

Louvain School of Management

What is the impact of M&A on the value of publicly traded acquiring companies in the cybersecurity sector?

Author: Olivia De Munter

Supervisor: Professor Grégoire Philippe

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Foreword

First of all, I would like to express my sincere gratitude to my thesis supervisor, Professor Philippe Grégoire, for his time, his valuable feedback and guidance.

I would also like to extend my deepest appreciation to my family, especially my parents, who gave me the opportunity to pursue higher education. I also want to thank them for their constant presence, support and unwavering encouragement throughout every stage of my academic journey.

Finally, I wish to thank all the people who accompanied me during my years at the Université catholique de Louvain and who made these past five years an unforgettable experience.

— Olivia De Munter

Abstract

This thesis investigates the impact of mergers and acquisitions (M&A) on the value of publicly traded acquiring firms in the cybersecurity sector. Despite the rapid consolidation that has reshaped the industry since the acceleration of digital transformation, no prior study has quantitatively examined the stock-market response to M&A announcements made by pure-play cybersecurity acquirers. This thesis addresses that gap.

Using an event study methodology, a sample of 71 acquisitions announced by 12 US-listed, pure-play cybersecurity firms between January 2021 and March 2026 is analysed. Cumulative abnormal returns are computed over three event windows $[-1, +1]$, $[-2, +2]$ and $[-5, +5]$ using the market model with the NASDAQ Composite as benchmark. The robustness of the findings is verified against the S&P 500. A cross-sectional regression then examines whether three deal-level determinants (method of payment, cross-border status and relative target size) explain variation in acquirer returns.

The results show that M&A announcements made by pure-play cybersecurity acquirers generate statistically significant negative abnormal returns at the 5% level across all three event windows, with a mean $CAR[-1, +1]$ of -1.31%. Only 42.3% of deals show a positive $CAR[-1, +1]$, indicating that the negative reaction is not driven by a few outliers. This finding contradicts the dominant tech literature, which typically documents positive bidder returns for high-tech acquirers. However, it aligns with the general M&A consensus of neutral-to-negative acquirer returns and is in line with theoretical explanations, such as the hubris hypothesis, free cash flow theory and investor uncertainty about target valuation. The cross-sectional analysis finds no robust evidence that the method of payment, cross-border status or relative target size explain differences in returns within the sample.

These results provide the first sector-specific evidence on cybersecurity M&A performance and they invite further research into the long-term performance of these deals and the sector-specific factors that shape investor response.

Keywords: mergers and acquisitions, cybersecurity, event study, cumulative abnormal returns, acquirer returns, platformisation

UNIVERSITÉ CATHOLIQUE DE LOUVAIN
Louvain School of Management

Place des Doyens, 1 bte L2.01.01, 1348 Louvain-la-Neuve
Boulevard Emile Devreux 6, 6000 Charleroi, Belgique
Chaussée de Binche 151, 7000 Mons, Belgique

www.uclouvain.be/lsm

Glossary of cybersecurity terms

Cloud computing: A model for enabling ubiquitous, convenient, on-demand network access to a shared pool of computing resources (e.g., networks, servers, storage, applications and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction (NIST, 2011, SP 800-145).

Cloud security: The set of policies, controls and technologies that protect data, applications and infrastructure hosted in cloud computing environments. It addresses the unique risks posed by the shared, on-demand nature of cloud resources (CrowdStrike, 2026).

Cloud workloads: A logical bundle of software and data that is present in, and processed by, a cloud computing technology. Securing cloud workloads means protecting the running applications and services rather than only the underlying infrastructure (NIST SP 1800-19B).

Code-to-cloud security: A unified security approach that protects cloud-native applications across their entire lifecycle, from the source code at the development stage through to the workloads running in production. It combines application security testing during development with runtime protection of the deployed application (CrowdStrike, 2026).

Containers: A method for packaging and securely running an application within an application virtualisation environment. Containers bundle an application with everything it needs to run (code, libraries, dependencies) and are widely used in cloud-native architectures (NIST SP 800-190).

DevOps: Development operations refers to a set of practices for automating the processes between software development and information technology operations teams enabling them to build, test and release software faster and more reliably. The goal is to shorten the systems development life cycle and improve reliability while delivering features, fixes and updates frequently in close alignment with business objectives. (NIST SP 800-16B).

Endpoints: Any device that is used to access a digital identity on a network, such as laptops, desktops, mobile phones, tablets, servers, Internet of Things devices and virtual environments. Endpoints are common entry points for cyberattacks (NIST SP 800-63-4).

Identity and access management (IAM): The administration of individual identities within a system. In enterprise IT, IAM establishes and manages the roles and access privileges of

network users, ensuring that the right individuals have access to the right resources at the right time (NIST SP 800-229).

Internet of Things (IoT): The network of devices that contain the hardware, software, firmware and actuators which allow the devices to connect, interact and freely exchange data and information. The rapid expansion of IoT has significantly enlarged the attack surface available to cybercriminals (NIST SP 1800-172).

Operational Technology (OT): OT refers to programmable systems or devices that interact with the physical environment, such as industrial control systems, building management systems and manufacturing equipment (NIST SP 800-82r3).

Privileged access management (PAM): Privileged access management helps organisations manage and secure access to their most critical systems, applications and data, which are typically reserved for privileged accounts. Privileged accounts have elevated permissions and capabilities, allowing these users to perform various administrative tasks, access sensitive information and make changes that typical users cannot. (CrowdStrike, 2026).

Security operations: Process intended to deny to potential adversaries information about capabilities and intentions by identifying, controlling and protecting generally unclassified evidence of the planning and execution of sensitive activities. (CNSSI 4009-2015).

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Chapter 1: Introduction

Cybersecurity has become one of the fastest-growing industries in the global economy. The accelerating digitalisation of business processes, as well as the rise of cloud computing and artificial intelligence lead to an increasingly hostile threat landscape marked by ransomware attacks. The global cybersecurity market reached approximately USD 271.8 billion in 2025 and is expected to grow at a compound annual growth rate of 11.9% until 2033 (Grand View Research, 2026). As the industry has grown, the way cybersecurity companies compete has changed. Leading players no longer position themselves as single-product vendors, but as integrated platforms that cover all enterprise security needs. In this platformisation context, combined with structural fragmentation and rapid threat evolution, mergers and acquisitions have emerged as the dominant strategy for cybersecurity companies' performance. Between 2021 and early 2026 alone, the sector experienced a wave of consolidation that included some of the largest deals in its history, most notably Palo Alto Networks' USD 25 billion acquisition of CyberArk in 2025.

The empirical evidence accumulated over several decades on mergers and acquisitions (M&A) is mixed, but a consensus can be reached. Targets are clear winners, with large positive abnormal returns around the announcement date, while acquirers experience reactions that are neutral to slightly negative (Agrawal et al., 1992; Andrade et al., 2001; Bruner, 2001; Campa & Hernando, 2004; Jensen & Ruback, 1983). However, some studies document positive effects in specific contexts, such as international acquisitions or cash-financed deals (Doukas & Travlos, 1988; Travlos, 1987). The technology sector stands out in M&A literature. Most studies suggest that investors react more favourably to high-tech acquisitions because of the innovation and intellectual property potential of the targets (Kohers & Kohers, 2000). Whether cybersecurity acquirers fit this general pattern or whether the platform dynamics that characterise the sector generate a distinctive market response remains an open empirical question.

The performance of an acquisition can be assessed through three main methodologies. First, accounting-based measures examine post-merger changes in financial statements. Second, qualitative assessments rely on interviews and case studies. Third, stock market-based measures capture investor expectations at the moment new information becomes available, they are particularly suitable for sectors with rapid technological change. Within this last category, the event study methodology, formalised by MacKinlay (1997), has become the dominant approach in the short-term M&A literature. It isolates the impact of a specific announcement on shareholder wealth by measuring abnormal stock returns around the event date. This is the methodology adopted in the present study.

Despite the importance of the cybersecurity sector and its recent consolidation wave, no event study has so far focused exclusively on US-listed, pure-play cybersecurity acquirers between 2021 and 2026. The few studies that address cybersecurity M&A either treat the sector as part of a broader technology sample or adopt a qualitative perspective. Given that acquirer returns vary significantly across industries, time periods and deal characteristics, the absence of a cybersecurity quantitative study constitutes a meaningful gap in the literature (Bruner, 2001; Netter et al., 2011). The period between 2021 and 2026 is particularly relevant, as it captures the post-pandemic acceleration of digital transformation, the rise of AI-powered threats and the platformisation of the cybersecurity industry. This thesis, therefore, addresses the following research question:

What is the impact of M&A on the value of publicly traded acquiring companies in the cybersecurity sector?

To answer this question, an event study methodology is applied to a sample of 71 acquisitions announced by 12 US-listed, pure-play cybersecurity firms between January 2021 and March 2026 (drawn from an initial dataset of 73 deals across 13 firms, with two deals excluded due to insufficient pre-event trading history). The sample is restricted to pure-play firms to ensure that observed returns reflect cybersecurity-specific dynamics rather than broader technology trends. Cumulative abnormal returns are computed for three event windows around the announcement date and tested for statistical significance against the null hypothesis of no market reaction. Beyond the average market effect, the study also investigates which deal-level metrics influence shareholder response, focusing on three consistently studied determinants in existing literature: the method of payment, the cross-border versus domestic nature of the transaction and the relative size of the target.

The remainder of this thesis is structured as follows. Chapter 2 reviews the academic literature on M&A performance. It highlights the different approaches used to measure it, summarises the empirical evidence on acquirer stock performance in the general M&A and tech literatures, examines the specific context of the cybersecurity sector and identifies the research gap. Chapter 3 describes the methodology, including the sample selection process, the hypotheses tested, the event study design and the market model used to estimate abnormal returns. Chapter 4 presents the empirical results, covering descriptive statistics, the cumulative abnormal returns and the cross-sectional analysis of deal determinants. Chapter 5 discusses the findings, highlights the practical implications for cybersecurity companies, managers and investors, and identifies the limitations of the study. Chapter 6 provides the conclusion of the thesis.

Chapter 2: Literature review

This chapter reviews the academic literature on which the study of acquirer stock performance in M&A cybersecurity is built. Its purpose is to describe the theoretical mechanisms of M&A, to justify the methodological choices made in Chapter 3 and to identify the gap that this thesis aims to fill.

Section 2.1: Motives and strategic drivers of M&A

The historical evolution of M&A activity shows a significant increase in deal volume over the past few decades, establishing M&A as a strategic tool for corporate growth. Academic research identifies several motives for companies initiating deals. These motives can be classified into three categories: value neutrality, value creation and value destruction (Bruner, 2004; Halebian et al., 2009). The value-neutral perspective states that the impact on company value is minimal, the objective being to maintain the company's market position. While this category provides useful background for understanding defensive or mimetic market behaviour towards competitors, this study will focus on the value-creation and value-destruction frameworks.

2.1.1 Theories of value creation

The value creation category aims to improve firm value, mainly by seeking synergies. Prior research highlights several key drivers, including increased market power and the acquisition of new resources (Halebian et al., 2009). Other research identifies factors like efficiency gains and cost reductions that are unified under one "umbrella term", called synergies, which are the key determinants for companies to take part in mergers and acquisitions (Bauer & Friesl, 2024).

2.1.1.1 The pursuit of synergy

Synergies are the main driver of M&A transactions that generate positive total shareholder returns (Berkovitch & Narayanan, 1993; Bradley et al., 1988). This term is often described by the phrase "the whole is greater than the sum of its parts," with the general understanding that $1+1=3$ (Bauer & Friesl, 2024). This means that the combined value of the acquirer and the target exceeds the sum of the two independent entities' value (Bauer & Friesl, 2024). Research emphasises that synergies can be categorised into different types: functional, business model and strategic synergies (Bauer & Friesl, 2024).

Functional synergies

Functional synergies arise when the combined firm achieves cost savings and efficiency gains beyond what the two firms could produce independently. These gains fall into two categories. Economies of scale occur when the average unit cost declines as output increases, typically

through the elimination of redundant operations, overlapping administrative functions and duplicated fixed costs (Motta, 2004). Economies of scope arise when producing several products or services jointly is cheaper than producing them separately, by leveraging shared resources across business lines (Motta, 2004).

Business model synergies

Business model synergies concentrate on improving the acquirer's revenue-generating potential. They are external, changing how the combined company generates and captures value in its market, while functional synergies emphasise on internal efficiency (Bauer & Friesl, 2024). This synergy category can be divided into two strategic mechanisms: revenue and portfolio optimisation, and competitive position improvement through pricing and brand perception (Bauer & Friesl, 2024).

Strategic synergies

Strategic synergies are forward-looking and aim to reshape the business, whereas functional and business model synergies concentrate on combining or enhancing current frameworks. By enabling the creation of completely new business models and revenue streams that neither of the companies could have realised independently, they represent the greatest potential for long-term wealth generation. These synergies can occur through R&D breakthroughs, capability development and business scaling (Bauer & Friesl, 2024).

2.1.2 Theories of value destruction

Despite mergers and acquisitions being frequently presented as a means of adding value, studies reveal that they can sometimes result in value destruction. This usually occurs when a managers' self-interest drives a transaction, rather than the interests of the shareholders.

2.1.2.1 Agency theory and empire building

The agency theory in M&A literature describes the separation between ownership and control, which occurs when the interests of shareholders (principals) and managers (agents) diverge (Jensen & Meckling, 1976). Instead of pursuing transactions that increase shareholder wealth, managers frequently make decisions to maximise their own personal interests. This is also illustrated by Jensen's (1986) free cash flow theory. Jensen (1986) claims that managers have two options when the company earns more than it can invest profitably: either spend the money or distribute it to shareholders as dividends. The author shows that managers often choose against shareholders and acquire companies even when they don't add value (Jensen, 1986). The empire-building motive is closely associated with Jensen's theories. Given that executive salaries are frequently correlated with the size and complexity of the company, managers in this situation primarily want to expand the company to enhance their own status, authority and

income (Jensen & Meckling, 1976). Haleblan et al. (2009) support this by demonstrating that industries with higher levels of CEO compensation generally exhibit greater acquisition activity.

2.1.2.2 Hubris theory and overpayment

In contrast to the agency theory, the hubris theory does not assume that managers act in their own best interests. According to the hubris hypothesis, managers frequently overestimate their ability to create value through acquisitions, which leads to overpaying for target companies (Roll, 1986). The hubris hypothesis suggests that managers are well-intentioned, but blinded by their own overconfidence. Executives' overconfidence can lead to a higher acquisition premium, which is the extra amount a company is ready to pay above market value to acquire a target. Evidence shows that excessive premiums are negative correlated with acquiring firm returns. The disproportionate premium paid constitutes a direct transfer of wealth from the acquirer's shareholders to the target's shareholders, rather than creating value through synergies (Haleblan et al., 2009).

2.1.2.3 Winner's curse and competitive bidding pressure

The winner's curse is another explanation for value destruction in M&A, which is caused by competitive bidding between several potential buyers (Roll, 1986). The winner's curse is a concept that explains why the winner of a bidding war is usually the loser financially (Varaiya, 1988). If there is competition between several potential buyers, the winning bid represents the most optimistic (and often incorrect) valuation of the target. This competition usually results in overpayment (Varaiya, 1988). In this situation, the value destruction is caused by the structural pressures of the auction process itself, rather than personal greed (agency) or ego (hubris). However, research shows that views on competitive pressure remain mixed. Studies suggest that competitive bidding can enhance a target's valuation and price setting. Improving price discovery through bidding wars is useful when the target's value is hard to determine (Mulherin et al., 2017). The effect of competition on M&A transactions often depends on external factors, such as market conditions and information asymmetry.

Section 2.2: Measuring M&A performance

Researchers have developed different approaches to measure the performance of an acquisition. These methodologies are generally divided into three distinct categories: qualitative or subjective assessments, accounting-based measures and stock-market-based measures (Adnan & Hossain, 2016).

2.2.1 Qualitative or subjective measures of performance

The finance literature describes qualitative or subjective performance measures as assessments of the strategic objectives of an M&A deal. These assessments of revenue growth, market share expansion and product development are made through surveys and interviews of executives or experts as well as clinical studies (in-depth case studies of individual transactions) (Brock, 2005; Bruner, 2001; Hayward, 2002).

2.2.2 Accounting-based measures of performance

The accounting-based method evaluates acquiring companies' accounting statements before and after the integration and is a long-term measure of performance. Different indicators can be used, such as net income, return on equity (ROE), return on assets (ROA) and liquidity. These indicators are then compared with similar non-acquirers, matched by industry and firm size. The objective is to determine whether acquiring firms perform better than comparable non-acquiring companies (Bruner, 2004; Motis, 2007). This approach intends to determine whether mergers generate efficiency gains, cost reductions or improvements in profitability (Kaplan, 2006).

Advantages and limitations

The accounting-based approach offers four main advantages. First, it captures actual operational results, allowing researchers to identify whether the expected synergies have materialised in practice. Second, it relies on audited financial statements rather than market reactions, providing factual and less volatile data than stock prices. Third, because financial statements are standardised, the method enables comparisons across firms, industries and time periods, and can also be applied to private firms that lack stock market data. Finally, evaluating performance over several years allows sufficient time for merger benefits to materialise (Bruner, 2001; Kaplan, 2006; Motis, 2007).

Despite these strengths, the accounting-based method suffers from several limitations. First, its reliance on peer comparisons may misrepresent the analysis when the acquisition itself influences competitor behaviour or broader industry dynamics. Second, external factors unrelated to the deal, such as macroeconomic conditions, can affect accounting performance and make it difficult to isolate the impact of the transaction. Third, post-acquisition adjustments in accounting practices, including asset revaluations and restructuring expenses, can distort financial statements and complicate before-and-after comparisons (Kaplan, 2006).

2.2.3 Stock market-based measures of performance

One of the most common ways researchers evaluate mergers and acquisitions are the stock market-based measures. This method assesses variations on the stock market and reflects whether shareholders expect value creation from the acquisition. This approach suggests that

financial markets absorb new information quickly, meaning that any changes in stock prices should reflect only investors' expectations of the acquisition's impact (Fama, 1970). Unlike the accounting method that reflects past operational performance, this method is forward-looking and reflects future expectations. This approach is commonly separated into long-term and short-term performance measures.

2.2.3.1 Long-term market performance

Long-term market performance means determining whether acquisitions create value for shareholders after the integration process is complete. Value creation is examined over long periods of time, typically three to five years after the transaction. However, while long-term analyses provide insights into the realised outcomes of acquisitions, many researchers consider short-term announcement returns to be a more reliable indicator of expected value creation (Renneboog & Vansteenkiste, 2019).

2.2.3.2 Short-term market performance

Short-term stock market performance looks at how investors react right after a merger or acquisition is announced. Analysts focus on stock price movements around the announcement to see how quickly and in what direction the market absorbs new information about the deal. This perspective demonstrates how financial markets evaluate a transaction's potential to create value as soon as information becomes publicly available.

2.2.3.2.1 Event study

The event study methodology is the most common way to measure the performance of an acquisition on the stock market in the short term. This approach measures the impact of a specific event on the value of a company (MacKinlay, 1997). In the M&A literature, this methodology examines a company's abnormal stock returns around the M&A announcement to determine whether the event creates or destroys value for shareholders (Haleblian & Finkelstein, 1999). Abnormal returns are equal to the difference between the actual return and the expected return of the stock given normal market movements (Brown & Warner, 1980). The event study is the dominant empirical method because it isolates the impact of a specific event. This approach will be used to evaluate if the value of cybersecurity firms increases after an acquisition.

The fundamental assumption for event studies is the market efficiency theory. The event study assumes that financial markets are efficient, meaning that stock prices quickly incorporate new public available information, as mentioned in Subsection 2.2.3 (Fama, 1970). In M&A deals, this means that the acquiring company's stock price reflects all available information about the

M&A announcement (Andrade et al., 2001). A second methodological assumption, often referred to as the absence of confounding events, is that no other corporate or sector-specific news occurs within the event window (MacKinlay, 1997). Such news would contaminate the abnormal returns. According to these theories, the market's response to the event under study can be deduced from the abnormal returns seen during the event window (Țilică et al., 2012). In practice, these assumptions are rarely fully met and the credibility of an event study rests on identifying any violations.

Advantages and limitations

The event study method offers three main advantages. First, the methodology gives an early signal of whether investors believe the acquisition will create or destroy value. Share price movements around the announcement reflect shareholders' expectations about the deal's potential synergies, integration risks and strategic implications. Second, the approach relies on a broad and transparent base of information. Stock prices aggregate the views of many informed market participants and allow researchers to study large samples of deals across industries, time periods and geographies. Third, as mentioned previously, by focusing on a narrow event window around the announcement, the method isolates the market's reaction to a specific event and limits, without fully removing, the influence of unrelated macroeconomic or industry trends (Fama, 1970; MacKinlay, 1997).

Despite these strengths, the stock market-based approach suffers from two main limitations. First, event studies rely on strong informational assumptions, namely market efficiency and the absence of confounding events. When these assumptions are violated, observed stock price reactions may not accurately reflect the deal's true economic impact and abnormal returns cannot be attributed solely to the acquisition announcement. Second, the method captures expectations rather than realised performance. Shareholders may expect synergies or strategic benefits, but these expectations do not always materialise in practice (Fama, 1970; MacKinlay, 1997).

Section 2.3: Empirical evidence on acquirer stock performance

2.3.1 General empirical consensus

2.3.1.1 Medium- and long-term stock performance

Medium- and long-term M&A performance on the market is considered even more complex and mixed than short-term performance. Stock returns in the long run are more sensitive to other events, making it more challenging to interpret the results (Andrade et al., 2001). However, past literature suggests that acquiring firms often suffer from long-term underperformance following a deal's completion. According to Agrawal et al. (1992), with an

analysis of 1,164 M&A deals between 1955 and 1987, shareholders of acquiring firms incur a significant loss of around 10.0% over five years. On the contrary, Alexandridis et al. (2017) document that after 2009, M&A transactions have become significantly value-creative for acquiring firm shareholders, mentioning 1.05% positive abnormal long-term returns between 2010 and 2015. The authors argue that it is due to better organisational skills and disciplined management teams after the 2009 crisis (Alexandridis et al., 2017).

2.3.1.2 Short-term stock performance

Research on M&A performance in the short term is also mixed; studies have demonstrated both positive and negative results. However, after a few decades of research, a consensus can be reached about short-term announcement effects. Stock market-based measures usually distinguish acquirer returns, target returns and combined (acquirer and target) returns. Overall, targets are clear winners, acquirer returns are neutral to slightly negative, while the combined returns are usually positive (Andrade et al., 2001; Bruner, 2001; Jensen & Ruback, 1983). However, acquirers' returns vary significantly by deal attributes, sample restrictions, market and time period (Bruner, 2001; Netter et al., 2011).

Andrade et al. (2001) report, in their study of 3,688 completed mergers in the US between 1973 and 1998, a positive combined abnormal return of 1.8%. Targets demonstrate larger gains of 16.0%, while acquirers show statistically weak results of -0.7% over three days (Andrade et al., 2001). This means that M&A deals, on average, create positive overall gains, benefit targets significantly and break even for the bidding-firm shareholders (Jensen & Ruback, 1983). Martynova & Renneboog (2011) find similar results by analysing European acquisitions between 1933 and 2001, with large abnormal returns of 9.1% for targets and a low statistically significant return of 0.53% for acquirers. Campa & Hernando (2004), through an analysis of 262 M&A announcements, also find that target firms gain value from acquisitions, while shareholders of bidder firms gain insignificantly negative returns around the M&A announcement. Other studies find positive bidder returns (Asquith et al., 1983; Douka & Travlos, 1988; Travlos, 1987). In Japan, van Schaik & Steenbeek (2004) report around 1.4% positive abnormal returns and in India, Rani et al. (2015) find approximately 3.5% of positive abnormal returns.

2.3.1.3 Tech sector stock performance

Scientific research on technology and high-tech industries is less extensive and shows that the stock market's response to an acquisition deviates slightly from the consensus on M&A performance. Even though the literature frequently reports small or negative abnormal returns for acquiring firms, shareholders perceive tech-sector M&A deals as more valuable. Research examining tech M&A deals finds that announcements of tech-oriented acquisitions can lead to

positive abnormal returns for acquiring firms. Finance literature on negative acquirer returns in tech M&A is harder to find. Kohers & Kohers (2000) show through an analysis of 1,634 mergers that occurred between 1987 and 1996, that high-tech acquirers of high-tech targets obtain significantly positive abnormal returns of 1.7%. They attribute this outcome to the market's confidence in the potential synergies associated with deals in the high-tech sector. Conn et al. (2005) also indicate that acquisitions in the high-tech sector lead to positive returns for bidder shareholders. Other sector-specific studies also document positive returns. Higgins & Rodriguez (2006) demonstrate that bidder shareholders in the pharmaceutical industry earn positive returns of 3.91%. Kallunki et al. (2009) find that when a tech firm acquires another tech firm, the magnitude of the stock price response to the acquirer's R&D spending increases by 107% in the year of the M&A, compared to non-technology acquirers where no such effect is observed.

Two main factors of M&A performance in the high-tech sector are innovation and the organisation capabilities of the acquiring firm. Acquisitions in tech-intensive industries are often driven by innovation, intellectual property and knowledge acquisition. Most shareholders view innovative targets as strategic investments that enhance the acquiring company's technological abilities. The long-term performance of the acquisition depends on the acquiring company's ability to integrate the new technologies and achieve the anticipated innovation synergies. Past experience shows that companies with good organisational skills or past acquisition experience typically have better post-acquisition results. Companies are better prepared to integrate new technologies and achieve superior financial performance when they build up on the knowledge gained from prior acquisitions (Zollo & Winter, 2002). A study by Kaufmann & Schiereck (2023) of 786 technology acquisitions in the US between 2000 and 2019 found that acquirers often pay higher prices for innovative targets. The authors report no negative stock returns for innovative acquirers, but do for non-innovative acquirers, highlighting the importance of the ability to integrate the innovative target (Kaufmann & Schiereck, 2023).

2.3.2 Determinants of acquirer returns

2.3.2.1 Method of payment

The most prominent determinant of the market reaction to an announcement is the payment method. An acquisition can be paid by cash, by stock or by a mix of both. Research shows that stock-financed deals predominantly lead to negative bidder's shareholders reactions, whereas all-cash bids yield higher target and bidder returns (Borodin et al., 2020; Martynova et al., 2006; Travlos, 1987). Andrade et al. (2001) demonstrate that acquirers using stock have a negative abnormal return of -1.5%, whereas acquirers using no stock have a positive abnormal return around of 0.4%, which is not statistically different from zero. When a transaction is paid in

stock, the bidder believes its shares are overvalued, whereas a full cash offer indicates the acquirer's stock is undervalued (Kaplan, 2006).

2.3.2.2. Type of target

A consistent finding across decades of research is that acquirers of private targets earn significantly higher returns than those who acquire public firms. Fuller et al. (2002) demonstrate larger returns for bidder shareholders when the firm acquires a private target compared to a public target. Martynova & Renneboog (2011) also state that the private status of the target is associated with higher acquirer returns. The main reason is that acquiring a private company is cheaper than a public target (Officer, 2006).

2.3.2.3 Cross-border versus domestic acquisitions

An acquisition can be made between two companies from the same country (domestic acquisition) or from different countries (cross-border acquisition). The market reaction in this case is quite mixed as cross-border M&A combines potential benefits (new markets, new resources) with potential value-destruction factors (distance, regulatory complexity, information asymmetry). Moeller & Schlingemann (2005), with a sample of 4,430 acquisitions in the US, demonstrate lower abnormal returns for acquiring cross-border targets. In contrast, Doukas & Travlos (1988) reveal larger abnormal returns when companies expand into new geographic markets, especially in less developed countries. There is no universal consensus in the literature regarding whether cross-border acquisitions outperform domestic deals; the effect depends heavily on the countries involved, the integration capability and deal-specific conditions.

2.3.2.4 Relative target size

The size of the target company is relatively important as it determines the acquirer's capacity to integrate the target. The evidence on this determinant is mixed. Some studies indicate lower returns for the acquirer's shareholders due to the complexity and uncertainty in big transactions (Alexandridis et al., 2011). In contrast, Asquith et al. (1983) show that acquiring firms earn higher abnormal returns when the target company is large relative to the acquirer's own size. For instance, a target half the size of the acquirer yields significantly better returns than one only a tenth of its size (Asquith et al., 1983).

Section 2.4: Cybersecurity market context

2.4.1. Cybersecurity sector dynamics

The cybersecurity industry is currently experiencing an important growth phase driven by accelerating digitalisation, geopolitical tensions and the increasing frequency of cyber threats.

The cybersecurity sector has become a key component of companies' corporate strategy. In 2025, the sector's market size was valued at USD 271.9 billion, as shown in Figure 1 in Appendix 1 (Grand View Research, 2026). The amount of cyber threats has significantly increased in the world due to the rapid development of cloud computing, AI integration, Internet of Things (IoT) ecosystems and industrial digitalisation. The AhnLab 2025 Threat Landscape & 2026 Outlook reports that the total number of cyberattacks detected in 2025 increased by 78% from the previous year. Around 880,000 complaints were filed by the American public in 2023, up 10% from 2022, according to the FBI's Internet Crime Complaint Centre (Fortune Business Insights, 2026). This change has led to a huge boom in the industry. Businesses are installing cybersecurity solutions to defend their vital networks, data, users and endpoints against such attacks. According to Fortune Business Insights' report (2026), cloud security, identity access management (IAM) and security operations platforms are the main drivers of the high growth in end-user spending on information security worldwide. The global cybersecurity market is anticipated to reach around USD 302 billion by 2026 and expand at a compound annual growth rate (CAGR) of 11.9% by 2033 (Grand View Research, 2026). The industry's growth trajectory is going to remain strong in the years to come. In the future, cybersecurity will likely remain one of the industries with the fastest growth rate due to the complexity of the threat landscape.

2.4.2. Consolidation drivers in the cybersecurity sector

The cybersecurity sector has experienced a sustained acceleration of M&A activity over the past years, especially since 2020, due to the following three main drivers (Figure 2 in Appendix 2).

2.4.2.1 Market fragmentation

For companies operating in a fragmented market, M&A is not just an option, but a strategic necessity to reach the scale required to compete with global digital giants. The growing diversity in the technological sector, with specialised domains such as cloud, DevOps, generative AI and IT/OT, expands the overall attack surface and increases the demand for cybersecurity. As a result, cybersecurity firms are likely to consolidate in order to offer broader, end-to-end coverage across these interconnected areas.

2.4.2.2 Rapid technological evolution

While market fragmentation provides the structural reason for consolidation, technological evolution provides the temporal pressure. The AI revolution and the rapid pace of tech development have made organic development increasingly difficult for many businesses. Companies are finding that the time required to build specialised tech internally is longer than

the competitive advantage it provides. Consequently, M&A becomes the only viable route to acquire technological capabilities before the market shifts again.

2.4.2.3 Platform strategies

An additional explanation lies in platform strategies or platformisation. An increasing share of cybersecurity firms have adopted a platform-based business model, in which value creation depends on managing network effects between distinct user groups rather than on the sale of stand-alone products (Belleflamme & Peitz, 2021; Belleflamme & Neysen, 2023). Acquisitions play a central role in this business model, which makes the platform angle particularly relevant for interpreting cybersecurity M&A activity.

According to Belleflamme & Peitz (2021), a platform is an entity that brings together economic agents and manages network effects between them. Network effects describe the impact that an additional user has on the value that other users attach to the product or service. This distinguishes platforms from vertically integrated firms, whose value creation is linear rather than networked (Belleflamme & Peitz, 2021). Leading cybersecurity firms no longer compete by selling a single product, but by offering an integrated platform that brings together multiple user sides. When rival platforms are incompatible with one another and/or users are restricted to be active on a single platform, a platform increases its audience at the expense of its competitors. Moreover, additional users make participation more valuable for existing users, generating a self-reinforcing dynamic where a few platforms capture a disproportionate share of value. Each new customer adds more threat data, helping the platform detect and respond to attacks more effectively for all its other customers. Therefore, as one platform grows, rival platforms tend to stagnate or even shrink, ultimately creating a winner-takes-all dynamic (Belleflamme & Peitz, 2021). These network effects explain why platform competition tends to tip toward dominant players and why cybersecurity companies face strong incentives to consolidate.

Next to network effects, economies of scope provide a significant justification for acquiring additional platforms. Belleflamme & Neysen (2023) advise platform companies, as a key growth strategy, to diversify their established platforms, which is expanding the platform into new features or adjacent user bases. Belleflamme & Peitz (2021) give two explanations for growing in adjacent markets. These are explicitly related to platforms. First, supply-side economies of scope arise when the joint provision of several services is cheaper than their separate provision. The reason is that spare capacities in the initial market (software, data and user base) can be efficiently reused. Second, demand-side economies of scope arise when users' willingness to pay for different products or services increases when they are available on the same platform rather than on different platforms. Several factors contribute to this:

complementarities, convenience, trust in the initial brand and the platform's ability to leverage its existing user base to activate network effects. Rather than building the new technology internally, the platform acquires a target that already possesses the relevant tech, user base or data, and integrates it into its existing business model to attain economies of scope (Belleflamme & Peitz, 2021).

2.4.3. Transaction trends

To illustrate the consolidation and platformisation dynamics described in the previous subsections, this subsection examines three acquisitions undertaken by sample firms. These three deals have been selected because they involve the biggest cybersecurity firms and capture the diversity of cybersecurity transactions.

2.4.3.1 Acquisition of CyberArk by Palo Alto

Acquirer: Palo Alto Networks is a US-based, global AI and cybersecurity leader. The company provides comprehensive AI-powered security solutions across the network, cloud, security operations and AI. The cybersecurity firm focuses on platformisation to streamline security at scale. With 80,000 customers, Palo Alto achieved USD 9.2 billion of revenue in 2025 (Palo Alto Networks, 2025).

Target: CyberArk, legally incorporated in Israel, was the global leader in identity security and focused on privileged access management (PAM). The company had an AI-powered identity security platform that controls the identity lifecycle through continuous threat prevention, detection and response. CyberArk achieved a revenue of USD 1.4 billion in 2025 thanks to its 10,000 clients (CyberArk, 2026).

Announcement/closing date: July 30, 2025/February 11, 2026

Price: USD 25 billion. Palo Alto acquired CyberArk in a cash-and-stock transaction. The company paid USD 45 in cash per CyberArk share and 2.2005 shares of Palo Alto stock per CyberArk share. The price implies a CyberArk's EV/Sales multiple of 19x, which even in the cybersecurity sector is high, as the sector's average is 17.1x and the median is 10.3x (M&A Watch, 2025).

Stock market reaction: The announcement triggered a negative market reaction, the acquirer's stock fell by 10.4%, from USD 193.84 to USD 173.6 over window[-1, +1] due to concerns about potential integration risks and the high price paid (Yahoo Finance, 2026).

Strategic importance: The acquisition of CyberArk enables Palo Alto to establish identity security as a central element of its platformisation strategy. The integration of the target allows Palo Alto to leverage its existing customer base to activate network effects in the identity layer and to secure every identity of humans, machines and AI agents across the firm. The deal is the third-largest in cybersecurity history. For CyberArk, the acquisition by Palo Alto secures its future by leveraging a leader's resources and AI capabilities to outpace giants like Microsoft and CrowdStrike (Palo Alto Networks, 2026).

2.4.3.2 Acquisition of Bionic by CrowdStrike

Acquirer: CrowdStrike is a US-based, global cybersecurity leader protecting critical areas of enterprise risk. The company created the Falcon platform, which delivers expert-level threat hunting with precise detections, automated protection and remediation. In 2026, the cybersecurity firm had a revenue of USD 4.8 billion and serves more than 74,000 organisations (CrowdStrike, 2026).

Target: Bionic was a US-based cybersecurity start-up, however, 55% of the firm's employees were based in Israel. The company is known for the creation of application security posture management (ASPM), which is the process of evaluating, managing, enhancing and mapping the organisation's security applications. The start-up raised a total of USD 83 million before being acquired and had dozens of clients (Ctech, 2023).

Announcement/closing date: September 19, 2023/September 28, 2023

Price: USD 350 million. The purchase price was mostly paid in cash, with a small portion paid in the form of stock and options (Ctech, 2023).

Stock market reaction: The stock market reaction was rather neutral to slightly negative. Looking at window[-1, +1], there is a slight decrease of 1.84% (from USD 166.97 to USD 163.89) (Yahoo Finance, 2026).

Strategic importance: By integrating Bionic's application security posture management, the acquisition expanded CrowdStrike's cloud native application protection platform (CNAPP). This positioned CrowdStrike as the first cybersecurity firm able to deliver code-to-cloud security from a single, unified platform. The transaction between the two companies allowed Bionic to accelerate the adoption of ASPM by organisations (CrowdStrike, 2023).

2.4.3.3 Acquisition of Attivo Networks by SentinelOne

Acquirer: SentinelOne is a leading cybersecurity company that provides customers with AI-powered prevention, detection, response and hunting across endpoints, containers, cloud

workloads and IoT devices, through an extended detection and response (XDR) platform. The firm works with 12,000 organisations and achieved, in 2025, an annual revenue of USD 1 billion (SentinelOne, 2026).

Target: Attivo Networks, a US-based company, was an expert in identity threat detection and response (ITDR). The company had an identity assessment tool that provides visibility of suspicious activity. The firm had more than 300 customers and a revenue of USD 30.2 million before its acquisition (SentinelOne, 2022).

Announcement/closing date: March 15, 2022/May 4, 2022

Price: USD 616.5 million. SentinelOne acquired Attivo Networks in a cash-and-stock transaction, with a 58% cash portion and a 42% stock portion (SentinelOne, 2022).

Stock market reaction: SentinelOne's stock rose by 18.6%, from USD 29.55 to USD 35.05 over window[-1, +1] (Yahoo Finance, 2026).

Strategic importance: The acquisition strategically aimed at strengthening SentinelOne's XDR platform by adding identity threat detection and response (ITDR) capabilities. It strengthened the company's security activity by adding a new layer of defence focused on identity and credential security. Joining SentinelOne enabled Attivo to accelerate its mission thanks to the scale, brand authority and capital of a big company (SentinelOne, 2022).

Section 2.5: Identification of the research gap and research question

The literature review provides a solid theoretical and empirical explanation for M&A performance. However, after a thorough examination of current research, several limitations appear. These gaps motivate this thesis and justify its specific scope.

2.5.1 The scientific gap

Most of the significant research on M&A performance was conducted on samples that are now several decades old. The known studies in the literature, such as Andrade et al. (2001), who analysed 3,688 US mergers between 1973 and 1998, were written in a different economic and technological environment. The period from 2021 to March 2026 is an understudied window. This period was marked by a surge in cybersecurity consolidation, driven by the post-pandemic acceleration of digitalisation and the emergence of AI-powered threats. As shown in Subsection 2.4.1, the cybersecurity market reached USD 271.9 billion in 2025 and is projected to grow at a CAGR of 11.9% through 2033 (Grand View Research, 2026). This growth wave triggered significant consolidation moves, including the USD 25 billion acquisition of CyberArk by Palo

Alto in 2025, one of the three largest deals in the sector's history. Despite its relevance, this consolidation wave has not yet been studied in the academic literature.

Secondly, the scientific literature on technology M&A is more recent, but remains quite general. The few studies that address cybersecurity M&A either treat the sector as part of a broader technology sample or adopt a qualitative, rather than a quantitative stock-market perspective. Studies such as Kohers & Kohers (2000), who examined 1,634 acquisitions between 1987 and 1996, as well as Kaufmann & Schiereck (2023), who analysed 786 technology deals between 2000 and 2019, cover the tech sector as a whole. The cybersecurity industry, however, has unique characteristics that set it apart from the broader tech sector. The cybersecurity sector is a rapidly evolving field, driven by an accelerating threat landscape and a structural need for platform consolidation (Belleflamme & Peitz, 2021; Fortune Business Insights, 2026). Without a sector-specific study, it is not possible to know whether the findings of the general and tech M&A literature apply to cybersecurity acquirers.

2.5.2 The research question

The gaps identified above point to a clear need for a sector-specific study of M&A performance in the cybersecurity industry. The existing M&A literature provides strong theoretical foundations and general empirical benchmarks, but it does not speak directly to the experience of cybersecurity acquirers in the most recent consolidation wave. This study, therefore, addresses the following research question:

What is the impact of M&A on the value of publicly traded acquiring companies in the cybersecurity sector?

To answer this question, an event study methodology will be applied to a sample of US-listed, pure-play cybersecurity acquirers from 2021 to March 2026. Using abnormal returns around deal announcement dates, the study aims to analyse the short-term stock market reaction to cybersecurity M&A. In addition, it will identify which deal determinants, such as the payment method, the target's geography or the target's relative size, influence shareholders' reactions. The objective of the research is to contribute a sector-specific and time-relevant piece of evidence to a literature that, so far, has not addressed this precise question.

Chapter 3: Methodology

This chapter describes the methodology used to answer the research question. It explains how the sample was established, how the data were collected and how the event study methodology was applied to measure the impact of M&A announcements on acquiring firm value.

Section 3.1: Research design

This study adopts a quantitative research design to evaluate shareholder's reactions, of the acquiring company, on the acquisition of a target. The objective is to analyse and measure the stock market's reaction to M&A announcements in the cybersecurity sector. To achieve this goal, the study employs an event study methodology, which is the dominant approach in the corporate finance literature for analysing the impact of a corporate event on firm value (MacKinlay, 1997). By measuring abnormal stock returns around acquisition announcements, the event study isolates investors' expectations on whether a deal creates or destroys value. An event study is especially well suited to the cybersecurity sector, which is characterised by rapid technological change and high growth.

Section 3.2 Sample selection and data collection

The sample is restricted to US-listed, pure-play cybersecurity companies that made at least one acquisition between January 2021 and March 2026.

3.2.1 Cybersecurity companies selection

Four key criteria guided the selection of cybersecurity companies. First, only US companies were included to ensure a homogeneous sample and minimise geographical or currency variations. North America is the world's primary hub for cybersecurity and within the continent, the US leads the market with an estimated market value of USD 81.6 billion in 2026 (Fortune Business Insights, 2026). Second, private companies were excluded from the sample because the lack of daily stock price data prevents the calculation of abnormal returns required for an event study. Third, the US market is home to both diversified companies, such as Microsoft, as well as specialised security providers, such as Palo Alto. However, to guarantee the integrity of the analysis, the research focuses only on pure-play cybersecurity firms. A pure-play company refers to an entity whose core activity and primary revenue streams (usually around 100%) come from cybersecurity products and services. Analysing pure-play companies prevents the dilution of the stock market's reaction. In diversified firms, the stock market's reaction to a specific acquisition can be influenced by the company's other business units, making it difficult to isolate the cybersecurity sector's impact. Fourth, the research focuses exclusively on the period between 1 January 2021 and 31 March 2026, which represents the most recent and intense consolidation wave in the cybersecurity sector.

Following these criteria, a final sample of 13 US-listed, pure-play cybersecurity acquirers was established, see Table 1 in Appendix 3.

3.2.2 Cybersecurity acquisitions selection

For each of these companies, all announced acquisitions within the study period were identified, resulting in a dataset of 73 acquisitions that forms the basis of the event study (see Table 2 in Appendix 4).

Any acquisition completed within the 2021-2026 observation period, but announced prior to January 2021, is excluded from the sample. Conversely, transactions announced within the study window that are still pending completion (expected in late 2026 or 2027) are included, as the investor reaction is captured at the time of the public announcement. Moreover, only transactions in which the acquirer obtained full control over the target, defined as acquiring 100% of the target's shares or assets, were included in the sample. Minority investments, partial stakes and joint ventures were excluded. Furthermore, the sample is restricted to acquisitions occurring while acquirers are publicly trading. For example, although Rubrik acquired the company Laminar in 2023, this transaction is excluded from the dataset. This is because Rubrik's Initial Public Offering (IPO) did not occur until 2024, meaning no public market data exists to measure the announcement's impact. Lastly, the dataset also includes acquisitions of Gen Digital before its name change. In 2022, NortonLifeLock changed its name to Gen Digital following its merger with Avast. Acquisitions initiated under the NortonLifeLock identity remain in the sample, as the company maintained its status as a pure-play cybersecurity firm and continued trading under the same equity structure.

3.2.3 Deal-level data

Deal-level data, including announcement dates, closing dates, deal values and determinants of acquirer returns, were collected from four different sources. The determinants were chosen based on prior research that identifies them as the principal drivers of differences in acquirer returns. First, an extensive manual search was conducted using press releases, company investor relations pages and financial news sources. Second, the Bloomberg Terminal was used to verify and complete the dataset, particularly for announcement dates, which are the critical input for the event study. The method of payment (cash, stock or mixed), the type of target (public or private), the geographic type of transaction (cross-border or domestic) and the deal size were also recorded for each transaction. The target type was then removed from the deal determinants' analysis, as only two public targets were recorded. The relative target size was computed using market capitalisation data and deal size. Third, the market capitalisation data was taken from Companies Market Cap. Fourth, daily stock price data during the five-year

period for all 13 companies were downloaded from Yahoo Finance on RStudio, along with daily closing prices for the NASDAQ Composite index and the S&P 500 index.

Section 3.3: Hypotheses

Based on the theoretical framework and empirical evidence reviewed in Chapter 2, this study tests the following hypotheses. The main hypothesis (H_0 vs H_1) addresses the overall market reaction to acquisition announcements, while the secondary hypotheses (H_2, H_3, H_4) examine the role of deal determinants in explaining differences in acquirer cumulative abnormal returns (CARs).

H_0 : Announcements of acquisitions made by US-listed, pure-play cybersecurity companies have no significant impact on shareholder wealth. ($CAR = 0$)

H_1 : Announcements of acquisitions made by US-listed, pure-play cybersecurity companies have a significant positive impact on shareholder wealth due to the sector's high growth and innovation-driven nature. ($CAR > 0$)

H_2 : Among acquisitions made by US-listed, pure-play cybersecurity acquirers, all-cash deals generate higher CARs than all-stock or mixed deals and mixed deals generate higher CARs than all-stock deals (Andrade et al., 2001; Travlos, 1987).

H_3 : Among acquisitions made by US-listed, pure-play cybersecurity acquirers, cross-border acquisitions may generate higher CARs than domestic acquisitions due to access to new markets and capabilities, but the effect is uncertain due to integration challenges (Doukas & Travlos, 1988; Moeller & Schlingemann, 2005).

H_4 : Among acquisitions made by US-listed, pure-play cybersecurity acquirers, a larger relative target size is associated with lower CARs due to increased integration complexity and risk (Alexandridis et al., 2011).

Section 3.4: Event study methodology

3.4.1 Event and event windows definition

This research uses an event study methodology to capture investors' reactions (MacKinlay, 1997). The event of interest is the public announcement of an acquisition by one of the 13 sample companies. The variable announcement date is critical for the event study and was obtained from Bloomberg and company press releases. Under the assumption of market efficiency, it is the moment when new information enters the market and, therefore, the moment when any abnormal stock price reaction should be concentrated (Fama, 1970). Three event windows are used in this study. The primary window is $[-1, +1]$, covering three trading days centred on the announcement date. This is the most commonly used window in the event study literature and captures the immediate market reaction while minimising exposure to unrelated

market noise (Andrade et al., 2001). A secondary window of [-2, +2] is also used to detect potential information leakage in the days leading up to the announcement date. Finally, a wider window of [-5, +5] is used as a robustness check. Similar results across all three windows strengthen the reliability of the findings. In a sector as news-driven and volatile as cybersecurity, limiting the event windows to a maximum of eleven days reduces the risk of capturing stock price movements unrelated to the acquisition.

3.4.2 Estimation window

To calculate abnormal returns, it is first necessary to compute the stock's return in the absence of the deal's announcement. This computation, called the expected return, is estimated using data from the estimation window. The estimation window covers the period from 250 to 30 trading days before the announcement date, written as [-250, -30]. This window provides approximately one year of clean trading data, providing enough observations to estimate parameters accurately. The estimation window ends 30 days before the announcement to ensure that any leakage of deal information does not contaminate the normal return estimate. Using a contaminated estimation window would bias the abnormal returns and undermine the validity of the results (MacKinlay, 1997).

3.4.3 The market model

The market model is used to estimate expected returns. It is the most commonly adopted return model in M&A event studies and provides a good balance between simplicity and statistical precision (MacKinlay, 1997). The model assumes a linear relationship between the return of a given stock and the market index return. For each company i on each day t in the estimation window, the following univariate regression is estimated:

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

Where,

$R_{i,t}$ is the daily stock return of company i on day t

$R_{m,t}$ is the daily return of the market index, NASDAQ Composite index, m on day t

α_i is the estimated intercept (the stock's baseline return independent of the market),

β_i is the estimated slope coefficient (the stock's sensitivity to market movements)

$\varepsilon_{i,t}$ is the error term (assumed to have a mean of zero)

The NASDAQ Composite is used as the market index because the price movements of all 13 sample companies are closely correlated with this index. The regression is estimated using Ordinary Least Squares (OLS) over the estimation window for each company and each deal.

This produces a set of company-specific parameters α_i and β_i , which are then used to compute expected returns during the event window. A positive α_i suggests that the company's stock outperformed the NASDAQ Composite. β_i measures the sensitivity of the stock's return to movements in the market index, capturing the risk. A beta of 1 means the stock moves on average in line with the market; when the index rises by 1%, the stock rises by 1%. A beta greater than 1 indicates that the stock is more volatile than the market. The fit of each market model regression is assessed using the coefficient of determination (R^2), which measures the proportion of the variance in the stock's daily returns explained by movements in the NASDAQ Composite. R^2 ranges from 0 to 1; a value close to 1 indicates that market movements explain most of the return variation.

3.4.4 Abnormal returns (AR) and cumulative abnormal returns (CAR)

Once the expected return is estimated for each day in the event window, the abnormal return (AR) is calculated as the difference between the actual return and the expected return:

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

The abnormal return captures the portion of the stock's daily return that cannot be explained by normal market movements. A positive abnormal return indicates that the market reacted favourably to the acquisition announcement, while a negative abnormal return reflects a negative market reaction. If the abnormal return is neutral and equal to zero, then the acquisition announcement had no detectable impact on the stock price. However, a single day's AR being close to zero doesn't mean much on its own. To capture the total market reaction over the event window, the daily abnormal returns are summed to obtain the cumulative abnormal return (CAR):

$$CAR(t_1, t_2) = \sum AR_{i,t} \text{ (from } t = t_1 \text{ to } t_2)$$

CARs are calculated for each of the three event windows defined before: [-1, +1], [-2, +2] and [-5, +5]. The average CAR across all deals in the sample is then computed to assess the overall impact of M&A announcements on acquiring firm value. Once the CARs are calculated for each event window, a statistical t-test is used to assess if the average CAR across all acquisitions is significantly different from zero. The t-test is the standard significance test used in event study research and directly tests the main hypothesis H_0 (CAR = 0) against H_1 (CAR > 0) (MacKinlay, 1997). If the resulting p-value is sufficiently small, the null hypothesis is rejected, indicating the market reaction is unlikely due to random variation and the abnormal return can be attributed to the acquisition announcement itself. This research uses the conventional significance levels. The 5% threshold is the standard in finance literature; if the results are significant at the 5% level, it means that there is less than 5% probability that the CAR occurred by chance.

3.4.5 Cross-sectional analysis

Beyond measuring average ARs, this study also investigates which deal determinants influence the magnitude of the CARs. As discussed previously, the M&A literature identifies several key determinants of acquirer returns. Three variables are tested in this study in a multivariate regression. The method of payment is coded as a categorical variable, distinguishing between all-cash deals, all-stock deals and mixed transactions. Two indicator variables are created to capture this distinction, using mixed payment as the reference category. The relative target size is measured as the deal value divided by the acquirer's market capitalisation at the time of the announcement. Finally, a binary variable is included to distinguish cross-border transactions and domestic deals. A cross-sectional regression is run with the CARs as the dependent variable and these three deal characteristics as independent variables or predictors.

The explanatory power of the cross-sectional regression is assessed using the adjusted R^2 . Unlike R^2 , which increases as more predictors are added, adjusted R^2 rises only when a new variable improves the model beyond what would be expected by chance. A low adjusted R^2 indicates that the deal-level variables tested explain only a small share of the variation in acquirer returns, suggesting that other factors play a more important role. The cross-sectional sample contains very different deal sizes, payment structures and acquirer characteristics, which makes the assumption of homoscedasticity (the variance of the error term is constant across observations) unlikely to hold. To address this concern, the regression is estimated using heteroscedasticity-consistent standard errors (HC1). The use of HC1 standard errors leaves the OLS coefficient estimates unchanged, but produces t-statistics and p-values that remain valid in the presence of heteroscedasticity.

Section 3.5: Market index and benchmark

As mentioned in Subsection 3.4.3, this study uses the NASDAQ Composite index as the primary market benchmark. This choice is motivated by the composition of the sample; 11 out of the 13 sample companies are listed on the NASDAQ index. Only two companies, SentinelOne and Rubrik, are listed on the New York Stock Exchange (NYSE). In addition, the two NYSE-listed companies are likely to be more correlated with a technology-heavy index like the NASDAQ than with the broader S&P 500, which includes sectors unrelated to technology. Using a benchmark that closely tracks the sample firms produces more accurate beta estimates. To ensure robustness to the choice of market index, the full analysis is replicated using the S&P 500 as an alternative benchmark. This robustness check is a standard practice in event study research. If the main findings hold under both benchmarks, the conclusions can be considered more credible and less dependent on a single methodological assumption.

Chapter 4: Results and findings

Building on the methodology developed in Chapter 3, this chapter analyses the stock market reaction to acquisition announcements in the cybersecurity sector and assesses whether specific deal determinants help explain differences in that reaction.

Section 4.1: Descriptive statistics

4.1.1 Sample composition

The initial dataset contained 73 acquisitions announced by 13 US-listed, pure-play cybersecurity companies between January 2021 and March 2026. Two deals were excluded from the event study due to insufficient pre-event trading history. First, the acquisition of Diamond Fortress Technologies by Telos Corporation was removed. Second, the acquisition of Attivo Networks by SentinelOne, discussed in Subsection 2.4.3.3 due to its illustration of the platformisation dynamic, was also excluded from the sample. These exclusions occurred because the companies' IPOs occurred less than 250 days before the acquisitions, making the estimation window too short to compute reliable expected returns. This leaves a final event study sample of 71 valid observations across 12 acquirers. Telos Corporation contributed no valid deals and is, therefore, absent from the final results. The distribution of deals across acquirers is uneven, as shown in Table 3 in Appendix 5. CrowdStrike is the most active acquirer with 10 deals, accounting for 14.1% of the sample. At the other extreme, Rubrik contributes only one valid observation. This reflects its recent listing history: the company completed its IPO on the NYSE in April 2024, leaving limited pre-event estimation data available for earlier transactions.

4.1.2 Deal determinants

The regression subsample is smaller than the event study sample because the regression analysis requires complete information on all explanatory variables. Of the 71 event study observations, 48 transactions contain complete deal-level data for the cross-sectional analysis. Deal value, payment method and target geography were not available for all transactions. As reported in Table 4 in Appendix 6, the sample is dominated by all-cash transactions, which account for 66.7% of deals. This is consistent with the broader M&A literature's findings that cash financing is the dominant payment method for acquisitions. Mixed payment accounts for 31.2% of deals. All-stock financing appears in only one transaction, creating a distributional imbalance with important implications for the interpretation of cross-sectional regression results. In terms of geography, 62.5% of deals are domestic and 37.5% are cross-border. This distribution reflects both the global nature of cybersecurity markets and the concentration of cybersecurity activity in the United States, which, as discussed in Subsection 3.2.1, has an estimated market value of USD 81.6 billion in 2026. Deal values are highly right-skewed. The mean deal value is USD

1,121.8 million, but the median is only USD 179.2 million. This gap indicates that a few very large transactions heavily inflate the average, such as Palo Alto's USD 25 billion acquisition of CyberArk and Gen Digital's merger with Avast for USD 9.36 billion. The relative target size, measured as deal value divided by acquirer market cap at the time of announcement, has a mean of 3.4% and a median of 0.62%. This confirms that the majority of deals represent small targets relative to the acquirer's size.

Section 4.2: Market model parameters

To calculate abnormal returns, the market model parameters, α_i and β_i , were estimated using a 221-day estimation window for each transaction. These parameters represent the relationship between the cybersecurity firm's stock performance and the NASDAQ Composite index. Table 3 in Appendix 5 summarises the computed market model parameters. Overall, the estimated alpha coefficients are very close to zero across the sample. It suggests that outside the event window, the acquirers' daily stock returns are largely explained by normal market movements. Average alpha values range from -0.0016 for Rapid7 to 0.0045 for Rubrik. Rubrik, CrowdStrike and Zscaler exhibit the highest average alphas, suggesting these firms were consistently generating positive returns above the market during their estimation windows. Rapid7, Okta, SentinelOne and Varonis show negative alphas. The beta coefficients, however, vary substantially across companies due to the heterogeneous nature of the cybersecurity sector. Beta reflects the different risk profiles of the entities. Several acquirers have average betas above 1.0, including Rubrik (1.498), SentinelOne (1.473), Zscaler (1.425), CrowdStrike (1.317), Okta (1.192), Tenable (1.065) and Rapid7 (1.035). Betas above 1.0 indicate that these stocks are more sensitive to market movements than the benchmark. This is consistent with the profile of growth-oriented cybersecurity firms, whose valuations tend to react strongly to changes in market sentiment. By contrast, more mature or defensive firms often have lower betas, such as Varonis (0.625) and Gen Digital (0.467). Qualys, Palo Alto Networks and Fortinet also remain below 1.0, with values of 0.953, 0.942 and 0.898, respectively.

The R^2 values also vary meaningfully across companies. This indicates that the explanatory power of the market model is not identical across firms; the average R-squared values range from 14.6% to 38.5%. At the lower end, Gen Digital and Varonis have average R^2 values of 0.146 and 0.148. For these companies, stock price movements are largely driven by firm-specific factors rather than by the NASDAQ Composite index, which explains only a small fraction of their return variation. At the upper end, CrowdStrike and Palo Alto Networks show average R^2 values of 0.385 and 0.384, while Zscaler and Rubrik also exhibit relatively strong fits for stock market research at 0.38 and 0.371. The remaining unexplained part is mainly driven by firm-specific news, such as product launches, earnings reports or the M&A announcements. These differences in R-squared between companies' values are economically

plausible. They suggest that some firms move more closely with broader market dynamics, while others are influenced more strongly by firm-specific news.

These results support the decision to estimate the market model separately for each firm and each deal rather than relying on a single common parameter for the whole sample. They validate, therefore, the use of the estimated expected returns as the basis for the abnormal return analysis presented in the next section.

Section 4.3: Abnormal returns

The average abnormal returns (AR) and their standard deviations were calculated for each of the 11 event days in the window[-5, +5] across all 71 deals in the sample. The results are represented in Table 5 in Appendix 7. The largest negative abnormal return is concentrated on day 0, the announcement day itself, with a mean AR of -0.81%. This is the most negative day in the event window and is consistent with the efficient market hypothesis. If markets rapidly incorporate new publicly available information, the main reaction should occur on the day the deal is announced (Fama, 1970). This already suggests that the market reacts unfavourably to acquisition announcements made by cybersecurity acquirers. The ARs in the pre-announcement window (days -5 to -1) are all slightly negative and close to zero, ranging from -0.004% to -0.26%, with no obvious trend. This suggests no evidence of information leakage or market anticipation before the official M&A announcement. If there had been leakage or anticipation, the market would have reacted more strongly before day 0. The post-announcement period (days +1 to +5) shows a mixed pattern with small positive and negative values. This indicates that the market's reaction is largely absorbed by the end of the announcement day and the following trading day. The relatively high standard deviations throughout the event window, particularly on days +1 and +2, reflect the substantial deal-level heterogeneity in the sample. They range from 0.0162 on day -4 to about 0.04 on days +1 and +2. This dispersion shows that some acquisitions are clearly welcomed by investors, while others are penalised more strongly.

Section 4.4: Cumulative abnormal returns (H_0 against H_1)

Once the abnormal returns are estimated, they are cumulated to obtain the cumulative abnormal returns (Figure 3 in Appendix 8). Table 6 presents the CARs for each of the three event windows, together with the t-test results and p-values for the main hypothesis (H_0 : CAR = 0 against H_1 : CAR > 0). Additionally, the share of deals with a positive CAR is also reported. The mean CAR is negative across all three windows, ranging from -1.31% for the narrow window[-1, +1] to -2.22% for the wider window[-5, +5]. The median CAR is also negative across each window, indicating that the sample's central tendency is negative. Furthermore, the fact that only 42.3% of deals generated a positive CAR[-1, +1] confirms that the negative

reaction is not driven by a few extreme negative outliers. The standard deviation increases as the event window becomes wider, rising from 5.45% in the three-day window to 9.02% in the eleven-day window. This is expected, since longer windows capture more noise and more variation across deals.

Table 6: Average cumulative abnormal returns and t-test results (NASDAQ benchmark)

Window	Mean CAR	Median CAR	Std. Dev.	t-statistic	p-value	% Positive
[-1,+1]	-1.31%	-0.77%	5.45%	-2.021	0.0472*	42.3%
[-2,+2]	-1.83%	-1.12%	7.51%	-2.052	0.0439*	35.2%
[-5,+5]	-2.22%	-2.26%	9.02%	-2.074	0.0418*	42.3%

*Note: Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. % positive is the share of deals with a positive CAR. Source: table prepared by the author.

To evaluate the statistical significance of the CARs, a one-sample t-test was performed against the null hypothesis (H_0 : CAR = 0). The results determine whether the observed market reactions are likely due to the acquisition announcements rather than random variation.

- CAR [-1, +1]: The 3-day window yielded a t-statistic of -2.02 with a p-value of 0.047. This result is statistically significant at the standard 5% (*) significance threshold.
- CAR [-2, +2]: The 5-day window yielded a t-statistic of -2.05 with a p-value of 0.044. This result is statistically significant at the 5% (*) level.
- CAR [-5, +5]: The 11-day window yielded a t-statistic of -2.07 with a p-value of 0.042. This result is statistically significant at the 5% (*) level.

The results in Table 6 lead to the rejection of H_0 for all three event windows at the 5% (*) significance level. The consistent negative direction across all windows, confirmed by median CARs, provides clear evidence that M&A announcements made by publicly traded, pure-play cybersecurity acquirers are associated with a statistically significant negative stock market reaction in the short term. The alternative hypothesis H_1 predicted a positive impact on firm value due to the sectors high-growth and innovation-driven nature. However, the data reveal that these acquisitions lead, on average, to a decrease in acquirer shareholder wealth around the announcement date. The magnitude of the effect is economically meaningful. A mean CAR of -1.31% over three days, on companies with market caps ranging from a few USD billion to over USD 100 billion, represents a substantial aggregate loss of shareholder value.

This result deviates noticeably from the literature focused on tech acquisitions (Conn et al., 2005; Higgins & Rodriguez, 2006; Kallunki et al., 2009). Kohers & Kohers (2000) show,

through an analysis of 1,634 mergers, that acquirers of high-tech targets experience significantly positive ARs and CARs. The results, however, are more consistent with Kaufmann & Schiereck's study (2023), which shows that acquisitions of innovative targets are often associated with weak or negative short-term stock market reactions for non-innovative acquirers, due to high acquisition premiums and uncertainty regarding synergies. The results of this thesis are also consistent with the dominant consensus in the general M&A literature, which generally finds that acquirer returns are close to zero or slightly negative around announcement dates (Andrade et al., 2001; Campa & Hernando, 2004; Jensen & Ruback, 1983).

Several theoretical explanations, discussed in the literature review, are relevant here. The first is the hubris theory, which indicates that managers frequently overestimate the value of targets and, therefore, overpay (Roll, 1986). In the cybersecurity sector, targets are often early-stage companies with high strategic values, making them difficult to value precisely. The winner's curse reinforces this interpretation, as several deals in the sample occurred in highly competitive bidding contexts, such as Okta/Auth0, Fortinet/Lacework and CrowdStrike/Bionic (Forrester, 2024; Levy, 2021; Lunden, 2023; Roll, 1986). Another explanation is the free cash flow theory, which predicts that managers with access to excess cash are likely to pursue acquisitions, even when value creation is uncertain (Jensen, 1986). Several of the acquiring companies in this sample, notably Palo Alto Networks, CrowdStrike and Zscaler, had substantial free cash flows. Lastly, when a cybersecurity acquirer announces a deal, investors have limited ability to independently assess the target's true value. The sample targets are predominantly private companies whose financial information is not publicly available. Moreover, investors observing a high premium paid for a target whose value lies primarily in network effects that have yet to materialise, are likely to react cautiously. In this context, the market's negative reaction can be interpreted as a rational response to uncertainty.

It is also worth noting that the negative reaction is not uniform across companies, see Table 7 in Appendix 9. Tenable, Fortinet and Qualys generate slightly positive average CARs across their acquisitions, while SentinelOne and Palo Alto Networks generate strongly negative returns. This heterogeneity suggests that the market rewards companies perceived as disciplined acquirers and punishes those with a history of risky deals. Tenable's deals are predominantly small acquisitions that each target a specific capability gap in its exposure management platform, whereas Palo Alto Networks pursues larger and more transformative transactions.

Section 4.5: Cross-sectional analysis (H_2 , H_3 , H_4)

To examine whether deal-level characteristics explain the variation in market reactions across acquisitions, a cross-sectional OLS regression was estimated with robust standard errors (HC1) on the subsample of 48 deals, see Table 8 in Appendix 10. In line with the methodology defined in Chapter 3, three determinants were tested: the method of payment, the cross-border character

of the transaction and the relative target size. The dependent variable is the CAR over each window. The reference category for the payment method is mixed financing, while domestic transactions constitute the reference category for the geographic variable. The analysis proceeds in two steps. First, Subsection 4.5.1 presents the main regression results for the full model. Second, Subsections 4.5.2 to 4.5.4 present the results of univariate regressions for each determinant separately, which is useful for assessing each variable's individual explanatory power without the influence of the other controls.

4.5.1 Main multivariate regressions

Table 9: Cross-sectional regression results (H_2 , H_3 , H_4)

Window		Intercept	Cash vs Mixed	Stock vs Mixed	Cross-border	Relative target size	R ²	Adj. R ²
[-1,+1]	Coef	-1.35%	-0.23%	-12.04%	1.34%	7.89%	13.64%	5.61%
	(Std. Dev.)	(1.51%)	(1.54%)	(2.52%)	(1.54%)	(10.66%)		
	<i>p-value</i>	0.377	0.881	<0.001***	0.389	0.463		
[-2,+2]	Coef	-0.68%	-0.68%	-18.18%	-0.94%	6.64%	11.00%	2.73%
	(Std. Dev.)	(1.98%)	(2.15%)	(2.49%)	(2.27%)	(10.09%)		
	<i>p-value</i>	0.732	0.753	<0.001***	0.681	0.514		
[-5,+5]	Coef	-1.28%	-1.21%	-16.08%	1.14%	1.78%	6.25%	-2.47%
	(Std. Dev.)	(2.97%)	(3.09%)	(2.92%)	(2.98%)	(10.96%)		
	<i>p-value</i>	0.670	0.698	<0.001***	0.705	0.872		

*Note: The dependent variable is CAR for each window. Reference categories: mixed payment, domestic deal. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Source: table prepared by the author.

Table 9 presents the main multivariate regression results for the full model across all three event windows, two observations emerge. First, the stock payment indicator is the only variable that is statistically significant. It is the case across all three windows, at the 0.1% (***) level. The coefficients are large and stock-financed deals are associated with CARs between 12.04% and 18.18% lower than those of mixed deals. This appears to support H_2 , which predicted that mixed-financed deals would be received more favourably than stock-financed transactions. However, this result must be interpreted with very strong caution. The stock category contains only one observation in the subsample. The estimate is, therefore, statistically significant in a mechanical sense, but it cannot be interpreted as a robust sector result. In addition, the coefficient for cash payment versus mixed payment is -0.23% in window[-1, +1], with a p-value of 0.881. The determinant is clearly not statistically significant in the three-day window as well as in the two other windows. There is, therefore, no evidence that cash-financed acquisitions generate CARs that differ significantly from those of mixed-financed deals in this

sample. For these reasons, H_2 cannot be confirmed. This finding is weaker than expected based on the broader M&A literature, which often associates all-cash deals with more favourable bidder reactions (Andrade et al., 2001; Kaplan, 2006; Travlos, 1987).

Second, the other variables, cross-border status and relative target size, are not statistically significant in any window. The cross-border dummy has a coefficient of 1.34% at window[-1, +1]. The sign is positive, consistent with the idea that international deals can provide access to new capabilities or markets (Doukas & Travlos, 1988). However, the result is not statistically significant, with a p-value of 0.389. The two wider windows are also insignificant. As a result, H_3 cannot be confirmed. Furthermore, the coefficient for relative target size is 7.89% at the window[-1, +1] and is positive for window[-2, +2] as well as window[-5, +5], which is opposite to the expected direction of H_4 . With p-values above 5% (*) for the three windows, the coefficients are also not statistically significant. These results reject H_4 , which predicted that larger relative deals would be associated with lower CARs because of greater integration complexity and execution risk uncertainty (Alexandridis et al., 2011).

Taken together, the multivariate regressions indicate that the selected determinants have limited explanatory power. The very low adjusted R-squared values (-2.47% to 5.61%) indicate that these standard deal determinants explain less than 6% of the variation in cybersecurity acquirer returns. This reflects the high deal-level heterogeneity typical of M&A event studies in specialised sectors (MacKinlay, 1997). It suggests that isolating each variable's marginal contribution could help clarify the source of the explanatory power. To understand each determinant in isolation, the following subsections report the results of the three univariate regressions, along with a descriptive breakdown of mean CARs by group, as seen in Tables 10 through 15 in Appendix 12 through 17. This approach allows each hypothesis to be assessed without the influence of the other covariates.

4.5.2 Method of payment (H_2)

Hypothesis H_2 predicted that all-cash deals would generate higher CARs than mixed or all-stock deals and that mixed deals generate higher CARs than all-stock transactions. This is in line with the well-established results of Travlos (1987) and Andrade et al. (2001) that cash deals deliver higher returns than stock-financed acquisitions. The stock payment results are similar to the multivariate regression findings (Table 10 in Appendix 12). The regression coefficient in the window[-1,+1] is -11.83% and is statistically significant at the 0.1% (***) level, the direction is consistent with the prediction of H_2 . However, as mentioned before, the entire stock category in the regression subsample consists of a single observation: Okta's acquisition of Auth0 in March 2021, a USD 6.5 billion all-stock deal. With n equal to 1, there are no degrees of freedom within the group, no standard deviation to estimate and no basis for statistical generalisation. What the regression is measuring is the difference between Auth0's CAR and

the average CAR of the mixed-deal group. It is not a general finding about stock-financed cybersecurity acquisitions. This result cannot be used to confirm H_2 with respect to stock payment. The only stock-financed deal in the sample generated negative mean and median CARs over the three windows, with a mean CAR[-1, +1] of -11.99% (Table 11 in Appendix 13). This could also reflect the market's rational response to the high price paid and the strategic uncertainty of integrating a company of Auth0's size (relative size of 20.3%).

Turning to the cash versus mixed comparison, the regression coefficient in the three-day window is -0.87 and is non-significant with a p-value of 0.615. Cash deals have a mean CAR[-1, +1] of -1.03%, compared to -1.62% for mixed deals. However, for window[-2, +2] and window[-5, +5], cash deals (-11.61% and -2.07%) generate lower mean CARs than mixed deals (-0.65% and -0.62%). This difference is in the wrong direction relative to H_2 's prediction, as cash deals perform slightly worse than mixed deals. The median CARs tell the same story, however, the mean and median results are not significant. Importantly, 50% of cash deals generate a positive CAR, compared to 46.7% for mixed deals, which is the correct direction, but is again not meaningful given the absence of statistical significance.

The adjusted R^2 ranges from 1.75% to 6.75% across the three windows, indicating that payment method explains a small, but non-negligible share of the variance in CARs. However, this explanatory power is driven entirely by the single stock-financed deal. Removing that observation would reduce the adjusted R^2 to approximately zero. These results cannot confirm H_2 , suggesting that in the cybersecurity sector, the payment method may matter less than in general M&A. It is possible that in a sector where valuations are extremely high for target companies, the payment method matters less than the price paid. Whether an acquirer uses cash or its own shares, investors focus primarily on whether the expected synergies justify the deal multiple.

4.5.3 Cross-border vs domestic deals (H_3)

Hypothesis H_3 examined whether cross-border deals, which combine access to new markets and capabilities with regulatory and cultural complexity, generate higher abnormal returns than domestic deals. The empirical evidence reviewed in Chapter 2 is mixed. Moeller & Schlingemann (2005) demonstrate lower abnormal returns for acquiring cross-border targets, while Doukas & Travlos (1988) reveal larger abnormal returns when companies expand into new geographic markets. When analysing the cross-border univariate regressions, the results show no statistical significance (Table 12 in Appendix 14). The cross-border coefficient shows a better performance with 1.5% against domestic deals across the shortest window. However, the p-values range from 0.33 to 0.83 across all windows, well above any conventional significance threshold. Descriptively, cross-border deals generate a slightly higher mean CAR[-

1,+1] than domestic deals (-0.05% vs -1.55%) (Table 13 in Appendix 15). However, this reversal is not robust; the average CAR[-2,+2] shows the opposite pattern, with cross-border deals slightly underperforming domestic ones. The inconsistency across windows suggests there is no meaningful or stable difference between the two groups. The median CARs for cross-border transactions outperform the domestic deals across all windows, with median CAR[-1, +1] being the only positive result. The 55.6% positive rate for cross-border deals against 43.3% for domestic deals and the better-performing median CARs are interesting, but statistically uninformative.

The adjusted R^2 is negative across all three windows, ranging from -2.07% to -0.06%, indicating that the cross-border dummy adds no meaningful explanatory power beyond the intercept alone. With these results, H_3 cannot be confirmed. The heterogeneity of the subsample is a possible explanation for the absence of significance. Out of 18 cross-border deals, several involve acquisitions of Israeli cybersecurity firms, while other targets are based in Denmark, Singapore, Spain, Japan or the United Kingdom, which involve very different regulatory and cultural contexts. Treating all of these transactions under a single binary cross-border dummy is a simplification that hides important subcategories. This finding highlights that the cross-border effect depends on the specific country pair as well as the institutional distance between the acquirer and the target.

4.5.4 Relative target size (H_4)

H_4 predicted a negative relationship between relative target size and acquirer CARs, based on the argument that larger deals involve greater integration complexity and uncertainty (Alexandridis et al., 2011). The data provide no support for this hypothesis, see Table 14 in Appendix 16. The predictor's coefficient for window[-1, +1] is 3.3%, which is not only insignificant ($p = 0.812$), but also in the wrong direction. The coefficients for the wider windows are similarly negligible with p -values above 5% (*). However, a quartile analysis reveals a pattern that the linear regression does not capture, as shown in Table 15 in Appendix 17. Across all three event windows, Q4 deals (the largest acquisitions relative to acquirer size) generate consistently negative mean and median CARs. They range from -2.90% to -4.71% in the mean and from -2.31% to -4.71% in the median. Q2 deals, by contrast, generate near-zero or slightly positive mean CARs. In addition, the gap between Q4 and the other quartiles becomes more pronounced in the wider event window[-5,+5], where Q4 mean CAR reaches -4.71% compared to 0.50% for Q1, 1.48% for Q2 and -3.64% for Q3. The pattern is broadly consistent with H_4 , larger deals are associated with lower acquirer returns, even though the regression coefficient on the relative size variable fails to reach statistical significance.

The adjusted R^2 is negative across all three windows, ranging from -2.11% to -1.76%, confirming that relative target size has no explanatory power over CARs in this sample. With these results, H_4 cannot be confirmed, even though the quartile analysis points in the right direction. Two specific characteristics of the sample could explain the absence of a size effect. First, the distribution of the relative target size in the sample is highly skewed. The median deal represents only 0.62% of the acquirer's market cap and three-quarters of deals have a relative target size below 2.4%. The vast majority of deals are simply too small relative to the acquirer for their size to matter. The largest deal by relative size is the Gen Digital/Avast merger at 64.1%, followed by Palo Alto/CyberArk at 21.2% and Okta/Auth0 at 20.3%, see Figure 4 in Appendix 17. These deals are extreme outliers relative to the 75th percentile of 2.4%. As a result, the distribution of the relative target size is too skewed for the regression to produce a meaningful estimate. The coefficient is driven by a few large deals rather than by a consistent pattern across the sample, making it impossible to draw conclusions about the effect of the relative target size on acquirer returns. Second, the few large deals in the sample produce conflicting signals. The Palo Alto/CyberArk acquisition generated a strongly negative reaction, in line with H_4 's prediction, while the Gen Digital/Avast deal generated a strongly positive reaction.

Overall, the univariate regressions do not materially change the conclusions of the multivariate analysis. They mainly confirm that the explanatory variables selected from the literature have limited power in this sample.

Section 4.6: Robustness check S&P 500 benchmark

To verify that the main results are not sensitive to the choice of market index, the full event study was replicated using the S&P 500 index as an alternative benchmark, which represents a broader US market benchmark. The robustness check confirms the stability of the main findings, see Table 16 in Appendix 18. The CARs obtained using the S&P 500 benchmark are almost identical to those obtained with the NASDAQ Composite, differing by less than 0.1%. The significance levels are also very similar, the S&P 500 results show $p = 0.05$ for $CAR[-1, +1]$, $p = 0.041$ and $p = 0.043$ for $CAR[-2, +2]$ and $CAR[-5, +5]$ respectively. This confirms that the negative market reaction documented in Section 4.4 is a robust finding. It does not depend on the particular benchmark chosen and reinforces the conclusion that cybersecurity acquisitions generate negative abnormal returns for shareholders of the acquiring firm. The cross-sectional regression conclusions also remain stable across both benchmarks. The lack of statistical significance for payment method, geography and relative size observed in the main model persists when using the S&P 500. This consistency suggests that the inability of these deal characteristics to explain acquirer returns is a robust finding.

Chapter 5: Discussion

This chapter discusses the specific contributions and differences of this study. It identifies the most notable individual deals in the sample, the temporal pattern that emerges across the study period and addresses this thesis' limitations as well as avenues for future research.

Section 5.1: Notable individual deals

This section identifies transactions that matter for understanding the empirical findings because they are unusually large, are associated with extreme stock market reactions or are potentially affected by concurrent events.

5.1.1 Okta / Auth0 (03-03-2021)

As noted in Subsection 4.5.2, the Auth0 acquisition by Okta is the only stock-financed deal in the regression subsample. It produced a strong negative stock market reaction, with CAR[-1, +1] of -12.0%, CAR[-2, +2] of -17.6% and CAR[-5, +5] of -17.1%. The USD 6.5 billion acquisition triggered a severe market reaction, reflecting investor concerns about dilution and the high price paid. While the reaction is economically interpretable and consistent with the M&A literature, the regression result should be interpreted cautiously, as it rests on a single observation.

5.1.2 Zscaler / Smokescreen (25-05-2021)

The acquisition of Smokescreen by Zscaler generates a large positive CAR[-1, +1] of 10.6%. The highest AR occurs on day +1, when Zscaler recorded an AR of 11.37%. This date coincides with Zscaler's Q3 FY2021 earnings release, which significantly exceeded expectations. This is a classic confounding event; the AR around the Smokescreen announcement is contaminated by another event announcement rather than by the market's reaction to the acquisition itself.

5.1.3 Fortinet / Next DLP (05-08-2024)

The acquisition of Next DLP by Fortinet generates extremely large positive CAR[-2, +2] of 28.0% and CAR[-5, +5] of 26.90%. This result is almost entirely driven by day +2 in the event window, where Fortinet recorded an AR of 26.16%. This date corresponds to the release of Fortinet's Q2 FY2024 earnings, which were well above analyst expectations and triggered a strong upward re-rating of the stock. As with the Zscaler case above, this AR is attributable to the earnings announcement rather than the Next DLP acquisition. Both transactions are retained in the main sample for transparency, but they are flagged because the observed stock market reaction may not be attributable solely to the M&A announcement.

5.1.4 Palo Alto Networks / CyberArk (30-07-2025)

The USD 25 billion acquisition of CyberArk by Palo Alto Networks generates a CAR[-1, +1] of -15.85% and a CAR[-5, +5] of -14.31%. This is the largest deal in the sample and one of the three largest in cybersecurity history. The extreme negative reaction is consistent with the qualitative analysis in Subsection 2.4.3.1, which noted that the announcement triggered a -10.4% window[-1, +1] stock decline due to investor concerns about the high price paid and integration risk. This deal also has the second-highest relative target size in the sample at 21.2%, making it an influential data point in the regression.

5.1.5 Gen Digital / Avast (10-08-21)

The merger of Avast by NortonLifeLock (later renamed Gen Digital), with a deal value of USD 9.36 billion, stands out as the largest deal by relative target size in the subsample, at 64.1%. The deal generated a strongly positive market reaction, with CAR[-1,+1] of 9.47%, CAR[-2,+2] of 8.80% and CAR[-5,+5] of 5.38%, suggesting that investors viewed the combination of the two consumer cybersecurity giants favourably, likely anticipating significant scale synergies. However, this positive reaction, combined with its extreme relative size makes it the most influential observation in the H_4 regression. It distorts the coefficient for relative target size and contributes to the absence of a meaningful size effect across the sample.

5.1.6 Varonis / Alltrue (03-02-2026)

The acquisition of Alltrue by Varonis yields the most extreme CAR in the sample: -20.37% over [-1, +1], -27.25% over [-2, +2] and -25.61% over [-5, +5]. The event window coincides with broad market turbulence in early February 2026, driven by tariff concerns. This caused significant sell-offs, particularly in technology stocks, which were not absorbed by the NASDAQ Composite. It is, therefore, likely that the ARs are partially contaminated by macroeconomic market stress rather than being attributable only to the firm's announcement.

Section 5.2: Temporal pattern of the worsening market reaction over time

A striking finding from the data is a clear temporal shift in market reactions across the study period, as shown in Figure 5 and Table 17 in Appendix 19. Deals announced in 2021 and 2022 generate mean CARs[-1,+1] of 0.08% and 2.41%, respectively. However, from 2023 a negative pattern becomes visible and progressively strengthens over the three-day window: -1.02%, -1.91%, -1.74%, -6.55%. No single year is significant on its own due to the small number of deals per year, but the accumulation of consistently negative averages across the second half of the sample increases the significance of the negative CARs. The percentage of positive CARs tells the same story. In 2022, 83% of the deals were positive and the percentage decreased in the following years, reaching a minimum in 2026, during which only 14% of acquisitions are positive. This demonstrates that the market reaction shifted from neutral/positive in the early

period to clearly negative in 2023-2026. An explanation could be the sharp rise in the cost of capital. Between March 2022 and July 2023, the Federal Reserve raised the federal funds target rate, which reduces the present value of future synergies expected from acquisitions (Henry et al., 2023). This makes it harder to justify the high acquisition premiums. Another explanation could be that the largest deals in the sample are concentrated in the 2024-2026 period. These larger deals naturally attract greater scrutiny and generate more pronounced market reactions, contributing to the more negative CARs in the later years.

Section 5.3: Practical implications for managers and investors

The consistent negative market reaction documented in this study carries a clear message for management teams and investors of pure-play cybersecurity companies. Acquisitions are not rewarded by the stock market. This does not mean acquisitions are strategically wrong, many deals in the sample offer genuine capabilities that would be difficult to build internally. The central implication is that the strategic rationale and the justification for the price paid must be communicated more clearly to investors. Managers should explain how a target generates network effects and economies of scope within the platform, rather than describing it as a stand-alone asset. For investors, the heterogeneity across acquirers suggest a systematic pattern that can inform portfolio management. Disciplined acquirers such as Tenable and Fortinet generate neutral reactions while more transformative acquirers such as Palo Alto Networks and SentinelOne generate consistently negative returns.

Section 5.4: Limitations and avenues for future research

Like any empirical study, this research has limitations that should be acknowledged and that point toward several avenues for future research.

5.4.1 Sample size and structure

The first limitation concerns the size and structure of the sample. The final event study sample contains 71 valid acquisitions from 12 acquirers and the cross-sectional regression subsample is reduced to 48 observations. These figures are modest by the standards of the M&A event study literature, where samples typically contain several hundred or several thousand transactions. The small sample reflects the deliberate decision to focus exclusively on US-listed pure-play cybersecurity firms, which is the study's contribution. In addition, the sample is concentrated among four acquirers, which account for almost half of all transactions and the study focuses exclusively on US acquirers. That is why future research could extend the sample by including European listed acquirers. Furthermore, the sample prevents the regression from producing a reliable estimate of the size effect, as three-quarters of deals have a relative target

size below 2.4% and one observation stands at 64.1%. Future research could replicate this analysis on a sample with a more uniform distribution of relative deal sizes.

5.4.2 Short-term evaluation

Second, this study measures only short-term stock market reactions. The CARs capture investor expectations at the moment of announcement, not the actual value created or destroyed by the acquisition over time. The short-term focus is a fundamental constraint of the methodology and the findings should not be interpreted as evidence that cybersecurity acquisitions are value-destructive in the long run. A long-term study using the buy-and-hold abnormal return (BHAR) approach could be added to this research. This would allow the assessment of whether the negative announcement effect persists, reverses or is amplified in the months and years following the deal.

5.4.3 Confounding events

Third, the event study relies on both hypotheses that the market is efficient and that the only relevant news during the event window is the acquisition announcement (Fama, 1970; MacKinlay, 1997). Section 5.1 documented that this assumption is violated in at least three deals, in which earnings announcements or macroeconomic shocks contaminated the abnormal returns. The consequence is that the measured CARs for these deals are unreliable indicators of the market's reaction to the acquisition. Although the standard event study practice is to retain such observations for transparency, future research could cross-reference each deal in the sample with the acquirer's earnings calendar and exclude observations where the event windows overlap.

5.4.4 Limited set of explanatory variables

The fourth limitation is the limited set of explanatory variables used in the cross-sectional analysis. Three deal-level determinants were tested: payment method, geographic type and relative target size. The variable for target type (public versus private) had to be removed because only two public targets were present in the sample. Other determinants identified in the literature, such as the acquirer's prior acquisition experience, the level of the acquisition premium, the strategic logic of the deal or the level of investors' attention to the deal, were not incorporated (Renneboog & Vansteenkiste, 2019; Zollo & Winter, 2002). Future research could enrich the cross-sectional model with these variables.

5.4.5 Cybersecurity-specific dimensions not captured

Finally, the current analysis treats all acquisitions as comparable transactions, but the sector contains very different segments (e.g., identity and access management, endpoint protection

and cloud security). It could be a possibility that the market reaction varies significantly across these segments. The strategic fit between the target and the acquirer's existing platform, and the segment's perceived growth potential, could influence investors' reactions. Future research could combine the quantitative event study approach with a detailed analysis of press releases, earnings calls and analyst reports to test whether specific segments of the cybersecurity sector influence investors' reactions.

Despite these limitations, the empirical evidence presented in this study provides a coherent and statistically robust contribution to understanding M&A performance in the cybersecurity sector.

Chapter 6: Conclusion

This thesis aimed to address the empirical question: what is the impact of mergers and acquisitions (M&A) on the value of publicly traded acquiring companies in the cybersecurity sector? Despite a record consolidation wave between 2021 and early 2026, including the USD 25 billion acquisition of CyberArk by Palo Alto, no event study had so far focused exclusively on US-listed, pure-play cybersecurity acquirers. The few studies touching on cybersecurity M&A treat the sector as part of a broader technology sample or adopt a qualitative perspective. This thesis addressed that gap through an event-study methodology applied to 71 acquisitions announced by 12 US-listed, pure-play cybersecurity firms between January 2021 and March 2026, after excluding two deals due to insufficient trading data. Cumulative abnormal returns were computed over three event windows around the announcement date and tested against the null hypothesis of no market reaction. A cross-sectional regression was then used to examine which deal characteristics influence shareholder response.

The analysis demonstrates that M&A announcements made by pure-play cybersecurity acquirers are, on average, associated with a negative short-term market reaction. The negative mean CARs over the three windows are statistically significant. The median CARs are also negative across all windows, confirming that the average is not driven by a few outliers. The null hypothesis is, therefore, rejected, as well as the alternative hypothesis H_1 , which predicted a positive effect based on the sector's high-growth and innovation-driven nature. The most plausible interpretations identified in Chapter 4 are the hubris and winner's curse theories, which point to managerial overconfidence and competitive bidding pressure in a sector characterised by very high valuations. These results are inconsistent with M&A tech literature (Kohers & Kohers, 2000).

Turning to the three subquestions, the cross-sectional analysis yields few significant effects. The first subquestion asked whether all-cash acquisitions generate higher CARs than stock-financed or mixed deals (H_2). There is no statistically significant difference in market reaction between cash and mixed deals, with cash deals even slightly underperforming. The only stock-financed deal produces a significant coefficient that cannot be generalised. H_2 is, therefore, not confirmed. A plausible explanation is that, in a sector with high target valuations, investors focus more on the price paid. The second subquestion asked whether cross-border acquisitions generate higher CARs than domestic deals (H_3). They do not in any statistically meaningful sense. The cross-border dummy has p-values between 0.33 and 0.83 and the sign of the CARs reverses between windows. The most likely structural explanation is the heterogeneity of the cross-border subsample. The sample consists of quite different targets and a single binary variable cannot capture this diversity. The third subquestion asked whether a larger relative

target size is associated with lower CARs (H_4). Although the quartile analysis appears to follow Alexandridis et al.'s (2011) prediction, the correlation between relative target size and CAR $[-1, +1]$ reveals a positive, but statistically insignificant relationship, meaning H_4 is rejected. The sample is heavily skewed toward small deals, while large transactions in the sample produce conflicting signals. The determinants identified in the general M&A literature, therefore, explain very little of the variation in cybersecurity acquirer returns, the multivariate-adjusted R-squared values never exceed 6%. What does seem to matter, as Section 5.2 shows, is the year of the deal, with the market reaction becoming progressively more negative from 2023 onwards, consistent with the rise in the cost of capital and the increasing size of the transactions.

The contribution of this thesis is threefold. First, to the author's knowledge, it provides the first event study focused exclusively on US-listed, pure-play cybersecurity acquirers. Second, it covers the platformisation era between 2021 and early 2026, a distinct phase of the sector marked by record consolidation, AI-powered threats and high valuations. Third, the thesis documents that the determinants; payment method, geography and relative target size, explain almost none of the variation in cybersecurity acquirer returns. This result is itself a contribution, it suggests that the cybersecurity sector may require a different set of explanatory variables, such as the level of the acquisition premium or the perceived strategic fit with the acquirer's platform.

For management teams, the central implication is that the strategic rationale and the justification for the price paid must be communicated more clearly to investors. For investors, the findings suggest meaningful heterogeneity across acquirers. Disciplined acquirers such as Tenable and Fortinet generate neutral reactions, while more transformative acquirers such as Palo Alto Networks and SentinelOne generate consistently negative ones.

The limitations of the study, explained in detail in Section 5.3, invite a more cautious interpretation of these conclusions. The sample is modest by event study standards, the cross-sectional analysis suffers from an unbalanced distribution of relative sizes, the methodology captures only the short-term market reaction rather than long-term value creation and three deals are affected by confounding events. Future research could extend the sample geographically to European listed acquirers, analyse long-term performance through a buy-and-hold abnormal return analysis, incorporate cybersecurity-specific explanatory variables or screen for confounding events. Despite these limitations, the evidence presented offer a coherent and statistically robust answer to the question of how the stock market values M&A in the cybersecurity sector during its most intense consolidation wave to date.

Chapter 7: Bibliography

- Adnan, A., & Hossain, A. (2016). Impact of M&A Announcement on Acquiring and Target Firm's Stock Price: An Event Analysis Approach. *International Journal of Finance and Accounting*, 5, 228-232.
- Agrawal, A., Jaffe, J. F., & Mandelker, G. N. (1992). The Post-Merger Performance of Acquiring Firms: A Re-Examination of an Anomaly. *The Journal of Finance*, 47(4), 1605-1621. <https://doi.org/10.2307/2328956>
- AhnLab. (2026). 2025 Threat landscape & 2026 outlook report. *AhnLab*. <https://www.ahnlab.com/en/contents/content-center/36029>
- Alexandridis, G., Antypas, N., & Travlos, N. (2017). Value creation from M&As: New evidence. *Journal of Corporate Finance*, 45, 632-650
- Alexandridis, G., Fuller, K. P., Terhaar, L., & Travlos, N. G. (2011). Deal Size, Acquisition Premia and Shareholder Gains. *Journal of Corporate Finance*, 20, 1–13.
- Andrade, G., Mitchell, M., & Stafford, E. (2001). New Evidence and Perspectives on Mergers. *The Journal of Economic Perspectives*, 15(2), 103-120. <https://www.jstor.org/stable/2696594>
- Asquith, P., Bruner, R. F., & Mullins, D. W. (1983). The gains to bidding firms from merger. *Journal of Financial Economics*, 11(1-4), 121-139. [https://doi.org/10.1016/0304-405X\(83\)90007-7](https://doi.org/10.1016/0304-405X(83)90007-7)
- Bauer, F., & Friesl, M. (2024). Synergy evaluation in mergers and acquisitions: An attention-based view. *Journal of Management Studies*, 61(1), 37-68. <https://doi.org/10.1111/joms.12804>
- Belleflamme, P., & Neysen, N. (2023). Platform strategies: A guidebook for entrepreneurs in the platform economy. *Routledge*. <https://doi.org/10.4324/9780429490873>
- Belleflamme, P., & Peitz, M. (2021). The economics of platforms: Concepts and strategy. *Cambridge University Press*.
- Berkovitch, E., & Narayanan, M. P. (1993). Motives for Takeovers: An Empirical Investigation. *The Journal of Financial and Quantitative Analysis*, 28(3), 347-362. <https://doi.org/10.2307/2331418>
- Borodin, A., Ziyadin, S., Islyam, G., & Panaedova, G. (2020). Impact of mergers and acquisitions on companies' financial performance. *Journal of International Studies*, 13(2), 34-47. <https://doi.org/10.14254/2071-8330.2020/13-2/3>

- Bradley, M., Desai, A., & Kim, E. H. (1988). Synergistic gains from corporate acquisitions and their division between the stockholders of target and acquiring firms. *Journal of Financial Economics*, 21(1), 3-40. [https://doi.org/10.1016/0304-405X\(88\)90030-X](https://doi.org/10.1016/0304-405X(88)90030-X)
- Brock, D. M. (2005). Multinational acquisition integration: The role of national culture in creating synergies. *International Business Review*, 14(3), 269-288. <https://doi.org/10.1016/j.ibusrev.2005.02.001>
- Brown, S. J., & Warner, J. B. (1980). Measuring security price performance. *Journal of Financial Economics*, 8(3), 205-258. [https://doi.org/10.1016/0304-405X\(80\)90002-1](https://doi.org/10.1016/0304-405X(80)90002-1)
- Bruner, R. F. (2001). Does M&A pay? A survey of evidence for the decision-maker. *Journal of Applied Finance*, 12(1), 48-68.
- Bruner, R. F. (2004). Where M&A pays and where it strays: A survey of the research. *Journal of Applied Corporate Finance*, 16(4), 63-76. <https://doi.org/10.1111/j.1745-6622.2004.00007.x>
- Campa, J. M., & Hernando, I. (2004). Shareholder Value Creation in European M&As. *European Financial Management*, 10(1), 47-81. <https://doi.org/10.1111/j.1468-036X.2004.00240.x>
- Conn, R., Cosh, A., Guest, P., & Hughes, A. (2005). The impact on UK acquirers of domestic, cross-border, public and private acquisitions. *Journal of Business Finance & Accounting*, 32(5-6), 815-870. <https://doi.org/10.1111/j.0306-686X.2005.00615.x>
- CrowdStrike. (2023, September 19). CrowdStrike to acquire Bionic to extend cloud security leadership with industry's most complete code-to-runtime cybersecurity platform. CrowdStrike. <https://www.crowdstrike.com/en-us/press-releases/crowdstrike-to-acquire-bionic-to-extend-cloud-security-leadership/>
- CrowdStrike (2026). What is Cloud Security. CrowdStrike. <https://www.crowdstrike.com/en-us/cybersecurity-101/cloud-security/>
- CrowdStrike (2026). What is Code-to-cloud Security. CrowdStrike. <https://www.crowdstrike.com/en-us/cybersecurity-101/cloud-security/code-to-cloud-security/>
- CrowdStrike Holdings, Inc. (2026). Annual report (Form 10-K) for the fiscal year ended January 31, 2026. U.S. Securities and Exchange Commission. <https://www.sec.gov/ix?doc=/Archives/edgar/data/0001535527/000153552726000010/crwd-20260131.htm>

- CyberArk. (2026, February 4). CyberArk announces record fourth quarter and full year 2025 results. *U.S. Securities and Exchange Commission*.
https://www.sec.gov/Archives/edgar/data/1598110/000110465926010015/tm264972d1_ex99-1.htm
- Doukas, J., & Travlos, N. G. (1988). The effect of corporate multinationalism on shareholders' wealth: Evidence from international acquisitions. *The Journal of Finance*, 43(5), 1161-1175.
<https://doi.org/10.2307/2328212>
- Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 25(2), 383-417. <https://doi.org/10.2307/2325486>
- Forrester. (2024, June 12). Fortinet acquires Lacework. *Forrester*.
<https://www.forrester.com/blogs/fortinet-acquires-lacework/>
- Fortinet, Inc. (2025). Annual report (Form 10-K) for the fiscal year ended December 31, 2025. *U.S. Securities and Exchange Commission*.
https://www.sec.gov/ix?doc=/Archives/edgar/data/1262039/000126203926000007/ftnt-20251231.htm#i71fcb98cc5f34eafa1d5d1bdeaf1bef2_61
- Fortune Business Insights. (2026, March 1). Cybersecurity market size, share, analysis. Global report 2034. *Fortune Business Insights*. <https://www.fortunebusinessinsights.com/industry-reports/cyber-security-market-101165>
- Fuller, K., Netter, J., & Stegemoller, M. (2002). What do returns to acquiring firms tell us? Evidence from firms that make many acquisitions. *The Journal of Finance*, 57(4), 1763-1793.
<https://doi.org/10.1111/1540-6261.00477>
- Gen Digital Inc. (2025). Annual report (Form 10-K) for the fiscal year ended March 28, 2025. *U.S. Securities and Exchange Commission*.
<https://www.sec.gov/ix?doc=/Archives/edgar/data/0000849399/000084939925000033/gen-20250328.htm#fact-identifier-208>
- GRV Next Generation Technologies Research Team. (2026). Cybersecurity market size & share, Industry report, 2033. *Grand View Research*. <https://www.grandviewresearch.com/industry-analysis/cyber-security-market>
- Haleblian, J., Devers, C. E., McNamara, G., Carpenter, M. A., & Davison, R. B. (2009). Taking Stock of What We Know About Mergers and Acquisitions: A Review and Research Agenda. *Journal of Management*, 35(3), 469-502. <https://doi.org/10.1177/0149206308330554>

- Haleblian, J., & Finkelstein, S. (1999). The influence of organizational acquisition experience on acquisition performance: A behavioral learning perspective. *Administrative Science Quarterly*, 44(1), 29-56. <https://doi.org/10.2307/2667030>
- Hayward, M. (2002). When do firms learn from their acquisition experience? Evidence from 1990–1995. *Strategic Management Journal*, 23(1), 21-39. <https://www.jstor.org/stable/3094272>
- Henry, E., Mulloy, C., & Sarte, P.-D. (2023). A rate cycle unlike any other (*Economic Brief No. 23-26*). *Federal Reserve Bank of Richmond*. https://www.richmondfed.org/publications/research/economic_brief/2023/eb_23-26
- Higgins, M., & Rodriguez, D. (2006). The outsourcing of R&D through acquisitions in the pharmaceutical industry. *Journal of Financial Economics*, 80(2), 351-383. <https://doi.org/10.1016/j.jfineco.2005.04.004>
- Inspired eLearning. (2017). Cyber 500 list. *Inspired eLearning*. <https://inspiredelearning.com/wp-content/uploads/2017/06/cyber-500-list.pdf>
- Jensen, M. C. (1986). Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers. *The American Economic Review*, 76(2), 323-329.
- Jensen, M. C., & Meckling, H. (1976). Theory of the firm: managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3, 305-360. [https://doi.org/10.1016/0304-405X\(76\)90026-X](https://doi.org/10.1016/0304-405X(76)90026-X)
- Jensen, M. C., & Ruback, R. S. (1983). The Market for Corporate Control: The Scientific Evidence. *Journal of Financial Economics*, 11(1-4), 5-50. [https://doi.org/10.1016/0304-405X\(83\)90004-1](https://doi.org/10.1016/0304-405X(83)90004-1)
- Kallunki, J.-P., Pyykkö, E., & Laamanen, T. (2009). Stock market valuation, profitability and R&D spending of the firm: The effect of technology mergers and acquisitions. *Journal of Business Finance & Accounting*, 36(7–8), 838-862. <https://doi.org/10.1111/j.1468-5957.2009.02161.x>
- Kaplan, S. N. (2006). Mergers and Acquisitions: A Financial Economics Perspective. *University of Chicago Graduate School of Business*.
- Kaufmann, M., & Schiereck, D. (2023). Acquiring for innovation: Evidence from the U.S. technology industry. *Journal of Economic Dynamics and Control*, 152. <https://doi.org/10.1016/j.jedc.2023.104673>

- Kohers, N., & Kohers, T. (2000). The value creation potential of high-tech mergers. *Financial Analysts Journal*, 56(3), 40-50. <https://www.jstor.org/stable/4480246>
- Lee, G. (2026, February 12). Palo Alto Networks completes \$25B CyberArk deal to ignite identity in AI era. *Sdx central*. <https://www.sdxcentral.com/news/palo-alto-networks-completes-25b-cyberark-deal-to-ignite-identity-in-ai-era/>
- Levy, A. (2021, March 3). Okta says it's buying security rival Auth0 for \$6.5 billion, sending stock plunging. *CNBC*. <https://www.cnbc.com/2021/03/03/okta-is-buying-security-rival-auth0-for-6point5-billion-stock-falls.html>
- Lunden, I. (2023, September 19). CrowdStrike confirms its Bionic.ai acquisition, sources say for \$350M. *TechCrunch*. <https://techcrunch.com/2023/09/19/crowdstrike-bionic-ai-acquisition/>
- M&A Watch. (2025, October 24). Palo Alto's \$25bn acquisition of CyberArk. *M&A Watch*. <https://mnawatch.com/financial-reports/palo-altos-25-bn-acquisition-of-cyberark>
- MacKinlay, A. C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature*, 35(1), 13-39.
- Martynova, M., Oosting, S., & Renneboog, L. (2006). The long-term operating performance of European mergers and acquisitions. *Finance Working Paper*, 137. <https://dx.doi.org/10.2139/ssrn.944407>
- Martynova, M., & Renneboog, L. (2011). The performance of the European market for corporate control: Evidence from the fifth takeover wave. *European Financial Management*, 17(2), 208-259. <https://doi.org/10.1111/j.1468-036X.2009.00497.x>
- Meir, O. (2023, September 19). CrowdStrike acquiring cyber startup Bionic for \$350 million. *CTech*. <https://www.calcalistech.com/ctechnews/article/hyquwtlka>
- Moeller, S. B., & Schlingemann, F. P. (2005). Global diversification and bidder gains: A comparison between cross-border and domestic acquisitions. *Journal of Banking & Finance*, 29(3), 533-564.
- Motis, J. (2007). Mergers and acquisitions motives. *Toulouse School of Economics*. <http://economics.soc.uoc.gr/wpa/docs/paper2mottis.pdf>
- Motta, M. (2004). Competition Policy. Theory and Practice. *Cambridge University Press*.

- Mulherin, J. H., Netter, J. M., & Poulsen, A. B. (2017). The Evidence on Mergers and Acquisitions: A Historical and Modern Report In *The Handbook of the Economics of Corporate Governance*, 1, 235-290. <https://doi.org/10.1016/bs.hecg.2017.11.006>
- National Institute of Standards and Technology (2026). Computer Security Resource Center (CSRC) Glossary. NIST. <https://csrc.nist.gov/glossary>
- Netter, J., Stegemoller, M., & Wintoki, M. B. (2011). Implications of data screens on merger and acquisition analysis: A large sample study of mergers and acquisitions from 1992 to 2009. *Review of Financial Studies*, 24(7), 2316-2357. <https://doi.org/10.1093/rfs/hhr010>
- Officer, M. S. (2006). The price of corporate liquidity: Acquisition discounts for unlisted targets. *Journal of Financial Economics*, 83(3), 571-598. <https://doi.org/10.1016/j.jfineco.2006.01.004>
- Okta, Inc. (2026). Annual report (Form 10-K) for the fiscal year ended January 31, 2026. U.S. Securities and Exchange Commission. https://www.sec.gov/ix?doc=/Archives/edgar/data/1660134/000166013426000020/okta-20260131.htm#ia9401731a2bf4c339820b039b38635b5_91
- Palo Alto Networks. (2024). Annual report (Form 10-K) for the quarterly period ended October 31, 2024. U.S. Securities and Exchange Commission. <https://www.sec.gov/Archives/edgar/data/1327567/000132756724000040/panw-20241031.htm>
- Palo Alto Networks. (2025). Annual report (Form 10-K) for the fiscal year ended July 31, 2025. U.S. Securities and Exchange Commission. https://www.sec.gov/ix?doc=/Archives/edgar/data/0001327567/000132756725000027/panw-20250731.htm#i7c6d02d19ae642d183bd6885f5b5223e_199
- Palo Alto Networks. (2026, February 11). Palo Alto Networks completes acquisition of CyberArk to secure the AI era. *Palo Alto Networks*. <https://www.paloaltonetworks.com/company/press/2026/palo-alto-networks-completes-acquisition-of-cyberark-to-secure-the-ai-era>
- Qualys, Inc. (2025). Annual report (Form 10-K) for the fiscal year ended December 31, 2025. U.S. Securities and Exchange Commission. <https://www.sec.gov/ix?doc=/Archives/edgar/data/0001107843/000110784326000008/qlys-20251231.htm>
- Rani, N., Yadav, S. S., & Jain, P. K. (2015). Impact of Mergers and Acquisitions on Shareholders' Wealth in the Short Run: An Event Study Approach. *Vikalpa*, 40(3), 293-312. <https://doi.org/10.1177/0256090915600842>

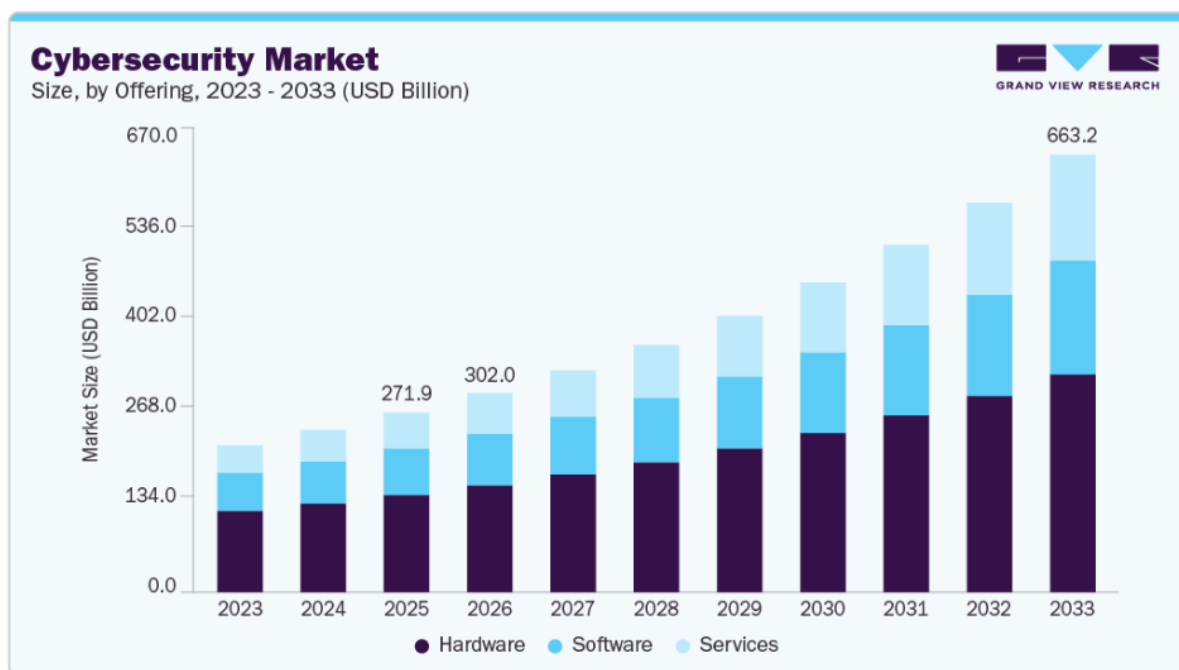
- Rapid7, Inc. (2025). Annual report (Form 10-K) for the fiscal year ended December 31, 2025. *U.S. Securities and Exchange Commission*.
<https://www.sec.gov/ix?doc=/Archives/edgar/data/1560327/000156032726000008/rp-20251231.htm>
- Renneboog, L., & Vansteenkiste, C. (2019). Failure and success in mergers and acquisitions. *Journal of Corporate Finance*, 58, 650-699. <https://doi.org/10.1016/j.jcorpfin.2019.07.010>
- Roll, R. (1986). The Hubris Hypothesis of Corporate Takeovers. *The Journal of Business*, 59(2), 197-216. <https://www.jstor.org/stable/2353017>
- Ropes & Gray. (2025, November). U.S. cybersecurity sector report - Q3 2025. *Ropes & Gray*.
<https://www.ropesgray.com/en/insights/alerts/2025/11/us-cybersecurity-sector-report-q3-2025>
- Rubrik, Inc. (2026). Annual report (Form 10-K) for the fiscal year ended January 31, 2026. *U.S. Securities and Exchange Commission*.
<https://www.sec.gov/ix?doc=/Archives/edgar/data/0001943896/000194389626000013/rbrk-20260131.htm>
- SentinelOne. (2022, March 15). Q4FY22 Letter to Shareholders. *SentinelOne, Inc.*
[https://s28.q4cdn.com/399982429/files/doc_financials/2022/q4/22_Finance_001_Investor_letter_Q4FY22_final-\(3'15-at-9.45am\).pdf](https://s28.q4cdn.com/399982429/files/doc_financials/2022/q4/22_Finance_001_Investor_letter_Q4FY22_final-(3'15-at-9.45am).pdf)
- SentinelOne. (2022, May 4). SentinelOne completes acquisition of Attivo Networks. *SentinelOne*.
<https://www.sentinelone.com/press/sentinelone-completes-acquisition-of-attivo-networks/>
- SentinelOne. (2025, March 12). SentinelOne, Inc. Form 8-K. U.S. *Securities and Exchange Commission*. <https://www.sec.gov/Archives/edgar/data/1583708/000158370825000051/s1-20250312.htm>
- SentinelOne, Inc. (2026). Annual report (Form 10-K) for the fiscal year ended January 31, 2026. *U.S. Securities and Exchange Commission*.
<https://www.sec.gov/ix?doc=/Archives/edgar/data/1583708/000158370826000020/s-20260131.htm>
- Telos Corporation. (2026). Annual report (Form 10-K) for the fiscal year ended December 31, 2025. *Securities and Exchange Commission*. <https://investors.telos.com/static-files/033da837-d21c-49c6-95f7-c7b8ccca30fe>

- Tenable Holdings, Inc. (2026). Annual report (Form 10-K) for the fiscal year ended December 31, 2025. *U.S. Securities and Exchange Commission*.
<https://www.sec.gov/ix?doc=/Archives/edgar/data/0001660280/000166028026000005/tenb-20251231.htm>
- Țilică, E., Oprea, D., & Ciobanu, R. (2012). The impact of M&A announcements on stock prices. *Bucharest University of Economic Studies*.
- Travlos, N. G. (1987). Corporate takeover bids, methods of payment, and bidding firms' stock returns. *The Journal of Finance*, 42(4), 943-963. <https://www.jstor.org/stable/2328300>
- Van Schaik, D., & Steenbeek, O. W. (2004). Price and volume effects of merger bids in Japan. *SSRN Electronic Journal*.
- Varaiya, N. P. (1988). The "winner's curse" hypothesis and corporate takeovers. *Managerial and Decision Economics*, 9(3), 209-219. <https://www.jstor.org/stable/2487100>
- Varonis Systems, Inc. (2025). Annual report (Form 10-K) for the fiscal year ended December 31, 2025. *U.S. Securities and Exchange Commission*.
<https://www.sec.gov/ix?doc=/Archives/edgar/data/0001361113/000162828026005450/vrns-20251231.htm>
- Whittaker, Z. (2022, March 15). SentinelOne scoops up Attivo Networks for \$617M. *TechCrunch*.
<https://techcrunch.com/2022/03/16/sentinelone-scoops-up-attivo-networks-for-617m/>
- Yahoo Finance. (2026). Historical stock price data [Data set]. *Yahoo*. <https://finance.yahoo.com/>
- Zollo, M., & Winter, S. (2002). Deliberate learning and the evolution of dynamic capabilities. *Strategic Management Journal*, 25(13), 1233-1256. <https://www.jstor.org/stable/27747463>
- Zscaler, Inc. (2025). Annual report (Form 10-K) for the fiscal year ended July 31, 2025. *U.S. Securities and Exchange Commission*.
https://www.sec.gov/ix?doc=/Archives/edgar/data/0001713683/000171368325000158/zs-20250731.htm#i6ab7dfbadace4cfb8966430e6e05b171_85

Chapter 8: Appendices

Appendix 1

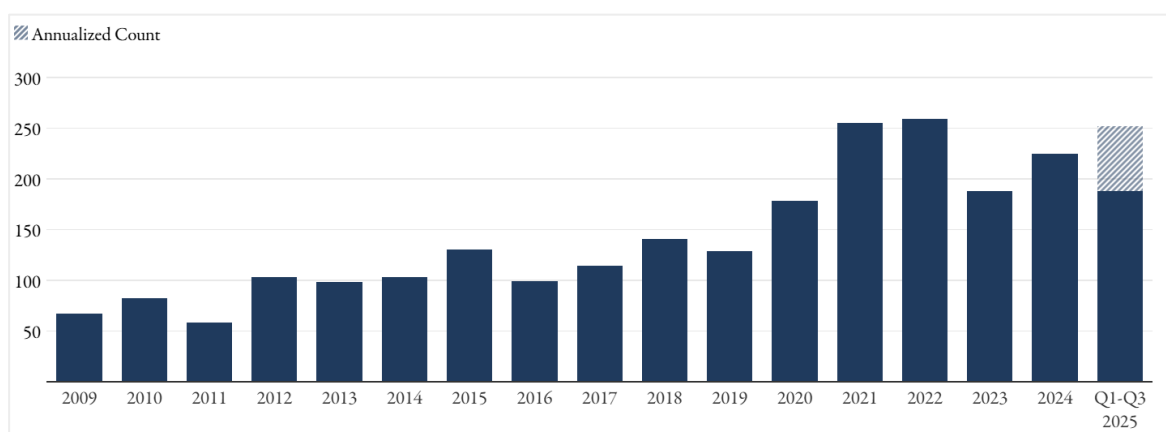
Figure 1: Growth of the global cybersecurity market



Source: Grand View Research (2025)

Appendix 2

Figure 2: Evolution of US cybersecurity M&A deal volumes



Source: Ropes & Gray (2025)

Appendix 3

Table 1: List of 13 US-listed, pure-play cybersecurity companies

Exchange	Company ticker	Company	Revenue (USD million)	Revenue period
NASDAQ	CRWD	CrowdStrike	4,812.0	Year ended January 31, 2026
NASDAQ	FTNT	Fortinet	6,799.6	Year ended December 31, 2025
NASDAQ	GEN	Gen Digital	3,935.0	Year ended March 28, 2025
NASDAQ	OKTA	Okta	2,919.0	Year ended January 31, 2026
NASDAQ	PANW	Palo Alto Networks	9,221.5	Year ended July 31, 2025
NASDAQ	QLYS	Qualys	669.1	Year ended December 31, 2025
NASDAQ	RPD	Rapid7	860.0	Year ended December 31, 2025
NYSE	RBRK	Rubrik	1,316.2	Year ended January 31, 2026
NYSE	S	SentinelOne	1,001.3	Year ended January 31, 2026
NASDAQ	TLS	Telos Corporation	164.8	Year ended December 31, 2025
NASDAQ	TENB	Tenable	999.4	Year ended December 31, 2025
NASDAQ	VRNS	Varonis	623.5	Year ended December 31, 2025
NASDAQ	ZS	Zscaler	2,673.1	Year ended July 31, 2025

Source: Table prepared by the author

Appendix 4

Table 2: List of 73 acquisitions of US-listed, pure-play cybersecurity companies

Acquirer ticker	Target	Announcement date		Acquirer ticker	Target	Announcement date
CRWD	Humio	2021-02-18		QLYS	Total Cloud	2021-08-09
CRWD	SecureCircle	2021-10-31		QLYS	Blue Hexagon	2022-10-04
CRWD	Reposify	2022-09-20		RPD	Alcide	2021-02-01
CRWD	Bionic	2023-09-19		RPD	Velocidex Enterprises	2021-04-21

Acquirer ticker	Target	Announcement date		Acquirer ticker	Target	Announcement date
CRWD	Flow security	2024-03-05		RPD	IntSights Cyber Intelligence	2021-07-19
CRWD	Adaptive Shield	2024-11-06		RPD	Minerva Labs	2023-03-14
CRWD	Onum	2025-08-27		RPD	Noetic Cyber	2024-07-01
CRWD	<u>Pangea</u>	<u>2025-09-15</u>		RPD	Kenzo	2026-03-26
CRWD	<u>SGNL</u>	<u>2026-01-08</u>		RBRK	Predibase	2025-06-25
CRWD	<u>Seraphic</u>	<u>2026-01-13</u>		S	Attivo Networks	2022-03-15
FTNT	ShieldX Networks	2021-03-22		S	Krebs Stamos	2023-11-09
FTNT	Sken ai	2021-07-07		S	PingSafe	2024-01-03
FTNT	Axala Networks Corporation	2021-09-06		S	Stride Security	2024-03-13
FTNT	Lacework	2024-06-10		S	Prompt Security	2025-08-05
FTNT	Next DLP Holdings Lt	2024-08-05		S	Observe AI	2025-09-08
FTNT	Perception Point Ltd	2024-12-11		TLS	Diamond Fortress Technologies	2021-08-02
FTNT	Suridata	2025-05-22		TENB	Alsid	2021-02-10
GEN	BullGuard	2021-02-05		TENB	Accurics	2021-09-13
GEN	Avast PLC	2021-08-10		TENB	Cymptom	2022-02-02
GEN	ReputationDefender	2021-09-15		TENB	Bit Discovery	2022-04-27
GEN	MoneyLion	2024-12-10		TENB	Ermetic	2023-09-07
GEN	GoBankingRates	2025-01-30		TENB	Eureka	2024-06-06
GEN	Trellis Technologies	2026-03-10		TENB	Vulcan	2025-01-29
OKTA	Auth0	2021-03-03		TENB	Apex	2025-05-29
OKTA	Townsend Street (atSpoke)	2021-08-01		VRNS	Cyral	2025-03-17
OKTA	Arengu	2023-06-12		VRNS	SlashNext	2025-09-02
OKTA	Uno	2023-10-04		VRNS	Alltrue	2026-02-03
OKTA	Spera	2023-12-19		ZS	Trustdome	2021-04-15
OKTA	Axiom Security	2025-08-26		ZS	Smokescreen	2021-05-25
PANW	Bridgecrew	2021-02-16		ZS	ShiftRight	2022-09-29
PANW	Cider Security	2022-11-17		ZS	Canonic	2023-02-14

Acquirer ticker	Target	Announcement date		Acquirer ticker	Target	Announcement date
PANW	Dig Security	2023-10-31		ZS	Avalor	2024-03-14
PANW	Talon Cyber Security	2023-11-05		ZS	Airgap	2024-04-11
PANW	Protect AI	2025-04-28		ZS	Red Canary	2025-05-27
PANW	CyberArk	2025-07-30		ZS	SPLX AI	2025-11-03
PANW	Chronosphere	2025-11-19		ZS	SquareX	2026-02-05
PANW	<u>KOI</u>	<u>2026-02-17</u>		/	/	/

Source: Table prepared by the author

*Note: Target and date = acquisition not completed as of March 2026

Appendix 5

Table 3: Market model parameters by company

Acquirer	N Deals	% N Deals	Avg alpha	Avg beta	Avg R ²	Beta range
CRWD	10	14.08%	0.0014	1.317	38.5%	0.96 - 1.58
FTNT	7	9.86%	0.0007	0.898	26.2%	0.44 - 1.14
GEN	6	8.45%	0.0002	0.467	14.6%	0.29 - 0.67
OKTA	6	8.45%	-0.0002	1.192	28.6%	0.87 - 1.44
PANW	8	11.27%	0.0006	0.942	38.4%	0.9 - 1.06
QLYS	2	2.82%	0.0007	0.953	28.6%	0.86 - 1.05
RPD	6	8.45%	-0.0016	1.035	31.8%	0.92 - 1.29
RBRK	1	1.41%	0.0045	1.498	37.1%	1.5 - 1.5
S	5	7.04%	-0.0006	1.473	29.8%	1.2 - 1.74
TENB	8	11.27%	0.0003	1.065	29.6%	0.64 - 1.38
VRNS	3	4.23%	-0.0008	0.625	14.8%	0.59 - 0.66
ZS	9	12.68%	0.0011	1.425	38.0%	1.03 - 1.87

Source: Table prepared by the author

*Note: Alpha and beta are estimated using OLS regression over the estimation window [-250, -30] relative to each announcement date, using the NASDAQ Composite as the market index.

Appendix 6

Table 4: Deal characteristics: payment method and geography

Payment method	N	%
Cash	32	66.7%
Mixed	15	31.2%
Stock	1	2.1%
Geography	N	%
Domestic	30	62.5%
Cross-border	18	37.5%

Source: Table prepared by the author

*Note: Cross-sectional regression subsample of N = 48 deals

Appendix 7

Table 5: Average abnormal returns by event day

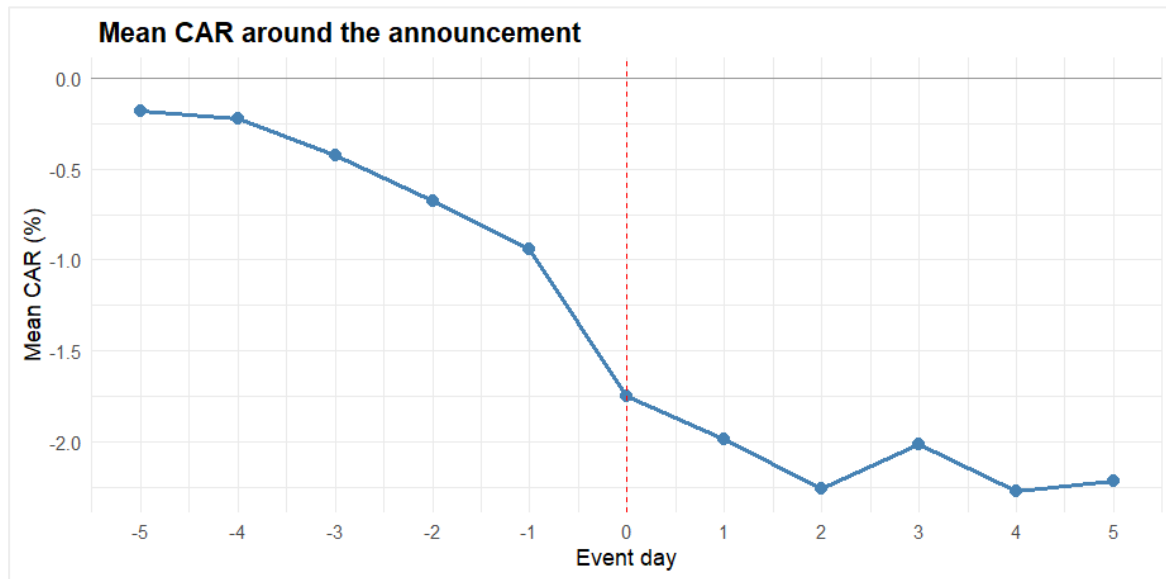
Event day	Mean AR	Std. Deviation	N
-5	-0.182%	2.658%	71
-4	-0.04%	1.62%	71
-3	-0.205%	2.088%	71
-2	-0.252%	2.152%	71
-1	-0.259%	1.749%	71
0	-0.809%	2.597%	71
+1	-0.238%	3.953%	71
+2	-0.272%	3.976%	71
+3	0.245%	2.655%	71
+4	-0.262%	2.526%	71
+5	0.055%	1.783%	71

Source: Table prepared by the author

*Note: Day 0 represents the announcement date. Std. Deviation is the standard deviation of the abnormal returns. N represents the number of deals in the sample.

Appendix 8

Figure 3: Average cumulative abnormal returns by event day



Source: Figure prepared by the author

*Note: Day 0 represents the announcement date.

Table 6: Average cumulative abnormal returns and t-test results (H_0 vs H_1) (NASDAQ benchmark)

Window	Mean CAR	Median CAR	Std. Dev.	t-statistic	p-value	% Positive
[-1,+1]	-1.31%	-0.77%	5.45%	-2.021	0.0472*	42.3%
[-2,+2]	-1.83%	-1.12%	7.51%	-2.052	0.0439*	35.2%
[-5,+5]	-2.22%	-2.26%	9.02%	-2.074	0.0418*	42.3%

Source: Table prepared by the author

*Note: H_0 : mean CAR = 0. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. % positive refers to the share of deals with a positive CAR.

Appendix 9

Table 7: Cumulative abnormal returns by acquirer

Acquirer	N	Mean CAR(-1,+1)	Median CAR (-1,+1)	Mean CAR (-2,+2)	Median CAR (-2,+2)	Mean CAR (-5,+5)	Median CAR (-5,+5)
CRWD	10	0.84%	1.69%	-1.65%	-0.14%	-1.26%	-2.06%
ZS	9	0.13%	-1.05%	-0.84%	-1.37%	1.61%	1.36%
PANW	8	-3.18%	-3.4%	-2.87%	-3.11%	-5.15%	-4.49%
TENB	8	0.37%	0.74%	0.4%	1.21%	-1.71%	1.94%
FTNT	7	0.34%	0.8%	3.91%	-0.43%	1.84%	-2.76%
GEN	6	-2.42%	-3.92%	-1.63%	-3.49%	-2.42%	-2.81%
OKTA	6	-1.82%	-0.52%	-2.5%	-1.4%	-1.07%	-2.23%
RPD	6	-0.53%	-1.43%	-2.96%	-1.89%	-2.34%	-1.76%
S	5	-6.81%	-5.89%	-7.81%	-8.74%	-8.72%	-10.2%
VRNS	3	-6.87%	-5.6%	-8.75%	-4.72%	-8.77%	-3.15%
QLYS	2	1.89%	1.89%	0.27%	0.27%	2.15%	2.15%
RBRK	1	-2.78%	-2.78%	-6.09%	-6.09%	-16.9%	-16.9%

Source: Table prepared by the author

*Note: Event-study sample of $N = 71$ deals across 12 acquirers

Appendix 10

Table 8: Cross-sectional results per acquisition announcement (H_2, H_3, H_4)

Acquirer	Announcement date	Alpha	Beta	R ²	CAR(-1,+1)	CAR(-2,+2)	CAR(-5,+5)	Payment	Cross-border	Deal value (USD million)	Market cap (USD million)	Relative size
CRWD	2021-02-18	0.0049	0.9588	0.2763	-0.0162	-0.0538	-0.0579	mixed	cross-border	400	52,900	0.0076
CRWD	2021-10-31	0.0017	1.5064	0.2538	-0.0713	-0.0941	-0.1044	cash	domestic	60.8	64,000	0.0010
CRWD	2022-09-20	0.0003	1.5762	0.4987	0.0207	-0.0353	0.0119	mixed	domestic	19.5	38,000	0.0005
CRWD	2023-09-19	-0.0013	1.1758	0.3004	0.0152	0.0184	0.0184	mixed	domestic	350	39,000	0.0090
CRWD	2024-03-05	0.0023	1.4458	0.3377	0.0679	-0.0041	-0.0185	cash	cross-border	200	76,500	0.0026
CRWD	2024-11-06	0.0005	1.3142	0.2411	0.0244	0.0102	0.0731	mixed	cross-border	300	80,000	0.0038
CRWD	2025-09-15	0.0018	1.3088	0.4879	0.0039	0.0164	0.0904	cash	domestic	260	115,000	0.0023
CRWD	2026-01-08	0.0009	1.2894	0.4799	0.0185	0.0012	-0.0579	mixed	domestic	740	117,500	0.0063
CRWD	2026-01-13	0.0009	1.2821	0.4744	-0.0131	-0.0264	-0.0227	mixed	cross-border	420	116,500	0.0036
FTNT	2021-03-22	-0.0006	1.1389	0.3903	0.0098	-0.0112	0.0086	cash	domestic	10.8	29,000	0.0004

Acquirer	Announcement date	Alpha	Beta	R ²	CAR(-1,+1)	CAR(-2,+2)	CAR(-5,+5)	Payment	Cross-border	Deal value (USD million)	Market cap (USD million)	Relative size
FTNT	2024-06-10	-0.0007	0.9566	0.1418	-0.0074	-0.0043	-0.0276	cash	domestic	152.3	46,000	0.0033
FTNT	2024-08-05	-0.0005	0.7672	0.1452	0.0144	0.2797	0.2690	cash	domestic	105	47,000	0.0022
FTNT	2024-12-11	0.0014	0.4404	0.0408	0.0080	-0.0210	-0.0325	cash	domestic	200	75,000	0.0027
GEN	2021-08-10	0.0004	0.4997	0.1175	0.0947	0.0880	0.0538	mixed	domestic	9363	14,600	0.6413
GEN	2024-12-10	0.0006	0.4059	0.0594	-0.0454	-0.0471	-0.0720	cash	domestic	954.25	18,800	0.0508
OKTA	2021-03-03	0.0019	0.8725	0.3632	-0.1199	-0.1768	-0.1704	stock	domestic	6500	32,000	0.2031
OKTA	2021-08-01	-0.0009	1.3381	0.3654	-0.0187	-0.0095	-0.0570	mixed	domestic	89	37,500	0.0024
OKTA	2023-12-19	-0.0008	1.2066	0.2025	0.0307	0.0830	0.1665	mixed	cross-border	80	14,000	0.0057
PANW	2021-02-16	0.0006	0.8952	0.5306	0.0129	-0.0005	0.0140	cash	domestic	156.9	38,420	0.0041
PANW	2022-11-17	0.0021	1.0617	0.4654	0.0473	0.0622	0.0250	mixed	cross-border	198.3	49,420	0.0040
PANW	2023-10-31	0.0008	0.9357	0.2234	-0.0077	-0.0002	-0.0672	cash	cross-border	255.4	74,000	0.0035
PANW	2023-11-05	0.0014	0.9095	0.2198	-0.0602	-0.0616	-0.0226	cash	cross-border	458.6	75,700	0.0061
PANW	2025-04-28	0.0007	0.9208	0.3257	0.0414	0.0630	0.0255	cash	domestic	700	120,000	0.0058
PANW	2025-07-30	0.0005	0.9445	0.4722	-0.1585	-0.1397	-0.1431	mixed	cross-border	25000	117,840	0.2122
PANW	2025-11-19	-0.0002	0.9260	0.4033	-0.0628	-0.0860	-0.1483	cash	domestic	3350	130,000	0.0258
QLYS	2022-10-04	0.0025	1.0482	0.4264	-0.0192	-0.0323	-0.0358	cash	domestic	10	4,400	0.0023
RBRK	2025-06-25	0.0045	1.4980	0.3713	-0.0278	-0.0609	-0.1692	cash	domestic	500	16,700	0.0299
RPD	2021-02-01	-0.0002	0.9691	0.5249	0.0160	-0.0344	-0.0595	cash	cross-border	50.5	4,500	0.0112
RPD	2021-07-19	0.0007	0.9691	0.3387	0.0610	0.0672	0.0927	mixed	cross-border	322.3	5,800	0.0556
RPD	2023-03-14	-0.0028	1.2879	0.3881	-0.0530	-0.1671	-0.1629	cash	cross-border	38	3,200	0.0119
RPD	2024-07-01	-0.0013	1.0974	0.1617	-0.0060	0.0188	0.0147	cash	domestic	51.2	2,600	0.0197
S	2024-01-03	-0.0008	1.7445	0.2221	-0.0886	-0.0874	-0.1025	cash	domestic	83	8,200	0.0101
S	2024-03-13	0.0017	1.5153	0.1285	-0.1461	-0.1977	-0.1291	cash	cross-border	7.5	7,000	0.0011
S	2025-08-05	-0.0014	1.2016	0.4636	-0.0589	-0.0921	-0.1913	mixed	domestic	250	5,500	0.0455
S	2025-09-08	-0.0016	1.2230	0.4343	-0.0134	-0.0232	0.0258	mixed	domestic	225	6,200	0.0363
TENB	2021-02-10	0.0020	1.0444	0.4262	0.0174	-0.0416	-0.2133	cash	cross-border	98.5	4,620	0.0213
TENB	2021-09-13	-0.0005	1.2157	0.2524	0.0154	0.0438	0.0363	cash	domestic	160	4,930	0.0325
TENB	2022-02-02	0.0002	1.3836	0.3908	0.0241	0.0132	0.0365	cash	cross-border	23	5,550	0.0041
TENB	2022-04-27	0.0019	1.3083	0.3882	0.0202	0.0120	-0.0376	cash	domestic	43.8	6,000	0.0073
TENB	2023-09-07	0.0005	1.1977	0.2951	-0.0006	0.0145	0.0533	cash	cross-border	243.8	5,150	0.0473
TENB	2025-01-29	-0.0012	0.7889	0.2111	-0.0321	0.0122	0.0681	mixed	cross-border	150	5,200	0.0288
VRNS	2025-03-17	-0.0008	0.6562	0.1298	0.0535	0.0572	0.0246	cash	domestic	25	4,500	0.0056
VRNS	2025-09-02	-0.0007	0.6296	0.2579	-0.0560	-0.0472	-0.0315	cash	domestic	150	6,500	0.0231
ZS	2023-02-14	-0.0010	1.7635	0.5424	0.0162	-0.0459	0.0666	cash	cross-border	16.5	19,250	0.0009
ZS	2024-03-14	0.0017	1.6899	0.3188	-0.0108	-0.0417	-0.0797	mixed	domestic	256.7	29,000	0.0089
ZS	2024-04-11	0.0018	1.7098	0.3020	-0.0300	-0.0185	-0.0211	cash	domestic	124.4	27,300	0.0046
ZS	2025-05-27	0.0009	1.1649	0.4327	-0.0105	-0.0137	0.1444	cash	domestic	675	40,000	0.0169
ZS	2025-11-03	0.0012	1.0862	0.4690	0.0269	0.0245	-0.0095	cash	domestic	17	52,000	0.0003

Source: Table prepared by the author

*Note: The table reports the full event-study and deal-level dataset for the 48 valid observations with complete deal-level data.

Appendix 11

Table 9: Cross-sectional regression results (H_2, H_3, H_4)

Window		Intercept	Cash vs Mixed	Stock vs Mixed	Cross-border	Relative target size	R ²	Adj. R ²
[-1,+1]	Coef (Std. Dev.) <i>p-value</i>	-1.35% (1.51%) 0.377	-0.23% (1.54%) 0.881	-12.04% (2.52%) <0.001***	1.34% (1.54%) 0.389	7.89% (10.66%) 0.463	13.64%	5.61%
[-2,+2]	Coef (Std. Dev.) <i>p-value</i>	-0.68% (1.98%) 0.732	-0.68% (2.15%) 0.753	-18.18% (2.49%) <0.001***	-0.94% (2.27%) 0.681	6.64% (10.09%) 0.514	11.00%	2.73%
[-5,+5]	Coef (Std. Dev.) <i>p-value</i>	-1.28% (2.97%) 0.670	-1.21% (3.09%) 0.698	-16.08% (2.92%) <0.001***	1.14% (2.98%) 0.705	1.78% (10.96%) 0.872	6.25%	-2.47%

Source: Table prepared by the author

*Note: The dependent variable is CAR for each window. Reference categories: mixed payment, domestic deal. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Appendix 12

Table 10: Univariate regression: payment method (cash vs stock vs mixed) (H_2)

Window		Intercept (mixed)	Cash vs Mixed	Stock vs Mixed	R ²	Adj. R ²
[-1,+1]	Coef (Std. Dev.) <i>p-value</i>	-0.16% (1.51%) 0.915	-0.87% (1.71%) 0.615	-11.83% (1.51%) <0.001***	10.71%	6.75%
[-2,+2]	Coef (Std. Dev.) <i>p-value</i>	-0.65% (1.66%) 0.696	-0.96% (2.18%) 0.661	-17.03% (1.66%) <0.001***	9.85%	5.84%
[-5,+5]	Coef (Std. Dev.) <i>p-value</i>	-0.62% (2.42%) 0.800	-1.45% (2.97%) 0.627	-16.42% (2.42%) <0.001***	5.93%	1.75%

Source: Table prepared by the author

*Note: The dependent variable is CAR for each window. Reference category: mixed payment. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Appendix 13

Table 11: Mean and median CARs by payment method (H_2)

Payment Method	Mean CAR[-1,+1]	Mean CAR[-2,+2]	Mean CAR[-5,+5]	Median CAR[-1,+1]	Median CAR[-2,+2]	Median CAR[-5,+5]
Mixed	-1.62%	-0.65%	-0.62%	-1.08%	-0.95%	1.19%
Cash	-1.03%	-1.61%	-2.07%	0.17%	-1.25%	-2.18%
Stock	-11.99%	-17.63%	-17.04%	-11.99%	-17.63%	-17.04%

Source: Table prepared by the author

Appendix 14

Table 12: Univariate regression: geography (cross-border vs domestic) (H_3)

Window		Intercept (domestic)	Cross-border dummy	R ²	Adj. R ²
[-1,+1]	Coef (Std. Dev.) p-value	-1.55% (0.94%) 0.108	1.50% (1.51%) 0.325	2.07%	-0.06%
[-2,+2]	Coef (Std. Dev.) p-value	-1.46% (1.47%) 0.327	-0.49% (2.24%) 0.827	0.10%	-2.07%
[-5,+5]	Coef (Std. Dev.) p-value	-2.57% (1.77%) 0.153	1.72% (2.86%) 0.550	0.77%	-1.38%

Source: Table prepared by the author

*Note: Cross-border dummy = 1 if the target is incorporated outside the US. Reference category: domestic. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Appendix 15

Table 13: Mean and median CARs by geography (H_3)

Geography	Mean CAR[-1,+1]	Mean CAR[-2,+2]	Mean CAR[-5,+5]	Median CAR[-1,+1]	Median CAR[-2,+2]	Median CAR[-5,+5]
Cross-border	-0.05%	-1.95%	-0.85%	1.56%	-0.21%	-0.004%
Domestic	-1.55%	-1.46%	-2.57%	-0.89%	-1.61%	-2.95%

Source: Table prepared by the author

Appendix 16

Table 14: Univariate regression: relative target size (H_4)

Window		Intercept	Relative target size	R ²	Adj. R ²
[-1,+1]	Coef (Std. Dev.) <i>p-value</i>	-1.10% (0.70%) 0.122	3.30% (13.83%) 0.812	0.40%	-1.76%
[-2,+2]	Coef (Std. Dev.) <i>p-value</i>	-1.74% (1.14%) 0.134	2.70% (14.55%) 0.854	0.12%	-2.05%
[-5,+5]	Coef (Std. Dev.) <i>p-value</i>	-1.85% (1.43%) 0.204	-2.41% (14.25%) 0.867	0.06%	-2.11%

Source: Table prepared by the author

*Note: Relative target size = deal value / acquirer market cap at announcement. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Appendix 17

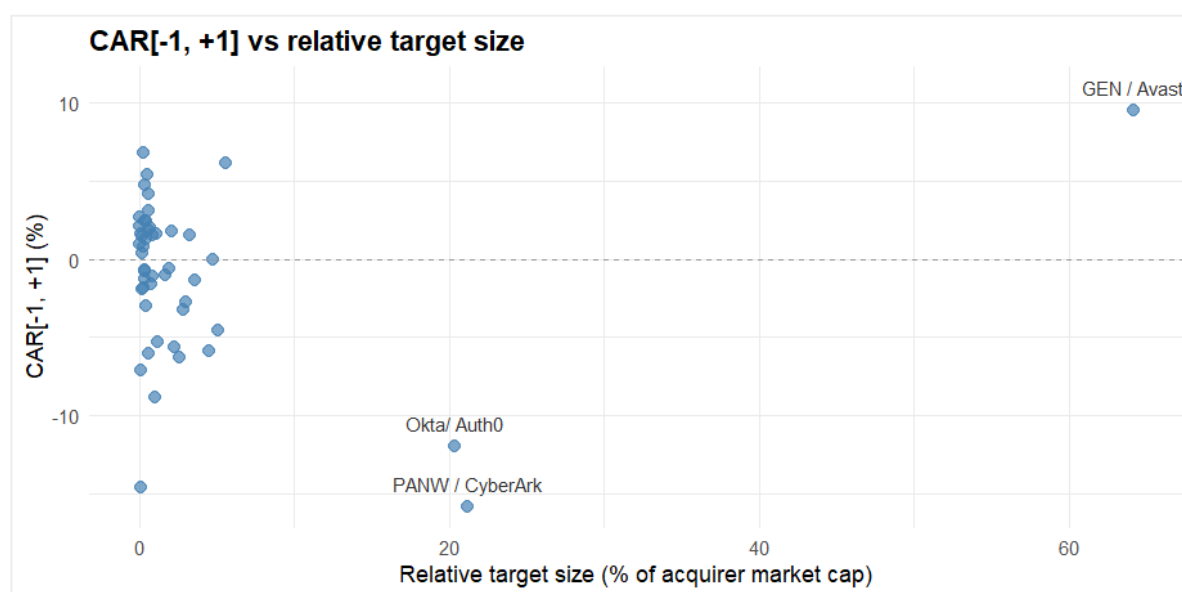
Table 15: Mean and median CARs by relative target size quartile (H_4)

Size Quartile	Mean CAR[-1,+1]	Mean CAR[-2,+2]	Mean CAR[-5,+5]	Median CAR[-1,+1]	Median CAR[-2,+2]	Median CAR[-5,+5]
Q1 (smallest)	-0.73%	-1.09%	0.50%	0.89%	-1.61%	-1.40%
Q2	0.45%	0.97%	1.48%	1.70%	0.50%	1.93%
Q3	1.28%	-1.28%	-3.64%	-5.21%	-3.80%	-5.79%
Q4 (largest)	-2.90%	-3.33%	-4.71%	-2.99%	-3.51%	-2.31%

Source: Table prepared by the author

*Note: Deals sorted into quartiles based on relative target size (deal value / acquirer market cap at announcement). Q1 = smallest deals relative to acquirer size, Q4 = largest. N = 48 deals, 12 per quartile.

Figure 4: Relative target size of sample acquisitions against their cumulative abnormal returns in window[-1, +1]



Source: Figure prepared by the author

*Note: Scatter plot of CAR[-1, +1] against relative target size (deal value / acquirer market cap at announcement)) for the 48 deals in the regression subsample. The dashed line indicates zero abnormal return.

Appendix 18

Table 16: Robustness check: NASDAQ vs S&P 500 benchmark

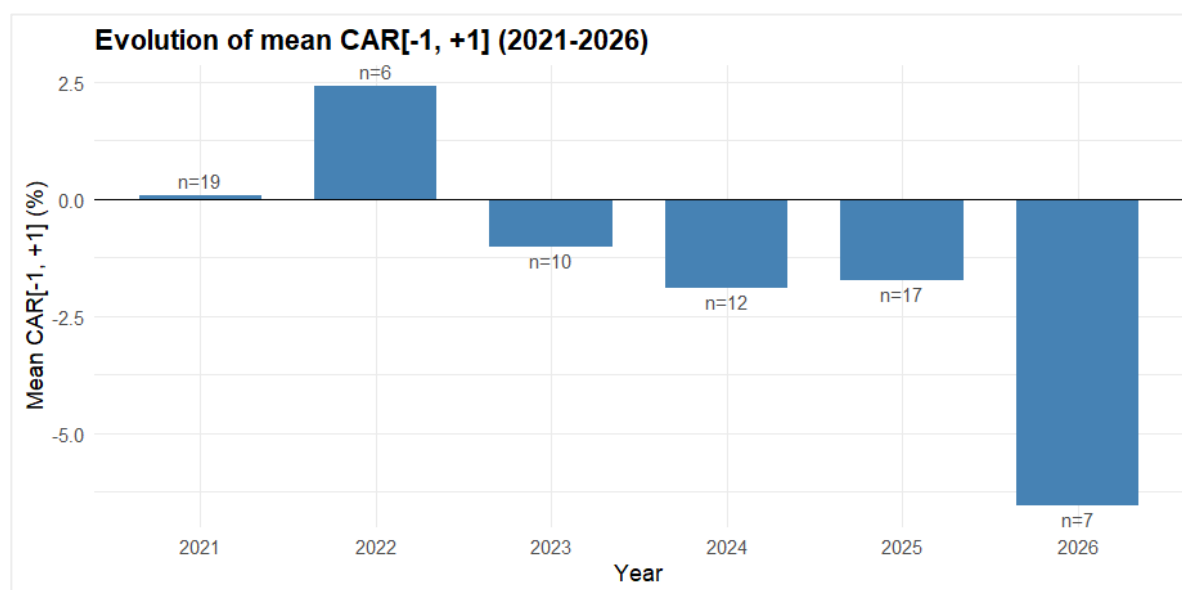
Window	Mean CAR (NASDAQ)	Mean CAR (S&P 500)	t-stat (NASDAQ)	t-stat (S&P 500)	p-value (NASDAQ)	p-value (S&P 500)	Difference
[-1,+1]	-1.31%	-1.34%	-2.021	-1.991	0.0472*	0.0503	0.029%
[-2,+2]	-1.83%	-1.89%	-2.052	-2.083	0.0439*	0.0409*	0.063%
[-5,+5]	-2.22%	-2.29%	-2.074	-2.059	0.0418*	0.0432*	0.066%

Source: Table prepared by the author

*Note: Mean CARs and t-statistics estimated using NASDAQ Composite and S&P 500 used as alternative benchmark. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The difference column shows the absolute difference in mean CARs between the two benchmarks.

Appendix 19

Figure 5: Evolution of cumulative abnormal returns through the years (2021-2026)



Source: Figure prepared by the author

Table 17: Cumulative abnormal returns by announcement year (2021-2026)

Year	N	Mean CAR (-1,+1)	Median CAR (-1,+1)	Mean CAR (-2,+2)	Median CAR (-2,+2)	Mean CAR (-5,+5)	Median CAR (-5,+5)	% Positive (-1,+1)
2021	19	0.08%	0.98%	-0.58%	-0.34%	-2.0%	0.86%	52.6%
2022	6	2.41%	2.24%	1.39%	1.26%	1.5%	1.85%	83.3%
2023	10	-1.02%	-0.41%	-2.02%	-0.94%	0.13%	-0.21%	40%
2024	12	-1.91%	-0.87%	-1.11%	-1.92%	-1.74%	-3.0%	33.3%
2025	17	-1.74%	-1.05%	-1.87%	-1.14%	-2.41%	-0.35%	35.3%
2026	7	-6.55%	-6.7%	-8.87%	-5.86%	-9.74%	-5.79%	14.3%

Source: Table prepared by the author

Appendix 20

Rcode

```

1 #Install packages
2 install.packages("quantmod")
3 install.packages("dplyr")
4 install.packages("readxl")
5 install.packages("writexl")
6 install.packages("ggplot2")
7 install.packages("broom")
8 install.packages("purrr")
9 install.packages("xts")
10 install.packages("sandwich")
11 install.packages("lmtest")
12
13 # Load them at the start of every session
14 library(quantmod)
15 library(dplyr)
16 library(readxl)
17 library(writexl)
18 library(ggplot2)
19 library(broom)
20 library(purrr)
21 library(xts)
22 library(sandwich)
23 library(lmtest)
24
25 # Download data from yahoo
26 tickers<-c('PANW', 'CRWD', 'S', 'FTNT', 'ZS', 'OKTA', 'QLYS', 'RPD', 'TENB', 'VRNS', 'GEN', 'TLS', 'RBRK')
27 getSymbols(tickers, src='yahoo', from = '2018-01-01', to='2026-05-01')
28 getSymbols(c("AIXIC", "AGSPC"), src = "yahoo",
29           from = "2018-01-01", to = "2026-05-01")
30
31 # Calculate daily returns for all 13 companies
32 # We use adjusted prices (Ad)
33 # Return_t = (Price_t / Price_(t-1)) - 1
34 returns_list <- lapply(tickers, function(ticker) {
35   dailyReturn(Ad(get(ticker)))
36 })
37 names(returns_list)<-tickers
38
39 # Combining all 13 return series into one table (rows = dates, columns = tickers)
40 all_returns <- do.call(merge, returns_list)
41 colnames(all_returns) <- tickers
42
43 # Benchmark returns
44 return_NASDAQ <- dailyReturn(Ad(IXIC))
45 return_SP500 <- dailyReturn(Ad(GSPC))
46 colnames(return_NASDAQ)<-"NASDAQ_ret"
47 colnames(return_SP500)<- "SP500_ret"
48
49 # Importing excel file with list of acquisitions
50 acquisitions <- read_excel(file.choose())
51 acquisitions$announcement_date<-as.Date(acquisitions$announcement_date)
52 acquisitions$acquirer <- as.character(acquisitions$acquirer)
53
54 # Function to run event study for one acquisition
55 run_event_study <- function(acquirer, event_date, stock_returns, market_returns, est_start=-250,
56                             est_end=-30, evt_start=-5, evt_end=5, min_est_obs=150) {
57   event_date<-as.Date(event_date)
58   if (!(acquirer %in% colnames(stock_returns))) {
59     message("Ticker not found in stock_returns: ", acquirer)
60     return(NULL)
61   }
62   acquirer_returns <- stock_returns[, acquirer, drop = FALSE]
63   # Merge stock returns with market returns
64   merged_data <- merge(acquirer_returns, market_returns, join = "inner")
65   colnames(merged_data) <- c("stock_ret", "market_ret")
66   merged_data <- na.omit(merged_data)
67   dates <- index(merged_data)
68   event_idx <- which(dates >= event_date)[1]
69   if (is.na(event_idx)) {
70     message("No trading date after event: ", event_date)
71     return(NULL)
72   }
73   # Checking if enough data before and after announcement
74   if ((event_idx + est_start) < 1) {
75     message("Not enough pre-event data for ", acquirer,
76           " on ", event_date)
77     return(NULL)

```

```

78 }
79
80 if ((event_idx + evt_end) > nrow(merged_data)) {
81   message("Not enough post-event data for ", acquirer,
82         " on ", event_date)
83   return(NULL)
84 }
85 est_idx <- (event_idx + est_start):(event_idx + est_end)
86 evt_idx <- (event_idx + evt_start):(event_idx + evt_end)
87
88 est_data <- merged_data[est_idx]
89 evt_data <- merged_data[evt_idx]
90
91 # Checking estimation window size
92 if (nrow(est_data) < min_est_obs) {
93   message("Too few estimation observations for ",
94         acquirer, " on ", event_date)
95   return(NULL)
96 }
97
98 # Market model: stock_ret=alpha+beta*market_ret+error
99 model<-lm(stock_ret ~ market_ret, data=est_data)
100 alpha <- coef(model)[1]
101 beta <- coef(model)[2]
102 r2 <- summary(model)$r.squared
103
104 # Calculating expected returns in the event window
105 evt_data$expected_ret <- alpha + beta * evt_data$market_ret
106
107 # Calculating abnormal returns (ARs): AR= actual return - expected return
108 evt_data$AR <- evt_data$stock_ret - evt_data$expected_ret
109
110 # Labeling event days
111 evt_data$event_day <- seq(evt_start, evt_end)
112
113 # Calculating cumulative abnormal returns (CARs)
114 # CAR[-1,+1]
115 CAR_1_1 <- sum(evt_data$AR[evt_data$event_day >= -1 &
116               evt_data$event_day <= 1])
117
118 # CAR[-2,+2]
119 CAR_2_2 <- sum(evt_data$AR[evt_data$event_day >= -2 &
120               evt_data$event_day <= 2])
121
122 # CAR[-5,+5]
123 CAR_5_5 <- sum(evt_data$AR[evt_data$event_day >= -5 &
124               evt_data$event_day <= 5])
125 # One-row summary result for this deal
126 summary_result <- data.frame(
127   acquirer = acquirer,
128   announcement_date = event_date,
129   alpha = as.numeric(alpha),
130   beta = as.numeric(beta),
131   r_squared = as.numeric(r2),
132   n_est_obs = nrow(est_data),
133   CAR_1_1 = as.numeric(CAR_1_1),
134   CAR_2_2 = as.numeric(CAR_2_2),
135   CAR_5_5 = as.numeric(CAR_5_5)
136 )
137
138 # Creating event-window dataset
139 detail_result <- data.frame(
140   acquirer = acquirer,
141   announcement_date = event_date,
142   date = as.Date(index(evt_data)),
143   event_day = evt_data$event_day,
144   stock_ret = as.numeric(evt_data$stock_ret),
145   market_ret = as.numeric(evt_data$market_ret),
146   expected_ret = as.numeric(evt_data$expected_ret),
147   abnormal_return = as.numeric(evt_data$AR)
148 )
149
150 return(list(
151   summary = summary_result,
152   detail = detail_result,
153   model = model
154 ))
155 }
156

```

```

157 # Testing the event_study function on one acquisition
158 test_result <- run_event_study(
159   acquirer = acquisitions$acquirer[1],
160   event_date = acquisitions$announcement_date[1],
161   stock_returns = all_returns,
162   market_returns = return_NASDAQ
163 )
164
165 # Show summary for the test deal
166 if (!is.null(test_result)) {
167   print(test_result$summary)
168   print(test_result$detail)
169   summary(test_result$model)
170 }
171
172 # Running event for all deals
173 results_list <- pmap(
174   list(acquisitions$acquirer, acquisitions$announcement_date),
175   function(acquirer, announcement_date) {
176     run_event_study(
177       acquirer = acquirer,
178       event_date = announcement_date,
179       stock_returns = all_returns,
180       market_returns = return_NASDAQ
181     )
182   }
183 )
184
185 # Extracting summary results for all valid deals
186 valid_results <- results_list[!sapply(results_list, is.null)]
187
188 summary_results <- bind_rows(lapply(valid_results, function(x) x$summary))
189 detail_results <- bind_rows(lapply(valid_results, function(x) x$detail))
190 print(summary_results)
191 print(head(detail_results))
192
193 # Statistics on CARs
194 summary(summary_results$CAR_1_1)
195 summary(summary_results$CAR_2_2)
196 summary(summary_results$CAR_5_5)
197
198 mean(summary_results$CAR_1_1, na.rm = TRUE)
199 mean(summary_results$CAR_2_2, na.rm = TRUE)
200 mean(summary_results$CAR_5_5, na.rm = TRUE)
201
202 sd(summary_results$CAR_1_1, na.rm = TRUE)
203 sd(summary_results$CAR_2_2, na.rm = TRUE)
204 sd(summary_results$CAR_5_5, na.rm = TRUE)
205
206 # T-tests for the main hypothesis
207 # H0: mean CAR=0, H1: mean CAR≠0
208 ttest_CAR_1_1 <- t.test(summary_results$CAR_1_1, mu = 0)
209 ttest_CAR_2_2 <- t.test(summary_results$CAR_2_2, mu = 0)
210 ttest_CAR_5_5 <- t.test(summary_results$CAR_5_5, mu = 0)
211
212 print(ttest_CAR_1_1)
213 print(ttest_CAR_2_2)
214 print(ttest_CAR_5_5)
215
216 # Average AR by event day
217 average_AR_by_day <- detail_results %>%
218   group_by(event_day) %>%
219   summarise(
220     mean_AR = mean(abnormal_return, na.rm = TRUE),
221     sd_AR = sd(abnormal_return, na.rm = TRUE),
222     n = n()
223   )
224
225 print(average_AR_by_day)
226
227 # Robustness check with S&P500
228 results_list_sp500 <- pmap(
229   list(acquisitions$acquirer, acquisitions$announcement_date),
230   function(acquirer, announcement_date) {
231     run_event_study(
232       acquirer = acquirer,
233       event_date = announcement_date,

```

```

234     stock_returns = all_returns,
235     market_returns = return_SP500
236   )
237 }
238 )
239
240 valid_results_sp500 <- results_list_sp500[!sapply(results_list_sp500, is.null)]
241
242 summary_results_sp500 <- bind_rows(lapply(valid_results_sp500, function(x) x$summary))
243
244 ttest_CAR_1_1_sp500 <- t.test(summary_results_sp500$CAR_1_1, mu = 0)
245 ttest_CAR_2_2_sp500 <- t.test(summary_results_sp500$CAR_2_2, mu = 0)
246 ttest_CAR_5_5_sp500 <- t.test(summary_results_sp500$CAR_5_5, mu = 0)
247
248 print(ttest_CAR_1_1_sp500)
249 print(ttest_CAR_2_2_sp500)
250 print(ttest_CAR_5_5_sp500)
251
252 # Cross-sectional regression
253 acquisitions <- acquisitions %>%
254   rename(cross_border=dom_or_crossb)
255 acquisitions <- acquisitions %>%
256   rename(market_cap = acquirer_mktcap)
257 acquisitions_det <- acquisitions %>%
258   select(acquirer,
259          announcement_date,
260          payment_method,
261          cross_border,
262          deal_value,
263          market_cap)
264 acquisitions_det$announcement_date <- as.Date(acquisitions_det$announcement_date)
265
266 # Merging event study results with determinants
267 regressions_det_data <- summary_results %>%
268   left_join(acquisitions_det,
269             by = c("acquirer", "announcement_date"))
270
271 # Preparing variables
272 regressions_det_data$payment_method <- factor(regressions_det_data$payment_method,
273                                               levels = c("mixed", "cash", "stock"))
274
275 regressions_det_data$cross_border_dummy <- ifelse(regressions_det_data$cross_border == "cross-border", 1, 0)
276
277 regressions_det_data$deal_value <- as.numeric(regressions_det_data$deal_value)
278 regressions_det_data$market_cap <- as.numeric(regressions_det_data$market_cap)
279
280 regressions_det_data$relative_target_size <- regressions_det_data$deal_value / regressions_det_data$market_cap
281
282 # Clean data
283 regressions_det_data <- regressions_det_data %>%
284   filter(!is.na(CAR_1_1),
285          !is.na(payment_method),
286          !is.na(cross_border_dummy),
287          !is.na(relative_target_size),
288          is.finite(relative_target_size))
289
290 # Main regression (3 variables together)
291 model_cs_1 <- lm(CAR_1_1 ~ payment_method +
292                 cross_border_dummy +
293                 relative_target_size,
294                 data = regressions_det_data)
295
296 summary(model_cs_1)
297
298 # Robust SE
299 robust_cs_1 <- coeftest(model_cs_1, vcov = vcovHC(model_cs_1, type = "HCl"))
300 print(robust_cs_1)
301
302 model_cs_2 <- lm(CAR_2_2 ~ payment_method +
303                 cross_border_dummy +
304                 relative_target_size,
305                 data = regressions_det_data)
306
307 model_cs_3 <- lm(CAR_5_5 ~ payment_method +
308                 cross_border_dummy +
309                 relative_target_size,
310                 data = regressions_det_data)
311

```

```

312 coeftest(model_cs_2, vcov = vcovHC(model_cs_2, type = "HC1"))
313 coeftest(model_cs_3, vcov = vcovHC(model_cs_3, type = "HC1"))
314
315 # Payment method only
316 regressions_det_payment <- regressions_det_data %>%
317   filter(!is.na(CAR_1_1),
318          !is.na(payment_method))
319
320 model_pay_1 <- lm(CAR_1_1 ~ payment_method,
321                  data = regressions_det_payment)
322
323 model_pay_2 <- lm(CAR_2_2 ~ payment_method,
324                  data = regressions_det_payment)
325
326 model_pay_3 <- lm(CAR_5_5 ~ payment_method,
327                  data = regressions_det_payment)
328
329 coeftest(model_pay_1, vcov = vcovHC(model_pay_1, type = "HC1"))
330 coeftest(model_pay_2, vcov = vcovHC(model_pay_2, type = "HC1"))
331 coeftest(model_pay_3, vcov = vcovHC(model_pay_3, type = "HC1"))
332
333 # Cross-border only
334 regressions_det_cross <- regressions_det_data %>%
335   filter(!is.na(CAR_1_1),
336          !is.na(cross_border_dummy))
337
338 model_cross_1 <- lm(CAR_1_1 ~ cross_border_dummy,
339                    data = regressions_det_cross)
340
341 model_cross_2 <- lm(CAR_2_2 ~ cross_border_dummy,
342                    data = regressions_det_cross)
343
344 model_cross_3 <- lm(CAR_5_5 ~ cross_border_dummy,
345                    data = regressions_det_cross)
346
347 coeftest(model_cross_1, vcov = vcovHC(model_cross_1, type = "HC1"))
348 coeftest(model_cross_2, vcov = vcovHC(model_cross_2, type = "HC1"))
349 coeftest(model_cross_3, vcov = vcovHC(model_cross_3, type = "HC1"))
350
351 # Relative size only
352 regressions_det_size <- regressions_det_data %>%
353   filter(!is.na(CAR_1_1),
354          !is.na(relative_target_size),
355          is.finite(relative_target_size))
356
357 model_size_1 <- lm(CAR_1_1 ~ relative_target_size,
358                   data = regressions_det_size)
359
360 model_size_2 <- lm(CAR_2_2 ~ relative_target_size,
361                   data = regressions_det_size)
362
363 model_size_3 <- lm(CAR_5_5 ~ relative_target_size,
364                   data = regressions_det_size)
365
366 coeftest(model_size_1, vcov = vcovHC(model_size_1, type = "HC1"))
367 coeftest(model_size_2, vcov = vcovHC(model_size_2, type = "HC1"))
368 coeftest(model_size_3, vcov = vcovHC(model_size_3, type = "HC1"))
369
370 # Export on excel
371 # Convert regression output
372 robust_cs_1_df <- data.frame(
373   variable = rownames(robust_cs_1),
374   estimate = robust_cs_1[,1],
375   std_error = robust_cs_1[,2],
376   t_value = robust_cs_1[,3],
377   p_value = robust_cs_1[,4]
378 )
379
380 # Export everything
381 write_xlsx(
382   list(
383     "Summary_Results" = summary_results,
384     "Detail_Results" = detail_results,
385     "Average_AR" = average_AR_by_day,
386     "SP500_Results" = summary_results_sp500,
387     "Regression_Data" = regressions_det_data,
388     "CS_Main_Model" = robust_cs_1_df
389   ),
390   "final_results3.xlsx"
391 )

```