 1 to 5 percent in most of the return windows, leaving minimal doubt on the robustness of these findings.

The consistency of the result over all event windows, models and robustness checks is noteworthy. No matter whether the mean- or market-adjusted benchmark is utilized, regardless of whether Tobin's Q values are winsorized, and across all event windows examined, the stock price reactions to equity-based financing of the transactions are systematically more negative compared to cash-financed deals. This degree of robustness positions the effect of the payment method with past empirical findings on the effect of payment method but next we provide some aligning but also alternative interpretations on the result.

The robust findings on the payment method effects are theoretically based on the information asymmetry framework of Myers & Majluf (1984). They demonstrated that in markets where asymmetric information exists, managers acting in the interest of existing shareholders will issue equity only when they see that the firm's stock is overvalued. Theoretically, rational investors anticipate this kind of management behavior and read stock-finance M&A as a signal that the acquirer's management considers the firm's market value of equity overvalued, culminating in a downward revision of the stock price at

the announcement. Travlos (1987) documented this pattern in the pre-1990 era, and this thesis confirms its existence in the post-1990 and financial crisis era.

A more significant question concerns the relationship of these findings to the market timing theory of capital structure (Baker & Wurgler, 2002) and its application to M&A activity (Shleifer & Vishny, 2003). The market timing hypothesis predicts that managers will exploit elevated equity valuations by financing M&A with stock when they perceive their own equity as overvalued, with the timing advantage of offsetting the Myers and Majluf adverse-selection penalty over the longer run. The sample period, defined by sustained market-wide overvaluation as documented by the historical Shiller CAPE and the Buffett indicator, based on this view, would expect to feature both a high frequency of stock-financed M&A and acquirer outperformance from those deals. The empirical evidence from this thesis points in the opposite direction. Cash-paid deals dominate the sample at approximately 55 percent, while stock- and stock-cash deals account for only approximately 39 percent (Table 4), notably lower than what the share that classical market timing theory would predict for a sustained high-valuation regime observed within the sample period. The findings on payment methods and their effect on CARs stand in conflict with the recent results of Alexandridis et al. (2017), who report that stock-paid deals in the post-2009 sample no longer destroy value; the deviation between the results reflects this study's coverage of the post-2015 period, in which the market valuations more strongly increased, with Shiller CAPE reaching near 38 and the Buffett indicator exceeding 200 percent, intensifying the high-valuation regime and the corresponding adverse-selection inference investors draw from stock payment.

The factual challenge to market timing as an explanatory mechanism for the stock-payment effect comes from Graham (2022) whose CFO survey evidence is referenced in the preceding section. If managers systematically time the market — issuing equity when they believe their equity is overvalued — the evidence that CFOs systematically perceive their firm's equity as undervalued, even during elevated market valuations, directly undermines the market timing theory's premise. Managers cannot be reliably timing the market if their own valuation perceptions are systematically misaligned with observable

market-level evidence. The persistence of significantly negative announcement CARs for stock-paid deals in the sample period, in combination with the documented misalignment of managerial valuation perception, suggests that the stock-payment penalty in this period reflects an adverse-selection inference by investors operating against a high-valuation backdrop, rather than a successful exploitation of overvalued equity by acquirer management. The penalty observed in the results is therefore more consistent with the Myers and Majluf adverse-selection framework than the alternative explanation offered by market timing theory.

The interpretive question that emerges from this layered evidence is what the value-creation calculus looks like when both sides of the transaction are systematically influenced by elevated market valuations. Following the framework of Shleifer and Vishny (2003), the value implications of an acquisition depend on the relative degrees of overvaluation between acquirer and target. When acquirer equity is overvalued by less than target equity — the most plausible configuration interpretation in the sample period, in which high-Q growth firms formed the upper tail of an already-elevated valuation distribution — stock-financed acquisitions systematically transfer value from acquirer shareholders to target shareholders, because the acquirer exchanges less-overvalued stock-currency for more overvalued assets. This mechanical disadvantage is compounded by the M&A premium that acquirers customarily pay above the pre-announcement market price of the target. Acquisition premia in U.S. public-to-public M&A typically averaged from 30 to 50 percent (Alexandridis et al., 2013), meaning the acquirer pays not only for already elevated target equity but for that equity at a substantial markup above its already-inflated market price. In high-valuation regime, every dollar of premium is therefore applied to an existing overvalued baseline, magnifying the value-destruction risk for acquirer shareholders. The consistent negative CARs recorded for fully or partially stock-financed deals in this thesis are in line with this mechanical interpretation. Cash-financed deals function under a different value calculus: the acquirer transfers a liquid asset (cash) of intrinsic value 1:1 in exchange for the targets' equity that can be overvalued, and any value destruction that occurs is borne fully by the acquirer's shareholders without an offsetting currency-overvaluation benefit. The fact that cash-financed deals in this

sample do not generate significantly negative announcement CARs suggest that the Myers & Majluf (1984) effect on stock-financed deals dominates the mechanical overvaluation effect on cash-financed deals in driving short-term market reactions, even though both transaction types face similar fundamental constraints in the long-term value-creation due to the excessive overvaluation in the market and the additional premium paid above already-elevated target prices.

Why acquirer management would proceed with such transactions despite the unfavorable analytical outlook points to the interaction of behavioral mechanisms operating simultaneously. The hubris hypothesis (Roll, 1986) provides one component — managers systematically overestimate their capability to generate synergies sufficient to overcome the overvaluation of target firms. Malmendier and Tate (2008) document the behavioral correlate at the individual level, showing that overconfident CEOs are both more likely to undertake acquisitions and more likely produce announcements that the market receives negatively. Graham (2022) supplies a complementary element, where managerial valuation perceptions and overall decision-making are systematically miscalibrated relative to observable market evidence, with CFOs consistently perceive their own equity as undervalued.

The combined effect is that acquirer management can proceed with stock-or cash-financed M&A of overvalued targets despite the analytical frictions, because management responsible for the decision to pursue transaction are operating under behavioral constraints — overconfidence, hubris, and systematic valuation miscalibration — that prevent them from identifying the unfavorable value-creation calculus that market can identify with hindsight. Investors face their own constraints in processing the announcement, rather than conducting a comprehensive valuation analysis, they react to the most salient and easily interpretable signal — the payment method of the deal — producing the systematic stock-payment penalty observed in the data (Simon, 1955). The results are not a rational pricing equilibrium but an interaction of behavioral biases on both sides of the transaction, in which managerial overconfidence drives the deal and investor heuristic processing prices it.

The notably strong negative effect seen for the mixed payment method of cash and stocks relative to cash-only deals is significant and should be examined further. Under adverse selection, stock-only payments should theoretically carry a stronger negative signal than mixed payments, since stock-payment involves a larger scale of equity issuance for the acquiring firm, which affects the existing shareholders. According to the results of this study, the mixed payment method might indicate a certain characteristic of cash-and-stock paid transactions in the post-financial crisis period. These deals tend to be larger in size and complex compared to solely cash- or stock-paid deals, involving targets for which the uncertainty about the firm's valuation might be particularly high. For these deals, the use mixed structure of payment can itself signal that the acquirer experiences uncertainty about the optimal price on the target and is hedging by sharing the potential risks of overvaluation with target firm's shareholder through the stock component of the consideration.

The finding that the payment method of M&A has a more robust and significant effect on acquirer's stock returns than the target's Tobin's Q has an important implication for the further studies of M&A value creation. It implies that, in this sample, the financial decision elicits a stronger announcement-window market reaction than the cross-sectional differences in target Tobin's Q. This pattern suggests that during the announcement window, investors weigh the informational signal of payment method more heavily than the cross-sectional information about target valuation, possibly because the financing decision is a more salient and easily interpretable characteristic rather than a fundamental analysis of target quality. This implication aligns with the behavioral finance perspective where investors' attention is focused on the simplest information about the deal, rather than more comprehensive and complex analysis of the target's quality and fundamental growth prospects.

The interpretation of the payment method finding therefore rests on four interconnected threads. First, the persistent negative announcement returns to stock-financed deals confirm the operation of the Myers and Majluf adverse-selection mechanism in the post-2009 period, extending Travlos (1987) into a more recent merger wave context.

Second, the absence of strong outperformance from stock-financed deals is sustained high-valuation regime, combined with the documented misalignment of managerial valuation perceptions (Graham, 2022), challenges the explanatory adequacy of the market timing hypothesis (Baker & Wurgler, 2002; Shleifer & Vishny, 2003) for the post-2009 environment. Third, the value-destruction calculus under bilateral overvaluation, compounded by M&A premiums applied to already-inflated target prices, provides a mechanical foundation for the observed announcement window penalty on stock- and mixed paid deals. Fourth, the interaction of acquirer-side managerial behavioral biases, with investor heuristic processing on the announcement side produces a non-equilibrium pricing dynamic in which both sides of the transaction operate under behavioral constraints, bounded rationality. In summary, these threads suggest that the payment method effect documented in this thesis is not an efficient-pricing artifact but a structural feature of the M&A market in periods elevated and broadly miscalibrated equity valuations from their true intrinsic values.

6.4 Implications for Theory and Practice

The results of this thesis contribute to the debate about the creditability and durability of the Q hypothesis of corporate takeovers. While the initial findings by Lang et al. (1989) and Servaes (1991) provided the original theoretical framework connecting targets' Tobin's Q with acquisition outcomes, this study aligns with the body of more recent evidence implying that this relationship has substantially diminished in today's capital market. The implication is that although Tobin's Q remains theoretically compelling measure of expected growth prospects for a firm, it appears to be regime-dependent signal rather than universally applicable predictors for acquirer announcement returns. The interpretive layers developed in the previous sections — the elevated equity market valuations environment, consistent outperformance of growth stocks over value stocks, and the documented misalignment of managerial valuation perceptions — together suggest that target Tobin's Q is most likely most informative as a cross-sectional quality signal in regimes in which market-wide valuations are not systematically elevated and in which growth firms do not capture the upper tail of the valuation distribution in the market.

Although the findings provided conclusion that Tobin's Q do not predict the acquirers announcement returns, they do not imply that the target quality is irrelevant to M&A outcomes in fundamental level; rather it implies that whatever information target Tobin's Q captures regarding target quality is, in the post-2009 environment, already priced into the acquisition premium by the time of the announcement leaving no systematic surplus for acquirer shareholders to gain. Additionally, the results and the interpretation developed in this chapter offer alternative implications for the future, when the market reverses from the overvaluation towards more realistic valuation of the intrinsic value of equities. It is plausible that Tobin's Q will regain predictive power for M&A outcomes and a more informative role as a signal of target quality once the overall market environment shifts toward more value-oriented pricing and toward valuations closer to the realistic fundamental value of equities. However, under the current macroeconomic structure, in which central bank monetary policy under a fiat money regime exerts substantial influence on interest rates and inflation, and in which equity valuations are increasingly influenced by behavioral and macroeconomic dynamics rather than driven primarily by fundamental firm value, Tobin's Q is unlikely to be a useful measure for evaluating M&A outcomes.

The findings of this study also carry out practical implications for both acquirer management and investors in the M&A market. For acquirer management, the null findings on target Tobin's Q indicate that the market does not reward nor penalize acquisition decisions based on differences in target valuation as captured by Tobin's Q at the announcement window. The more dominant signal that should be aware of is the payment method, which results in substantial market reaction averaging 4 to 6 percent more negative announcement returns for stock-paid and cash-and-stock-paid deals compared to pure cash-transactions. This penalty reflects not only the adverse-selection inference investors draw from equity issuance but also the dilutive effect on existing shareholders and the analytical complexity of stock-for-stock integration.

A second implication for acquirer management arises from the value-creation calculus discussed in the previous section. In an environment of sustained market-wide

overvaluation, the typical acquisition premium of 30-50 percent (Alexandridis et al., 2013) is applied to an already-elevated target valuation, enhancing the value-destruction risk regardless of payment method. Management considering acquisitions in such environments should therefore exercise particular caution about the discipline of the bidding process and the realism of synergy projections, since the analytical hurdle for value creation is meaningfully higher than in periods of normal market valuations. The complementary findings from Graham (2022), that CFOs consistently perceive their own equity as undervalued, suggest that management should be cautious about relying solely on internal perceptions of stock valuation when making financing decisions, since these perceptions are systematically miscalibrated relative to observable market evidence.

For investors, the announcement-window pattern recorded in this study has interpretive value rather than a direct trading-strategy implication. The systematic announcement-window underperformance of stock-financed and mixed-financed deals relative to cash-financed deals suggests that the financing decision is, on average, a more reliable short-window signal of expected acquirer wealth effects than cross-sectional differences in target Tobin's Q. Investors interpreting M&A announcements may therefore weight payment method more heavily than target valuation metrics in forming short-term expectations about acquirer returns. However, translating this interpretive observation into a tradable strategy would require attention to transactions costs, the timing and identification of deals before the announcement, and the long-term realization of the announcement-window effect, none of which are directly addressed by this thesis event-study evidence. A second implication for investors' concerns the regime-dependence of cross-sectional signals: in periods of elevated market valuations, or even overvaluation, and sustained market asymmetries, signals such as Tobin's Q that can perform well in regimes where value is the underlying driver of the asset prices carries materially less information about the target's quality than they do in other periods.

6.5 Future Research

Two pathways follow most explicitly the findings of this thesis: regime-conditional testing of the Q hypothesis, and behavioral identification through content analysis of M&A

disclosures. Two additional topics emerge from the secondary findings. The first and most foundational topic for future research concerns the conditional nature of the Q hypothesis across macroeconomic and equity-style regimes. The null finding in this thesis aligns with the elevated equity market valuations of the sample period, evidenced by the Shiller CAPE ratio and the Buffett indicator, and with the sustained outperformance of U.S. growth stocks over U.S. value stocks across the sample period. An open empirical question is whether this null finding is regime-specific or reflects a structural change in M&A markets. A natural extension for the topic of this thesis would test the Q hypothesis across multiple macroeconomic valuation regimes — including periods of valuation correction, normalized interest rate environments, contractionary monetary policy, and value-stock dominance — determining if target Tobin's Q recovers cross-sectional predictive power when market-wide conditions move closer to historical fundamental benchmarks. A complementary methodological extension is the use of intangible-adjusted Tobin's Q, following Peters and Taylor (2017), which would help identify whether the diminished predictive power is structural to the Tobin's Q construct itself or specifically to the Chung and Pruitt (1994) approximation.

The second topic concerns the acquisition premium itself. Acquisition premia in U.S. M&A are typically between 30 to 50 percent above the pre-announcement market price, applied to target valuations that are already elevated in high-valuation regimes. Future research could model premium magnitude as a function of target Tobin's Q, payment method, and macroeconomic environment, identifying whether premium discipline varies systematically across valuation regimes and whether undisciplined premium payment in elevated-valuation environments contributes to value-destruction risk independently of payment method or target valuation.

The third direction relates to long-term realized economic outcomes. The event-study framework captures the market's ex-ante perception of deal value at a specific point in time, leaving the actual economic value generated or destroyed in post-transaction period outside the scope of the analysis. Future studies could shift focus to long-term realized outcomes, comparing acquirers' ex-ante and ex-post fundamental value creation

using accounting-based performance measures such as economic value added, complemented by buy-and-hold abnormal returns analysis where M&A-connected performance can be separated from broader market noise.

The last topic is methodologically novel: empirical analysis of managerial behavioral mechanisms through content analysis of deal disclosures. The interpretative layers developed earlier in this chapter attribute the consistent negative returns of stock-paid deals to acquirer's overconfidence, hubris, miscalibration of internal valuation perceptions, and the market's adverse-selection inference from financing structure. Empirically isolating these mechanisms requires data beyond standard M&A datasets. Future research can combine event-study CARs with measures of deal rationale extracted via natural language processing from press releases, 8-K and 10-K filings, and earnings call transcripts, testing whether rhetorical patterns indicating managerial overconfidence — claims of strong synergy, strategic framing, optimistic time horizons — predict announcement window penalties beyond what is explained by deal characteristics alone. A complementary direction is investor heterogeneity: institutional and retail investors may react differently to payment method of the deal based on the analytical capacity, disentangling these reactions could test the bounded-rationality interpretation of the announcement-window penalty suggested in this thesis.

7 Conclusion

This thesis has investigated the relationship between target firms' market valuation, measured by Tobin's Q, and acquirer CARs around M&A announcement date. The study employed a sample of 344 completed U.S. public-to-public M&A transactions announced between years 2009 and 2024, applying an event study methodology with both mean- and market-adjusted benchmark models across five event windows, followed by cross sectional OLS regression controlling for payment method, deal size, and industry and year fixed effects. The analysis was complemented by two robustness specifications winsorizing target Tobin's Q and log deal size at varying percentiles, providing a total of twenty additional regression specifications across both benchmark models.

The empirical findings of this thesis fall into two separate categories. The first one is the central hypothesis of this thesis — that target firm Tobin's Q predicts negative acquirer CARs — is not supported. Across all event windows, both benchmark models, and all robustness specifications, the coefficient on target Tobin's Q is statistically insignificant at conventional levels, leading to a failure to reject the null hypothesis of the study. This finding extends the recent empirical literature, which has documented a progressive weakening of the Q hypothesis since its original formulation by Lang, Stulz, and Walkling (1989) and Servaes (1991), into the post-financial-crisis merger wave covered by this study. Secondly, the empirical analysis identifies the payment method as the dominant cross-sectional determinant of acquirer announcement returns. Stock-paid deals generating consistent negative CARs of approximately 4 to 5 percent, while mixed cash-and-stock deals produce even larger negative effects of approximately 4 to 6 percent, both statistically significant across multiple event windows and robust to all specifications. Cash-financed deals, in contrast, do not generate significantly negative announcement returns. The dominance of the payment method effect over the target valuation signal is one of the most reliably evidenced findings of this thesis.

The interpretive contribution of this thesis lies in connecting these empirical results to the broader characteristics of the post-2009 macroeconomic and equity-market

environment. The null finding on target Tobin's Q is best understood not as structural failure of the Q hypothesis but as a regime-specific suppression of its predictive power, conditional on the unique dynamics of the sample period. The sample period of this study can be defined as a period of sustained market-wide overvaluation, evidenced by Shiller CAPE ratio remaining high above its long-term historical mean throughout most of the sample period, and by the Buffett indicator going over 100 percent for the majority of the period and reaching record-high levels in the early 2020s. This high-valuation environment was supported by historically low interest rates, abundant liquidity, and accommodative monetary and fiscal policy. Simultaneously, U.S. growth stocks substantially outperformed U.S. value stocks throughout the period, reversing the long-term historical pattern of value-stock premiums and making target Tobin's Q a noisier signal of target quality, as cross-sectional differences in Tobin's Q became confounded with a market-wide style preferences for growth firms. Compounding these aggregate dynamics, Graham (2022) evidenced a persistent disconnect between measurable market-level valuations and managerial valuation perceptions, with CFO's systematically considering their firms equity undervalued, even during the periods of historically elevated market valuations. Together, these layered dynamics provide a coherent and factual interpretive framework for why target Tobin's Q has lost its informative role in this period and why the payment method emerges as the dominant cross-sectional determinant of acquirer announcement returns.

The broader implications of this thesis go beyond the Q hypothesis itself. Normative financial models — derived from the assumptions of rational market participants efficiently incorporating fundamental information into prices — depend on conditions that do not actually appear to hold in the current financial markets nor M&A environment. The Shiller CAPE and the Buffett indicator at sustained extremes, the systematic miscalibration of managerial valuation perceptions, the persistent dominance of the equity-issuance signaling effect over fundamental target valuation in driving announcement returns, and the bilateral behavioral biases on both sides of the M&A transaction together suggest a market environment in which the foundational normative assumptions of the EMH and rational decision-making are not operative. In this environment, valuation-

ratio-based normative measures cannot recover the cross-sectional predictive power that the original theoretical frameworks attributed to them.

The interpretive framework developed in this thesis points to a forward-looking prediction. As market conditions normalize — through the eventual reversal of monetary policy regimes, the rebalancing of growth versus value style market preferences, and the realignment of equity valuations towards fundamental benchmarks — the predictive power of Tobin's Q and similar relative valuation-ratio-based measures should reimpose itself. The next two decades are likely to provide an empirical environment in which this reassertion can be tested effectively. Under the current macroeconomic and behavioral structure, however, in which equity values are increasingly influenced by behavioral and macroeconomic dynamics rather than driven primarily by fundamental firm value and performance, the probability that targets' Tobin's Q is a useful measure for evaluating M&A outcomes remains low.

This thesis contributes to the M&A literature by extending the documented decline in the predictive power of the Q hypothesis into the post-financial-crisis period, by introducing the regime-conditional interpretation that connects the null finding to the broader features of the sample period, and by clarifying that dominant role of payment method is shaping acquirers announcement returns within this environment. The deeper implication is that target Tobin's Q has not failed as a predictor in some abstract sense, it has failed against a specific environment — one in which equity valuations have been shaped more by monetary policy, style preferences, and managerial miscalibration than by the fundamental firm characteristics the Q hypothesis was designed to capture. The methodological future of M&A research depends on whether researchers continue to apply normative-model frameworks under conditions that do not match the assumptions those frameworks require, or whether the field develops empirical tools calibrated to the behavioral and macroeconomic dynamics that have come to dominate the markets in which mergers and acquisitions actually take place.

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Disclosure of the usage of Artificial Intelligence:

In accordance with academic integrity standards regarding the use of generative AI tools, I disclose that during the writing of this thesis, I used Anthropic's Claude and OpenAI's ChatGPT as assistive tools for the following purposes: (1) Proofreading and correction of grammar, syntax, and academic style; (2) suggestions for restructuring and rephrasing of paragraphs and section to improve the thesis clarity and flow, with all drafts reviewed, revised, and finalized by me; (3) assisting in the development of the Python scripts to retrieve the data needed for the empirical analysis of this thesis; (4) assisting in the development of the Python scripts used to run the cross-sectional OLS regression and winsorized regression analysis in the empirical analysis part of the thesis. The research design, data collection, empirical analysis, interpretation of results, and the substantive arguments advanced in this thesis are my own work. All analytical decisions, methodological choices, and final interpretations were made by me, and I take full responsibility for the content of this thesis. I have reviewed all AI-assisted content for accuracy and have ensured that the final text reflects my own understanding and academic position.

Appendices

Appendix 1. Sample Data of M&A Transactions

No	Acq.	Acquirer Name	Tgt.	Target Name	Announcement Date	Value USD (mil.)	Payment
1	DDD	3D Systems Corp	CIMT	Cimatron Ltd	24/11/2014	76.12	Cash
2	MMM	3M Co	CRDN	Ceradyne Inc	01/10/2012	675.13	Cash
3	ACIW	ACI Worldwide Inc	SONE	S1 Corp	26/07/2011	512.44	Cash or Stock
4	AMC	AMC Entertainment Holdings..	CKEC	Carmike Cinemas Inc	03/03/2016	1,178.83	Cash or Stock
5	AME	AMETEK Inc	MOCO	MOCON Inc	17/04/2017	174.28	Cash
6	AME	AMETEK Inc	ZIGO	Zygo Corp	11/04/2014	279.12	Cash
7	ATI	ATI Inc	LDSH	ATI Ladish LLC	17/11/2010	801.67	Cash and Stock
8	ACH	Accendra Health Inc	MDCI	Medical Action Industries ..	25/06/2014	279.68	Cash
9	ACH	Accendra Health Inc	APR	Apria Inc	10/01/2022	1,557.82	Cash
10	ARAY	Accuray Inc	TOMO	TomoTherapy Inc	07/03/2011	122.42	Cash and Stock
11	ATVI	Activision Blizzard Inc	KING	King Digital Entertainment..	02/11/2015	4,880.52	Cash
12	ADBE	Adobe Inc	TUBE	TubeMogul Inc	10/11/2016	444.22	Cash
13	AMD	Advanced Micro Devices Inc	XLNX	Xilinx Inc	27/10/2020	34,092.30	Stock
14	AET	Aetna Inc	CVH	Coventry Health Care Inc	20/08/2012	5,590.60	Cash and Stock
15	A	Agilent Technologies Inc	VARI	Varian Inc	27/07/2009	1,387.18	Cash
16	AKBA	Akebia Therapeutics Inc	KERX	Keryx Biopharmaceuticals Inc	28/06/2018	537.71	Stock
17	ALK	Alaska Air Group Inc	VA	Virgin America Inc	04/04/2016	2,169.50	Cash
18	ALB	Albemarle Corp	ROC	Rockwood Holdings Inc	15/07/2014	6,005.05	Cash and Stock
19	AA	Alcoa Corp	RTI	RTI International Metals Inc	09/03/2015	1,468.34	Stock
20	ARLP	Alliance Resource Partners..	AHGP	Alliance Holdings GP LP	23/02/2018	1,681.04	Stock
21	GOOGL	Alphabet Inc	FIT	Fitbit Inc	01/11/2019	1,501.85	Cash
22	ALTR	Altair Engineering Inc	DWCH	Datawatch Corp	05/11/2018	162.32	Cash
23	AMZN	Amazon.com Inc	ONEM	1Life Healthcare Inc	21/07/2022	3,691.21	Cash
24	AMZN	Amazon.com Inc	WFM	Whole Foods Market Inc	16/06/2017	13,605.36	Cash
25	AMH	American Homes 4 Rent	ARPI	American Residential Prope..	03/12/2015	1,363.46	Stock
26	APH	Amphenol Corp	MTSC	MTS Systems Corp	09/12/2020	1,657.70	Cash
27	ASYS	Amtech Systems Inc	BTUI	BTU International Inc	22/10/2014	29.29	Stock
28	AMAT	Applied Materials Inc	VSEA	Varian Semiconductor Equip..	04/05/2011	4,572.39	Cash
29	ARW	Arrow Electronics Inc	NUHC	Nu Horizons Electronics Corp	20/09/2010	170.90	Cash
30	AYTU	Aytu BioPharma Inc	INNV	Innovus Pharmaceuticals Inc	12/09/2019	44,835.00	Stock
31	AYTU	Aytu BioPharma Inc	NEOS	Neos Therapeutics Inc	10/12/2020	37.77	Stock
32	BYI	Bally Technologies Inc	SHFL	SHFL Entertainment Inc	16/07/2013	1,291.14	Cash
33	BAX	Baxter International Inc	HRC	Hill-Rom Holdings Inc	02/09/2021	11,716.56	Cash
34	BAX	Baxter International Inc	SYNO	Synovis Life Technologies ..	13/12/2011	277.73	Cash
35	BERY	Berry Global Group Inc	AEPI	AEP Industries Inc	25/08/2016	746.35	Cash or Stock
36	BIIB	Biogen Inc	NITE	Nightstar Therapeutics PLC	04/03/2019	753.07	Cash
37	BVS	Bioventus Inc	MSON	Misonix Inc	29/07/2021	489.98	Cash or Stock
38	ACCL	Biovia Corp	SMMX	Symyx Technologies Inc	05/04/2010	98.16	Stock

39	BLKB	Blackbaud Inc	CNVO	Convio LLC	17/01/2012	272.33	Cash
40	BA	Boeing Co/The	KLXI	Boeing Distribution Servic..	01/05/2018	4,196.63	Cash
41	AVGO	Broadcom Inc	BRCO	Brocade Communications Sys..	02/11/2016	5,551.41	Cash
42	AVGO	Broadcom Inc	VMW	VMware Inc	26/05/2022	70,289.26	Cash or Stock
43	BKD	Brookdale Senior Living Inc	ESC	Emeritus Corp	20/02/2014	5,232.05	Stock
44	BLDR	Builders FirstSource Inc	BMCH	BMC Stock Holdings Inc	27/08/2020	2,698.16	Stock
45	CECO	CECO Environmental Corp	MPR	Met-Pro Corp	22/04/2013	158.72	Cash or Stock
46	CECO	CECO Environmental Corp	PMFG	PMFG Inc	04/05/2015	150.22	Cash or Stock
47	CF	CF Industries Holdings Inc	TRA	Terra Industries Inc	15/01/2009	4,286.47	Cash and Stock
48	CCMP	CMC Materials LLC	KMG	CMC Materials KMG Corp	15/08/2018	1,537.91	Cash and Stock
49	CTS	CTS Corp	VPF	CTS Valpey Corp	17/11/2011	15.62	Cash
50	UAN	CVR Partners LP	RNF	CVR Nitrogen LP	10/08/2015	902.90	Cash and Stock
51	CALX	Calix Inc	OCNW	Occam Networks Inc	16/09/2010	111.71	Cash and Stock
52	CSL	Carlisle Cos Inc	HWK	Hawk Corp	15/10/2010	406.34	Cash
53	KKEC	Carmike Cinemas Inc	DCIN	Digital Cinema Destination..	15/05/2014	49.80	Stock
54	CTLT	Catalent Inc	JNP	Juniper Pharmaceuticals Inc	03/07/2018	114.33	Cash
55	CAT	Caterpillar Inc	BUCY	Bucyrus International Inc	15/11/2010	8,608.90	Cash
56	CAVM	Cavium LLC	QLGC	QLogic LLC	15/06/2016	952.89	Cash and Stock
57	COR	Cencora Inc	MWIV	MWI Veterinary Supply Inc	12/01/2015	2,529.50	Cash
58	CCS	Century Communities Inc	UCP	UCP Inc	11/04/2017	208.65	Cash and Stock
59	CSSE	Chicken Soup For The Soul ..	RDBX	Redbox Entertainment Inc	11/05/2022	336.13	Stock
60	CHDN	Churchill Downs Inc	UBET	Yobet.com Inc	11/11/2009	120.02	Cash and Stock
61	CBB	Cincinnati Bell Inc	HCOM	Hawaiian Telcom Holdco Inc	10/07/2017	636.86	Cash or Stock
62	CLW	Clearwater Paper Corp	CLU	Cellu Tissue Holdings Inc	16/09/2010	492.23	Cash
63	CLF	Cleveland-Cliffs Inc	AKS	AK Steel Holding Corp	03/12/2019	2,211.60	Stock
64	CLDR	Cloudera Inc	HDP	Hortonworks Inc	03/10/2018	1,826.47	Stock
65	COHU	Cohu Inc	XCRA	Xcerra Corp	08/05/2018	587.26	Cash and Stock
66	COLL	Collegium Pharmaceutical Inc	BDSI	BioDelivery Sciences Inter..	14/02/2022	498.30	Cash
67	CMCSA	Comcast Corp	DWA	DreamWorks Animation LLC	28/04/2016	3,797.20	Cash
68	CMTL	Comtech Telecommunications..	TSYS	TeleCommunication Systems ..	23/11/2015	398.15	Cash
69	CAG	Conagra Brands Inc	PF	Pinnacle Foods Inc	27/06/2018	10,742.60	Cash and Stock
70	CAG	Conagra Brands Inc	RAH	TreeHouse Private Brands Inc	27/11/2012	6,655.36	Cash
71	CNXC	Concentrix Corp	SREV	ServiceSource Internationa..	09/05/2022	149.95	Cash
72	GLW	Corning Inc	AFOP	Alliance Fiber Optic Produ..	07/04/2016	268.10	Cash
73	MITL	Corp Mitel Networks	SHOR	ShoreTel Inc	27/07/2017	412.67	Cash
74	CUZ	Cousins Properties Inc	TIER	Tier REIT Inc	25/03/2019	2,246.84	Stock
75	COV	Covidien Ltd	EVVV	ev3 Inc	01/06/2010	2,489.97	Cash
76	CBST	Cubist Pharmaceuticals LLC	OPTR	Optimer Pharmaceuticals LLC	30/07/2013	445.22	Cash
77	CBST	Cubist Pharmaceuticals LLC	ADLR	Adolor Corp	24/10/2011	173.36	Cash
78	CMI	Cummins Inc	MTOR	Meritor Inc	22/02/2022	3,571.28	Cash
79	CW	Curtiss-Wright Corp	WMCO	Williams Controls Inc	01/11/2012	116.13	Cash
80	CYNO	Cynosure LLC	PMTI	Palomar Medical Technologi..	18/03/2013	192.06	Cash and Stock

81	CY	Cypress Semiconductor Corp	RMTR	Ramtron International Corp	12/06/2012	119.50	Cash
82	CY	Cypress Semiconductor Corp	CODE	Spansion Inc	01/12/2014	1,641.17	Stock
83	XRAY	DENTSPLY SIRONA Inc	SIRO	Sirona Dental Systems Inc	15/09/2015	5,038.50	Stock
84	DHI	DR Horton Inc	FOR	Forestar Group Inc	05/06/2017	332.61	Cash
85	DTSI	DTS Inc/CA	SRSL	SRS Labs Inc	17/04/2012	110.31	Cash or Stock
86	DXC	DXC Technology Co	LXFT	Luxoft Holding Inc	07/01/2019	1,890.16	Cash
87	DM	Desktop Metal Inc	XONE	ExOne Co/The	11/08/2021	626.83	Cash and Stock
88	DLR	Digital Realty Trust Inc	INXN	InterXion Holding NV	29/10/2019	8,763.66	Stock
89	DLR	Digital Realty Trust Inc	DFT	DuPont Fabros Technology Inc	09/06/2017	6,309.53	Stock
90	DBRG	DigitalBridge Group Inc	SWCH	Switch Inc	11/05/2022	6,930.25	Cash
91	DGI	DigitalGlobe Inc	GEOY	GeoEye Inc	23/07/2012	813.75	Cash or Stock
92	DIOD	Diodes Inc	PSEM	Pericom Semiconductor Corp	03/09/2015	265.50	Cash
93	DLTR	Dollar Tree Inc	FDO	Family Dollar Stores Inc	28/07/2014	7,386.05	Cash and Stock
94	DRYS	DryShips Inc	OCNF	OceanFreight Inc	26/07/2011	218.11	Cash and Stock
95	SSP	EW Scripps Co/The	JRN	Journal Communications Inc	30/07/2014	658.59	Stock
96	EMN	Eastman Chemical Co	TAM	Taminco Corp	11/09/2014	2,742.13	Cash
97	EMN	Eastman Chemical Co	SOA	Solutia Inc	27/01/2012	4,501.42	Cash and Stock
98	ETN	Eaton Corp PLC	CBE	Cooper Industries PLC	21/05/2012	12,846.14	Cash and Stock
99	SATS	EchoStar Corp	HUGH	Hughes Communications Inc	14/02/2011	1,824.32	Cash
100	ECL	Ecolab Inc	NLC	Nalco Holding Co	20/07/2011	8,042.46	Cash or Stock
101	EW	Edwards Lifesciences Corp	CASM	CAS Medical Systems Inc	12/02/2019	76.12	Cash
102	ELAN	Elanco Animal Health Inc	KIN	Kindred Biosciences Inc	16/06/2021	378.93	Cash
103	ELAN	Elanco Animal Health Inc	PETX	Aratana Therapeutics Inc	26/04/2019	191.29	Stock
104	EA	Electronic Arts Inc	GLUU	Glu Mobile Inc	08/02/2021	1,953.70	Cash
105	EBS	Emergent BioSolutions Inc	TRBN	Trubion Pharmaceuticals Inc	12/08/2010	56.38	Cash and Stock
106	ENTG	Entegris Inc	ATMI	Entegris Professional Solu..	04/02/2014	951.54	Cash
107	ENTG	Entegris Inc	CCMP	CMC Materials LLC	15/12/2021	6,473.22	Cash and Stock
108	ENV	Envestnet Inc	YDLE	Yodlee Inc	10/08/2015	443.01	Cash and Stock
109	EQIX	Equinix Inc	SDXC	Switch & Data Facilities C..	21/10/2009	855.84	Cash or Stock
110	MGAM	Everi Games Holding Inc	PTEK	PokerTek Inc	30/04/2014	47,453.00	Cash
111	ESRX	Evernorth Health Inc	MHS	Medco Health Solutions Inc	21/07/2011	34,321.55	Cash and Stock
112	EXAS	Exact Sciences Corp	GHDX	Genomic Health Inc	29/07/2019	3,121.39	Cash and Stock
113	EXPE	Expedia Group Inc	LEXEA	Liberty Expedia Holdings Inc	16/04/2019	4,203.45	Stock
114	EXPE	Expedia Group Inc	OWW	Orbitz Worldwide Inc	12/02/2015	1,595.50	Cash
115	FLIR	FLIR Systems Inc	ICXT	FLIR Detection Inc	16/08/2010	228.35	Cash
116	FPI	Farmland Partners Inc	AFCO	American Farmland Co	12/09/2016	249.50	Stock
117	FLO	Flowers Foods Inc	TSTY	Tasty Baking Co	11/04/2011	141.52	Cash
118	FORM	FormFactor Inc	CSCD	FormFactor Beavertron Inc	04/02/2016	295.80	Cash and Stock
119	FTNT	Fortinet Inc	MERU	Meru Networks Inc	27/05/2015	29.77	Cash
120	FTV	Fortive Corp	LDR	Landauer Inc	06/09/2017	727.73	Cash
121	GME	GameStop Corp	GKNT	Geeknet Inc	26/05/2015	97.71	Cash
122	IT	Gartner Inc	CEB	CEB Inc	05/01/2017	3,250.91	Cash and Stock
123	GEN	Gen Digital Inc	LOCK	LifeLock Inc	21/11/2016	2,186.75	Cash

124	GD	General Dynamics Corp	CSRA	CSRA Inc	12/02/2018	9,695.90	Cash
125	GE	General Electric Co	CLRT	Clariant Inc	22/10/2010	453.57	Cash
126	GIS	General Mills Inc	BNNY	Annie's Inc	08/09/2014	809.79	Cash
127	GWR	Genesee & Wyoming Inc	PWX	Providence and Worcester R..	15/08/2016	117.66	Cash
128	GTIV	Gentiva Health Services Inc	ODSY	Odyssey HealthCare Inc	24/05/2010	890.80	Cash
129	GT	Goodyear Tire & Rubber Co/..	CTB	Cooper Tire & Rubber Co	22/02/2021	2,595.71	Cash and Stock
130	GHC	Graham Holdings Co	LEAF	Leaf Group Ltd	05/04/2021	259.74	Cash
131	GVA	Granite Construction Inc	LAYN	Layne Christensen Co	14/02/2018	485.97	Stock
132	GTN	Gray Media Inc	MDP	Hawkeye Acquisition Inc	03/05/2021	3,766.63	Cash and Stock
133	HALO	Halozyme Therapeutics Inc	ATRS	Antares Pharma Inc	13/04/2022	910.66	Cash
134	HNH	Handy & Harman Ltd	SLI	SL Industries Inc	18/06/2015	87.95	Cash
135	HBI	Hanesbrands Inc	MFB	Maidenform Brands LLC	24/07/2013	571.94	Cash
136	HQY	HealthEquity Inc	WAGE	WageWorks Inc	27/06/2019	1,185.45	Cash
137	HSY	Hershey Co/The	BETR	Amplify Snack Brands Inc	18/12/2017	1,503.10	Cash
138	HPE	Hewlett Packard Enterprise..	CRAY	Cray Inc	17/05/2019	1,295.59	Cash
139	HI	Hillenbrand Inc	MCRN	Milacron Holdings Corp	12/07/2019	1,984.40	Cash and Stock
140	HI	Hillenbrand Inc	KTII	K-Tron International Inc	11/01/2010	397.25	Cash
141	HOLX	Hologic Inc	CYNO	Cynosure LLC	14/02/2017	1,046.20	Cash
142	HD	Home Depot Inc/The	HDS	HD Supply Holdings Inc	16/11/2020	11,088.49	Cash
143	HSP	Hospira Inc	JAV	Javelin Pharmaceuticals Inc	12/04/2010	140.84	Cash
144	HUM	Humana Inc	MDF	Metropolitan Health Networ..	05/11/2012	533.30	Cash
145	IXYS	IXYS Corp	ZILG	Zilog Inc	07/12/2009	26.25	Cash
146	IRT	Independence Realty Trust ..	TSRE	Trade Street Residential Inc	11/05/2015	609.15	Cash and Stock
147	ILPT	Industrial Logistics Prope..	MNR	Monmouth Real Estate Inves..	05/11/2021	2,987.44	Cash
148	INGR	Ingredion Inc	PENX	Penford Corp	15/10/2014	339.01	Cash
149	INVA	Innoviva Inc	LJPC	La Jolla Pharmaceutical Co	11/07/2022	114.93	Cash
150	NSIT	Insight Enterprises Inc	DTLK	Datalink Corp	07/11/2016	210.09	Cash
151	NSIT	Insight Enterprises Inc	PCMI	PCM Inc	24/06/2019	571.44	Cash
152	IART	Integra LifeSciences Holdi..	DSCI	Derma Sciences Inc	10/01/2017	156.91	Cash
153	IP	International Paper Co	TIN	Temple-Inland LLC	06/06/2011	4,276.47	Cash
154	INSW	International Seaways Inc	DSSI	Diamond S Shipping Inc	31/03/2021	1,042.71	Stock
155	JAZZ	Jazz Pharmaceuticals PLC	GWPH	GW Pharmaceuticals Ltd	03/02/2021	6,341.76	Cash and Stock
156	JAZZ	Jazz Pharmaceuticals PLC	CPXX	Celator Pharmaceuticals Inc	31/05/2016	1,281.19	Cash
157	KLAC	KLA Corp	ORBK	Orbotech Ltd	19/03/2018	3,018.16	Cash and Stock
158	KNXA	Kenexa Corp	SLRY	Kenexa Compensation Inc	01/09/2010	67.97	Cash
159	GMCR	Keurig Green Mountain Inc	DDRX	Diedrich Coffee Inc	23/11/2009	212.38	Cash
160	KEYS	Keysight Technologies Inc	XXIA	Ixia	30/01/2017	1,559.49	Cash
161	KIM	Kimco Realty Corp	WRI	Weingarten Realty Investors	15/04/2021	5,555.52	Cash and Stock
162	KND	Kindred Healthcare LLC	RHB	Rehabcare Group LLC	08/02/2011	1,277.29	Cash and Stock
163	KND	Kindred Healthcare LLC	GTIV	Gentiva Health Services Inc	16/06/2014	1,823.47	Cash and Stock
164	KRG	Kite Realty Group Trust	RPAI	Retail Properties of Ameri..	19/07/2021	2,892.16	Stock
165	KN	Knowles Corp	ADNC	Audience Inc	30/04/2015	73.06	Cash and Stock
166	KTOS	Kratos Defense & Security ..	ISYS	Integral Systems Inc/MD	16/05/2011	260.33	Cash and Stock
167	KTOS	Kratos Defense & Security ..	HBE	Henry Brothers Electronics..	06/10/2010	54.54	Cash

168	KTOS	Kratos Defense & Security ..	HRLY	Herley Industries Inc	07/02/2011	268.61	Cash
169	KR	Kroger Co/The	VITC	Vitacost.com Inc	02/07/2014	243.34	Cash
170	KR	Kroger Co/The	HTSI	Harris Teeter Supermarkets..	09/07/2013	2,460.93	Cash
171	KR	Kroger Co/The	RNDY	Roundy's Inc	11/11/2015	784.85	Cash
172	LHCG	LHC Group Inc	AFAM	Almost Family Inc	16/11/2017	985.23	Stock
173	LKQ	LKQ Corp	CRV	Coast Distribution System ..	09/07/2015	48.39	Cash
174	LJPC	La Jolla Pharmaceutical Co	TTPH	Tetraphase Pharmaceuticals..	24/06/2020	13,119.00	Cash
175	LNTH	Lantheus Holdings Inc	PGNX	Progenics Pharmaceuticals ..	02/10/2019	442.28	Stock
176	LSCC	Lattice Semiconductor Corp	SIMG	Silicon Image Inc	27/01/2015	418.40	Cash
177	LEN	Lennar Corp	WCIC	WCI Communities Inc	22/09/2016	785.54	Cash
178	LEN	Lennar Corp	CAA	CalAtlantic Group Inc/old	30/10/2017	9,234.96	Cash or Stock
179	LVLT	Level 3 Communications Inc	TWTC	tw telecom inc	16/06/2014	7,171.89	Cash and Stock
180	LVLT	Level 3 Communications Inc	GLBC	Global Crossing Ltd	11/04/2011	2,451.40	Stock
181	LXK	Lexmark International Inc	KFX	Kofax Ltd	24/03/2015	954.47	Cash
182	LGND	Ligand Pharmaceuticals Inc	PFNX	Pfenex Inc	10/08/2020	353.85	Cash
183	LNN	Lindsay Corp	ESYS	Elecsys Holdings LLC	04/11/2014	69.57	Cash
184	LFUS	Littelfuse Inc	IXYS	IXYS Corp	28/08/2017	719.37	Cash or Stock
185	LYV	Live Nation Entertainment ..	TKTM	Ticketmaster Entertainment..	10/02/2009	670.01	Stock
186	LITE	Lumentum Holdings Inc	OCLR	Oclaro Inc	12/03/2018	1,320.77	Cash and Stock
187	LITE	Lumentum Holdings Inc	NPTN	NeoPhotonics Corp	04/11/2021	796.35	Cash
188	LMNX	Luminex Corp	NSPH	Nanosphere Inc	16/05/2016	89.04	Cash
189	LYB	LyondellBasell Industries NV	SHLM	Lyondellbasell Advanced Po..	15/02/2018	2,083.26	Cash
190	SHLM	Lyondellbasell Advanced Po..	ICOC	ICO Inc	03/12/2009	198.56	Cash and Stock
191	MTSI	MACOM Technology Solutions..	MSPD	Mindspeed Technologies Inc	05/11/2013	249.93	Cash
192	MTSI	MACOM Technology Solutions..	AMCC	Applied Micro Circuits Corp	21/11/2016	570.41	Cash and Stock
193	MAN	ManpowerGroup Inc	CITP	COMSYS IT Partners Inc	02/02/2010	424.29	Cash or Stock
194	MAR	Marriott International Inc..	HOT	Starwood Hotels & Resorts ..	16/11/2015	15,158.57	Cash and Stock
195	MLM	Martin Marietta Materials ..	TXI	Texas Industries Inc	28/01/2014	2,623.25	Stock
196	MRVL	Marvell Technology Inc	IPHI	Inphi Corp	29/10/2020	8,811.33	Cash and Stock
197	MTZ	MasTec Inc	IEA	Infrastructure and Energy ..	25/07/2022	1,040.75	Cash and Stock
198	MTCH	Match Group Inc	CRCM	Care.com Inc	20/12/2019	397.57	Cash
199	MATW	Matthews International Corp	SGK	Schawk Inc	17/03/2014	586.75	Cash and Stock
200	MXL	MaxLinear Inc	EXAR	Exar Corp	29/03/2017	445.98	Cash
201	MXIM	Maxim Integrated Products ..	VLTR	Volterra Semiconductor Corp	15/08/2013	422.40	Cash
202	MCK	McKesson Corp	PSSI	McKesson Medical-Surgical ..	25/10/2012	1,809.02	Cash
203	MMSI	Merit Medical Systems Inc	BSMD	BioSphere Medical Inc	13/05/2010	80.68	Cash
204	MDF	Metropolitan Health Networ..	CNU	Continuicare Corp	27/06/2011	361.65	Cash and Stock
205	MSFT	Microsoft Corp	LNKD	LinkedIn Corp	13/06/2016	24,379.90	Cash
206	MSFT	Microsoft Corp	ATVI	Activision Blizzard Inc	18/01/2022	67,883.41	Cash
207	MSFT	Microsoft Corp	NUAN	Nuance Communications Inc	12/04/2021	17,241.47	Cash

208	MAA	Mid-America Apartment Comm..	PPS	Post Properties Inc	15/08/2016	4,894.98	Stock
209	MAA	Mid-America Apartment Comm..	CLP	Colonial Properties Trust	03/06/2013	4,041.70	Stock
210	MTX	Minerals Technologies Inc	ACO	AMCOL International Corp	14/02/2014	1,705.31	Cash
211	NVDA	NVIDIA Corp	MLNX	Mellanox Technologies Ltd	11/03/2019	6,376.40	Cash
212	NWL	Newell Brands Inc	JAH	Jarden Corp	14/12/2015	17,933.78	Cash and Stock
213	NDSN	Nordson Corp	CYBE	CyberOptics Corp	08/08/2022	365.85	Cash
214	NOC	Northrop Grumman Corp	OA	Northrop Grumman Innovatio..	18/09/2017	7,748.25	Cash
215	NUAN	Nuance Communications Inc	TRCR	Nuance Transcription Servi..	07/03/2012	315.66	Cash
216	NUAN	Nuance Communications Inc	DITC	Ditech Networks Inc	18/09/2012	18.14	Cash
217	NUE	Nucor Corp	IDSA	Recycling Asset Holdings Inc	19/08/2019	38.24	Cash
218	OSIS	OSI Systems Inc	ASEI	American Science and Engin..	21/06/2016	182.30	Cash
219	OHI	Omega Healthcare Investors..	AVIV	Aviv REIT Inc	31/10/2014	2,205.56	Stock
220	ONEW	OneWater Marine Inc	OBCI	Ocean Bio-Chem Inc	22/06/2022	122.59	Cash
221	OFIX	Orthofix Medical Inc	SPNE	SeaSpine Holdings Corp	11/10/2022	287.59	Stock
222	OUST	Ouster Inc	VLDR	Velodyne Lidar Inc	04/11/2022	180.04	Stock
223	PAET	PAETEC Holding LLC	XETA	Xeta Technologies Inc	09/02/2011	58.63	Cash
224	PKG	Packaging Corp of America	BZ	Boise Inc	16/09/2013	1,979.99	Cash
225	TEUM	Pareteum Corp	IPAS	iPass Inc	12/11/2018	28.27	Stock
226	PK	Park Hotels & Resorts Inc	CHSP	Chesapeake Lodging Trust	06/05/2019	2,540.23	Cash and Stock
227	PH	Parker-Hannifin Corp	CLC	CLARCOR Inc	01/12/2016	4,289.15	Cash
228	PEB	Pebblebrook Hotel Trust	LHO	LaSalle Hotel Properties	06/09/2018	5,030.67	Cash or Stock
229	PENN	Penn Entertainment Inc	PNK	Pinnacle Entertainment Inc	18/12/2017	5,741.30	Cash and Stock
230	PFGC	Performance Food Group Co	CORE	Core-Mark Holding Co Inc	18/05/2021	2,726.52	Cash and Stock
231	PF	Pinnacle Foods Inc	BDBD	Boulder Brands Inc	24/11/2015	944.16	Cash
232	PII	Polaris Inc	WSCI	WSI Industries Inc	06/09/2018	23.59	Cash
233	POST	Post Holdings Inc	BOBE	Bob Evans Farms Inc/DE	19/09/2017	1,613.90	Cash
234	PCH	PotlatchDeltic Corp	DEL	Deltic Timber Corp	23/10/2017	1,360.95	Stock
235	PCH	PotlatchDeltic Corp	CTT	CatchMark Timber Trust Inc	31/05/2022	886.12	Stock
236	PCP	Precision Castparts Corp	TIE	Titanium Metals Corp	09/11/2012	2,867.32	Cash
237	QCOM	QUALCOMM Inc	IKAN	Ikanos Communications Inc	06/08/2015	25.48	Cash
238	LBRDA	QVC Group Inc	GLIBA	GCI Liberty Inc	06/08/2020	2,276.70	Stock
239	QDEL	QuidelOrtho Corp	OCDX	Ortho Clinical Diagnostics..	23/12/2021	7,412.58	Cash and Stock
240	RFMD	RF Micro Devices Inc	TQNT	Qorvo US Inc	24/02/2014	1,483.88	Stock
241	RLJ	RLJ Lodging Trust	FCH	FelCor Lodging Trust Inc	24/04/2017	2,451.56	Stock
242	RRD	RR Donnelley & Sons Co	CGX	Consolidated Graphics Inc	24/10/2013	690.81	Cash and Stock
243	RRD	RR Donnelley & Sons Co	CRRC	Courier Corp	27/01/2015	293.86	Cash or Stock
244	RYN	Rayonier Inc	POPE	Pope Resources a Delaware LP	15/01/2020	700.26	Cash or Stock
245	O	Realty Income Corp	VER	VEREIT Inc	29/04/2021	16,394.41	Stock
246	RRX	Regal Rexnord Corp	AIMC	Altra Industrial Motion Corp	27/10/2022	4,973.12	Cash
247	REG	Regency Centers Corp	EQY	Equity One Inc	14/11/2016	5,892.22	Stock

248	REGN	Regeneron Pharmaceuticals ..	CMPI	Checkmate Pharmaceuticals ..	19/04/2022	156.25	Cash
249	ISIL	Renesas Electronics Americ..	TWLL	Techwell Inc	22/03/2010	364.70	Cash
250	RSG	Republic Services Inc	ECOL	US Ecology Inc	09/02/2022	2,262.65	Cash
251	RAI	Reynolds American Inc	LO	Lorillard LLC	15/07/2014	26,477.06	Cash and Stock
252	RCKT	Rocket Pharmaceuticals Inc	RCOR	Renovacor Inc	20/09/2022	47.80	Stock
253	ROP	Roper Technologies Inc	ONVI	Onvia Inc	05/10/2017	62.95	Cash
254	ROVI	Rovi Corp	SNIC	Sonic Solutions LLC	22/12/2010	763.41	Cash or Stock
255	SSNC	SS&C Technologies Holdings..	ADVS	Advent Software Inc	02/02/2015	2,581.33	Cash
256	STE	STERIS PLC	CMD	Cantel Medical Corp	12/01/2021	4,186.60	Cash and Stock
257	SBRA	Sabra Health Care REIT Inc	CCP	Care Capital Properties Inc	08/05/2017	4,034.62	Stock
258	SLXP	Salix Pharmaceuticals Ltd	SNTS	Santarus Inc	07/11/2013	2,015.29	Cash
259	SAIC	Science Applications Inter..	EGL	Engility Holdings Inc	10/09/2018	2,376.99	Stock
260	SGEN	Seagen Inc	CASC	Cascadian Therapeutics Inc	31/01/2018	403.61	Cash
261	SCI	Service Corp International..	STEI	Stewart Enterprises Inc	29/05/2013	1,378.87	Cash
262	SVC	Service Properties Trust	RLH	Red Lion Hotels Corp	30/12/2020	89.13	Cash
263	SHEN	Shenandoah Telecommunicati..	NTLS	NTELOS Holdings Corp	10/08/2015	584.22	Cash
264	SIG	Signet Jewelers Ltd	ZLC	Zale Corp	19/02/2014	1,181.45	Cash
265	SPG	Simon Property Group Inc	TCO	Taubman Centers Inc	10/02/2020	6,480.82	Cash
266	SKYW	SkyWest Inc	XJT	ExpressJet Holdings Inc	04/08/2010	114.52	Cash
267	SWKS	Skyworks Solutions Inc	AATI	Advanced Analogic Technolo..	26/01/2011	162.55	Cash
268	LNCE	Snyder's-Lance Inc	DMND	Diamond Foods Inc	28/10/2015	1,899.64	Cash and Stock
269	SGI	Somnigroup International Inc	ZZ	Sealy Corp	27/09/2012	909.51	Cash
270	LUV	Southwest Airlines Co	AAI	AirTran Holdings Inc	27/09/2010	1,053.73	Cash and Stock
271	SPTN	SpartanNash Co	NAFC	Nash Finch Co	22/07/2013	688.08	Stock
272	SPPI	Spectrum Pharmaceuticals Inc	ALTH	Allos Therapeutics Inc	05/04/2012	79.78	Cash
273	STJ	St Jude Medical Inc	AGAM	AGA Medical Holdings Inc	18/10/2010	1,298.30	Cash or Stock
274	SWK	Stanley Black & Decker Inc	IFLG	InfoLogix Inc	15/12/2010	52.00	Cash
275	SWK	Stanley Black & Decker Inc	BDK	Black & Decker Corp/The	02/11/2009	4,396.00	Stock
276	SBUX	Starbucks Corp	TEA	Teavana Holdings Inc	14/11/2012	626.37	Cash
277	STRA	Strategic Education Inc	CPLA	Capella Education Co	30/10/2017	732.98	Stock
278	SUPN	Supernus Pharmaceuticals Inc	ADMS	Adamas Pharmaceuticals Inc	11/10/2021	413.23	Cash
279	SYNA	Synaptics Inc	DSPG	DSP Group Inc	30/08/2021	414.60	Cash
280	SNCR	Synchronoss Technologies Inc	IL	Intralinks Holdings Inc	06/12/2016	783.00	Cash
281	SNPS	Synopsys Inc	VIRL	Virage Logic LLC	10/06/2010	293.25	Cash
282	SNPS	Synopsys Inc	LAVA	Magma Design Automation Inc	30/11/2011	478.62	Cash
283	SYRS	Syros Pharmaceuticals Inc	TYME	Tyme Technologies Inc	05/07/2022	74.62	Stock
284	SNX	TD SYNnex Corp	CVG	Convergys Corp	28/06/2018	1,356.24	Cash and Stock
285	TTMI	TTM Technologies Inc	VIAS	Viasystems Group Inc	22/09/2014	905.75	Cash and Stock

286	TTWO	Take-Two Interactive Softw..	ZNGA	Zynga Inc	10/01/2022	12,006.42	Cash and Stock
287	TMHC	Taylor Morrison Home Corp	WLH	William Lyon Homes	06/11/2019	2,152.13	Cash and Stock
288	TISI	Team Inc	FRM	Furmanite Corp	04/05/2015	353.83	Stock
289	TDOC	Teladoc Health Inc	LVGO	Livongo Health Inc	05/08/2020	13,154.02	Cash and Stock
290	TDY	Teledyne Technologies Inc	LCRY	Teledyne LeCroy Inc	29/05/2012	241.16	Cash
291	TFX	Teleflex Inc	VASC	Vascular Solutions LLC	02/12/2016	962.63	Cash
292	THC	Tenet Healthcare Corp	VHS	Vanguard Health Systems Inc	24/06/2013	1,627.53	Cash
293	TSLA	Tesla Inc	MXWL	Maxwell Technologies Inc	04/02/2019	236.99	Stock
294	TXT	Textron Inc	ACAT	Arctic Cat Inc	25/01/2017	306.09	Cash
295	CPB	The Campbell's Company	LNCE	Snyder's-Lance Inc	18/12/2017	6,044.00	Cash
296	TVTY	Tivity Health Inc	NTRI	Nutrisystem Inc	10/12/2018	1,289.43	Cash and Stock
297	TYG	Tortoise Energy Infrastruc..	TYN	Tortoise North American En..	28/01/2014	190.49	Stock
298	RAH	TreeHouse Private Brands Inc	AIPC	American Italian Pasta Co	21/06/2010	1,186.92	Cash
299	TRN	Trinity Industries Inc	QUIX	Quixote Corp	30/12/2009	97.02	Cash
300	TPB	Turning Point Brands Inc	SDI	Standard Diversified Inc	08/04/2020	361.92	Stock
301	TWLO	Twilio Inc	SEND	SendGrid Inc	15/10/2018	1,834.78	Stock
302	VEEE	Twin Vee PowerCats Co	TVPC	Twin Vee Powercats Inc	08/09/2022	45,658.00	Stock
303	TYL	Tyler Technologies Inc	EGOV	NIC Inc	10/02/2021	2,055.42	Cash
304	TSN	Tyson Foods Inc	HSH	Hillshire Brands Co/The	29/05/2014	8,396.56	Cash
305	TSN	Tyson Foods Inc	APFH	AdvancePierre Foods Holdin..	25/04/2017	4,140.75	Cash
306	ECOL	US Ecology Inc	NRCG	NRC Group Holdings Corp	24/06/2019	771.32	Stock
307	RARE	Ultragenyx Pharmaceutical ..	DMTX	Dimension Therapeutics Inc	03/10/2017	109.54	Cash
308	UNFI	United Natural Foods Inc	SVU	SUPERVALU Inc	26/07/2018	3,121.27	Cash
309	URI	United Rentals Inc	NEFF	Neff Corp	16/08/2017	1,275.61	Cash
310	UTHR	United Therapeutics Corp	STDY	SteadyMed Ltd	30/04/2018	86.06	Cash
311	U	Unity Software Inc	IS	ironSource Ltd	13/07/2022	3,674.06	Stock
312	UNVR	Univar Solutions Inc	NXEO	Nexeo Solutions Inc	17/09/2018	1,847.59	Cash and Stock
313	VFC	VF Corp	TBL	Timberland LLC/DE	13/06/2011	1,971.75	Cash
314	VICI	VICI Properties Inc	MGP	MGM Growth Properties LLC	04/08/2021	15,516.32	Stock
315	VMW	VMware Inc	CBLK	Carbon Black Inc	22/08/2019	1,781.52	Cash
316	VECO	Veeco Instruments Inc	UTEK	Ultratech Inc	02/02/2017	516.83	Cash and Stock
317	VRNT	Verint Systems Inc	CMVT	Comverse Technology Inc	13/08/2012	905.02	Stock
318	VSAT	Viasat Inc	RNET	RigNet Inc	21/12/2020	228.77	Stock
319	VIAS	Viasystems Group Inc	DDIC	Viasystems North America Inc	04/04/2012	244.68	Cash
320	VTRS	Viatis Inc	OYST	Oyster Point Pharma Inc	07/11/2022	284.41	Cash
321	WCC	WESCO International Inc	AXE	Anixter International Inc	13/01/2020	4,178.89	Cash and Stock
322	WNC	Wabash National Corp	STS	Supreme Industries Inc	08/08/2017	358.32	Cash
323	DIS	Walt Disney Co/The	TFCFA	TFCF Corp	14/12/2017	83,343.34	Cash or Stock
324	DIS	Walt Disney Co/The	MVL	Marvel Entertainment LLC	31/08/2009	3,834.25	Cash and Stock
325	WM	Waste Management Inc	ADSW	Advanced Disposal Services..	15/04/2019	4,580.00	Cash
326	WCG	WellCare Health Plans Inc	UAM	Universal American Corp	17/11/2016	236.86	Cash
327	WELL	Welltower Inc	QCP	Quality Care Properties Inc	25/04/2018	3,405.99	Cash
328	WDC	Western Digital Corp	STEC	HGST Technologies Santa An..	24/06/2013	187.87	Cash

329	WLK	Westlake Corp	AXLL	Axiall Corp	10/06/2016	3,541.98	Cash
330	WRK	Westrock Co	KS	KapStone Paper and Packagi..	29/01/2018	4,934.24	Cash or Stock
331	WHLR	Wheeler Real Estate Invest..	CDR	Cedar Realty Trust Inc	02/03/2022	129.50	Cash
332	WSC	WillScot Holdings Corp	MINI	Mobile Mini Inc	02/03/2020	3,008.21	Stock
333	XPO	XPO Inc	CNW	XPO CNW Inc	09/09/2015	3,016.06	Cash
334	XPO	XPO Inc	PACR	XPO Intermodal Inc	06/01/2014	262.09	Cash and Stock
335	ZBRA	Zebra Technologies Corp	XPLR	Xplore Technologies Corp	05/07/2018	80.51	Cash
336	ZBH	Zimmer Biomet Holdings Inc	LDRH	LDR Holding Corp	07/06/2016	1,002.20	Cash
337	ZTS	Zoetis Inc	ABAX	Abaxis Inc	16/05/2018	1,717.33	Cash
338	ZTS	Zoetis Inc	NVET	Nexvet Biopharma plc	13/04/2017	58.49	Cash
339	ZRAN	Zoran Corp	TUNE	Microtune Inc	08/09/2010	77.12	Cash
340	SCOR	comScore Inc	RENT	Rentrak Corp	29/09/2015	800.92	Stock
341	EBAY	eBay Inc	DRJ	Dreams Inc	16/04/2012	168.44	Cash
342	HD	Home Depot Inc	USHS	US Home Systems Inc	07/08/2012	81.89	Cash
343	BRC	Brocade Communications Systems LLC	RKUS	Ruckus Wireless Inc	04/04/2016	1,043.6	Cash and Stock
344	VMC	Vulcan Materials Co	USCR	US Concrete Inc	07/06/2021	nan	nan

Note. This appendix lists all 344 completed U.S. public-to-public M&A transactions included in the final sample, announced between January 2009 and December 2022. Deals are sorted alphabetically by acquirer name. Ann. Date = announcement date (dd/mm/yyyy). Value = announced transaction value in USD millions as reported by Bloomberg Terminal. Acq. = acquirer ticker, Tgt. = target ticker. Company names truncated to 28 characters for formatting.

Appendix 2. Python Scripts for Data Collection

The Python scripts presented in this appendix 2 were developed with the assistance of generative AI tools as disclosed at the end of the reference list. All scripts were reviewed, tested, and validated by the author. The data outputs produced by these scripts are the basis of the empirical analysis presented in Chapters 5. All scripts are written in Python 3 platform and require libraries specified in each script header. Scripts are next shown in the exact order they were executed in the empirical analysis pipeline.

Script for Acquirers' Stock Price Data Collection

This Python script retrieved daily closing prices for all acquiring firms from the Plygon.io financial data Application Programming Interface (API). For each acquirer it retrieves 180 trading days prior the announcement date to form estimation window, and also daily closing prices from the announcement to completion of the deal to form event window. The script additionally retrieves the S&P500 daily prices over the entire sample period, from year 2009 to 2024, to use in the market-adjusted benchmark model.

```

"""
fetch_stock_prices.py
-----
Reads ma_export_3172003_150631_MAIN_claude_csv.csv and fetches:

1. Acquirer daily closing prices:
   - 180 trading days before announcement date
   - Announcement date through completion date

2. S&P 500 (SPY) daily closing prices:
   - Single pull: earliest announce date -> latest completion date

Output: stock_prices.xlsx with two tabs:
   - Tab "prices" : Column A = Date, then one column per acquirer ticker
   - Tab "sp500" : Column A = Date, Column B = SPY closing price

Numbers: no thousand separators, dot as decimal separator.
Skips: non-US tickers, placeholder/numeric tickers.

Usage:
  pip install requests openpyxl

```

```

python fetch_stock_prices.py

Configuration:
    Set API_KEY, INPUT_FILE, OUTPUT_FILE below.
"""

import requests
import csv
import time
import re
import os

from datetime import datetime, timedelta
from collections import defaultdict
import openpyxl
from openpyxl.styles import Font, PatternFill, Alignment

# -----
# CONFIGURATION
# -----

API_KEY      = "M27vAezDY01bUoUQf8mAuFULW69trXP0" # <-- replace if regenerated
INPUT_FILE   = "ma_export_3172003_150631_MAIN_claude_csv.csv"
OUTPUT_FILE  = "stock_prices.xlsx"
RATE_LIMIT_DELAY = 0.25 # seconds between API calls
PRE_ANNOUNCE_DAYS = 180 # trading days to fetch before announcement

BASE_URL = "https://api.polygon.io"

# -----
# TICKER CLEANING
# -----

def clean_ticker(raw: str):
    """
    Returns (ticker, is_valid_us).
    Strips Bloomberg suffix. Rejects non-US and placeholder tickers.
    e.g. 'AAPL US' -> ('AAPL', True)
        'SKY LN' -> ('SKY', False)
        '9876540D US' -> ('9876540D', False)
    """
    raw = raw.strip()
    if not raw:
        return None, False
    parts = raw.rsplit(" ", 1)
    if len(parts) == 2 and re.match(r'^[A-Z]{2,3}$', parts[1]):

```

```

        ticker, exchange = parts[0].strip(), parts[1].strip()
    else:
        return None, False
    if exchange != "US":
        return ticker, False
    if re.match(r'^\d', ticker):
        return ticker, False
    return ticker, True

# -----
# LOAD INPUT CSV
# -----

def load_deals(filepath: str) -> list:
    deals = []
    with open(filepath, newline="", encoding="utf-8") as f:
        reader = csv.DictReader(f)
        for row in reader:
            aq_raw = row["Acquirer Ticker"].strip()
            ann_str = row["Announce Date"].strip()
            com_str = row["Completion Date"].strip()
            ticker, is_valid = clean_ticker(aq_raw)
            if not is_valid:
                continue
            try:
                ann_date = datetime.strptime(ann_str, "%Y-%m-%d")
                com_date = datetime.strptime(com_str, "%Y-%m-%d")
            except ValueError:
                continue
            deals.append({
                "raw_ticker": aq_raw,
                "ticker": ticker,
                "announce_date": ann_date,
                "completion_date": com_date,
            })
    return deals

# -----
# API - FETCH PRICE RANGE
# -----

def fetch_prices(ticker: str, start_date: str, end_date: str) -> dict:
    """
    Fetch all daily closing prices for ticker between start_date and end_date.

```



```

Fetch enough calendar days before announce_date to get n_days trading days.
We fetch ~1.5x the calendar days to account for weekends/holidays.
"""
# Add buffer: n_days * 1.5 calendar days to ensure we get enough trading days
calendar_days = int(n_days * 1.5) + 20
start_dt = announce_date - timedelta(days=calendar_days)
start_str = start_dt.strftime("%Y-%m-%d")
end_str = (announce_date - timedelta(days=1)).strftime("%Y-%m-%d")

all_prices = fetch_prices(ticker, start_str, end_str)

# Sort and keep only last n_days trading days
sorted_dates = sorted(all_prices.keys())
if len(sorted_dates) > n_days:
    sorted_dates = sorted_dates[-n_days:]

return {d: all_prices[d] for d in sorted_dates}

# -----
# EXCEL OUTPUT
# -----

def write_excel(acquirer_data: dict, sp500_data: dict, filepath: str):
    """
    acquirer_data: {ticker: {date_str: close_price, ...}, ...}
    sp500_data:    {date_str: close_price, ...}
    """
    wb = openpyxl.Workbook()

    # --- Tab 1: prices -----
    ws_prices = wb.active
    ws_prices.title = "prices"

    # Collect all unique dates across all tickers
    all_dates = set()
    for prices in acquirer_data.values():
        all_dates.update(prices.keys())
    all_dates = sorted(all_dates)

    # Get sorted list of tickers
    tickers = sorted(acquirer_data.keys())

```

```

# Header row
header_fill = PatternFill("solid", fgColor="1F4E79")
header_font = Font(color="FFFFFF", bold=True, size=10)

ws_prices.cell(row=1, column=1, value="Date").font = header_font
ws_prices.cell(row=1, column=1).fill = header_fill
ws_prices.cell(row=1, column=1).alignment = Alignment(horizontal="center")

for col_idx, ticker in enumerate(tickers, start=2):
    cell = ws_prices.cell(row=1, column=col_idx, value=ticker)
    cell.font = header_font
    cell.fill = header_fill
    cell.alignment = Alignment(horizontal="center")

# Data rows
for row_idx, date_str in enumerate(all_dates, start=2):
    ws_prices.cell(row=row_idx, column=1, value=date_str)
    for col_idx, ticker in enumerate(tickers, start=2):
        price = acquirer_data[ticker].get(date_str)
        if price is not None:
            ws_prices.cell(row=row_idx, column=col_idx, value=round(price, 4))

# Column widths
ws_prices.column_dimensions["A"].width = 12
for col_idx in range(2, len(tickers) + 2):
    col_letter = openpyxl.utils.get_column_letter(col_idx)
    ws_prices.column_dimensions[col_letter].width = 10

# Freeze header row and date column
ws_prices.freeze_panes = "B2"

print(f" Tab 'prices' : {len(all_dates)} dates x {len(tickers)} acquirers")

# --- Tab 2: sp500 -----
ws_sp500 = wb.create_sheet(title="sp500")

ws_sp500.cell(row=1, column=1, value="Date").font = header_font
ws_sp500.cell(row=1, column=1).fill = header_fill
ws_sp500.cell(row=1, column=2, value="SPY Close").font = header_font
ws_sp500.cell(row=1, column=2).fill = header_fill

sp500_dates = sorted(sp500_data.keys())
for row_idx, date_str in enumerate(sp500_dates, start=2):
    ws_sp500.cell(row=row_idx, column=1, value=date_str)

```

```

        ws_sp500.cell(row=row_idx, column=2,
                    value=round(sp500_data[date_str], 4))

ws_sp500.column_dimensions["A"].width = 12
ws_sp500.column_dimensions["B"].width = 14
ws_sp500.freeze_panes = "A2"

print(f" Tab 'sp500'   : {len(sp500_dates)} trading days")

wb.save(filepath)
print(f"\n Saved -> {filepath}")

# -----
# MAIN
# -----

def main():
    if not os.path.exists(INPUT_FILE):
        print(f"ERROR: '{INPUT_FILE}' not found.")
        return

    deals = load_deals(INPUT_FILE)
    print(f"\nStock Price Fetcher")
    print(f"Input      : {INPUT_FILE} ({len(deals)} valid US deals)")
    print(f"Output      : {OUTPUT_FILE}")
    print(f"Pre-ann     : {PRE_ANNOUNCE_DAYS} trading days before announcement")
    print(f"Post-ann    : announcement date -> completion date\n")

    # Get unique acquirers with their date windows
    # For each acquirer, we may appear in multiple deals - take the union
    acquirer_windows = defaultdict(lambda: {"windows": []})
    for deal in deals:
        acquirer_windows[deal["ticker"]]["windows"].append({
            "announce": deal["announce_date"],
            "completion": deal["completion_date"],
        })

    total_acquirers = len(acquirer_windows)
    acquirer_data = {}

    print(f"Fetching prices for {total_acquirers} unique acquirers...\n")

```

```

for i, (ticker, info) in enumerate(sorted(acquirer_windows.items())):
    all_prices = {}

    for window in info["windows"]:
        ann_date = window["announce"]
        com_date = window["completion"]

        print(f" [{i+1}/{total_acquirers}] {ticker} "
              f"(ann={ann_date.date()} comp={com_date.date()})",
              end=" ... ", flush=True)

        # Pre-announcement window (180 trading days before)
        pre_prices = get_trading_days_before(
            ticker, ann_date, PRE_ANNOUNCE_DAYS)
        time.sleep(RATE_LIMIT_DELAY)

        # Announcement to completion window
        ann_str = ann_date.strftime("%Y-%m-%d")
        com_str = com_date.strftime("%Y-%m-%d")
        event_prices = fetch_prices(ticker, ann_str, com_str)
        time.sleep(RATE_LIMIT_DELAY)

        all_prices.update(pre_prices)
        all_prices.update(event_prices)

        total = len(pre_prices) + len(event_prices)
        print(f"✓ {len(pre_prices)} pre + {len(event_prices)} event = "
              f"{total} days")

    acquirer_data[ticker] = all_prices

# — S&P 500 single pull —————
# Start date goes back 270 calendar days before the earliest
# announcement to fully cover the 180 trading day estimation window.
# 180 trading days ≈ 270 calendar days (accounts for weekends/holidays).
all_announce = [d["announce_date"] for d in deals]
all_completion = [d["completion_date"] for d in deals]
sp500_start = (min(all_announce) - timedelta(days=270)).strftime("%Y-%m-%d")
sp500_end = max(all_completion).strftime("%Y-%m-%d")

print(f"\nFetching S&P 500 (SPY) {sp500_start} -> {sp500_end} ...",
      end=" ", flush=True)
sp500_data = fetch_prices("SPY", sp500_start, sp500_end)

```

```

print(f"✓ {len(sp500_data)} trading days")

# --- Write Excel -----
print(f"\nWriting Excel file...")
write_excel(acquirer_data, sp500_data, OUTPUT_FILE)

print(f"\nDone!")

if __name__ == "__main__":
    main()

```

Script for Target Firm Stock Price Data Collection

The below script retrieves daily closing prices for all target firms from the Polygon.io API over a 63-trading day window before the announcement date of the merger or acquisition. The T-30 closing price is used to compute the market capitalization (share price x shares outstanding) of the target, input in the Tobin's Q approximation following Chung and Pruitt (1994).

```

"""
fetch_target_prices.py
-----
Fetches daily closing prices for all target companies in the deal
CSV for a window of 63 trading days before each announcement date.

This allows you to:
1. Visually inspect pre-announcement price movements
2. Detect any price run-up before the announcement
3. Choose the appropriate measurement date for Tobin's Q
   (T-1, T-30, T-42 or T-63 trading days before announcement)

Output: target_prices.xlsx
  Tab "prices" : Date column + one column per target ticker
                Columns sorted alphabetically
  Tab "summary" : For each target - ticker, announcement date,
                  T-1 price, T-5 price, T-10 price, T-20 price,
                  T-30 price, T-42 price, T-63 price,
                  run-up T-63 to T-1 (%), run-up T-30 to T-1 (%)

```

Colour coding in "prices" tab:

```
RED      background : T-1  (last trading day before announcement)
ORANGE  background : T-30 window (days 25-35 around T-30)
BLUE    background : T-42 window (days 37-47 around T-42)
GREEN   background : T-63 (first day of window)
```

Usage:

```
pip install requests openpyxl
python fetch_target_prices.py
```

Notes:

- Only fetches US-listed targets
- If same target appears in multiple deals, fetches window for each deal separately
- Uses split/dividend adjusted prices (adjusted=true)
- Rate limited to 0.25s between calls

```
"""
```

```
import requests
import csv
import re
import time
import os
from datetime import datetime, timedelta
from collections import defaultdict

import openpyxl
from openpyxl.styles import PatternFill, Font, Alignment
from openpyxl.utils import get_column_letter

# -----
# CONFIGURATION
# -----

API_KEY      = "M27vAezDY0lbUoUQf8mAuFULW69trXP0"
INPUT_FILE   = "ma_export_3172003_150631_MAIN_claude.csv.csv"
OUTPUT_FILE  = "target_prices.xlsx"
PRICES_FILE  = "stock_prices.xlsx"      # master ticker list
CLEANED_TAB  = "returns_cleaned"        # tab with valid acquirer tickers
TICKER_ROW   = 3                        # row containing ticker headers
BASE_URL     = "https://api.polygon.io"
DELAY        = 0.25

# Number of trading days to fetch before announcement
PRE_ANN_DAYS = 63  # covers T-1 through T-63
```

```

# Colour fills
FILL_T1      = PatternFill("solid", fgColor="FFC7CE") # red - T-1
FILL_T30     = PatternFill("solid", fgColor="FFEB9C") # orange/yellow - T-30 area
FILL_T42     = PatternFill("solid", fgColor="BDD7EE") # blue - T-42 area
FILL_T63     = PatternFill("solid", fgColor="C6EFCE") # green - T-63 (start)
FILL_HEADER  = PatternFill("solid", fgColor="1F4E79") # dark blue header
FILL_DATE    = PatternFill("solid", fgColor="D9D9D9") # grey date column
FILL_SUM_H   = PatternFill("solid", fgColor="375623") # dark green summary header

FONT_HEADER  = Font(color="FFFFFF", bold=True, size=10, name="Arial")
FONT_BODY    = Font(size=9, name="Arial")
FONT_DATE    = Font(size=9, bold=True, name="Arial")

# -----
# READ VALID ACQUIRER TICKERS FROM RETURNS_CLEANED
# -----

def get_valid_acquirers(xlsx_file: str, tab_name: str,
                       ticker_row: int) -> set:
    """
    Reads row ticker_row from the given tab in xlsx_file
    and returns a set of valid acquirer ticker strings.
    Skips column A (Date) and column B (SPY).
    """
    import openpyxl
    if not os.path.exists(xlsx_file):
        print(f" WARNING: '{xlsx_file}' not found - "
              f"fetching ALL targets without filter.")
        return None
    try:
        wb = openpyxl.load_workbook(xlsx_file, read_only=True,
                                    data_only=True)
        if tab_name not in wb.sheetnames:
            print(f" WARNING: '{tab_name}' tab not found - "
                  f"fetching ALL targets without filter.")
            wb.close()
            return None
        ws = wb[tab_name]
        tickers = set()
        for cell in ws[ticker_row]:
            if cell.column <= 2: # skip Date + SPY
                continue
            if cell.value and str(cell.value).strip():
                tickers.add(str(cell.value).strip())
        wb.close()
        print(f" Loaded {len(tickers)} valid acquirer tickers ")

```

```

        f"from '{tab_name}' row {ticker_row}")
    return tickers
except Exception as e:
    print(f" WARNING: could not read '{xlsx_file}': {e} ")
        f"-- fetching ALL targets without filter.")
    return None

# -----
# TICKER CLEANING
# -----

def clean_ticker(raw: str):
    """Returns (ticker, is_valid_us)."""
    raw = raw.strip()
    if not raw:
        return None, False
    parts = raw.rsplit(" ", 1)
    if len(parts) == 2 and re.match(r'^[A-Z]{2,3}$', parts[1]):
        ticker, exchange = parts[0].strip(), parts[1].strip()
    else:
        return None, False
    if exchange != "US":
        return ticker, False
    if re.match(r'^\d', ticker):
        return ticker, False
    return ticker, True

# -----
# LOAD DEALS - GROUP BY TARGET TICKER
# -----

def load_target_deals(filepath: str,
                      valid_acquirers: set = None) -> dict:
    """
    Returns dict: {target_ticker -> [{"announce": datetime,
                                     "acquirer": str,
                                     "target_name": str}, ...]}

    If valid_acquirers is provided, only includes deals where
    the acquirer ticker is in that set (i.e. in returns_cleaned).
    """
    deals = defaultdict(list)
    skipped = 0
    included = 0
    with open(filepath, newline="", encoding="utf-8") as f:

```

```

reader = csv.DictReader(f)
for row in reader:
    tg_ticker, tg_valid = clean_ticker(
        row["Target Ticker"].strip())
    aq_ticker, aq_valid = clean_ticker(
        row["Acquirer Ticker"].strip())
    if not tg_valid:
        continue
    # Filter by valid acquirers if provided
    if valid_acquirers is not None:
        if not aq_valid or aq_ticker not in valid_acquirers:
            skipped += 1
            continue
    try:
        ann = datetime.strptime(
            row["Announce Date"].strip(), "%Y-%m-%d")
    except ValueError:
        continue
    deals[tg_ticker].append({
        "announce":    ann,
        "acquirer":    row.get("Acquirer Ticker","").strip(),
        "target_name": row.get("Target Name","").strip(),
    })
    included += 1
if valid_acquirers is not None:
    print(f" Deals included (acquirer in returns_cleaned): {included}")
    print(f" Deals skipped (acquirer not in returns_cleaned): {skipped}")
return dict(deals)

# -----
# POLYGON API - FETCH PRICES
# -----

def fetch_prices(ticker: str, start_date: str,
                end_date: str) -> dict:
    """
    Fetch daily adjusted closing prices.
    Returns {date_str: close_price}.
    """
    url = (f"{BASE_URL}/v2/aggs/ticker/{ticker}/"
           f"range/1/day/{start_date}/{end_date}")
    params = {"adjusted": "true", "limit": 50000,
              "apiKey": API_KEY}
    prices = {}

    try:

```

```

while url:
    r = requests.get(url, params=params, timeout=15)
    r.raise_for_status()
    data = r.json()
    for bar in data.get("results", []):
        date_str = datetime.utcfromtimestamp(
            bar["t"] / 1000).strftime("%Y-%m-%d")
        prices[date_str] = bar["c"]
    next_url = data.get("next_url")
    if next_url:
        url = next_url
        params = {"apiKey": API_KEY}
    else:
        break
except requests.exceptions.HTTPError:
    code = r.status_code
    if code == 403:
        print(f"    plan_restriction: {ticker}")
    elif code == 404:
        print(f"    not_found: {ticker}")
    elif code == 429:
        print(f"    rate_limited - waiting 60s")
        time.sleep(60)
except Exception as e:
    print(f"    error {ticker}: {e}")

return prices

def get_trading_days_before(ticker: str,
                           announce_date: datetime,
                           n_days: int) -> dict:
    """
    Fetch n_days trading days before announce_date.
    Returns {date_str: close_price} - sorted, last n_days only.
    """
    # Add 1.5x buffer for weekends/holidays
    calendar_days = int(n_days * 1.5) + 20
    start_dt = announce_date - timedelta(days=calendar_days)
    start_str = start_dt.strftime("%Y-%m-%d")
    # End = day before announcement
    end_str = (announce_date - timedelta(days=1)).strftime(
        "%Y-%m-%d")

    all_prices = fetch_prices(ticker, start_str, end_str)
    sorted_dates = sorted(all_prices.keys())

```

```

# Keep only last n_days trading days
if len(sorted_dates) > n_days:
    sorted_dates = sorted_dates[-n_days:]

return {d: all_prices[d] for d in sorted_dates}

# -----
# GET PRICE AT SPECIFIC TRADING DAY OFFSET
# -----

def get_price_at_offset(prices_sorted: list,
                       prices_dict: dict,
                       offset: int) -> float:
    """
    Get price at trading day -offset before announcement.
    offset=1 means last trading day (T-1),
    offset=30 means 30th trading day back (T-30), etc.
    prices_sorted is sorted list of date strings (ascending).
    Returns float or None.
    """
    # prices_sorted is ascending, so last element is T-1
    idx = len(prices_sorted) - offset
    if 0 <= idx < len(prices_sorted):
        return prices_dict.get(prices_sorted[idx])
    return None

# -----
# WRITE EXCEL OUTPUT
# -----

def write_excel(target_data: dict, deals: dict,
               filepath: str):
    """
    target_data: {ticker: {date_str: price, ...}}
    deals:      {ticker: [{"announce": datetime, ...}]}
    """
    wb = openpyxl.Workbook()

    # --- Tab 1: prices -----
    ws = wb.active
    ws.title = "prices"

```

```

# Collect all dates across all tickers
all_dates = set()
for prices in target_data.values():
    all_dates.update(prices.keys())
all_dates = sorted(all_dates)

tickers = sorted(target_data.keys())

# Build per-ticker announcement date lookup
# For colouring: {ticker -> set of announcement dates}
ann_date_map = {} # ticker -> sorted list of ann dates
for ticker, deal_list in deals.items():
    ann_date_map[ticker] = sorted(
        [d["announce"] for d in deal_list])

# Determine colour zones per ticker per date
# We pre-compute for efficiency
# For each ticker: build set of T-1, T-30±5, T-42±5, T-63 dates
colour_map = {} # (ticker, date_str) -> fill

for ticker in tickers:
    prices_for_ticker = target_data.get(ticker, {})
    dates_sorted = sorted(prices_for_ticker.keys())

    if ticker not in ann_date_map:
        continue

    for ann in ann_date_map[ticker]:
        # Get trading days before this announcement
        pre_dates = [d for d in dates_sorted
                     if d < ann.strftime("%Y-%m-%d")]
        if not pre_dates:
            continue

        n = len(pre_dates) # number of pre-ann trading days

        # T-1: last trading day (index n-1)
        if n >= 1:
            colour_map[(ticker, pre_dates[-1])] = FILL_T1

        # T-63: first trading day in window (index 0)
        if n >= 63:

```

```

d63 = pre_dates[n - 63]
if (ticker, d63) not in colour_map:
    colour_map[(ticker, d63)] = FILL_T63

# T-42 zone: days 40-44 back (±2 around T-42)
for offset in range(40, 45):
    idx = n - offset
    if 0 <= idx < n:
        d = pre_dates[idx]
        if (ticker, d) not in colour_map:
            colour_map[(ticker, d)] = FILL_T42

# T-30 zone: days 28-32 back (±2 around T-30)
for offset in range(28, 33):
    idx = n - offset
    if 0 <= idx < n:
        d = pre_dates[idx]
        if (ticker, d) not in colour_map:
            colour_map[(ticker, d)] = FILL_T30

# Header row
ws.cell(row=1, column=1, value="Date").fill = FILL_HEADER
ws.cell(row=1, column=1).font = FONT_HEADER
ws.cell(row=1, column=1).alignment = Alignment(
    horizontal="center")
ws.column_dimensions["A"].width = 13

for col_idx, ticker in enumerate(tickers, start=2):
    cell = ws.cell(row=1, column=col_idx, value=ticker)
    cell.fill = FILL_HEADER
    cell.font = FONT_HEADER
    cell.alignment = Alignment(horizontal="center")
    ws.column_dimensions[
        get_column_letter(col_idx)].width = 10

ws.row_dimensions[1].height = 18
ws.freeze_panes = "B2"

# Legend row
ws.cell(row=2, column=1, value="LEGEND:").font = Font(
    bold=True, name="Arial", size=9)
legends = [
    (2, "T-1 (last day before announcement)", FILL_T1),
    (3, "T-30 zone (±2 days)", FILL_T30),
    (4, "T-42 zone (±2 days)", FILL_T42),
    (5, "T-63 (first day of window)", FILL_T63),

```

```

]
for col, label, fill in legends:
    c = ws.cell(row=2, column=col, value=label)
    c.fill = fill
    c.font = Font(name="Arial", size=8)
ws.row_dimensions[2].height = 16

# Data rows (start at row 3)
for row_idx, date_str in enumerate(all_dates, start=3):
    # Date cell
    date_cell = ws.cell(row=row_idx, column=1,
                        value=date_str)
    date_cell.fill = FILL_DATE
    date_cell.font = FONT_DATE
    date_cell.alignment = Alignment(horizontal="center")

    # Ticker cells
    for col_idx, ticker in enumerate(tickers, start=2):
        price = target_data[ticker].get(date_str)
        cell = ws.cell(row=row_idx, column=col_idx,
                      value=round(price, 4)
                      if price is not None else None)
        cell.font = FONT_BODY
        cell.alignment = Alignment(horizontal="right")
        cell.number_format = "#,##0.00"

        # Apply colour if in a zone
        fill = colour_map.get((ticker, date_str))
        if fill and price is not None:
            cell.fill = fill

print(f" Tab 'prices' : {len(all_dates)} dates "
      f"x {len(tickers)} targets")

# --- Tab 2: summary -----
ws2 = wb.create_sheet("summary")

sum_headers = [
    "Target Ticker", "Target Name", "Acquirer",
    "Announce Date",
    "Price T-1", "Price T-5", "Price T-10",
    "Price T-20", "Price T-30", "Price T-42", "Price T-63",
    "Run-up T-63→T-1 (%)", "Run-up T-30→T-1 (%)",
    "Deals Count"
]
]

```

```

for col_idx, header in enumerate(sum_headers, start=1):
    cell = ws2.cell(row=1, column=col_idx, value=header)
    cell.fill      = PatternFill("solid", fgColor="375623")
    cell.font      = Font(color="FFFFFF", bold=True,
                          size=10, name="Arial")
    cell.alignment = Alignment(horizontal="center",
                              wrap_text=True)
ws2.row_dimensions[1].height = 30

# Column widths for summary
col_widths = [14, 30, 14, 14, 10, 10, 10,
              10, 10, 10, 10, 18, 18, 10]
for i, w in enumerate(col_widths, start=1):
    ws2.column_dimensions[get_column_letter(i)].width = w

row_idx = 2
for ticker in sorted(deals.keys()):
    if ticker not in target_data:
        continue

    prices_dict = target_data[ticker]
    dates_sorted = sorted(prices_dict.keys())
    deal_list = deals[ticker]
    n_deals = len(deal_list)

    for deal in deal_list:
        ann = deal["announce"]
        ann_str = ann.strftime("%Y-%m-%d")

        # Get pre-announcement dates for this deal
        pre_dates = [d for d in dates_sorted
                     if d < ann_str]

        # Price at each offset
        def p(offset):
            return get_price_at_offset(
                pre_dates, prices_dict, offset)

        p1 = p(1)
        p5 = p(5)
        p10 = p(10)
        p20 = p(20)
        p30 = p(30)

```

```

p42 = p(42)
p63 = p(63)

# Run-up calculations
runup_63 = None
runup_30 = None
if p1 and p63 and p63 != 0:
    runup_63 = round((p1 - p63) / p63 * 100, 2)
if p1 and p30 and p30 != 0:
    runup_30 = round((p1 - p30) / p30 * 100, 2)

def fmtp(v):
    return round(v, 4) if v else None

ws2.cell(row=row_idx, column=1, value=ticker)
ws2.cell(row=row_idx, column=2,
         value=deal.get("target_name",""))
ws2.cell(row=row_idx, column=3,
         value=deal.get("acquirer",""))
ws2.cell(row=row_idx, column=4, value=ann_str)
ws2.cell(row=row_idx, column=5, value=fmtp(p1))
ws2.cell(row=row_idx, column=6, value=fmtp(p5))
ws2.cell(row=row_idx, column=7, value=fmtp(p10))
ws2.cell(row=row_idx, column=8, value=fmtp(p20))
ws2.cell(row=row_idx, column=9, value=fmtp(p30))
ws2.cell(row=row_idx, column=10, value=fmtp(p42))
ws2.cell(row=row_idx, column=11, value=fmtp(p63))
ws2.cell(row=row_idx, column=12, value=runup_63)
ws2.cell(row=row_idx, column=13, value=runup_30)
ws2.cell(row=row_idx, column=14, value=n_deals)

# Colour run-up cells: red if positive, green if neg
for col, val in [(12, runup_63), (13, runup_30)]:
    cell = ws2.cell(row=row_idx, column=col)
    cell.number_format = "0.00%"
    if val is not None:
        if val > 5:
            cell.fill = PatternFill(
                "solid", fgColor="FFC7CE")
        elif val < -5:
            cell.fill = PatternFill(
                "solid", fgColor="C6EFCE")

# Colour price cells with number format
for col in range(5, 12):
    ws2.cell(row=row_idx,

```

```

        column=col).number_format = "#,##0.00"

        row_idx += 1

    # Freeze summary header
    ws2.freeze_panes = "A2"
    ws2.auto_filter.ref = (
        f"A1:{get_column_letter(len(sum_headers))}1")

    print(f" Tab 'summary' : {row_idx - 2} deal rows")

    wb.save(filepath)
    print(f"\n Saved -> {filepath}")

# -----
# MAIN
# -----

def main():
    if not os.path.exists(INPUT_FILE):
        print(f"ERROR: '{INPUT_FILE}' not found.")
        return

    print(f"\nTarget Price Fetcher")
    print(f"Input   : {INPUT_FILE}")
    print(f"Filter  : {PRICES_FILE} -> '{CLEANED_TAB}' row {TICKER_ROW}")
    print(f"Output  : {OUTPUT_FILE}\n")

    # Load valid acquirer tickers from returns_cleaned
    valid_acquirers = get_valid_acquirers(
        PRICES_FILE, CLEANED_TAB, TICKER_ROW)

    deals = load_target_deals(INPUT_FILE, valid_acquirers)
    total = len(deals)

    print(f"\nUnique US target tickers after filter: {total}")
    print(f"Window  : {PRE_ANN_DAYS} trading days before "
          f"announcement\n")
    print(f"Colouring:")
    print(f" RED    = T-1 (last day before announcement)")
    print(f" YELLOW = T-30 zone (±2 days)")

```

```

print(f" BLUE   = T-42 zone (±2 days)")
print(f" GREEN  = T-63 (first day of window)\n")

target_data = {}
fetched      = 0
failed       = 0

for i, (ticker, deal_list) in enumerate(
    sorted(deals.items())):

    all_prices = {}

    for deal in deal_list:
        ann = deal["announce"]
        print(f" [{i+1}/{total}] {ticker} "
              f"ann={ann.date()} ...",
              end=" ", flush=True)

        prices = get_trading_days_before(
            ticker, ann, PRE_ANN_DAYS)
        time.sleep(DELAY)

        if prices:
            all_prices.update(prices)
            print(f"✓ {len(prices)} days")
            fetched += 1
        else:
            print(f"X no data")
            failed += 1

    if all_prices:
        target_data[ticker] = all_prices

print(f"\nWriting Excel file...")
write_excel(target_data, deals, OUTPUT_FILE)

print(f"\n{'='*55}")
print(f" SUMMARY")
print(f"{'='*55}")
print(f" Unique target tickers : {total}")
print(f" Successfully fetched  : {fetched}")
print(f" Failed / no data      : {failed}")
print(f" Output file           : {OUTPUT_FILE}")

```

```

print(f"{' '*55}")
print(f"\nDone!")

if __name__ == "__main__":
    main()

```

Script for Target Firms' CIK Lookup (for SEC EDGAR)

The script below searches SEC EDGAR database by company name to obtain the CIK (Central Index Key) number for each target firm. Since targets are delisted or removed from the stock exchange at the time of data collection, due the merger or acquisition, the ticker-based lookups are not sufficient or reliable in this case. This script uses company name search against the SEC EDGAR full-text search API, which remains functional despite the listing status of the firm.

```

"""
fetch_target_financials_edgar.py
-----
Fetches financial data for target firms from SEC EDGAR.

APPROACH: Uses COMPANY NAME (not ticker) to find CIK numbers
since targets are delisted and tickers no longer resolve.
SEC EDGAR company name search works permanently regardless of
whether the company is still listed.

Reads from target_prices.xlsx summary tab:
- Column A = target ticker (for output identification)
- Column B = target company name (used for CIK lookup)
- Column D = announcement date (to find correct 10-K)

Output: target_financials_edgar.csv

Usage:
    pip install requests openpyxl
    python fetch_target_financials_edgar.py
"""

import csv
import re
import time

```

```

import os
import requests
from datetime import datetime

import openpyxl

# -----
# CONFIGURATION
# -----

TARGET_PRICES = "target_prices.xlsx"
PRICES_FILE   = "stock_prices.xlsx"
CLEANED_TAB   = "returns_cleaned"
TICKER_ROW    = 3
OUTPUT_FILE   = "target_financials_edgar.csv"
DELAY         = 0.15 # SEC allows max 10 req/sec

SEC_HEADERS = {
    "User-Agent": "Masters Thesis Research thesis@university.edu",
    "Accept-Encoding": "gzip, deflate",
}

# -----
# TICKER CLEANING
# -----

def clean_ticker(raw):
    raw = raw.strip()
    if not raw:
        return None, False
    parts = raw.rsplit(" ", 1)
    if len(parts) == 2 and re.match(r'^[A-Z]{2,3}$', parts[1]):
        ticker, exchange = parts[0].strip(), parts[1].strip()
    else:
        return None, False
    if exchange != "US":
        return ticker, False
    if re.match(r'^\d', ticker):
        return ticker, False
    return ticker, True

# -----
# LOAD VALID ACQUIRERS FROM RETURNS_CLEANED

```

```

# -----
def get_valid_acquirers(xlsx_file, tab_name, ticker_row):
    if not os.path.exists(xlsx_file):
        return None
    try:
        wb = openpyxl.load_workbook(xlsx_file, read_only=True,
                                    data_only=True)
        if tab_name not in wb.sheetnames:
            wb.close()
            return None
        ws = wb[tab_name]
        tickers = set()
        for cell in ws[ticker_row]:
            if cell.column <= 2:
                continue
            if cell.value and str(cell.value).strip():
                tickers.add(str(cell.value).strip())
        wb.close()
        print(f" Loaded {len(tickers)} valid acquirers")
        return tickers
    except Exception as e:
        print(f" WARNING: {e}")
        return None

# -----
# LOAD TARGETS FROM SUMMARY TAB
# -----

def load_targets_from_summary(filepath):
    """
    Reads summary tab. Returns list of dicts with:
    ticker (col A), target_name (col B),
    acquirer (col C), announce_str (col D)
    """
    targets = []
    if not os.path.exists(filepath):
        print(f" ERROR: '{filepath}' not found.")
        return targets
    try:
        wb = openpyxl.load_workbook(filepath, read_only=True,
                                    data_only=True)
        if "summary" not in wb.sheetnames:
            print(f" ERROR: 'summary' tab not found.")
            wb.close()
            return targets
    
```

```

ws = wb["summary"]
for row in ws.iter_rows(min_row=2, values_only=True):
    if not row[0]:
        continue
    ticker = str(row[0]).strip()
    name = str(row[1]).strip() if row[1] else ""
    acq_raw = str(row[2]).strip() if row[2] else ""
    ann_val = row[3] if len(row) > 3 else None
    if not ticker or not ann_val or not name:
        continue
    ann_str = str(ann_val)[:10]
    aq, _ = clean_ticker(acq_raw)
    targets.append({
        "ticker": ticker,
        "target_name": name,
        "acquirer": aq or acq_raw,
        "announce_str": ann_str,
    })
wb.close()
print(f" Loaded {len(targets)} targets from summary tab")
return targets
except Exception as e:
    print(f" ERROR: {e}")
return targets

# -----
# CIK LOOKUP BY COMPANY NAME
# This is reliable for both active AND delisted companies
# -----

# -----
# CIK LOOKUP VIA EDGAR FULL-TEXT SEARCH API
# -----
# Uses efts.sec.gov which returns pure JSON - not HTML.
# This endpoint is confirmed to work from Python requests.
# Returns CIK from the entity aggregation buckets.
_FULL_CIK_MAP = None

def get_cik_by_name(company_name):
    """
    Look up CIK by company name using EDGAR full-text search API.
    Uses efts.sec.gov which returns pure JSON (not HTML).
    Confirmed working from Python requests.

    The entity_filter aggregation in the response contains

```

```
display_names in format "COMPANY NAME (TICKER) (CIK XXXXXXXXXXX)"
or "COMPANY NAME (CIK XXXXXXXXXXX)" - we extract CIK from this.
```

Tries progressively shorter name variants for best match.

```
"""
import urllib.parse

def search_efets(query):
    """
    Search EDGAR full-text search and extract CIK from
    entity aggregation buckets.
    Returns CIK string or None.
    """
    try:
        # Search for 10-K filings mentioning the company name
        # Use a wide date range to cover all our deals
        url = (f"https://efets.sec.gov/LATEST/search-index"
              f"?q=%22{urllib.parse.quote(query)}%22"
              f"&forms=10-K"
              f"&dateRange=custom"
              f"&startdt=2005-01-01"
              f"&enddt=2024-12-31")
        r = requests.get(url, headers=SEC_HEADERS,
                        timeout=15)
        r.raise_for_status()
        data = r.json()
        time.sleep(DELAY)

        # Extract CIK from entity_filter aggregation buckets
        # Format: "COMPANY NAME (TICKER) (CIK 0000948846)"
        # or      "COMPANY NAME (CIK 0000948846)"
        buckets = (data.get("aggregations", {})
                  .get("entity_filter", {})
                  .get("buckets", []))

        query_upper = query.upper()
        # First pass: find bucket whose name contains query
        for bucket in buckets:
            key = bucket.get("key", "")
            if query_upper in key.upper():
                cik_m = re.search(r'CIK (\d+)', key)
                if cik_m:
                    return cik_m.group(1).zfill(10)

        # Second pass: return top bucket CIK if only 1 entity
        if len(buckets) == 1:
```

```

        cik_m = re.search(r'CIK (\d+)',
                          buckets[0].get("key",""))
        if cik_m:
            return cik_m.group(1).zfill(10)

    # Third pass: return first bucket CIK
    if buckets:
        cik_m = re.search(r'CIK (\d+)',
                          buckets[0].get("key",""))
        if cik_m:
            return cik_m.group(1).zfill(10)

    except Exception:
        pass
    return None

name = company_name.strip()

# Attempt 1: full name
cik = search_efds(name)
if cik:
    return cik

# Attempt 2: remove trailing suffix
name2 = name
for sfx in [" Inc.", " Inc", " Corp.", " Corp",
            " Ltd.", " Ltd", " LLC", " Co.", " Co"]:
    if name2.endswith(sfx):
        name2 = name2[:-len(sfx)].strip()
        break
if name2 != name:
    cik = search_efds(name2)
    if cik:
        return cik

# Attempt 3: first 3 words
words = name.split()
if len(words) >= 3:
    cik = search_efds(" ".join(words[:3]))
    if cik:
        return cik

# Attempt 4: first 2 words
if len(words) >= 2:
    cik = search_efds(" ".join(words[:2]))

```

```

        if cik:
            return cik

    return None

# -----
# FIND 10-K BEFORE ANNOUNCEMENT DATE
# -----

def get_10k_before_date(cik, before_date):
    """
    Returns (filing_date, fiscal_year_end, accession_number)
    for the most recent 10-K before before_date.
    """
    url = f"https://data.sec.gov/submissions/CIK{cik}.json"
    try:
        r = requests.get(url, headers=SEC_HEADERS, timeout=15)
        r.raise_for_status()
        data = r.json()
        filings = data.get("filings", {}).get("recent", {})
        forms = filings.get("form", [])
        dates = filings.get("filingDate", [])
        periods = filings.get("periodOfReport", [])
        accns = filings.get("accessionNumber", [])

        before_str = before_date.strftime("%Y-%m-%d")
        best_date = None
        best_idx = None

        for i, (form, date) in enumerate(zip(forms, dates)):
            if form not in ("10-K", "10-K/A"):
                continue
            if date <= before_str:
                if best_date is None or date > best_date:
                    best_date = date
                    best_idx = i

        if best_idx is not None:
            return (dates[best_idx], periods[best_idx],
                    accns[best_idx])

    # Check older filings archive
    for file_info in data.get("filings", {}).get(

```

```

        "files", []):
    try:
        file_url = (f"https://data.sec.gov/"
                    f"submissions/{file_info['name']}")
        r2 = requests.get(file_url,
                           headers=SEC_HEADERS,
                           timeout=15)

        r2.raise_for_status()
        old = r2.json()
        for i, (form, date) in enumerate(
            zip(old.get("form", []),
                old.get("filingDate", []))):
            if form not in ("10-K", "10-K/A"):
                continue
            if date <= before_str:
                if best_date is None or date > best_date:
                    best_date = date
                    best_idx = i
                    o_periods = old.get(
                        "periodOfReport", [])
                    o_accns = old.get(
                        "accessionNumber", [])
                    if best_idx < len(o_periods):
                        return (best_date,
                                o_periods[best_idx],
                                o_accns[best_idx])

            time.sleep(DELAY)
    except Exception:
        continue

except Exception:
    pass

return None, None, None

# -----
# FETCH XBRL FINANCIAL DATA
# -----

def get_xbrl_facts(cik):
    url = (f"https://data.sec.gov/api/xbrl/"
           f"companyfacts/CIK{cik}.json")
    try:
        r = requests.get(url, headers=SEC_HEADERS, timeout=20)
        r.raise_for_status()

```

```

        return r.json()
    except Exception:
        return None

def get_fact_value(facts, concept, filing_date_str):
    """Get most recent annual value for a concept."""
    if not facts:
        return None
    us_gaap = facts.get("facts", {}).get("us-gaap", {})
    concept_data = us_gaap.get(concept, {})

    for unit in ["USD", "shares"]:
        values = concept_data.get("units", {}).get(unit, [])
        best_val = None
        best_end = None
        for entry in values:
            if entry.get("form") not in ("10-K", "10-K/A"):
                continue
            filed = entry.get("filed", "")
            end = entry.get("end", "")
            val = entry.get("val")
            if val is None:
                continue
            if filed == filing_date_str:
                return float(val)
            if filed <= filing_date_str:
                if best_end is None or end > best_end:
                    best_val = float(val)
                    best_end = end
        if best_val is not None:
            return best_val
    return None

def extract_financials(facts, filing_date_str):
    def get(concept, fallbacks=[]):
        v = get_fact_value(facts, concept, filing_date_str)
        if v is not None:
            return v
        for fb in fallbacks:
            v = get_fact_value(facts, fb, filing_date_str)
            if v is not None:
                return v
        return None

```

```

total_assets = get("Assets")
cash         = get("CashAndCashEquivalentsAtCarryingValue",
                  ["CashCashEquivalentsAndShortTermInvestments"])
ltd          = get("LongTermDebtAndCapitalLeaseObligations",
                  ["LongTermDebtNoncurrent", "LongTermDebt"])
std          = get("DebtCurrent",
                  ["ShortTermBorrowings",
                  "LongTermDebtCurrent"])

book_equity = get(
    "StockholdersEquityIncludingPortionAttributable"
    "ToNoncontrollingInterest",
    ["StockholdersEquity"])

shares      = get("CommonStockSharesOutstanding",
                  ["WeightedAverageNumberOfSharesOutstanding"
                  "Basic"])

net_income  = get("NetIncomeLoss",
                  ["NetIncomeLossAvailableTo"
                  "CommonStockholdersBasic"])

op_income   = get("OperatingIncomeLoss")
revenue     = get("Revenues",
                  ["RevenueFromContractWithCustomer"
                  "ExcludingAssessedTax",
                  "SalesRevenueNet"])

total_debt = None
if ltd is not None and std is not None:
    total_debt = ltd + std
elif ltd is not None:
    total_debt = ltd
elif std is not None:
    total_debt = std

return {
    "total_assets":    total_assets,
    "long_term_debt": ltd,
    "short_term_debt": std,
    "total_debt":     total_debt,
    "cash":           cash,
    "book_equity":    book_equity,
    "shares_outstanding": shares,
    "net_income":     net_income,
    "operating_income": op_income,
    "revenue":        revenue,
}

```

```

# NUMBER FORMAT
# -----

def fmt(v):
    if v is None:
        return ""
    try:
        return f"{float(v):.2f}"
    except:
        return ""

# -----
# CSV OUTPUT
# -----

OUTPUT_FIELDS = [
    "ticker", "target_name", "acquirer",
    "announce_date", "cik",
    "filing_date", "fiscal_year_end",
    "total_assets", "long_term_debt", "short_term_debt",
    "total_debt", "cash", "book_equity",
    "shares_outstanding", "net_income",
    "operating_income", "revenue",
    "status", "note"
]

def save_csv(rows, filepath):
    with open(filepath, "w", newline="",
              encoding="utf-8") as f:
        writer = csv.DictWriter(f, fieldnames=OUTPUT_FIELDS,
                               extrasaction="ignore")

        writer.writeheader()
        writer.writerows(rows)

    ok = sum(1 for r in rows if r.get("status") == "ok")
    par = sum(1 for r in rows if r.get("status") == "partial")
    err = sum(1 for r in rows if r.get("status") == "error")
    print(f" Saved -> {filepath} "
          f"({len(rows)} rows | "
          f"ok={ok} partial={par} error={err})")

# -----
# MAIN
# -----

```

```

def main():
    print(f"\nTarget Financials Fetcher (SEC EDGAR - name based)")
    print(f"Source : {TARGET_PRICES} → summary tab")
    print(f"      col A=ticker col B=name col D=announce date")
    print(f"Output : {OUTPUT_FILE}\n")

    # Load valid acquirers
    valid_acquirers = get_valid_acquirers(
        PRICES_FILE, CLEANED_TAB, TICKER_ROW)

    # Load targets from summary tab
    print("Loading targets from summary tab...")
    targets = load_targets_from_summary(TARGET_PRICES)

    # Filter by valid acquirers
    if valid_acquirers:
        before = len(targets)
        targets = [t for t in targets
                   if t.get("acquirer","") in valid_acquirers]
        print(f"  After acquirer filter: "
              f"{len(targets)} / {before} targets")

    total = len(targets)
    print(f"\n  Total targets to process: {total}\n")

    # Resume: skip ok rows, retry partial/error
    results = []
    completed_keys = set()

    if os.path.exists(OUTPUT_FILE):
        try:
            with open(OUTPUT_FILE, newline="",
                    encoding="utf-8") as f:
                reader = csv.DictReader(f)
                ok_n = 0
                rt_n = 0
                for row in reader:
                    status = row.get("status","").strip()
                    key = (row.get("ticker",""),
                          row.get("announce_date","")[:10])
                    if status == "ok":
                        results.append(dict(row))
                        completed_keys.add(key)
                        ok_n += 1

```

```

        else:
            rt_n += 1
            print(f" Resuming: {ok_n} ok (skip), "
                  f"{rt_n} partial/error (retry)\n")
    except Exception:
        results = []
        completed_keys = set()

ok_count = 0
par_count = 0
err_count = 0

for i, target in enumerate(targets):
    ticker = target["ticker"]
    name = target["target_name"]
    ann_str = target["announce_str"]
    acq = target["acquirer"]
    key = (ticker, ann_str[:10])

    if key in completed_keys:
        print(f" [{i+1}/{total}] {ticker} "
              f"... skipped (ok)")
        continue

    print(f" [{i+1}/{total}] {ticker} | {name[:35]} "
          f"ann={ann_str} ...",
          end=" ", flush=True)

    try:
        ann_date = datetime.strptime(ann_str, "%Y-%m-%d")
    except ValueError:
        print("invalid date")
        continue

    # Step 1: resolve CIK by company name
    cik = get_cik_by_name(name)
    time.sleep(DELAY)

    if not cik:
        print(f"CIK not found for '{name}'")
        results.append({
            "ticker": ticker, "target_name": name,
            "acquirer": acq, "announce_date": ann_str,
            "cik": "", "filing_date": "",
            "fiscal_year_end": "",

```

```

        "total_assets": "", "long_term_debt": "",
        "short_term_debt": "", "total_debt": "",
        "cash": "", "book_equity": "",
        "shares_outstanding": "", "net_income": "",
        "operating_income": "", "revenue": "",
        "status": "error",
        "note": f"cik_not_found_for_{name[:30]}"
    })
    err_count += 1
    continue

# Step 2: find last 10-K before announcement
filing_date, fiscal_end, accn = get_10k_before_date(
    cik, ann_date)
time.sleep(DELAY)

if not filing_date:
    print(f"no 10-K (CIK={cik})")
    results.append({
        "ticker": ticker, "target_name": name,
        "acquirer": acq, "announce_date": ann_str,
        "cik": cik, "filing_date": "",
        "fiscal_year_end": "",
        "total_assets": "", "long_term_debt": "",
        "short_term_debt": "", "total_debt": "",
        "cash": "", "book_equity": "",
        "shares_outstanding": "", "net_income": "",
        "operating_income": "", "revenue": "",
        "status": "error",
        "note": f"no_10k_found_CIK{cik}"
    })
    err_count += 1
    continue

# Step 3: fetch XBRL facts
facts = get_xbri_facts(cik)
time.sleep(DELAY)

if not facts:
    print(f"no XBRL data (CIK={cik})")
    results.append({
        "ticker": ticker, "target_name": name,
        "acquirer": acq, "announce_date": ann_str,
        "cik": cik, "filing_date": filing_date,
        "fiscal_year_end": fiscal_end or "",
        "total_assets": "", "long_term_debt": "",
        "short_term_debt": "", "total_debt": "",

```

```

        "cash": "", "book_equity": "",
        "shares_outstanding": "", "net_income": "",
        "operating_income": "", "revenue": "",
        "status": "error", "note": "no_xbrl_data"
    })
    err_count += 1
    continue

# Step 4: extract financial items
fin = extract_financials(facts, filing_date)
filled = sum(1 for v in [
    fin["total_assets"], fin["total_debt"],
    fin["shares_outstanding"], fin["book_equity"]]
    if v is not None)
status = ("ok" if filled >= 3
         else "partial" if filled >= 1
         else "error")
note = (" " if status == "ok"
       else f"only_{filled}_of_4_key_items")

print(f"{status} | CIK={cik} "
      f"filed={filing_date} | "
      f"assets={fmt(fin['total_assets'][:12])}")

results.append({
    "ticker": ticker,
    "target_name": name,
    "acquirer": acq,
    "announce_date": ann_str,
    "cik": cik,
    "filing_date": filing_date,
    "fiscal_year_end": fiscal_end or "",
    "total_assets": fmt(fin["total_assets"]),
    "long_term_debt": fmt(fin["long_term_debt"]),
    "short_term_debt": fmt(fin["short_term_debt"]),
    "total_debt": fmt(fin["total_debt"]),
    "cash": fmt(fin["cash"]),
    "book_equity": fmt(fin["book_equity"]),
    "shares_outstanding": fmt(fin["shares_outstanding"]),
    "net_income": fmt(fin["net_income"]),
    "operating_income": fmt(fin["operating_income"]),
    "revenue": fmt(fin["revenue"]),
    "status": status,
    "note": note,
})

if status == "ok": ok_count += 1

```

```

elif status == "partial": par_count += 1
else:                      err_count += 1

# Checkpoint every 25 targets
if (i + 1) % 25 == 0:
    save_csv(results, OUTPUT_FILE)
    print(f"\n [checkpoint] {len(results)} rows\n")

save_csv(results, OUTPUT_FILE)

print(f"\n{' '*55}")
print(f"  FINAL SUMMARY")
print(f"{' '*55}")
print(f"  Total rows   : {len(results)}")
print(f"  OK           : {ok_count}")
print(f"  Partial      : {par_count}")
print(f"  Error        : {err_count}")
print(f"{' '*55}")
print(f"\nDone!")

if __name__ == "__main__":
    main()

```

Script for Targets' Financial Data Collection via XBRL (SEC EDGAR)

The below script uses the CIK numbers retrieved with the previous Python code to extract data from the 10-K filings' financial statements from SEC EDGAR's XBRL structured data API. For each target firm in the sample, it identifies the most recent 10-K filing posted prior to the announcement of the merger or acquisition. From the 10-K filing, the script extracts total assets, long-term debt, short-term debt, cash, book value of equity, shares outstanding, net income, operating income, and revenue line items. Most of these variables are used to compute the approximate Tobin's Q (Chung & Pruitt, 1994) which is the dependent variable of this study.

```

"""
fetch_target_financials_xbrl.py
-----
Reads target_financials_edgar.csv which already contains CIK
numbers for each target. Uses those CIK numbers to fetch

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financial data directly from SEC EDGAR's submissions and XBRL facts APIs.

This is a focused script that skips the CIK lookup step (already done) and goes straight to fetching financials.

Steps per target:

1. Read CIK from target_financials_edgar.csv
2. Call data.sec.gov/submissions/CIK{}.json to find the last 10-K filing before announcement date
3. Call data.sec.gov/api/xbrl/companyfacts/CIK{}.json to get all XBRL financial data
4. Extract: total_assets, long_term_debt, short_term_debt, total_debt, cash, book_equity, shares_outstanding, net_income, operating_income, revenue

Output: target_financials_xbrl.csv

- Same structure as target_financials_edgar.csv
- Overwrites error rows with successful data
- Preserves ok rows from previous runs

Usage:

```
pip install requests
python fetch_target_financials_xbrl.py
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"""

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import csv
import re
import time
import os
import requests
from datetime import datetime

# -----
# CONFIGURATION
# -----

INPUT_FILE = "target_financials_edgar.csv" # has CIK column
OUTPUT_FILE = "target_financials_xbrl.csv"
DELAY = 0.12 # SEC rate limit: max 10 req/sec

SEC_HEADERS = {
    "User-Agent": "Masters Thesis Research thesis@university.edu",
    "Accept-Encoding": "gzip, deflate",
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}

OUTPUT_FIELDS = [
    "ticker", "target_name", "acquirer",
    "announce_date", "cik",
    "filing_date", "fiscal_year_end",
    "total_assets", "long_term_debt", "short_term_debt",
    "total_debt", "cash", "book_equity",
    "shares_outstanding", "net_income",
    "operating_income", "revenue",
    "status", "note"
]

# -----
# FIND LAST 10-K BEFORE DATE
# -----

def get_10k_before_date(cik, before_date):
    """
    Fetch submissions for CIK and find last 10-K
    filed before before_date.
    Checks both recent filings and all older archive files.
    Returns (filing_date, fiscal_year_end, accession_no)
    or (None, None, None).
    """
    url = f"https://data.sec.gov/submissions/CIK{cik}.json"
    try:
        r = requests.get(url, headers=SEC_HEADERS, timeout=20)
        r.raise_for_status()
        data = r.json()
        time.sleep(DELAY)

        before_str = before_date.strftime("%Y-%m-%d")
        best_date = None
        best_result = None # (filing_date, period, accn)

    def scan_filings(forms, dates, periods, accns):
        nonlocal best_date, best_result
        for i, (form, date) in enumerate(zip(forms, dates)):
            if form not in ("10-K", "10-K/A"):
                continue
            if date <= before_str:
                if best_date is None or date > best_date:
                    best_date = date
                    per = periods[i] if i < len(periods) else ""

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        acc = accns[i] if i < len(accns) else ""
        best_result = (date, per, acc)

# Check recent filings
recent = data.get("filings", {}).get("recent", {})
scan_filings(
    recent.get("form", []),
    recent.get("filingDate", []),
    recent.get("periodOfReport", []),
    recent.get("accessionNumber", []))

# Check ALL older archive files
for file_info in data.get("filings", {}).get("files", []):
    try:
        fname = file_info.get("name", "")
        file_url = (f"https://data.sec.gov/submissions/"
                   f"{fname}")
        r2 = requests.get(file_url, headers=SEC_HEADERS,
                          timeout=20)
        r2.raise_for_status()
        old_data = r2.json()
        time.sleep(DELAY)
        scan_filings(
            old_data.get("form", []),
            old_data.get("filingDate", []),
            old_data.get("periodOfReport", []),
            old_data.get("accessionNumber", []))
    except Exception:
        continue

    if best_result:
        return best_result

except Exception:
    pass

return None, None, None

# -----
# FETCH XBRL FACTS
# -----

def get_xbml_facts(cik):

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"""Fetch all XBRL company facts for a CIK."""
url = (f"https://data.sec.gov/api/xbrl/"
       f"companyfacts/CIK{cik}.json")
try:
    r = requests.get(url, headers=SEC_HEADERS, timeout=30)
    if r.status_code == 404:
        return None # No XBRL data for this company
    r.raise_for_status()
    time.sleep(DELAY)
    return r.json()
except Exception:
    return None

# -----
# EXTRACT FINANCIAL VALUES FROM XBRL FACTS
# -----

def get_fact_value(facts, concept, filing_date_str,
                  ann_date_str):
    """
    Extract the best matching annual value for a concept.
    Checks both us-gaap and dei namespaces.
    Prioritises exact filing date match, then most recent
    annual value filed on or before filing_date.
    """
    if not facts:
        return None

    all_facts = facts.get("facts", {})

    # Check us-gaap and dei namespaces
    for namespace in ("us-gaap", "dei", "invest"):
        ns_data = all_facts.get(namespace, {})
        cdata = ns_data.get(concept, {})
        if not cdata:
            continue

        best_val = None
        best_end = None

        for unit_vals in cdata.get("units", {}).values():
            for entry in unit_vals:
                form = entry.get("form", "")
                filed = entry.get("filed", "")

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end = entry.get("end", "")
val = entry.get("val")

if val is None:
    continue
if filed > filing_date_str:
    continue

# Accept annual filings and instant values
is_annual = form in ("10-K", "10-K/A",
                    "10-KT", "10-KT/A")
# Also accept 10-K period data from quarterly
# filings (some companies restate annually)
if not is_annual:
    continue

# Prefer exact filing date match
if filed == filing_date_str:
    return float(val)

# Otherwise take most recent value
# filed on or before filing_date
if best_end is None or end > best_end:
    best_val = float(val)
    best_end = end

if best_val is not None:
    return best_val

return None

def extract_financials(facts, filing_date_str, ann_date_str):
    """
    Extract all needed financial items from XBRL facts.
    Uses comprehensive fallback tag lists to handle the full
    variety of XBRL tagging conventions used 2009-2024.
    """

    def get(*concepts):
        for concept in concepts:
            v = get_fact_value(facts, concept,
                              filing_date_str, ann_date_str)
            if v is not None:

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        return v
    return None

# --- Total Assets -----
total_assets = get(
    "Assets",
    "AssetNet",
    "TotalAssets",
    "AssetsNet",
)
# Fallback: sum current + noncurrent
if total_assets is None:
    curr = get("AssetsCurrent")
    non  = get("AssetsNoncurrent")
    if curr is not None and non is not None:
        total_assets = curr + non

# --- Cash -----
cash = get(
    "CashAndCashEquivalentsAtCarryingValue",
    "CashCashEquivalentsAndShortTermInvestments",
    "CashAndCashEquivalents",
    "Cash",
    "CashEquivalentsAtCarryingValue",
    "CashAndDueFromBanks",
)

# --- Long-term Debt -----
ltd = get(
    "LongTermDebtAndCapitalLeaseObligations",
    "LongTermDebtNoncurrent",
    "LongTermDebt",
    "LongTermNotesPayable",
    "LongTermLineOfCredit",
    "SeniorLongTermNotes",
    "LongTermDebtFairValue",
    "LongTermBorrowings",
    "LongTermLoansPayable",
    "ConvertibleLongTermNotesPayable",
    "SubordinatedLongTermDebt",
    "CapitalLeaseObligationsNoncurrent",
    "FinanceLeaseLiabilityNoncurrent",
    "OperatingLeaseLiabilityNoncurrent",
)

# --- Short-term Debt -----
std = get(

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    "DebtCurrent",
    "ShortTermBorrowings",
    "LongTermDebtCurrent",
    "NotesPayableCurrent",
    "LongTermDebtAndCapitalLeaseObligationsCurrent",
    "ShortTermNonBankLoansAndNotesPayable",
    "CommercialPaper",
    "BankOverdrafts",
    "CapitalLeaseObligationsCurrent",
    "FinanceLeaseLiabilityCurrent",
    "LinesOfCreditCurrent",
)

# --- Book Equity -----
book_equity = get(
    "StockholdersEquity",
    "StockholdersEquityIncludingPortionAttributable"
    "ToNoncontrollingInterest",
    "PartnersCapital",
    "MembersEquity",
    "EquityAttributableToParent",
    "CommonStockholdersEquity",
    "RetainedEarningsAccumulatedDeficit",
    "LiabilitiesAndStockholdersEquity",
)

# If we got LiabilitiesAndStockholdersEquity,
# subtract liabilities to get equity
if book_equity is not None:
    liab_key = "LiabilitiesAndStockholdersEquity"
    if get_fact_value(facts, liab_key,
                      filing_date_str, ann_date_str) == book_equity:
        liab = get(
            "Liabilities",
            "LiabilitiesCurrent",
        )
        if liab is not None:
            book_equity = book_equity - liab

# --- Shares Outstanding -----
shares = get(
    "CommonStockSharesOutstanding",
    "WeightedAverageNumberOfSharesOutstandingBasic",
    "SharesOutstanding",
    "CommonStockSharesIssued",
    "WeightedAverageNumberOfDilutedSharesOutstanding",
    "EntityCommonStockSharesOutstanding",
    "CommonStockSharesIssuedAndOutstanding",
    "CommonSharesOutstanding",
)

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)

# --- Net Income -----
net_income = get(
  "NetIncomeLoss",
  "NetIncomeLossAvailableToCommonStockholdersBasic",
  "ProfitLoss",
  "NetIncomeLossAttributableToParent",
  "IncomeLossFromContinuingOperationsAfterTax",
  "NetIncome",
  "ComprehensiveIncomeNetOfTax",
)

# --- Operating Income -----
op_income = get(
  "OperatingIncomeLoss",
  "IncomeLossFromContinuingOperations",
  "IncomeLossFromContinuingOperationsBeforeIncomeTax",
  "ExtraordinaryItemsNoncontrollingInterest",
  "OperatingIncome",
  "GrossProfit", # last resort
)

# --- Revenue -----
revenue = get(
  "Revenues",
  "RevenueFromContractWithCustomerExcludingAssessedTax",
  "SalesRevenueNet",
  "RevenueFromContractWithCustomerIncludingAssessedTax",
  "SalesRevenueGoodsNet",
  "SalesRevenueServicesNet",
  "RevenueNet",
  "TotalRevenues",
  "NetRevenues",
  "RevenueFromContractWithCustomer",
  "RevenuesNetOfInterestExpense", # financial firms
  "InterestAndDividendIncomeOperating", # banks
  "RealEstateRevenueNet", # REITs
  "HealthCareOrganizationRevenue",
  "OilAndGasRevenue",
  "SalesRevenueNet",
  "ContractRevenue",
  "NetPremiumsEarned", # insurance
  "PremiumsEarnedNet",
)

# --- Total Debt -----

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total_debt = None
if ltd is not None and std is not None:
    total_debt = ltd + std
elif ltd is not None:
    total_debt = ltd
elif std is not None:
    total_debt = std

return {
    "total_assets":    total_assets,
    "long_term_debt":  ltd,
    "short_term_debt": std,
    "total_debt":     total_debt,
    "cash":           cash,
    "book_equity":    book_equity,
    "shares_outstanding": shares,
    "net_income":     net_income,
    "operating_income": op_income,
    "revenue":        revenue,
}

# -----
# NUMBER FORMAT
# -----

def fmt(v):
    if v is None:
        return ""
    try:
        return f"{float(v):.2f}"
    except:
        return ""

# -----
# SAVE CSV
# -----

def save_csv(rows, filepath):
    with open(filepath, "w", newline="",
              encoding="utf-8") as f:
        writer = csv.DictWriter(f, fieldnames=OUTPUT_FIELDS,
                               extrasaction="ignore")
        writer.writeheader()

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        writer.writerows(rows)

    ok = sum(1 for r in rows if r.get("status") == "ok")
    par = sum(1 for r in rows if r.get("status") == "partial")
    err = sum(1 for r in rows if r.get("status") == "error")
    print(f" Saved -> {filepath} "
          f"({len(rows)} rows | "
          f"ok={ok} partial={par} error={err})")

# -----
# MAIN
# -----

def main():
    print(f"\nTarget Financials - XBRL Fetcher")
    print(f"Input   : {INPUT_FILE} (uses CIK column)")
    print(f"Output  : {OUTPUT_FILE}\n")

    if not os.path.exists(INPUT_FILE):
        print(f"ERROR: '{INPUT_FILE}' not found.")
        return

    # Load input - all rows with a CIK
    all_rows = []
    with open(INPUT_FILE, newline="", encoding="utf-8") as f:
        reader = csv.DictReader(f)
        for row in reader:
            all_rows.append(dict(row))

    # Split: ok rows keep as-is, error/partial rows retry
    ok_rows = [r for r in all_rows
               if r.get("status") == "ok"]
    retry_rows = [r for r in all_rows
                 if r.get("status") != "ok"
                 and r.get("cik", "").strip()]
    no_cik = [r for r in all_rows
             if r.get("status") != "ok"
             and not r.get("cik", "").strip()]

    print(f" Total rows loaded   : {len(all_rows)}")
    print(f" Already OK (keep)   : {len(ok_rows)}")
    print(f" Has CIK (retry)     : {len(retry_rows)}")
    print(f" No CIK (skip)       : {len(no_cik)}\n")

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# Check resume from output file
completed_keys = set()
results = list(ok_rows) # start with ok rows

if os.path.exists(OUTPUT_FILE):
    try:
        with open(OUTPUT_FILE, newline="",
                  encoding="utf-8") as f:
            for row in csv.DictReader(f):
                if row.get("status") == "ok":
                    key = (row.get("ticker", ""),
                          row.get("announce_date", "")[:10])
                    completed_keys.add(key)
                    # Add to results if not from ok_rows
                    if not any(
                        r.get("ticker") == row.get("ticker")
                        and r.get("announce_date", "")[:10]
                        == row.get("announce_date", "")[:10]
                        for r in results):
                            results.append(dict(row))
            print(f" Resume: {len(completed_keys)} ok rows "
                  f"from previous output\n")
    except Exception:
        pass

total = len(retry_rows)
ok_n = 0
par_n = 0
err_n = 0

for i, row in enumerate(retry_rows):
    ticker = row.get("ticker", "")
    name = row.get("target_name", "")
    acq = row.get("acquirer", "")
    ann_str = row.get("announce_date", "")[:10]
    cik = row.get("cik", "").strip().zfill(10)
    key = (ticker, ann_str)

    if key in completed_keys:
        print(f" [{i+1}/{total}] {ticker} "
              f"... skipped (ok)")
        continue

    print(f" [{i+1}/{total}] {ticker} | {name[:30]} "
          f"CIK={cik} ann={ann_str} ...",
          end=" ", flush=True)

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try:
    ann_date = datetime.strptime(ann_str, "%Y-%m-%d")
except ValueError:
    print("invalid date")
    continue

# Step 1: find 10-K filing before announcement
filing_date, fiscal_end, accn = get_10k_before_date(
    cik, ann_date)

if not filing_date:
    print(f"no 10-K found")
    result = {**row,
              "filing_date": "",
              "fiscal_year_end": "",
              "total_assets": "",
              "long_term_debt": "",
              "short_term_debt": "",
              "total_debt": "",
              "cash": "",
              "book_equity": "",
              "shares_outstanding": "",
              "net_income": "",
              "operating_income": "",
              "revenue": "",
              "status": "error",
              "note": f"no_10k_CIK{cik}"}
    results.append(result)
    err_n += 1
    continue

# Step 2: fetch XBRL facts
facts = get_xbri_facts(cik)

if not facts:
    print(f"no XBRL (filed={filing_date})")
    result = {**row,
              "filing_date": filing_date,
              "fiscal_year_end": fiscal_end or "",
              "total_assets": "",
              "long_term_debt": "",
              "short_term_debt": "",
              "total_debt": "",
              "cash": "",
              "book_equity": "",

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        "shares_outstanding": "",
        "net_income": "",
        "operating_income": "",
        "revenue": "",
        "status": "error",
        "note": f"no_xbrl_CIK{cik}"
    results.append(result)
    err_n += 1
    continue

# Step 3: extract financial items
fin = extract_financials(facts, filing_date,
                        ann_str)

filled = sum(1 for v in [
    fin["total_assets"], fin["total_debt"],
    fin["shares_outstanding"], fin["book_equity"]]
    if v is not None)
status = ("ok" if filled >= 3
         else "partial" if filled >= 1
         else "error")
note = (" " if status == "ok"
       else f"only_{filled}_of_4_key_items")

print(f"{status} | filed={filing_date} | "
      f"assets={fmt(fin['total_assets'][:14])} | "
      f"shares={fmt(fin['shares_outstanding'][:12])}")

result = {
    "ticker": ticker,
    "target_name": name,
    "acquirer": acq,
    "announce_date": ann_str,
    "cik": cik,
    "filing_date": filing_date,
    "fiscal_year_end": fiscal_end or "",
    "total_assets": fmt(fin["total_assets"]),
    "long_term_debt": fmt(fin["long_term_debt"]),
    "short_term_debt": fmt(fin["short_term_debt"]),
    "total_debt": fmt(fin["total_debt"]),
    "cash": fmt(fin["cash"]),
    "book_equity": fmt(fin["book_equity"]),
    "shares_outstanding": fmt(fin["shares_outstanding"]),
    "net_income": fmt(fin["net_income"]),
    "operating_income": fmt(fin["operating_income"]),
    "revenue": fmt(fin["revenue"]),
    "status": status,
    "note": note,

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    }
    results.append(result)

    if status == "ok":          ok_n += 1
    elif status == "partial":  par_n += 1
    else:                      err_n += 1

    # Checkpoint every 25 targets
    if (i + 1) % 25 == 0:
        save_csv(results, OUTPUT_FILE)
        print(f"\n [checkpoint] {len(results)} rows\n")

    # Add no-CIK rows as errors
    for row in no_cik:
        key = (row.get("ticker", ""),
              row.get("announce_date", "")[:10])
        if key not in completed_keys:
            results.append(**row,
                          "status": "error",
                          "note": "no_cik_available")

    save_csv(results, OUTPUT_FILE)

    print(f"\n{'='*55}")
    print(f"  FINAL SUMMARY")
    print(f"{'='*55}")
    print(f"  Total rows          : {len(results)}")
    print(f"  OK                   : {len(ok_rows) + ok_n}")
    print(f"  Partial              : {par_n}")
    print(f"  Error                 : {err_n + len(no_cik)}")
    print(f"  New OK this run      : {ok_n}")
    print(f"{'='*55}")
    print(f"\nDone!")

if __name__ == "__main__":
    main()

```

Financial Data Processing for Error Targets

The below script handles the target firms for which the standard XBRL extraction script failed to obtain financial data from 10-Ks. The reasons for failures were due to filing index

URL formatting issues or missing XBRL tags in older 10-K filings. It uses revised URL construction approach based on the SEC EDGAR filing index page format to directly access the 10-K HTML document for each “error target”. According to the script, the financial variables are then extracted by using text parsing of the HTML filings content.

```

fetch_edgar_targets_v3.py
=====
FIXED: Uses EDGAR's filing index page via the known-working URL format
instead of constructing accession-based URLs that fail for some filings.

Run locally:
    pip install requests openpyxl
    python fetch_edgar_targets_v3.py

Output: error_targets_financials.xlsx
"""

import re, time, requests
from datetime import datetime, timedelta
from openpyxl import Workbook
from openpyxl.styles import Font, PatternFill, Alignment
from openpyxl.utils import get_column_letter

HDR = {"User-Agent": "thesis-research contact@university.edu", "Accept-Encoding":
"gzip"}

TARGETS = [
    ("CLU", "Cellu Tissue Holdings Inc", "CLW", "2010-09-16", 1295976),
    ("CLRT", "Clariant Inc", "GE", "2010-10-22", 1038223),
    ("CNU", "Continucare Corp", "MDF", "2011-06-27", 1311538),
    ("DDRX", "Diedrich Coffee Inc", "GMCR", "2009-11-23", 947661),
    ("DTLK", "Datalink Corp", "NSIT", "2016-11-07", 1056923),
    ("GLBC", "Global Crossing Ltd", "LVLT", "2011-04-11", 1061322),
    ("HBE", "Henry Bros Electronics Inc", "KTOS", "2010-10-06", 1006459),
    ("HRLY", "Herley Industries Inc", "KTOS", "2011-02-07", 47035),
    ("HUGH", "Hughes Communications Inc", "SATS", "2011-02-14", 1345840),
    ("HWK", "Hawk Corp", "CSL", "2010-10-15", 1398659),
    ("ICOC", "ICO Inc", "SHLM", "2009-12-03", 353567),
    ("IFLG", "InfoLogix Inc", "SWK", "2010-12-15", 1315320),
    ("INXN", "InterXion Holding NV", "DLR", "2019-10-29", 946155),
    ("ISYS", "Integral Systems Inc", "KTOS", "2011-05-16", 718130),
    ("JAH", "Jarden Corp", "NWL", "2015-12-14", 878375),
    ("JAV", "Javelin Pharmaceuticals Inc", "HSP", "2010-04-12", 50710),
    ("KTII", "K-Tron International Inc", "HI", "2010-01-11", 20),
    ("LAVA", "Magma Design Automation Inc", "SNPS", "2011-11-30", 1065034),

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("MPR", "Met-Pro Corp",	"CECO", "2013-04-22", 1515156),
("MVL", "Marvel Entertainment LLC",	"DIS", "2009-08-31", 1001039),
("NEFF", "Neff Corp",	"URI", "2017-08-16", 1057725),
("NITE", "Nightstar Therapeutics PLC",	"BIIB", "2019-03-04", 1711675),
("NLC", "Nalco Holding Co",	"ECL", "2011-07-20", 1405041),
("NUHC", "Nu Horizons Electronics Corp",	"ARW", "2010-09-20", 718074),
("OCDX", "Ortho Clinical Diagnostics",	"QDEL", "2021-12-23", 1828443),
("OCNF", "OceanFreight Inc",	"DRYS", "2011-07-26", 1429764),
("OCNW", "Occam Networks Inc",	"CALX", "2010-09-16", 1108185),
("ODSY", "Odyssey HealthCare Inc",	"GTIV", "2010-05-24", 1129623),
("ONT", "On2 Technologies Inc",	"GOOGL", "2009-08-05", 1045280),
("QUIX", "Quixote Corp",	"TRN", "2009-12-30", 720851),
("RENT", "Rentrak Corp",	"SCOR", "2015-09-29", 1171218),
("RHB", "Rehabcare Group LLC",	"KND", "2011-02-08", 812191),
("RMTR", "Ramtron International Corp",	"CY", "2012-06-12", 1167896),
("RNDY", "Roundy's Inc",	"KR", "2015-11-11", 314423),
("SDXC", "Switch & Data Facilities",	"EQIX", "2009-10-21", 1262276),
("SLRY", "Kenexa Compensation Inc",	"KNXA", "2012-08-27", 1114714),
("SMMX", "Symyx Technologies Inc",	"ACCL", "2010-04-05", 1095330),
("SNIC", "Sonic Solutions LLC",	"ROVI", "2010-12-22", 1424454),
("SOA", "Solutia Inc",	"EMN", "2012-01-27", 1043382),
("SONE", "S1 Corp",	"ACIW", "2011-07-26", 779152),
("TKTM", "Ticketmaster Entertainment",	"LYV", "2009-02-10", 1335258),
("TOMO", "TomoTherapy Inc",	"ARAY", "2011-03-07", 1317872),
("TQNT", "TriQuint Semiconductor",	"RFMD", "2014-02-24", 1604778),
("TRA", "Terra Industries Inc",	"CF", "2009-01-15", 722079),
("TRBN", "Trubion Pharmaceuticals Inc",	"EBS", "2010-08-12", 1298521),
("TUNE", "Microtune Inc",	"ZRAN", "2010-09-08", 1108058),
("TWLL", "Techwell Inc",	"ISIL", "2010-03-22", 1171529),
("UBET", "Youbet.com Inc",	"CHDN", "2009-11-11", 814055),
("USHS", "US Home Systems Inc",	"HD", "2012-08-07", 919567),
("VARI", "Varian Inc",	"A", "2009-07-27", 1079028),
("VER", "VEREIT Inc",	"O", "2021-04-29", 1528059),
("VIRL", "Virage Logic LLC",	"SNPS", "2010-06-10", 883241),
("WCIC", "WCI Communities Inc",	"LEN", "2016-09-22", 1137778),
("XETA", "Xeta Technologies Inc",	"PAET", "2011-02-09", 742550),
("XJT", "ExpressJet Holdings Inc",	"SKYW", "2010-08-04", 1144331),
("ZILG", "Zilog Inc",	"IXYS", "2009-12-07", 319450),
("AAI", "AirTran Holdings Inc",	"LUV", "2010-09-27", 948846),
("AATI", "Advanced Analogic Technologies",	"SWKS", "2011-01-26", 1104042),
("ADLR", "Adolor Corp",	"CBST", "2011-10-24", 1076167),
("AHGP", "Alliance Holdings GP LP",	"ARLP", "2018-02-23", 909992),
("AIPC", "American Italian Pasta Co",	"RAH", "2010-06-21", 1320695),
("APR", "Apria Inc",	"ACH", "2022-01-10", 1735803),
("BDK", "Black & Decker Corp",	"SWK", "2009-11-02", 93556),
("BSMD", "BioSphere Medical Inc",	"MMSI", "2010-05-13", 919015),
("CFN", "CareFusion Corp",	"BDX", "2014-10-05", 1837607),
("CITP", "COMSYS IT Partners Inc",	"MAN", "2010-02-02", 948850),
("CLP", "Colonial Properties Trust",	"MAA", "2013-06-03", 909111),

```

("ESYS", "Elecsys Corp", "LNN", "2014-11-04", 1060349),
("EVVV", "ev3 Inc", "COV", "2010-06-01", 1285785),
("EXAR", "Exar Corp", "MXL", "2017-03-29", 753568),
("MDP", "Meredith Corp", "GTN", "2021-05-03", 65011),
("MTOR", "Meritor Inc", "CMI", "2022-02-22", 799292),
("PCL", "Plum Creek Timber Co Inc", "WY", "2015-11-08", 849213),
("TBL", "Timberland Co", "VFC", "2011-06-13", 98718),
("XONE", "ExOne Co", "DM", "2021-08-11", 1561627),
]

# Pre-extracted data
KNOWN = {
    "CLU": dict(filing_date="2010-04-30", fiscal_year_end="2010-02-28",
                total_assets=502706386, long_term_debt=242538125,
                short_term_debt=760000,
                total_debt=243298125, cash=3299033, book_equity=110832025,
                shares_outstanding=20145176, net_income=3762621,
                operating_income=52175953, revenue=511280798, status="ok",
                note="pdf"),
    "CLRT": dict(filing_date="2010-03-16", fiscal_year_end="2009-12-31",
                 total_assets=66947000, long_term_debt=604000, short_term_debt=645000,
                 total_debt=1249000, cash=10903000, book_equity=7877000,
                 shares_outstanding=84092000, net_income=-6052000,
                 operating_income=-3121000, revenue=91599000, status="ok", note="pdf"),
    "CNU": dict(filing_date="2011-09-07", fiscal_year_end="2011-06-30",
                 total_assets=180905008, long_term_debt=0, short_term_debt=0,
                 total_debt=0, cash=50480963, book_equity=162016802,
                 shares_outstanding=60663266, net_income=23911949,
                 operating_income=37413744, revenue=333458208, status="ok",
                 note="pdf"),
    "DDR": dict(filing_date="2009-09-22", fiscal_year_end="2009-06-24",
                 total_assets=26928000, long_term_debt=1594000, short_term_debt=0,
                 total_debt=1594000, cash=3572000, book_equity=13774000,
                 shares_outstanding=5507000, net_income=1592000,
                 operating_income=960000, revenue=62310000, status="ok", note="ed-
gar_html"),
}

COLS = ["ticker", "target_name", "acquirer", "announce_date", "cik",
        "filing_date", "fiscal_year_end", "total_assets", "long_term_debt",
        "short_term_debt", "total_debt", "cash", "book_equity", "shares_outstanding",
        "net_income", "operating_income", "revenue", "status", "note"]

def get_url(url, retries=3):
    for i in range(retries):
        try:

```



```

        except Exception:
            pass

    if not best_acc:
        return None
    return best_dt.strftime("%Y-%m-%d"), best_acc, best_per

def get_doc_url(cik, acc):
    """
    Get the primary 10-K HTML document URL.
    Uses EDGAR's filing index page - acc must be in format XXXXXXXXXXX-YY-ZZZZZZ
    """
    if not acc or not acc.strip():
        return None, "empty_accession"

    acc = acc.strip()
    # Normalize: EDGAR accessions are always 18 digits with 2 dashes
    # Format: 0001193125-09-195824
    # If it comes without dashes (18 digits), add them
    if re.match(r'^\d{18}$', acc):
        acc = f"{acc[:10]}-{acc[10:12]}-{acc[12:]}"

    acc_clean = acc.replace("-", "") # folder name = no dashes

    # Try the index page
    idx_url = (f"https://www.sec.gov/Archives/edgar/data/{cik}/"
              f"{acc_clean}/{acc}-index.htm")
    try:
        html = get_url(idx_url).text
    except Exception:
        # Try without leading zeros in CIK for older filings
        try:
            idx_url = (f"https://www.sec.gov/Archives/edgar/data/{int(cik)}/"
                      f"{acc_clean}/{acc}-index.htm")
            html = get_url(idx_url).text
        except Exception as e:
            return None, f"index_404:{e}"

    # Parse links from index page - find the primary 10-K document
    links = re.findall(
        r'href="(./Archives/edgar/data/[^\s]+\.\htm[l]?)"',
        html, re.I
    )
    for href in links:

```

```

    fname = href.split("/")[-1].lower()
    # Skip exhibits, XBRL viewers (R-files), cover pages
    if not re.match(r'^ex\d|^exhibit|^r\d+\.|^cover|^fp\d', fname):
        return "https://www.sec.gov" + href, None

if links:
    return "https://www.sec.gov" + links[0], None

return None, "no_htm_in_index"

def extract(html):
    """Extract financial line items from 10-K HTML."""
    scale = 1
    head = html[:80000]
    if re.search(r'in\s+thousands', head, re.I):
        scale = 1_000
    elif re.search(r'in\s+millions', head, re.I):
        scale = 1_000_000

    text = re.sub(r'<[^>]{1,500}>', ' ', html)
    text = re.sub(r'&[a-zA-Z#0-9]+;', ' ', text)
    text = re.sub(r'\s+', ' ', text)

    N = r'[\s$]*([\(-]?[\d,]+(?:\.\d+)?[\)])?'

    def num(*pats):
        for pat in pats:
            for m in re.finditer(pat + N, text, re.I):
                raw = m.group(1).replace(',', '').strip()
                neg = (raw.startswith('(') and raw.endswith(')')) or raw.startswith('-')
                try:
                    v = float(raw.strip('(')-'))
                    if v > 0:
                        return (-v if neg else v) * scale
                except Exception:
                    pass
        return None

    def shares():
        for pat in [
            r'(\d[\d,]+)\s+(?:and\s+\d[\d,]+\s+)?(?:common\s+)?shares?\s+(?:is-sued\s+and\s+)?outstanding',
            r'(\d[\d,]+)\s+shares?\s+outstanding',
        ]:

```

```

    m = re.search(pat, text, re.I)
    if m:
        try:
            v = float(m.group(1).replace(',',''))
            if v > 100:
                return v
            except Exception:
                pass
        return None

return dict(
    total_assets      = num(r'Total assets\b', r'TOTAL ASSETS\b'),
    cash              = num(r'Cash and cash equivalents?\b', r'Cash and cash equiv'),
    long_term_debt    = num(r'Long[- ]term debt,?\s*(?:net of|less|excl|w+)\s*\s*cur-
rent\b',
                           r'Long[- ]term debt\b(?:.*current)',
                           r'Long[- ]term notes?\s*payable\b(?:.*current)',
                           r'Long[- ]term borrowings\b(?:.*current)'),
    short_term_debt   = num(r'Current (?:portion|maturi-
ties?)\s+of(?:\s+long[- ]term)?\s+debt\b',
                           r'Current maturities\s+of',
                           r'Short[- ]term (?:debt|borrowings|notes)\b',
                           r'Notes payable,?\s*current\b'),
    book_equity       = num(r"Total stockholders['\u2019\s]*(?:equity|deficit)\b",
                           r"Total shareholders['\u2019\s]*(?:equity|deficit)\b",
                           r'Total equity\b(?:\s*attrib)',
                           r"Partners['\u2019]?*\s*(?:capital|equity)\b",
                           r"Members['\u2019]?*\s*equity\b"),
    revenue           = num(r'(?:Total\s+)?(?:Net\s+)?revenues?\b',
                           r'Net sales\b', r'Total revenues?\b'),
    operating_income  = num(r'(?:Income|Loss)\s+from\s+operations\b',
                           r'Operating\s+(?:income|loss|profit)\b'),
    net_income        = num(r'Net\s+(?:income|loss)\b(?:\s*per)'),
    shares_outstanding = shares(),
)

def run():
    rows = []
    for ticker, company, acquirer, ann_str, cik in TARGETS:
        ann = datetime.strptime(ann_str, "%Y-%m-%d")
        print(f"[{ticker}]", end=" ", flush=True)

        if ticker in KNOWN:
            rec = {"ticker": ticker, "target_name": company,
                  "acquirer": acquirer, "announce_date": ann_str, "cik": cik or ""}
            rec.update(KNOWN[ticker])

```

```

rows.append(rec)
print(f"pre-extracted ✓")
continue

rec = {c: "" for c in COLS}
rec.update({"ticker": ticker, "target_name": company,
           "acquirer": acquirer, "announce_date": ann_str,
           "cik": cik or "", "status": "error"})

try:
    # 1. Find 10-K filing
    result = find_10k(cik, ann)
    if not result:
        rec["note"] = "no_10k_found"
        rows.append(rec)
        print("no 10-K found")
        continue
    fdate_str, acc, period = result
    rec["filing_date"] = fdate_str
    rec["fiscal_year_end"] = period
    print(f"filing={fdate_str} acc={acc}", end=" ", flush=True)

    # 2. Get document URL
    doc_url, err = get_doc_url(cik, acc)
    if not doc_url:
        rec["note"] = err or "no_doc_url"
        rows.append(rec)
        print(f"doc_url error: {err}")
        continue

    # 3. Fetch & extract
    html = get_url(doc_url).text
    fins = extract(html)
    for k, v in fins.items():
        if v is not None:
            rec[k] = int(round(v))

    lt = rec.get("long_term_debt") or 0
    st = rec.get("short_term_debt") or 0
    rec["total_debt"] = int(lt) + int(st) if (lt or st) else ""

    k4 = [rec.get(k) for k in ("total_assets", "book_equity", "net_income", "rev-
enue")]
    n = sum(1 for v in k4 if v not in ("", None, 0))
    rec["status"] = "ok" if n == 4 else ("partial" if n >= 2 else "error")

```

```

        rec["note"] = "" if n == 4 else f"only_{n}_of_4_key_items"
        print(f"{'√' if rec['status']=='ok' else '~'} assets={rec.get('total_as-
sets','')} rev={rec.get('revenue','')}")

    except Exception as e:
        rec["note"] = str(e)[:120]
        print(f"ERROR: {e}")

    rows.append(rec)

# Write Excel
wb = Workbook()
ws = wb.active
ws.title = "Financials"
hf = Font(bold=True, color="FFFFFF", name="Calibri", size=11)
hfil = PatternFill("solid", fgColor="1F4E79")
for ci, col in enumerate(COLS, 1):
    c = ws.cell(1, ci, col); c.font = hf; c.fill = hfil
    c.alignment = Alignment(horizontal="center")

fills = {"ok": "E2EFDA", "partial": "FFF2CC", "error": "FCE4D6"}
int_cols = {"total_assets", "long_term_debt", "short_term_debt", "total_debt",
            "cash", "book_equity", "net_income", "operating_income", "revenue"}

for ri, rec in enumerate(rows, 2):
    color = fills.get(rec.get("status", "error"), "FCE4D6")
    for ci, col in enumerate(COLS, 1):
        val = rec.get(col, "")
        if val is None: val = ""
        if col in int_cols and val != "":
            try: val = int(float(str(val).replace(",","")))
            except Exception: pass
        c = ws.cell(ri, ci, val)
        c.font = Font(name="Calibri", size=10)
        if col == "ticker":
            c.fill = PatternFill("solid", fgColor=color)

widths = dict(ticker=8, target_name=32, acquirer=10, announce_date=13, cik=10,
              filing_date=13, fiscal_year_end=15, total_assets=16, long_term_debt=16,
              short_term_debt=16, total_debt=13, cash=14, book_equity=15,
              shares_outstanding=18, net_income=14, operating_income=16,
              revenue=14, status=10, note=30)
for ci, col in enumerate(COLS, 1):
    ws.column_dimensions[get_column_letter(ci)].width = widths.get(col, 14)
ws.freeze_panes = "A2"

```

```

out = "error_targets_financials.xlsx"
wb.save(out)
ok = sum(1 for r in rows if r.get("status")=="ok")
partial = sum(1 for r in rows if r.get("status")=="partial")
err = sum(1 for r in rows if r.get("status")=="error")
print(f"\n√ Saved {len(rows)} rows → {out} | OK={ok} PARTIAL={partial} ER-
ROR={err}")

if __name__ == "__main__":
    run()

```

Cross-Sectional OLS Regression – Mean-Adjusted Model

The below script runs OLS cross-sectional regressions by using mean-adjusted CARs as the dependent variable. The regression is estimated separately for each of the five event windows: T0, (-1,+1), (-2,+2), (-5,+5), and (-20,+5). The independent variables used in the regression are Tobin's Q (main variable), log deal size, and payment method dummy where cash is the reference category. Industry and announcement year fixed effects are controlled by two-digit SIC code of the acquirer and the year when the announcement occurred. HC3 heteroskedasticity-robust standard errors are applied throughout the regressions.

```

"""
regression_mean_adjusted.py
=====
Reads data from 'Regression mean_adjusted (2)' tab and runs OLS cross-sectional
regressions of CARs on Target Tobin's Q and control variables.

Data layout (all starting from column B):
Row 20: CAR T-0
Row 21: CAR (-1,+1)
Row 22: CAR (-2,+2)
Row 23: CAR (-5,+5)
Row 24: CAR (-20,+5)
Row 38: Target ticker
Row 44: Target Tobin's Q
Row 45: Acquirer ticker

```

```

Row 46: Deal size (LN transformed)
Row 48: Payment method (1=Cash, 2=Stock, 3=Cash and Stock, 0=Cash or Stock)
Row 49: 2-digit industry SIC code
Row 50: Announcement year

```

Regression model (run 5 times, once per CAR window):

$$\text{CAR}_i = \alpha + \beta_1 \times \text{Tobin's Q} + \beta_2 \times \text{Deal Size} + \beta_3 \times \text{Payment_Stock} + \beta_4 \times \text{Payment_CashandStock} + \text{Industry FE} + \text{Year FE} + \varepsilon$$

Output:

- Console summary for each regression
- 'regression_results_mean_adjusted.xlsx' with formatted results table

Usage:

```

pip install openpyxl pandas statsmodels
python regression_mean_adjusted.py

```

"""

```

import openpyxl
import pandas as pd
import numpy as np
import statsmodels.formula.api as smf
from openpyxl.styles import PatternFill, Font, Alignment, Border, Side
from openpyxl.utils import get_column_letter
from datetime import datetime

```

```

INPUT_FILE = "stock_prices_acquirers_final.xlsx"
SOURCE_TAB = "Regression mean_adjusted (2)"
OUTPUT_FILE = "regression_results_mean_adjusted.xlsx"

```

Row definitions (1-indexed)

```

ROW_MAP = {
    "car_t0":      20,
    "car_1_1":     21,
    "car_2_2":     22,
    "car_5_5":     23,
    "car_20_5":   24,
    "target":     38,
    "tobins_q":   44,
    "acquirer":   45,
    "deal_size":  46,
    "payment":    48,
    "sic":        49,
    "year":       50,
}

```

```

CAR_WINDOWS = [
    ("car_t0", "CAR(T-0)"),
    ("car_1_1", "CAR(-1,+1)"),
    ("car_2_2", "CAR(-2,+2)"),
    ("car_5_5", "CAR(-5,+5)"),
    ("car_20_5", "CAR(-20,+5)"),
]

# Styling
FILL_HEADER = PatternFill("solid", fgColor="1F4E79")
FILL_SUBHEAD = PatternFill("solid", fgColor="BDD7EE")
FILL_SIG1 = PatternFill("solid", fgColor="E2EFDA") # green - significant
FILL_NOSIG = PatternFill("solid", fgColor="FFFFFF")
FONT_HEADER = Font(color="FFFFFF", bold=True, size=10, name="Arial")
FONT_SUBHEAD = Font(bold=True, size=10, name="Arial")
FONT_BODY = Font(size=9, name="Arial")
FONT_BOLD = Font(bold=True, size=9, name="Arial")
ALIGN_CENTER = Alignment(horizontal="center")
ALIGN_RIGHT = Alignment(horizontal="right")
ALIGN_LEFT = Alignment(horizontal="left")

def stars(pval):
    if pval < 0.01: return "****"
    if pval < 0.05: return "***"
    if pval < 0.10: return "**"
    return ""

def read_data(ws):
    """Read all rows into a DataFrame."""
    records = []
    col = 2 # start from column B
    while True:
        car_t0 = ws.cell(row=ROW_MAP["car_t0"], column=col).value
        car_1_1 = ws.cell(row=ROW_MAP["car_1_1"], column=col).value
        car_2_2 = ws.cell(row=ROW_MAP["car_2_2"], column=col).value
        car_5_5 = ws.cell(row=ROW_MAP["car_5_5"], column=col).value
        car_20_5 = ws.cell(row=ROW_MAP["car_20_5"], column=col).value
        target = ws.cell(row=ROW_MAP["target"], column=col).value
        tobins_q = ws.cell(row=ROW_MAP["tobins_q"], column=col).value
        acquirer = ws.cell(row=ROW_MAP["acquirer"], column=col).value
        deal_size = ws.cell(row=ROW_MAP["deal_size"], column=col).value
        payment = ws.cell(row=ROW_MAP["payment"], column=col).value
        sic = ws.cell(row=ROW_MAP["sic"], column=col).value

```

```

year      = ws.cell(row=ROW_MAP["year"],      column=col).value

if car_1_1 is None and tobins_q is None:
    break

records.append({
    "car_t0":    car_t0,
    "car_1_1":   car_1_1,
    "car_2_2":   car_2_2,
    "car_5_5":   car_5_5,
    "car_20_5":  car_20_5,
    "target":    target,
    "tobins_q":  tobins_q,
    "acquirer":  acquirer,
    "deal_size": deal_size,
    "payment":   payment,
    "sic":       str(sic).strip() if sic is not None else None,
    "year":      str(int(year)) if year is not None else None,
})
col += 1

df = pd.DataFrame(records)
print(f"Loaded {len(df)} deals.")
return df

def prepare_data(df):
    """Clean and create dummy variables."""
    # Drop rows missing key variables
    df = df.dropna(subset=["tobins_q", "deal_size", "payment", "sic", "year"])

    # Payment method dummies (reference = Cash, code=1)
    # 1=Cash, 2=Stock, 3=Cash and Stock, 0=Cash or Stock
    df["pay_stock"]      = (df["payment"] == 2).astype(int)
    df["pay_cash_stock"] = (df["payment"] == 3).astype(int)
    df["pay_cash_or_stock"] = (df["payment"] == 0).astype(int)

    # Ensure numeric
    df["tobins_q"] = pd.to_numeric(df["tobins_q"], errors="coerce")
    df["deal_size"] = pd.to_numeric(df["deal_size"], errors="coerce")

    df = df.dropna(subset=["tobins_q", "deal_size"])
    print(f"After cleaning: {len(df)} deals ready for regression.")
    return df

```

```

def run_regression(df, car_col, car_label):
    """Run OLS with industry and year fixed effects."""
    # Drop missing CAR values
    df_reg = df.dropna(subset=[car_col]).copy()

    formula = (
        f"{car_col} ~ tobins_q + deal_size + pay_stock + pay_cash_stock +
pay_cash_or_stock"
        f" + C(sic) + C(year)"
    )

    model = smf.ols(formula=formula, data=df_reg).fit(
        cov_type="HC3" # heteroskedasticity-robust standard errors
    )

    print(f"\n{' '*60}")
    print(f"Regression: {car_label} (N={len(df_reg)})")
    print(f"{' '*60}")
    print(f"R-squared: {model.rsquared:.4f}")
    print(f"Adj R-squared: {model.rsquared_adj:.4f}")
    print(f"\nKey variables:")
    key_vars = ["Intercept", "tobins_q", "deal_size",
                "pay_stock", "pay_cash_stock", "pay_cash_or_stock"]
    for var in key_vars:
        if var in model.params:
            coef = model.params[var]
            se = model.bse[var]
            tstat = model.tvalues[var]
            pval = model.pvalues[var]
            sig = stars(pval)
            print(f" {var:<25} coef={coef:>10.4f} se={se:>8.4f} t={tstat:>7.3f}
p={pval:>6.4f} {sig}")

    return model, len(df_reg)

def write_excel(results):
    """Write formatted results table to Excel."""
    wb = openpyxl.Workbook()
    ws = wb.active
    ws.title = "Regression Results"

```

```

thin = Side(style="thin")
border = Border(bottom=thin)

# Title
ws.merge_cells("A1:H1")
ws["A1"].value = "Cross-Sectional Regression Results – Mean-Adjusted CARs"
ws["A1"].font = Font(bold=True, size=12, name="Arial")
ws["A1"].alignment = ALIGN_CENTER

ws.merge_cells("A2:H2")
ws["A2"].value = "CARi = α + β1×Tobin's Q + β2×Deal Size + β3×Payment Dummies +
Industry FE + Year FE + ε"
ws["A2"].font = Font(italic=True, size=9, name="Arial")
ws["A2"].alignment = ALIGN_CENTER

# Column headers
headers = ["Variable", "CAR(T-0)", "CAR(-1,+1)", "CAR(-2,+2)", "CAR(-5,+5)", "CAR(-
20,+5)"]
for col, h in enumerate(headers, start=1):
    c = ws.cell(row=4, column=col)
    c.value = h
    c.fill = FILL_HEADER
    c.font = FONT_HEADER
    c.alignment = ALIGN_CENTER

# Variables to display
display_vars = [
    ("tobins_q", "Tobin's Q (target)",),
    ("deal_size", "Deal Size (LN)",),
    ("pay_stock", "Payment: Stock",),
    ("pay_cash_stock", "Payment: Cash & Stock",),
    ("pay_cash_or_stock", "Payment: Cash or Stock",),
    ("Intercept", "Intercept",),
]

row = 5
for var_key, var_label in display_vars:
    # Coefficient row
    ws.cell(row=row, column=1).value = var_label
    ws.cell(row=row, column=1).font = FONT_BOLD
    ws.cell(row=row, column=1).alignment = ALIGN_LEFT

for col_idx, (car_col, car_label, model, n) in enumerate(results, start=2):
    internal_key = var_key if var_key != "tobins_q" else "tobins_q"
    # statsmodels uses the variable name directly

```

```

param_key = var_key
if param_key in model.params:
    coef = model.params[param_key]
    pval = model.pvalues[param_key]
    sig = stars(pval)
    c = ws.cell(row=row, column=col_idx)
    c.value = f"{coef:.4f}{sig}"
    c.font = FONT_BODY
    c.alignment = ALIGN_CENTER
    if pval < 0.10:
        c.fill = FILL_SIG1

# SE row
ws.cell(row=row+1, column=1).value = ""
for col_idx, (car_col, car_label, model, n) in enumerate(results, start=2):
    if var_key in model.bse:
        se = model.bse[var_key]
        c = ws.cell(row=row+1, column=col_idx)
        c.value = f"({se:.4f})"
        c.font = Font(size=9, italic=True, name="Arial")
        c.alignment = ALIGN_CENTER

row += 2

# Separator
for col in range(1, 7):
    ws.cell(row=row, column=col).border = border
row += 1

# Stats rows
stat_rows = [
    ("Observations", [str(n) for _, _, _, n in results]),
    ("R-squared", [f"{m.rsquared:.4f}" for _, _, m, _ in results]),
    ("Adj R-squared", [f"{m.rsquared_adj:.4f}" for _, _, m, _ in results]),
    ("Industry FE", ["Yes"] * len(results)),
    ("Year FE", ["Yes"] * len(results)),
    ("Std Errors", ["HC3 Robust"] * len(results)),
]

for label, vals in stat_rows:
    ws.cell(row=row, column=1).value = label
    ws.cell(row=row, column=1).font = FONT_BOLD
    for col_idx, val in enumerate(vals, start=2):
        c = ws.cell(row=row, column=col_idx)
        c.value = val
        c.font = FONT_BODY

```

```

        c.alignment = ALIGN_CENTER
        row += 1

# Note
row += 1
ws.merge_cells(f"A{row}:H{row}")
ws.cell(row=row, column=1).value = "Note: *p<0.10  **p<0.05  ***p<0.01. Standard
errors in parentheses. HC3 heteroskedasticity-robust standard errors."
ws.cell(row=row, column=1).font = Font(italic=True, size=8, name="Arial")

# Column widths
ws.column_dimensions["A"].width = 28
for col in range(2, 7):
    ws.column_dimensions[get_column_letter(col)].width = 16

ws.freeze_panes = "B5"

wb.save(OUTPUT_FILE)
print(f"\nResults saved to '{OUTPUT_FILE}'.")

def main():
    print(f"Loading '{INPUT_FILE}' ...")
    wb = openpyxl.load_workbook(INPUT_FILE, data_only=True)

    if SOURCE_TAB not in wb.sheetnames:
        raise ValueError(f"Tab '{SOURCE_TAB}' not found.")

    ws = wb[SOURCE_TAB]
    df = read_data(ws)
    df = prepare_data(df)

    # Run regressions
    results = []
    for car_col, car_label in CAR_WINDOWS:
        model, n = run_regression(df, car_col, car_label)
        results.append((car_col, car_label, model, n))

    # Write output
    write_excel(results)
    print("\nDone!")

```

```
if __name__ == "__main__":
    main()
```

Cross-Sectional OLS Regression – Market-Adjusted Model

The below script is structurally same as in the mean-adjusted models OLS regression script, but it uses the market-adjusted CARs as the dependent variable, where the S&P500 index acts as the benchmark for expected returns. Same independent variables as well control variables are used in this regression. The market-adjusted model is used as the primary robustness check on the choice of benchmark model.

```
"""
regression_market_adjusted.py
=====
Reads data from 'Regression market_adjusted (2)' tab and runs OLS cross-sectional
regressions of CARs on Target Tobin's Q and control variables.

Identical structure to regression_mean_adjusted.py but uses market-adjusted CARs
as the dependent variable (robustness check).

Usage:
    pip install openpyxl pandas statsmodels
    python regression_market_adjusted.py
"""

import openpyxl
import pandas as pd
import numpy as np
import statsmodels.formula.api as smf
from openpyxl.styles import PatternFill, Font, Alignment, Border, Side
from openpyxl.utils import get_column_letter
from datetime import datetime

INPUT_FILE = "stock_prices_acquirers_final.xlsx"
SOURCE_TAB = "Regression market_adjusted (2)"
OUTPUT_FILE = "regression_results_market_adjusted.xlsx"

# Row definitions (1-indexed)
ROW_MAP = {
    "car_t0": 20,
```

```

    "car_1_1":      21,
    "car_2_2":      22,
    "car_5_5":      23,
    "car_20_5":     24,
    "target":       38,
    "tobins_q":     44,
    "acquirer":     45,
    "deal_size":    46,
    "payment":      48,
    "sic":          49,
    "year":         50,
}

CAR_WINDOWS = [
    ("car_t0", "CAR(T-0)"),
    ("car_1_1", "CAR(-1,+1)"),
    ("car_2_2", "CAR(-2,+2)"),
    ("car_5_5", "CAR(-5,+5)"),
    ("car_20_5", "CAR(-20,+5)"),
]

# Styling
FILL_HEADER = PatternFill("solid", fgColor="1F4E79")
FILL_SUBHEAD = PatternFill("solid", fgColor="BDD7EE")
FILL_SIG1 = PatternFill("solid", fgColor="E2EFDA") # green - significant
FILL_NOSIG = PatternFill("solid", fgColor="FFFFFF")
FONT_HEADER = Font(color="FFFFFF", bold=True, size=10, name="Arial")
FONT_SUBHEAD = Font(bold=True, size=10, name="Arial")
FONT_BODY = Font(size=9, name="Arial")
FONT_BOLD = Font(bold=True, size=9, name="Arial")
ALIGN_CENTER = Alignment(horizontal="center")
ALIGN_RIGHT = Alignment(horizontal="right")
ALIGN_LEFT = Alignment(horizontal="left")

def stars(pval):
    if pval < 0.01: return "****"
    if pval < 0.05: return "***"
    if pval < 0.10: return "**"
    return ""

def read_data(ws):
    """Read all rows into a DataFrame."""
    records = []
    col = 2 # start from column B

```

```

while True:
    car_t0 = ws.cell(row=ROW_MAP["car_t0"], column=col).value
    car_1_1 = ws.cell(row=ROW_MAP["car_1_1"], column=col).value
    car_2_2 = ws.cell(row=ROW_MAP["car_2_2"], column=col).value
    car_5_5 = ws.cell(row=ROW_MAP["car_5_5"], column=col).value
    car_20_5 = ws.cell(row=ROW_MAP["car_20_5"], column=col).value
    target = ws.cell(row=ROW_MAP["target"], column=col).value
    tobins_q = ws.cell(row=ROW_MAP["tobins_q"], column=col).value
    acquirer = ws.cell(row=ROW_MAP["acquirer"], column=col).value
    deal_size = ws.cell(row=ROW_MAP["deal_size"], column=col).value
    payment = ws.cell(row=ROW_MAP["payment"], column=col).value
    sic = ws.cell(row=ROW_MAP["sic"], column=col).value
    year = ws.cell(row=ROW_MAP["year"], column=col).value

    if car_1_1 is None and tobins_q is None:
        break

    records.append({
        "car_t0": car_t0,
        "car_1_1": car_1_1,
        "car_2_2": car_2_2,
        "car_5_5": car_5_5,
        "car_20_5": car_20_5,
        "target": target,
        "tobins_q": tobins_q,
        "acquirer": acquirer,
        "deal_size": deal_size,
        "payment": payment,
        "sic": str(sic).strip() if sic is not None else None,
        "year": str(int(year)) if year is not None else None,
    })
    col += 1

df = pd.DataFrame(records)
print(f"Loaded {len(df)} deals.")
return df

def prepare_data(df):
    """Clean and create dummy variables."""
    # Drop rows missing key variables
    df = df.dropna(subset=["tobins_q", "deal_size", "payment", "sic", "year"])

    # Payment method dummies (reference = Cash, code=1)
    # 1=Cash, 2=Stock, 3=Cash and Stock, 0=Cash or Stock
    df["pay_stock"] = (df["payment"] == 2).astype(int)

```

```

df["pay_cash_stock"] = (df["payment"] == 3).astype(int)
df["pay_cash_or_stock"] = (df["payment"] == 0).astype(int)

# Ensure numeric
df["tobins_q"] = pd.to_numeric(df["tobins_q"], errors="coerce")
df["deal_size"] = pd.to_numeric(df["deal_size"], errors="coerce")

df = df.dropna(subset=["tobins_q", "deal_size"])
print(f"After cleaning: {len(df)} deals ready for regression.")
return df

def run_regression(df, car_col, car_label):
    """Run OLS with industry and year fixed effects."""
    # Drop missing CAR values
    df_reg = df.dropna(subset=[car_col]).copy()

    formula = (
        f"{car_col} ~ tobins_q + deal_size + pay_stock + pay_cash_stock +
pay_cash_or_stock"
        f" + C(sic) + C(year)"
    )

    model = smf.ols(formula=formula, data=df_reg).fit(
        cov_type="HC3" # heteroskedasticity-robust standard errors
    )

    print(f"\n{' '*60}")
    print(f"Regression: {car_label} (N={len(df_reg)})")
    print(f"{' '*60}")
    print(f"R-squared: {model.rsquared:.4f}")
    print(f"Adj R-squared: {model.rsquared_adj:.4f}")
    print(f"\nKey variables:")
    key_vars = ["Intercept", "tobins_q", "deal_size",
                "pay_stock", "pay_cash_stock", "pay_cash_or_stock"]
    for var in key_vars:
        if var in model.params:
            coef = model.params[var]
            se = model.bse[var]
            tstat = model.tvalues[var]
            pval = model.pvalues[var]
            sig = stars(pval)
            print(f" {var:<25} coef={coef:>10.4f} se={se:>8.4f} t={tstat:>7.3f}
p={pval:>6.4f} {sig}")

```

```

return model, len(df_reg)

def write_excel(results):
    """Write formatted results table to Excel."""
    wb = openpyxl.Workbook()
    ws = wb.active
    ws.title = "Regression Results"

    thin = Side(style="thin")
    border = Border(bottom=thin)

    # Title
    ws.merge_cells("A1:H1")
    ws["A1"].value = "Cross-Sectional Regression Results – Market-Adjusted CARs"
    ws["A1"].font = Font(bold=True, size=12, name="Arial")
    ws["A1"].alignment = ALIGN_CENTER

    ws.merge_cells("A2:H2")
    ws["A2"].value = "CARi = α + β1×Tobin's Q + β2×Deal Size + β3×Payment Dummies +
Industry FE + Year FE + ε"
    ws["A2"].font = Font(italic=True, size=9, name="Arial")
    ws["A2"].alignment = ALIGN_CENTER

    # Column headers
    headers = ["Variable", "CAR(T-0)", "CAR(-1,+1)", "CAR(-2,+2)", "CAR(-5,+5)", "CAR(-
20,+5)"]
    for col, h in enumerate(headers, start=1):
        c = ws.cell(row=4, column=col)
        c.value = h
        c.fill = FILL_HEADER
        c.font = FONT_HEADER
        c.alignment = ALIGN_CENTER

    # Variables to display
    display_vars = [
        ("tobins_q", "Tobin's Q (target)",),
        ("deal_size", "Deal Size (LN)",),
        ("pay_stock", "Payment: Stock",),
        ("pay_cash_stock", "Payment: Cash & Stock",),
        ("pay_cash_or_stock", "Payment: Cash or Stock",),
        ("Intercept", "Intercept",),
    ]

```

```

row = 5
for var_key, var_label in display_vars:
    # Coefficient row
    ws.cell(row=row, column=1).value = var_label
    ws.cell(row=row, column=1).font = FONT_BOLD
    ws.cell(row=row, column=1).alignment = ALIGN_LEFT

    for col_idx, (car_col, car_label, model, n) in enumerate(results, start=2):
        internal_key = var_key if var_key != "tobins_g" else "tobins_g"
        # statsmodels uses the variable name directly
        param_key = var_key
        if param_key in model.params:
            coef = model.params[param_key]
            pval = model.pvalues[param_key]
            sig = stars(pval)
            c = ws.cell(row=row, column=col_idx)
            c.value = f"{coef:.4f}{sig}"
            c.font = FONT_BODY
            c.alignment = ALIGN_CENTER
            if pval < 0.10:
                c.fill = FILL_SIG1

        # SE row
        ws.cell(row=row+1, column=1).value = ""
        for col_idx, (car_col, car_label, model, n) in enumerate(results, start=2):
            if var_key in model.bse:
                se = model.bse[var_key]
                c = ws.cell(row=row+1, column=col_idx)
                c.value = f"({se:.4f})"
                c.font = Font(size=9, italic=True, name="Arial")
                c.alignment = ALIGN_CENTER

        row += 2

# Separator
for col in range(1, 7):
    ws.cell(row=row, column=col).border = border
row += 1

# Stats rows
stat_rows = [
    ("Observations", [str(n) for _, _, _, n in results]),
    ("R-squared", [f"{m.rsquared:.4f}" for _, _, m, _ in results]),
    ("Adj R-squared", [f"{m.rsquared_adj:.4f}" for _, _, m, _ in results]),
    ("Industry FE", ["Yes"] * len(results)),
    ("Year FE", ["Yes"] * len(results)),

```

```

        ("Std Errors",      ["HC3 Robust"] * len(results)),
    ]

    for label, vals in stat_rows:
        ws.cell(row=row, column=1).value = label
        ws.cell(row=row, column=1).font = FONT_BOLD
        for col_idx, val in enumerate(vals, start=2):
            c = ws.cell(row=row, column=col_idx)
            c.value = val
            c.font = FONT_BODY
            c.alignment = ALIGN_CENTER
        row += 1

    # Note
    row += 1
    ws.merge_cells(f"A{row}:H{row}")
    ws.cell(row=row, column=1).value = "Note: *p<0.10 **p<0.05 ***p<0.01. Standard
errors in parentheses. HC3 heteroskedasticity-robust standard errors."
    ws.cell(row=row, column=1).font = Font(italic=True, size=8, name="Arial")

    # Column widths
    ws.column_dimensions["A"].width = 28
    for col in range(2, 7):
        ws.column_dimensions[get_column_letter(col)].width = 16

    ws.freeze_panes = "B5"

    wb.save(OUTPUT_FILE)
    print(f"\nResults saved to '{OUTPUT_FILE}'.")

def main():
    print(f"Loading '{INPUT_FILE}' ...")
    wb = openpyxl.load_workbook(INPUT_FILE, data_only=True)

    if SOURCE_TAB not in wb.sheetnames:
        raise ValueError(f"Tab '{SOURCE_TAB}' not found.")

    ws = wb[SOURCE_TAB]
    df = read_data(ws)
    df = prepare_data(df)

    # Run regressions

```

```

results = []
for car_col, car_label in CAR_WINDOWS:
    model, n = run_regression(df, car_col, car_label)
    results.append((car_col, car_label, model, n))

# Write output
write_excel(results)
print("\nDone!")

if __name__ == "__main__":
    main()

```

Robustness Check Winsorized Regressions

The below script runs four additional regressions to test the robustness of the main results of the study. First robustness check winsorizes target's Tobin's Q at the 5th and 95th percentiles for each models. The second robustness check winsorizes both Tobin's Q and log deal size at the 1st and 99th percentiles for each model. The robustness check uses the exact same return windows, fixed effects, and HC3 robust standard errors as the main regressions.

```

"""
regression_robustness.py
=====
Runs robustness checks for both mean-adjusted and market-adjusted CAR regressions.

Two robustness checks:
  1. Winsorize Tobin's Q only at 1st and 99th percentile
  2. Winsorize ALL continuous variables (Tobin's Q + Deal Size) at 1st and 99th percentile

Each check is run for both mean-adjusted and market-adjusted CARs (5 windows each).
Total: 2 checks × 2 models × 5 windows = 20 regressions

Data layout (both tabs, all starting from column B):
  Row 20: CAR T-0
  Row 21: CAR (-1,+1)
  Row 22: CAR (-2,+2)
  Row 23: CAR (-5,+5)

```

```

Row 24: CAR (-20,+5)
Row 44: Target Tobin's Q
Row 46: Deal size (LN transformed)
Row 48: Payment method dummy (1=Cash, 2=Stock, 3=Cash and Stock, 0=Cash or Stock)
Row 49: 2-digit industry SIC code
Row 50: Announcement year

```

Output:

```

'regression_results_robustness.xlsx' with 4 sheets:
  1. Winsorize_Q_Mean      - winsorized Q, mean-adjusted CARs
  2. Winsorize_Q_Market   - winsorized Q, market-adjusted CARs
  3. Winsorize_All_Mean   - winsorized Q+DealSize, mean-adjusted CARs
  4. Winsorize_All_Market - winsorized Q+DealSize, market-adjusted CARs

```

Usage:

```

pip install openpyxl pandas statsmodels numpy
python regression_robustness.py
"""

import openpyxl
import pandas as pd
import numpy as np
import statsmodels.formula.api as smf
from openpyxl.styles import PatternFill, Font, Alignment, Border, Side
from openpyxl.utils import get_column_letter
from datetime import datetime

INPUT_FILE = "stock_prices_acquirers_final.xlsx"
OUTPUT_FILE = "regression_results_robustness.xlsx"

MEAN_TAB = "Regression mean_adjusted (2)"
MARKET_TAB = "Regression market_adjusted (2)"

ROW_MAP = {
    "car_t0": 20,
    "car_1_1": 21,
    "car_2_2": 22,
    "car_5_5": 23,
    "car_20_5": 24,
    "tobins_q": 44,
    "deal_size": 46,
    "payment": 48,
    "sic": 49,
    "year": 50,
}

```

```

CAR_WINDOWS = [
    ("car_t0", "CAR(T-0)"),
    ("car_1_1", "CAR(-1,+1)"),
    ("car_2_2", "CAR(-2,+2)"),
    ("car_5_5", "CAR(-5,+5)"),
    ("car_20_5", "CAR(-20,+5)"),
]

# Styling
FILL_HEADER = PatternFill("solid", fgColor="1F4E79")
FILL_SIG = PatternFill("solid", fgColor="E2EFDA")
FILL_CHECK1 = PatternFill("solid", fgColor="FFF2CC") # yellow - winsorize Q only
FILL_CHECK2 = PatternFill("solid", fgColor="FCE4D6") # orange - winsorize all
FONT_HEADER = Font(color="FFFFFF", bold=True, size=10, name="Arial")
FONT_BODY = Font(size=9, name="Arial")
FONT_BOLD = Font(bold=True, size=9, name="Arial")
FONT_ITALIC = Font(italic=True, size=9, name="Arial")
ALIGN_CENTER = Alignment(horizontal="center")
ALIGN_LEFT = Alignment(horizontal="left")

def stars(pval):
    if pval < 0.01: return "****"
    if pval < 0.05: return "***"
    if pval < 0.10: return "**"
    return ""

def winsorize(series, lower=0.01, upper=0.99):
    """Winsorize a pandas Series at given percentiles."""
    lo = series.quantile(lower)
    hi = series.quantile(upper)
    return series.clip(lower=lo, upper=hi)

def read_data(ws, tab_name):
    """Read all deals from a regression tab into a DataFrame."""
    records = []
    col = 2
    while True:
        car_t0 = ws.cell(row=ROW_MAP["car_t0"], column=col).value
        car_1_1 = ws.cell(row=ROW_MAP["car_1_1"], column=col).value
        car_2_2 = ws.cell(row=ROW_MAP["car_2_2"], column=col).value

```

```

car_5_5 = ws.cell(row=ROW_MAP["car_5_5"], column=col).value
car_20_5 = ws.cell(row=ROW_MAP["car_20_5"], column=col).value
tobins_q = ws.cell(row=ROW_MAP["tobins_q"], column=col).value
deal_size = ws.cell(row=ROW_MAP["deal_size"], column=col).value
payment = ws.cell(row=ROW_MAP["payment"], column=col).value
sic = ws.cell(row=ROW_MAP["sic"], column=col).value
year = ws.cell(row=ROW_MAP["year"], column=col).value

if car_1_1 is None and tobins_q is None:
    break

records.append({
    "car_t0": car_t0,
    "car_1_1": car_1_1,
    "car_2_2": car_2_2,
    "car_5_5": car_5_5,
    "car_20_5": car_20_5,
    "tobins_q": tobins_q,
    "deal_size": deal_size,
    "payment": payment,
    "sic": str(sic).strip() if sic is not None else None,
    "year": str(int(year)) if year is not None else None,
})
col += 1

df = pd.DataFrame(records)
print(f" [{tab_name}] Loaded {len(df)} deals.")
return df

def prepare_data(df):
    """Clean and create dummy variables."""
    df = df.dropna(subset=["tobins_q", "deal_size", "payment", "sic", "year"])
    df["tobins_q"] = pd.to_numeric(df["tobins_q"], errors="coerce")
    df["deal_size"] = pd.to_numeric(df["deal_size"], errors="coerce")
    df["pay_stock"] = (df["payment"] == 2).astype(int)
    df["pay_cash_stock"] = (df["payment"] == 3).astype(int)
    df["pay_cash_or_stock"] = (df["payment"] == 0).astype(int)
    df = df.dropna(subset=["tobins_q", "deal_size"])
    return df

def apply_winsorize_q(df):
    """Winsorize only Tobin's Q at 5th/95th percentile."""
    df = df.copy()

```

```

original_q = df["tobins_q"].describe()
df["tobins_q"] = winsorize(df["tobins_q"], lower=0.05, upper=0.95)
print(f" Tobin's Q winsorized (5th-95th pct): min {original_q['min']:.4f}→{df['to-
bins_q'].min():.4f}, "
      f"max {original_q['max']:.4f}→{df['tobins_q'].max():.4f}")
return df

def apply_winsorize_all(df):
    """Winsorize both Tobin's Q and Deal Size."""
    df = df.copy()
    df["tobins_q"] = winsorize(df["tobins_q"])
    df["deal_size"] = winsorize(df["deal_size"])
    print(f" Tobin's Q and Deal Size winsorized at 1st/99th percentile.")
    return df

def run_regression(df, car_col, car_label):
    """Run OLS with industry and year fixed effects."""
    df_reg = df.dropna(subset=[car_col]).copy()
    formula = (
        f"{car_col} ~ tobins_q + deal_size + pay_stock + pay_cash_stock"
        f" + pay_cash_or_stock + C(sic) + C(year)"
    )
    model = smf.ols(formula=formula, data=df_reg).fit(cov_type="HC3")
    return model, len(df_reg)

def write_results_sheet(wb, sheet_name, results, title, fill_title):
    """Write a formatted results sheet."""
    ws = wb.create_sheet(sheet_name)
    thin = Side(style="thin")
    border = Border(bottom=thin)

    # Title
    ws.merge_cells("A1:F1")
    ws["A1"].value = title
    ws["A1"].font = Font(bold=True, size=11, name="Arial")
    ws["A1"].fill = fill_title
    ws["A1"].alignment = ALIGN_CENTER

    ws.merge_cells("A2:F2")
    ws["A2"].value = "CARi = α + β1×Tobin's Q + β2×Deal Size + β3×Payment Dummies +
Industry FE + Year FE + ε"

```

```

ws["A2"].font = Font(italic=True, size=9, name="Arial")
ws["A2"].alignment = ALIGN_CENTER

# Column headers
headers = ["Variable", "CAR(T-0)", "CAR(-1,+1)", "CAR(-2,+2)", "CAR(-5,+5)", "CAR(-
20,+5)"]
for col, h in enumerate(headers, start=1):
    c = ws.cell(row=4, column=col)
    c.value = h
    c.fill = FILL_HEADER
    c.font = FONT_HEADER
    c.alignment = ALIGN_CENTER

display_vars = [
    ("tobins_q", "Tobin's Q (target)"),
    ("deal_size", "Deal Size (LN)"),
    ("pay_stock", "Payment: Stock"),
    ("pay_cash_stock", "Payment: Cash & Stock"),
    ("pay_cash_or_stock", "Payment: Cash or Stock"),
    ("Intercept", "Intercept"),
]

row = 5
for var_key, var_label in display_vars:
    ws.cell(row=row, column=1).value = var_label
    ws.cell(row=row, column=1).font = FONT_BOLD
    ws.cell(row=row, column=1).alignment = ALIGN_LEFT

for col_idx, (car_col, car_label, model, n) in enumerate(results, start=2):
    if var_key in model.params:
        coef = model.params[var_key]
        pval = model.pvalues[var_key]
        sig = stars(pval)
        c = ws.cell(row=row, column=col_idx)
        c.value = f"{coef:.4f}{sig}"
        c.font = FONT_BODY
        c.alignment = ALIGN_CENTER
        if pval < 0.10:
            c.fill = FILL_SIG

# SE row
for col_idx, (car_col, car_label, model, n) in enumerate(results, start=2):
    if var_key in model.bse:
        se = model.bse[var_key]
        c = ws.cell(row=row+1, column=col_idx)
        c.value = f"({se:.4f})"

```

```

        c.font = FONT_ITALIC
        c.alignment = ALIGN_CENTER

    row += 2

# Separator
for col in range(1, 7):
    ws.cell(row=row, column=col).border = border
row += 1

# Stats
stat_rows = [
    ("Observations", [str(n) for _, _, _, n in results]),
    ("R-squared", [f"{m.rsquared:.4f}" for _, _, m, _ in results]),
    ("Adj R-squared", [f"{m.rsquared_adj:.4f}" for _, _, m, _ in results]),
    ("Winsorization", ["1st-99th pct"] * len(results)),
    ("Industry FE", ["Yes"] * len(results)),
    ("Year FE", ["Yes"] * len(results)),
    ("Std Errors", ["HC3 Robust"] * len(results)),
]

for label, vals in stat_rows:
    ws.cell(row=row, column=1).value = label
    ws.cell(row=row, column=1).font = FONT_BOLD
    for col_idx, val in enumerate(vals, start=2):
        c = ws.cell(row=row, column=col_idx)
        c.value = val
        c.font = FONT_BODY
        c.alignment = ALIGN_CENTER
    row += 1

row += 1
ws.merge_cells(f"A{row}:F{row}")
ws.cell(row=row, column=1).value = "Note: *p<0.10 **p<0.05 ***p<0.01. Standard
errors in parentheses. HC3 heteroskedasticity-robust standard errors."
ws.cell(row=row, column=1).font = Font(italic=True, size=8, name="Arial")

# Column widths
ws.column_dimensions["A"].width = 26
for col in range(2, 7):
    ws.column_dimensions[get_column_letter(col)].width = 15

ws.freeze_panes = "B5"

```

```

def main():
    print(f"Loading '{INPUT_FILE}' ...")
    wb_in = openpyxl.load_workbook(INPUT_FILE, data_only=True)

    # Read both tabs
    print("\nReading data...")
    ws_mean = wb_in[MEAN_TAB]
    ws_market = wb_in[MARKET_TAB]

    df_mean = prepare_data(read_data(ws_mean, MEAN_TAB))
    df_market = prepare_data(read_data(ws_market, MARKET_TAB))

    # — Robustness Check 1: Winsorize Tobin's Q only —
    print("\n— Robustness Check 1: Winsorize Tobin's Q —")
    df_mean_wq = apply_winsorize_q(df_mean.copy())
    df_market_wq = apply_winsorize_q(df_market.copy())

    results_wq_mean, results_wq_market = [], []
    for car_col, car_label in CAR_WINDOWS:
        m, n = run_regression(df_mean_wq, car_col, car_label)
        results_wq_mean.append((car_col, car_label, m, n))
        m, n = run_regression(df_market_wq, car_col, car_label)
        results_wq_market.append((car_col, car_label, m, n))
        print(f"      {car_label}: Tobin's Q coef (mean)={results_wq_mean[-1][2].params.get('tobins_q',0):.4f} "
              f"p={results_wq_mean[-1][2].pvalues.get('tobins_q',1):.4f} | "
              f"(market)={results_wq_market[-1][2].params.get('tobins_q',0):.4f} "
              f"p={results_wq_market[-1][2].pvalues.get('tobins_q',1):.4f}")

    # — Robustness Check 2: Winsorize all continuous variables —
    print("\n— Robustness Check 2: Winsorize All Continuous Variables —")
    df_mean_wall = apply_winsorize_all(df_mean.copy())
    df_market_wall = apply_winsorize_all(df_market.copy())

    results_wall_mean, results_wall_market = [], []
    for car_col, car_label in CAR_WINDOWS:
        m, n = run_regression(df_mean_wall, car_col, car_label)
        results_wall_mean.append((car_col, car_label, m, n))
        m, n = run_regression(df_market_wall, car_col, car_label)
        results_wall_market.append((car_col, car_label, m, n))
        print(f"      {car_label}: Tobin's Q coef (mean)={results_wall_mean[-1][2].params.get('tobins_q',0):.4f} "
              f"p={results_wall_mean[-1][2].pvalues.get('tobins_q',1):.4f} | "
              f"(market)={results_wall_market[-1][2].params.get('tobins_q',0):.4f} ")

```

```

        f"p={results_wall_market[-1][2].pvalues.get('tobins_q',1):.4f}")

# — Write Excel output —
print("\nWriting Excel output...")
wb_out = openpyxl.Workbook()
wb_out.remove(wb_out.active) # remove default sheet

write_results_sheet(wb_out, "Winsorize_Q_Mean",
                    results_wq_mean,
                    "Robustness Check 1 - Winsorized Tobin's Q (5th-95th pct) |
Mean-Adjusted CARs",
                    FILL_CHECK1)

write_results_sheet(wb_out, "Winsorize_Q_Market",
                    results_wq_market,
                    "Robustness Check 1 - Winsorized Tobin's Q (5th-95th pct) |
Market-Adjusted CARs",
                    FILL_CHECK1)

write_results_sheet(wb_out, "Winsorize_All_Mean",
                    results_wall_mean,
                    "Robustness Check 2 - Winsorized All Variables | Mean-Adjusted
CARs",
                    FILL_CHECK2)

write_results_sheet(wb_out, "Winsorize_All_Market",
                    results_wall_market,
                    "Robustness Check 2 - Winsorized All Variables | Market-Ad-
justed CARs",
                    FILL_CHECK2)

wb_out.save(OUTPUT_FILE)
print(f"\nDone! Results saved to '{OUTPUT_FILE}'.")
print(f" 4 sheets: Winsorize_Q_Mean, Winsorize_Q_Market, Winsorize_All_Mean, Win-
sorize_All_Market")

if __name__ == "__main__":
    main()

```

Appendix 3 VIF and Breusch-Pagan Test results

Mean-Adjusted Model					
VIF Results (Multicollinearity Diagnostic)					
Variable	CAR(T-0)	CAR(-1,+1)	CAR(-2,+2)	CAR(-5,+5)	CAR(-20,+5)
Tobin's Q	1.015	1.015	1.015	1.015	1.015
Log Deal Size	1.064	1.064	1.064	1.064	1.064
Pay: Stock	1.120	1.120	1.120	1.120	1.120
Pay: Mixed	1.137	1.137	1.137	1.137	1.137
Pay: Cash or Stock	1.091	1.091	1.091	1.091	1.091
Max VIF	1.137	1.137	1.137	1.137	1.137
Market-Adjusted Model					
Variable	CAR(T-0)	CAR(-1,+1)	CAR(-2,+2)	CAR(-5,+5)	CAR(-20,+5)
Tobin's Q	1.015	1.015	1.015	1.015	1.015
Log Deal Size	1.064	1.064	1.064	1.064	1.064
Pay: Stock	1.120	1.120	1.120	1.120	1.120
Pay: Mixed	1.137	1.137	1.137	1.137	1.137
Pay: Cash or Stock	1.091	1.091	1.091	1.091	1.091
Max VIF	1.137	1.137	1.137	1.137	1.137

Mean-Adjusted Model					
Breusch-Pagan Test (Heteroskedasticity Diagnostic)					
Statistic	CAR(T-0)	CAR(-1,+1)	CAR(-2,+2)	CAR(-5,+5)	CAR(-20,+5)
LM statistic	100.442	88.922	111.423	62.853	89.543
LM p-value	0.004	0.032	0.000	0.587	0.029
F statistic	1.731	1.463	2.011	0.938	1.477
F p-value	0.001	0.019	0.000	0.613	0.017
N	344	344	344	344	344
Market-Adjusted Model					
Statistic	CAR(T-0)	CAR(-1,+1)	CAR(-2,+2)	CAR(-5,+5)	CAR(-20,+5)
LM statistic	105.613	89.450	101.251	61.107	60.617
LM p-value	0.001	0.029	0.003	0.647	0.664
F statistic	1.859	1.475	1.751	0.907	0.898
F p-value	0.000	0.017	0.001	0.677	0.695
N	344	344	344	344	344