Market Reactions and Value Creation: Acquisitions by Swedish M&A Compounders

Exploring short-term announcement returns and the role of target financial characteristics and interest rate environments in Sweden

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Abstract

This paper investigates whether Swedish M&A compounders earn short-term abnormal returns when announcing acquisitions, focusing on the impact of target firm financial characteristics and the moderating role of different interest rate environments. Using an event study methodology, we analyze 224 acquisitions conducted by publicly listed Swedish M&A compounders from 2000 to 2023. Our results reveal that M&A compounders generate statistically significant positive abnormal returns over the event window [-1, 1], while no significant effect is observed for the [-2, 2] event window. Contrary to expectations, acquisitions of more asset-heavy targets are associated with higher abnormal returns, whereas the target's profitability has no significant effect. Moreover, growth displays a weak but positive relationship of abnormal returns, particularly during periods with zero or negative interest rates. This study contributes to the underexplored academic literature on M&A compounders and underscores the importance of target selection and macroeconomic conditions in shaping investor responses.

Keywords: Serial acquirers, M&A compounders, Target financial characteristics, CAR

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1. Introduction

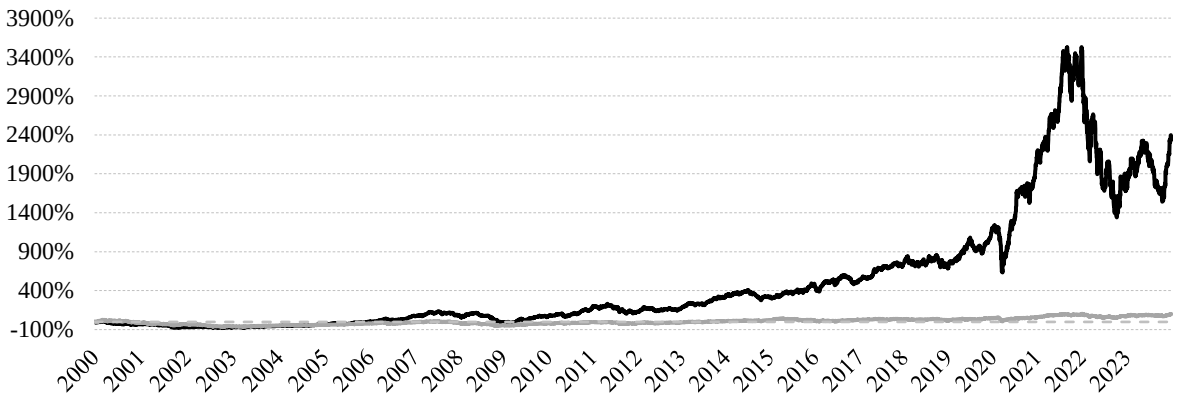
Mergers and Acquisitions (M&A) has become a pivotal force in modern corporate strategy, ranging from multi-billion-dollar deals to acquisitions of small- and medium-sized enterprises. Today, the M&A market spans across all industries and nationalities, creating a global ecosystem worth $3.4 trillion in 2024 (Henry and Van Oostende, 2025). Consequently, a growing body of research has been established to determine whether M&A is value-creating or not. Nevertheless, as seen in Table 1, a large share of existing research has focused on the U.S. market or other major economies, while smaller economies, including Sweden, have received limited attention in the academic literature.

This study aims to narrow this gap by creating a link between value creation and the Swedish M&A market. This is achieved by studying a growing subset of the Swedish financial sponsors landscape, namely M&A compounders. Although commonly seen as a Nordic phenomenon, several well-known firms exist beyond the Nordic region. Moreover, as seen in Figure 1, M&A compounders have historically been able to consistently outperform leading benchmark indices such as OMXS30. Part of this success stems from their unique investment strategy of acquiring growing, profitable and well-run private niche businesses (Hadziefendic et al, 2023). Another part originates from their decentralized and asset-light business model, where M&A compounders often acquire a wide range of businesses in a diverse array of industries (Hadziefendic et al, 2023; Kujala, 2021). Additionally, by constructing a diversified portfolio of businesses, M&A compounders often exhibit resilience during periods of economic downturn, as their revenue streams are derived from a broad range of products and industries (Hadziefendic et al, 2023).

To explore this growing subset of financial sponsors, this paper seeks to determine if M&A compounders earn abnormal returns when announcing new acquisitions. This is achieved by conducting an event study of publicly listed Swedish M&A compounders. Moreover, the relationship between key financial screening criteria commonly associated with M&A compounders is also examined. By doing so, this paper aims to create a comprehensive understanding of whether acquisitions, which are an integral part of the M&A compounders' business model, create abnormal returns for their shareholders and whether the underlying target's financial attributes can help explain the abnormal returns.

Figure 1. M&A Compounder Index versus OMXS30

This figure shows the performance of a custom-made *M&A compounder* index (black line) relative to the benchmark index *OMXS30* (gray line) from January 2000 to December 2023. The custom-made index is a dividend-adjusted, market capitalization-weighted index composed of the following entities listed on OMX Stockholm: ADDT B, ALIF B, ANOD B, AQ, BEIA B, BEIJ B, BERG B, BERNER B, FG, GREEN, IDUN B, INDT, INFREA, INSTAL, LAGR B, LIFCO B, MMGR B, NORB B, OEM B, SDIP B, SEAF, STOR B, TEQ, VESTUM, VIT B, VOLO, XANO B. Both indices are rebased to zero as of January 3, 2000. The horizontal dashed line denotes the zero baseline. Source: S&P Capital IQ.



The findings in this thesis indicate that M&A compounders earn a significant mean cumulative abnormal return (CAR) of 0.599% over the event window [-1, 1], whereas no statistically significant CAR is observed in the event window [-2, 2]. In addition to CAR, the study finds a significant positive relationship between *Asset light* and CAR for the event window [-1, 1]. Since *Asset light* is measured as PPE divided by total asset, the result stands in contrast to M&A compounders' business model as they aim to be asset-light. In addition to *Asset light*, no significant relationship is detected for *Profitability* and only a weak relationship for *Growth*. Furthermore, investigation of moderating effects on the relationship between *Growth* and CAR, as well as *Profitability* and CAR, suggests that CAR can be explained by *Growth* during periods of zero or negative interest rates. By contrast, no statistically meaningful association between CAR and *Profitability* is detected.

Given the underexplored research topic of M&A compounders, this paper addresses a notable gap in the academic literature. In the same manner, while there is an extensive body of research exploring the effect of deal-specific attributes on abnormal returns, studies focusing on target-specific financial characteristics remain limited. Hence, there is a gap in the academic literature, underscoring the need for further research on how target firm financial attributes impact CAR.

2. Literature Review

As a relatively recent phenomenon, M&A compounders have received limited attention in academic research, highlighting a gap in existing literature. Even so, M&A compounders can be viewed as part of a broader group of acquirers, namely serial acquirers. By contrast, serial acquirers have been extensively researched, providing a solid foundation for further investigation into M&A compounders. Nevertheless, despite extensive empirical attention, there is no consensus in the literature regarding a universal definition of a serial acquirer. Definitions often vary depending on the frequency of acquisitions and the time frame considered. For example, Kengelbach et al (2012) and Fuller et al (2002) classify firms as serial acquirers if they have completed at least two or five acquisitions over a three-year period. In a separate study, Laamanen and Keil (2008) adopt a longer time horizon, defining serial acquirers as firms that have completed four or more acquisitions within a ten-year period. Meanwhile, Hossain et al (2021) define serial acquirers as firms that have announced two or more deals within a 24-month period. Other researchers, rather than applying a binary classification, adopt a more continuous or pattern-based segmentation. This is shown in Morillon's (2020) paper, who classifies acquirers along a spectrum ranging from "loners" to "marathoners" based on their acquisition patterns.

Furthermore, given the limited academic attention to M&A compounders, there is not yet a universally accepted definition of the term. Still, a consensus has emerged within the investor community. For instance, Scott Management LLC (2020) outlines four categories of serial acquirers based on level of integration, namely Roll-up, Platform, Accumulator and HoldCo. The author argues that Platforms and Accumulators are characterized by a low level of integration, a high level of product differentiation and shared excellence programs. This stands in contrast to Roll-ups and HoldCos, which are characterized by either a high level of integration or by traits more typically associated with investment companies. In addition to Scott Management LLC, Kujala (2021) defines M&A compounders as companies that operate with a high degree of decentralization, acquire targets at lower multiples than their own and adopt an asset-light business model. Hadziefendic et al (2023) extend the definition and add that M&A compounders, or "acquisition-driven compounders", are characterized by small management teams and strong internal cash flows used to acquire new companies.

Kujala (2021) and Hadziefendic et al (2023) also identify common traits among the acquired companies. Both argue that companies acquired by M&A compounders often are characterized by: (I) Asset-light operations, (II) Small and medium-sized enterprises, (III)

Market leader in niche industry, (IV) Solid financial record and organic growth, (V) Profitable, and (VI) Private (Hadziefendic et al, 2023; Kujala, 2021).

While the investor community explores common traits of acquired companies, academic research focuses on the underlying motivations driving M&A activity. Contemporary literature is generally divided into two schools of thought: Neoclassical and behavioral. According to the neoclassical framework, acquisitions are motivated by value-maximizing behavior under rational expectations. Gugler et al (2012) explain that the theory rests on three key assumptions: (I) Mergers generate synergies, (II) Managers act to maximize shareholder value, and (III) Financial markets are efficient. Therefore, acquisitions are grounded in economic rationality, aiming to improve operational efficiency and strategic positioning (Capron, 1999).

By contrast, the behavioral perspective challenges the assumption of rational decision-making. It emphasizes the role of managerial psychology and incentive structures in shaping acquisition outcomes (Schleifer and Vishny, 1991). Moreover, the behavioral perspective can be further divided into hubris, agency, and learning theories. The hubris hypothesis suggests that managers may overestimate their ability to extract synergies, thereby leading to value destruction (Billett and Qian, 2008; Hossain et al, 2021). In a similar manner, the agency theory, grounded in the principal-agent framework, suggests that acquisitions may be driven by managerial self-interest rather than shareholder value creation, particularly in the absence of effective governance mechanisms (Amihud and Lev, 1981). Lastly, the learning hypothesis offers a more dynamic view, proposing that firms may improve their acquisition capabilities over time through experiential learning, thereby enhancing post-acquisition outcomes (Chatterjee, 2009; Aktas et al, 2009).

Research also explores the relationship between acquisition frequency and market expectations through the lens of the efficient market hypothesis (EMH). Fama (1970) proposes three forms of market efficiency: weak, semi-strong and strong, with the semi-strong form asserting that stock prices reflect all publicly available information. Under this assumption, investors anticipate repeated acquisitions by serial acquirers, leading to declining abnormal returns, observed in Billett and Qian's study (2008). They show a downward trend in CAR as acquisition frequency increases. Macias et al (2023) further develop this argument by introducing the concept of anticipation-adjusted abnormal returns. Their findings suggest that the observed decline in CAR is driven not by diminished market confidence but by the failure to adjust for the market's anticipation of future deals. When adjusting for anticipation, the returns for so-called "marathoners", firms that rarely pause their acquisition activity, do

not exhibit a diminishing return. However, this interpretation is not universally accepted. Ahern (2008) argues that the decline in returns is more plausibly attributed to deal-specific characteristics rather than acquisition frequency.

Beyond this theoretical debate, the broader empirical literature on M&A and value creation is both extensive and nuanced. Academics have identified a range of factors that may explain variations in abnormal returns, often linked to characteristics of the acquiring firm, the target, or the deal itself. For instance, Moeller et al (2004) find that smaller acquirers tend to achieve significantly higher CAR compared to larger acquirers. Similarly, Billett and Qian (2008) report that acquisition frequency plays a significant role as returns decline with subsequent acquisition. Hossain et al (2021) show that serial acquirers earn negative abnormal returns. Nevertheless, Fuller et al (2002) report that serial acquirers earn positive abnormal returns when acquiring private targets. Kengelbach et al (2012) show a similar relationship but also explain that single acquirers earn higher abnormal returns compared to frequent acquirers.

Moeller et al (2004), and Lys and Yehuda (2015) find that acquisitions of private companies yield higher abnormal returns than acquisitions of public firms. One explanation for this is that private companies often have more intangible assets compared to public companies (Lys and Yehuda, 2015). Their research finds that acquisitions of companies with a higher degree of intangible assets often result in greater realized synergies for the acquirer. Findings from Masulis et al (2023) further support this notion, showing that a one standard deviation increase in target intangibility is associated with a 0.40% increase in CAR. Similarly, Lussi et al (2023) show that hotel companies with a higher degree of PPE-to-total assets ratio perform worse compared to more asset-light businesses.

In addition to asset lightness, past research shows that higher pre-acquisition profitability of the target has a negative impact on the acquirer's abnormal return. Rogova and Oleg (2022) report a negative relationship between target profitability and post-merger outcomes in BRIC countries and suggest this can be explained by overvaluation of profitable firms. Similarly, Višić (2013) finds evidence linking pre-acquisition profitability to worse post-deal performance in Croatia. This stands in contrast to the business model of M&A compounders proposed by Hadziefendic et al (2023), Kujala (2021) and Scott Management LLC (2020). Hadziefendic et al (2023) further suggest that profitable companies are preferred targets considering their beneficial cash flow generation.

Furthermore, Hazelkorn et al's (2004) study shows that companies in low growth, mature industries characterized by low EPS-growth often create better abnormal returns. The

authors further note that acquirers often tend to overpay for growth. This finding aligns with Scott Management LLC's (2020) finding that M&A compounders often target companies in "fragmented, low growth industries where a lack of available structural competitive advantages means it is hard to steal market share rapidly".

Altavilla et al's (2022) study focus instead on the impact of negative interest rates and corporate investment decisions. They find that when interest rates are negative, firms with high liquidity tend to increase investments. Similar conclusions are presented in Mauboussin et al's (2023) report, suggesting corporate investments have an inverse relationship with interest rates as cost of capital increases with higher interest rates. The authors also note that the opportunity cost for investors increases with interest rates. Consequently, investors must be appropriately rewarded for the higher risk associated with the investment as cost of capital increases. This is evident in traditional valuation methodologies such as weighted average cost of capital (WACC), which typically utilizes government bond yields as a proxy for the risk-free rate (Damodaran, 2016). Moreover, Santosuosso's (2014) study show a link between profitability and cost of debt. Their findings indicate that profitable companies often have lower cost of debt compared to less profitable firms.

While the aforementioned studies offer important theoretical and empirical contributions to the understanding of acquirer performance, they differ considerably in terms of scope, methodological design, and contextual applicability. Table 1 outlines these distinctions, illustrating that most prior research concentrates on the U.S. market and employs minimum deal size thresholds that exclude smaller transactions. Additionally, the average market capitalization of acquirers in these studies ranges from USD 5.2 billion to USD 7.3 billion, while average deal sizes vary between USD 265 million and USD 2.1 billion.

Table 1. Scope and Design of Selected Empirical Studies on M&A Performance

This table provides an overview of key descriptive characteristics of prior empirical studies focusing on M&A performance. It includes: *Authors (year)*, *Regional focus*, *Focus areas*, *Period*, *Number of acquirers*, *Avg. MCAP*[1] *acquirers*, *Number of deals*, *Avg. deal value*, *Target type*, *Min. deal size*, *Min. ownership acquired* for each selected study.

Authors (year)	**Regional focus**	**Focus areas**	**Period**	**Number of acquirers**	**Avg. MCAP acquirers,** USDm	**Number of deals**	**Avg. deal value,** USDm	**Target type**	**Min. deal size**[2, 3]**,** USDm	**Min. ownership acquired**
Lys and Yehuda (2015)	U.S.	Deal & target	2002–2006	1,004	7,318	1,481	1,245	Private & public		100%
Rogova and Oleg (2022)	BRICS	Deal & target	2000–2017			70		Public	5	51%
Hazelkorn et al (2004)	U.S.	Deal & target	1990–2002			1,547	2,081	Public, private, or subsidiary	250 or >5[2]	
Masulis et al (2023)	U.S.	Target	2002–2021	2,687	5,200	5,420	624	Public, private, or subsidiary	1 or >1[2]	
Višić (2013)	Croatia	Target	2003–2008					Public		
Ismail (2008)	U.S.	Acquirer & deal	1985–2004	5,655		16,221		Public, private, or subsidiary	1	50%
Moeller et al (2004)	U.S.	Acquirer & deal	1980–2001			12,023		Public, private, or subsidiary	1	50%
Fuller et al (2002)	U.S.	Acquirer & deal	1990–2000	539	5,240	3,135	265	Public, private, or subsidiary		50%
Hossain et al (2021)	Australia	Acquirer & deal	2000-2016	1,143		2,696		Public or private	0.75[3]	
Kengelbach et al (2012)	Global (62% U.S.)	Acquirer & deal	1989–2010			20,975	503	Public, private, or subsidiary	25	75%
Billett and Qian (2008)	U.S.	Acquirer & deal	1985–2002	2,068		3,537		Public	1	

Note: [1] Market Cap, [2] Relative to acquirer size in %, [3] Converted to USD from AUD using the average 2021 exchange rate (source: ExchangeRates, May 2025).

3. Research Questions and Hypotheses Development

The purpose of this study is to determine whether Swedish M&A compounders generate abnormal returns when announcing acquisitions as well as to explore the relationship between key financial characteristics of the target, and the acquirer's CAR. This is achieved by first exploring different relationships within the full sample. Secondly, different interest rate settings are explored to investigate whether the interest rate environment moderates the relationship between *Growth* and CAR as well as between *Profitability* and CAR.

3.1 Do M&A Compounders Experience Abnormal Returns When Announcing Acquisitions?

M&A is a core component of a serial acquirer's corporate strategy and remains a central topic in academic research on these firms. However, the contextual settings of studies differ significantly across several dimensions, including the time period examined, filtering criteria and sample size (see Table 1). Consequently, the findings across studies are mixed, leading to inconclusive evidence on whether serial acquirers earn abnormal returns when announcing acquisitions. To illustrate this, Fuller et al (2002) provide evidence that serial acquirers earn positive abnormal returns when acquiring private targets. Kengelbach et al's (2012) findings align with those of Fuller et al (2002) and further state that single acquirers earn higher abnormal returns compared to serial acquirers. In contrast, studies by Hossain et al (2021) and Billett and Qian (2008) report that serial acquirers earn negative abnormal returns when announcing acquisitions.

In addition to the inconclusive findings from previous research on serial acquirers, M&A appears to be a value-creating strategy for M&A compounders. These acquirers pursue a core strategy of acquiring new firms, often private targets. Given their outperformance relative to a leading benchmark index (see Figure 1), it is evident that this approach has created shareholder value. Consequently, the following hypothesis is formulated:

> H1: *M&A compounders experience positive short-term abnormal returns when announcing acquisitions*

3.2 To What Extent Do a Target's Financial Characteristics Explain CAR?

The business model of M&A compounders, as described by Hadziefendic et al (2023) and Kujala (2021), is based on acquiring companies with specific financial characteristics and integrating them into a decentralized organizational structure. Consequently, it warrants closer examination whether key financial characteristics of targets can help explain abnormal returns for the acquirer.

Previous research has investigated whether asset lightness of the target influences the acquirer's abnormal returns. Lys and Yehuda (2015) find that acquisitions of companies with higher level of intangible assets often result in greater realized synergies for the acquirer. Similarly, Masulis et al's (2023) study shows that acquirers earn a higher abnormal return if the target has more intangible assets. Lussi et al's (2023) study confirms these findings but focus on the target's PPE-to-total assets ratio rather than intangible assets.

Consequently, since past research shows that asset lightness is a driver of CAR and that M&A compounders often adopt an asset-light business model (Hadziefendic et al, 2023; Kujala, 2021), it was considered relevant to investigate the relationship between CAR and asset lightness through the following hypothesis:

H2: *The targets asset lightness has a positive relationship with the acquirer's CAR*

In a similar manner, it was deemed appropriate to examine the relationship between the acquirer's CAR and the target's profitability. Hadziefendic et al (2023), Kujala (2021) and Scott Management LLC (2020) argues that profitability is a central part of the M&A compounder business model. This is also reflected on the acquirers' websites, where profitability is frequently highlighted as a key investment criteria. Hadziefendic et al (2023) also note that profitable targets are linked to increased cash flow for the acquirer, highlighting the value of targeting profitable firms. Historical stock performance further reinforces the notion that acquiring profitable firms can lead to sustained abnormal returns over time (see Figure 1).

Nevertheless, broader M&A literature shows a clear negative relationship between profitability and the acquirer's CAR. For instance, Rogova and Oleg (2022) report a negative relationship between target profitability and post-merger outcomes. Similarly, Višić (2013) finds evidence that higher pre-acquisition profitability leads to worse long-term performance

of the acquirer. Even so, based on the strong emphasis on profitability in M&A compounders' investment strategies and M&A compounders' outperformance of OMXS30, the following hypothesis is formulated:

H3: *The target's profitability has a positive relationship with the acquirer's CAR*

Scott Management LLC (2020) also emphasizes that M&A compounders often prefer targets with strong market positions in low-growth industries over those in high-growth sectors. Furthermore, Hazelkorn et al's (2004) study shows that companies in low growth and mature industries often create better abnormal returns as acquirers tend to overpay for growth. Consequently, as research suggests that lower growth increases abnormal returns for acquirers, and the fact that M&A compounders often seek more stable companies, the following hypothesis is formulated:

H4: *The target's growth has a negative relationship with the acquirer's CAR*

3.3 Does the Interest Rate Environment Moderate the Relationship Between Target Firm Characteristics and CAR?

We further examine whether interest rate environments affect the link between CAR and select target-specific characteristics. According to Mauboussin et al (2023), interest rates are linked to the level of risk investors associate with their investments as opportunity cost increases with interest rates. This is further supported by traditional valuation methods such as WACC, where rising interest rates increase the hurdle rate for investments as investors demand higher returns. In contrast, Altavilla et al (2022) focus on corporate investment behavior and find that during periods of negative interest rates, firms with high liquidity tend to increase their investment activity. This is in line with Mauboussin et al's (2023) report, suggesting that corporate investments increase when interest rates are low. Since the opportunity cost for investors increases with higher interest rates, and firms' willingness to invest declines, the following hypotheses are formulated:

> H5: *The target's growth has a negative relationship with the acquirer's CAR in a positive interest rate environment*

> H6: *The target's growth has a positive relationship with the acquirer's CAR in a zero or negative interest rate environment*

Profitability, alongside growth, was also identified as a key variable when comparing periods with differing interest rate environments. By applying the same logic as for growth, it is evident that investors would prefer a more profitable company in times of higher interest rates as cost of capital increases. This is supported by Santosuosso's (2014) study, suggesting that profitable companies often have lower cost of debt. Consequently, the following hypotheses are formulated:

> H7: *The target's profitability has a positive relationship with the acquirer's CAR in a positive interest rate environment*

> H8: *The target's profitability has a negative relationship with the acquirer's CAR in a zero or negative interest rate environment*

4. Data Description and Methodology

4.1 Definitions and Sample Construction

According to Laamanen and Keil (2008), a serial acquirer is defined as a firm that has completed four or more acquisitions within a ten-year period. The same definition is adopted for this paper, as it allows for the inclusion of more acquirers compared to other definitions, creating a larger sample of transactions. In addition to Laamanen and Keil's (2008) definition of a serial acquirer, this paper adopts the descriptions of Kujala (2021) and Hadziefendic et al (2023) for defining an M&A compounder, as outlined in the literature review.

Following the definitions of a serial acquirer and what constitutes a M&A compounder, daily share price data was downloaded from Capital IQ (S&P Capital IQ, 2025) for all identified acquirers between 2000 and 2023 as well as the benchmark index OMXS30. The daily share price data is adjusted for stock-splits, dividends and spin-offs, allowing for a better comparison between acquirers. The period 2000 to 2023 was selected because few M&A compounders were publicly listed before 2000, and no target data was available beyond 2023 in the Serrano database (Serrano, 2025). In addition to daily share price data, transaction data, as well as total assets for each acquirer were retrieved from Capital IQ (S&P Capital IQ, 2025).

The transaction data was first filtered to include only platform investments made by the parent company, excluding those made by subsidiaries. Since M&A compounders often acquire firms much smaller than themselves, including acquisitions made by subsidiaries would risk diluting the results. In addition to limiting the sample to platform investments, only acquisitions of Swedish targets were included, as the Serrano database only covers Swedish companies. Furthermore, all transactions with a financial report released during the event window were excluded. All remaining transactions were filtered based on criteria used in prior academic papers (Fuller et al, 2002; Tunyi, 2021):

- (I) The target is a public firm, a private firm or a subsidiary of a public firm
- (II) The bidder acquires more than 50% of the firm
- (III) The acquirer has return data covering the whole event window
- (IV) The deal must be completed or withdrawn
- (V) Transactions where bidders have done more than one takeover over a five-day window are excluded

By applying the filters described, the sample of transactions was reduced to 290 transactions. Due to missing data for one or more variables as well as only partial estimation windows, the sample size was further reduced to 230 transactions. Upon reviewing the final sample, six substantial outliers were identified. They were either the only observation within their respective industry or not representative. For example, one transaction involved a target that was several times larger than the acquirer. These transactions were subsequently excluded from the sample, resulting in a final sample of 224 transactions.

In addition to the full sample, two additional sub-samples were constructed based on interest rate environments following Riksbanken's policy rates from 2000 to 2023 (Riksbanken, 2025). The first sub-sample includes all transactions made during periods of zero or negative interest rates (from October 29, 2014, to May 3, 2022). The second sub-sample includes all transactions made during periods of positive interest rates. Comparing transactions across the two interest rate environments enable analysis of whether interest rates moderate the relationship between CAR and *Profitability* and *Growth*.

4.2 Summary Statistics

Tables 2 and 3 provide an overview of the underlying data for the three samples described in section 4.1. In both tables, Panel A reports descriptive statistics for the full sample, Panel B covers transactions conducted during periods of positive interest rates, and Panel C shows data for transactions made during periods of zero or negative interest rates.

Table 2 presents summary statistics for each independent variable across the three constructed samples. Column (3) of Panel A highlights the average characteristics of targets acquired by M&A compounders. On average, targets tend to be profitable (11.50%), growing (8.73%), being relatively small compared to the acquirer (2.00%) and asset light (10.82%). These attributes align with Kujala's (2021) and Hadziefendic et al's (2023) descriptions of preferred targets for M&A compounders. Moreover, column (5) reports the standard deviation for each independent variable. *Growth* and *Asset light* exhibit higher variability (12.99% and 14.26%, respectively), whereas *Profitability* and *Relative size* show lower variability (7.91% and 4.23%, respectively). This suggests greater heterogeneity among targets in terms of growth and asset lightness, compared to profitability and relative size. Furthermore, columns (6) and (7) indicate the presence of outliers for each independent variable, as the minimum-, maximum or both values differ substantially from the median shown in column (4).

Similar patterns to those of Panel A of Table 2 are observed in panel B of the same table. A comparison of column (3) across the two panels reveals that during periods of positive interest rates (Panel B), M&A compounders tend to acquire targets with slightly lower growth (7.71% compared to 8.73% for the full sample). Furthermore, during periods of positive interest rates, companies acquired are marginally asset heavier, as indicated by a higher value of the *Asset light*, which is inversely related to actual asset lightness (12.30% compared to 10.82% for the full ample). In terms of variability, Panel B exhibits marginally greater variability in both *Asset light* and *Growth* (15.24% and 13.70%, respectively), compared to the full sample in Panel A (14.26% and 12.99%, respectively). In contrast, the standard deviations for *Profitability* and *Relative size* are marginally lower in Panel B (6.75% and 2.05%, respectively) than in the full sample (7.91% and 4.23%, respectively). The differences in both mean and standard deviation can be partially explained by the smaller sample size in Panel B compared to Panel A (85 versus 224 for the full sample). Moreover, a comparison of minimum- and maximum values across both panels indicate that the most extreme outliers in *Growth*, as well as the highest observed *Profitability*, occurred during periods of positive interest rates.

In contrast to Panel B of Table 2, column (3) in Panel C of the Table 2 shows that during periods of zero or negative interest rates, M&A compounders tend to acquire slightly faster-growing and marginally more asset-light targets (9.35% and 9.91%, respectively) compared to the full sample (8.73% and 10.82%, respectively). In terms of variability, Panel C exhibits marginally lower variability in both *Asset light* and *Growth* (13.61% and 12.54%, respectively), compared to the full sample in Panel A (14.26% and 12.99%, respectively). In contrast, the standard deviation for *Profitability* and *Relative size* are slightly higher in Panel C (8.56% and 5.10%, respectively) than in the full sample (7.91% and 4.23%, respectively). Moreover, a comparison of minimum- and maximum values across both panels indicate that the highest observed *Relative size* as well as lowest *Profitability* occurred during periods of zero or negative interest rates.

Table 3 presents an industry-level overview for the three samples described in section 4.1. Column (2) of Panel A indicates that M&A compounders often acquire firms in the industrial sector, with 134 acquisitions compared to 90 acquisitions across all other sectors combined. Columns (3) through (6) report the mean values by industry for *Profitability*, *Relative size*, *Growth* and *Asset light*. A comparison across industries in columns (3), (4), and (5) reveal relatively limited variability, apart from Information Technology in terms of *Profitability*, Materials in terms of *Relative size*, and Consumer Discretionary in terms of

Growth. In contrast, column (6) exhibits substantial variation across industries: Health Care and Information Technology show higher asset lightness (5.93% and 6.87%, respectively), while Materials, Industrials, and Consumer Discretionary show lower asset lightness (19.35%, 11.02%, and 15.04%). This suggests that asset lightness varies between sectors, despite all sectors exhibiting a relatively high level of asset lightness. This aligns with the concept of asset lightness, as certain industries, such as Industrials, typically require more physical assets, whereas Information Technology tend to operate with fewer tangible assets.

In Panel B of Table 3, similar patterns are observed in columns (2), (3), and (4) as in Panel A of the same table. However, columns (5) and (6), which report *Growth* and *Asset light*, display relatively high variability across sectors. In terms of *Growth* (column 5), Consumer Discretionary and Information Technology exhibit lower growth rates (-1.77% and 4.99%) compared to Health Care, Industrials and Materials (8.55%, 10.46%, and 11.36%). For *Asset light* (column 6), Health Care and Information Technology show higher asset lightness (5.78% and 8.84%), whereas Consumer Discretionary, Industrials, and Materials report lower asset lightness (15.57%, 13.59%, and 18.48%). These differences suggest that during periods of positive interest rates, there is unobserved heterogeneity in target characteristics across industries, particularly in terms of growth and asset lightness.

For Panel C of Table 3, columns (3) through (6) present substantial variability across industries for all four independent variables. This contrasts with Panels A and B of Table 3, where high between-industry variability is observed only for one or two variables. This suggests that during periods of zero or negative interest rates, industry-level differences become more pronounced across multiple target characteristics.

Table 4 presents a summary of transactions made per year, along with the mean value of each independent variable by year. As seen in column (2), few transactions are between 2000 and 2012. This can be partially explained by fewer listed M&A compounders (see Appendix 1) as well as the lack of available information from each acquirer. Furthermore, columns (3), (4) and (5) reveal that M&A compounders are on average persistent in their investment criteria for acquiring small, profitable and asset-light companies. *Growth* on the other hand exhibits greater variability, suggesting that M&A compounders view growth as a less prioritized investment criteria.

Table 2. Summary Statistics of Independent Variables

This table presents summary statistics for the full sample and two sub-samples divided by interest rate environments. Panel A reports descriptive statistics for the full sample of 224 transactions between 2000-2023, including number of transactions and the mean, median, standard deviation, minimum, and maximum values for each independent variable: *Asset light*, *Growth*, *Profitability*, and *Relative size*. Panel B shows statistics for the 85 transactions conducted during periods of positive interest rates (January 1, 2000, to October 28, 2014, and May 4, 2022, to December 31, 2023), while Panel C summarizes the 139 transactions made during periods of zero or negative interest rates (October 29, 2014, to May 3, 2022). Definitions for each independent variable are provided in Appendix 3.

Panel A. Full Sample

Variable	Transactions	Mean	Median	Std. dev	Min	Max
Asset light	224	10.82%	4.34%	14.26%	0.03%	66.10%
Growth	224	8.73%	7.32%	12.99%	-51.31%	75.60%
Profitability	224	11.50%	10.32%	7.91%	-19.44%	39.54%
Relative size	224	2.00%	0.89%	4.23%	0.09%	46.56%

Panel B. Positive Interest Rate Environment

Variable	Transactions	Mean	Median	Std. dev	Min	Max
Asset light	85	12.30%	5.66%	15.24%	0.04%	59.34%
Growth	85	7.71%	7.29%	13.70%	-51.31%	75.60%
Profitability	85	11.43%	10.44%	6.75%	-0.12%	39.54%
Relative size	85	1.51%	0.89%	2.05%	0.09%	11.91%

Panel C. Zero or Negative Interest Rate Environment

Variable	Transactions	Mean	Median	Std. dev	Min	Max
Asset light	139	9.91%	3.21%	13.61%	0.03%	66.10%
Growth	139	9.35%	7.35%	12.54%	-38.59%	54.31%
Profitability	139	11.54%	10.30%	8.56%	-19.44%	39.52%
Relative size	139	2.30%	0.89%	5.10%	0.09%	46.56%

Table 3. Summary Statistics by Industry

This table presents summary statistics for the full sample and two sub-samples divided by interest rate environments, organized by industry. Panel A reports descriptive statistics for the full sample of 224 transactions between 2000–2023 across five industries: Consumer Discretionary, Health Care, Industrials, Information Technology, and Materials. Panel B shows statistics for the 85 transactions conducted during periods of positive interest rates (January 1, 2000, to October 28, 2014, and May 4, 2022, to December 31, 2023), while Panel C summarizes the 139 transactions made during periods of zero or negative interest rates (October 29, 2014, to May 3, 2022). For each industry, the number of transactions and average values for *Profitability*, *Relative size*, *Growth*, and *Asset light* are reported. Definitions for each independent variable are provided in Appendix 3.

Panel A. Full Sample

Industry	Transactions	Profitability	Relative size	Growth	Asset light
Consumer Discretionary	16	10.42%	1.65%	1.49%	15.04%
Health Care	15	9.15%	1.73%	9.02%	5.93%
Industrials	134	10.96%	1.96%	9.78%	11.02%
Information Technology	42	15.15%	1.44%	8.26%	6.87%
Materials	17	9.79%	4.30%	8.16%	19.35%

Panel B. Positive Interest Rate Environment

Industry	Transactions	Profitability	Relative size	Growth	Asset light
Consumer Discretionary	10	8.53%	1.20%	-1.77%	15.57%
Health Care	10	13.07%	0.85%	8.55%	5.78%
Industrials	40	11.48%	1.43%	10.46%	13.59%
Information Technology	18	12.22%	1.88%	4.99%	8.84%
Materials	7	10.91%	2.39%	11.36%	18.48%

Panel C. Zero or Negative Interest Rate Environment

Industry	Transactions	Profitability	Relative size	Growth	Asset light
Consumer Discretionary	6	13.55%	2.42%	6.91%	14.15%
Health Care	5	1.31%	3.49%	9.96%	6.24%
Industrials	94	10.74%	2.18%	9.49%	9.92%
Information Technology	24	17.35%	1.12%	10.71%	5.39%
Materials	10	9,00%	5.63%	5.92%	19.95%

Table 4. Year-by-Year Summary Statistics

This table presents annual summary statistics for the 224 transactions included in the final sample, covering the period from 2000 to 2023. For each year, the number of transactions is reported along with the average values for four independent variables: *Relative size*, *Profitability*, *Growth*, and *Asset light*. Definitions of each independent variable are provided in Appendix 3.

Year	Transactions	Relative size	Profitability	Growth	Asset light
2003	1	5.77%	3.94%	3.78%	4.17%
2004	2	1.71%	10.96%	13.35%	5.58%
2006	6	1.67%	8.20%	8.05%	18.97%
2007	8	1.28%	9.39%	10.91%	27.16%
2008	6	0.80%	13.68%	3.46%	8.96%
2009	2	0.34%	8.77%	8.78%	11.74%
2010	5	4.02%	16.89%	-3.64%	18.95%
2011	5	0.69%	13.16%	8.37%	9.83%
2012	5	0.69%	8.00%	-1.85%	18.74%
2013	3	4.12%	10.53%	1.86%	4.55%
2014	9	2.56%	12.04%	2.88%	3.91%
2015	10	2.12%	9.80%	7.22%	6.97%
2016	8	2.31%	10.12%	5.79%	7.73%
2017	11	0.78%	13.86%	5.94%	8.97%
2018	16	4.10%	11.74%	8.44%	7.13%
2019	28	1.58%	10.64%	12.79%	12.37%
2020	22	1.26%	10.27%	13.11%	13.65%
2021	31	3.10%	12.19%	6.52%	9.73%
2022	26	1.39%	15.20%	10.81%	10.01%
2023	20	1.64%	8.99%	12.81%	8.01%

4.3 Event Study Methodology

To assess whether M&A compounders earn abnormal returns upon acquisition announcements, an event study was conducted in line with previous studies (Fuller et al, 2002; Ismail, 2008; Masulis et al, 2023). Event studies are commonly used to analyze abnormal share price movements for specific events (MacKinlay, 1997). Consequently, for an event study to be efficient, noise should be minimized, and the event window must be appropriately defined to capture all relevant information. Furthermore, as MacKinlay (1997) notes, one of the most common approaches to estimate abnormal returns in event studies is the market model, which is also applied in this study:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_i \quad (1)$$

where $R_{i,t}$ and $R_{m,t}$ are the returns for the security and the market, respectively. ε_i represents the error term, capturing the portion of the return not explained by market movements. The parameters α_i and β_i are estimated during the estimation window and serve as proxies for the normal return. Using the estimated parameters α_i and β_i, abnormal returns are calculated according to equation (2):

$$AR_{i,t} = R_{i,t} - \left(\widehat{\alpha_i} + \widehat{\beta_i} R_{m,t}\right) \quad (2)$$

where $AR_{i,t}$, $R_{i,t}$ and $R_{m,t}$ are defined as the abnormal return, the actual return of the security and the actual return of the market, respectively. $\widehat{\alpha_i}$ and $\widehat{\beta_i}$ are the estimated parameters from the market model. The abnormal return is then calculated for each day within the event window and subsequently aggregated into the cumulative abnormal return (CAR):

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t} \quad (3)$$

where $CAR_i(t_1, t_2)$ is the sum of abnormal returns over the event window $[t_1, t_2]$.

To capture all relevant market reactions for the events studied, the event window [-2, 2] was selected, following the approach of Ismail's (2008) and Fuller et al's (2002) studies. In addition to the 5-day event window, the event window [-1, 1] was selected to see whether the event window of [-2, 2] includes irrelevant noise or not. Moreover, an estimation window of

150 days, [-154, -5], was selected to estimate the normal return for each event, in line with Peterson's (1989) paper explains that typical estimation windows range from 100-300 days. The length of the estimation window was determined based on two factors: Low trading volume during the estimation window for certain acquirers and the sample size. Since some acquirers exhibited low trading volume during the estimation window, its length must be sufficient to capture enough data points for reliable estimation of alpha and beta. Furthermore, because many transactions occurred shortly after the acquirer's IPO, extending the estimation window would have significantly reduced the sample size.

4.4 Statistical Tests of CAR Significance

Two types of statistical tests were employed to determine the significance of CAR. The first test is a parametric test called Student's t-test (Student, 1908) that assumes normal distribution across the sample. The t-test is calculated as "the ratio of the mean excess return to its estimated standard deviation" (Brown and Warner, 1985). In addition to the t-test, the non-parametric Wilcoxon signed-rank test was employed as a robustness check, as the distribution of CAR was suspected to deviate from normality due to low trading volumes on multiple days during the estimation window. The Wilcoxon signed-rank test allows for a combination of sign and rank test as each observation is ranked based on the magnitude from the hypothesized mean of zero. Furthermore, each observation is also assigned (+) or (-) based on its original values (Wilcoxon, 1945).

4.5 Zero Returns and Estimation Window Robustness

After reviewing the underlying data of the daily returns, a pattern of low to no trading volume appeared for certain bidders, leading to multiple days of zero in returns during the estimation window. Low to no trading volume during the estimation window could potentially interfere with the regression model and therefore introduce a source of bias for the estimates. According to Brown and Warner (1985), non-synchronous trading between bidders with high trading volume and bidders with low trading volume could lead to "downward biased β estimates" for shares traded infrequently and "upward biased β estimates" for shares traded frequently.

To determine whether the study should include days with zero return, a robustness test was conducted, seen in Appendix 2. The test is a comparative analysis between one

regression using CAR with all days included in the estimation window and one where we exclude all trading days with zero in return. The results of the robustness test indicate that the findings remain consistent whether days with zero returns are included or excluded. Consequently, all data points were included as days with zero return also provide valuable information about the acquirer.

4.6 Model Specification

This section presents the empirical model used to examine the relationship between the acquirer's CAR and different financial characteristics of target firms. Specifically, we aim to investigate how the acquirer's CAR is influenced by profitability, growth and asset lightness. We do so by specifying the following regression model (equation 4) for the full sample:

$$CAR_i = \alpha_i + \delta_{Industry} + \beta_1 Relative\ size_i + \beta_2 Profitability_i + \beta_3 Growth_i + \beta_4 Asset\ light_i + \varepsilon_i \quad (4)$$

Industry fixed effects are included to control for differences across industries, in line with Masulis et al's (2023) study. *Relative size* is included as a control variable to control for deal size as prior studies (Ismail, 2008; Moeller et al, 2004) find that *Relative size* has a significant positive relationship with abnormal returns, indicating that larger deals tend to generate stronger market reactions.

Regarding the explanatory variables *Profitability*, *Growth* and *Asset light*, limited research directly links them to the acquirer's CAR. The acquirers' investment strategies were instead reviewed on their websites. Notably, profitability and growth were mentioned most frequently as determining factors for acquiring a company. Consequently, it was considered of academic relevance to examine whether the market reacts more positively to acquisitions of fast-growing and profitable firms in contrast to companies with lower growth and profitability.

Asset light was included in the regression following Hadziefendic et al's (2023) and Kujala's (2021) descriptions of a M&A compounder. According to Varadarajan et al (2021), an asset-light business model "involves transferring capabilities … in order to enable companies to transition fixed costs to a variable cost structure, enhance agility, and facilitate a shift of resources that allows a focus on core capabilities". It was therefore considered

relevant to test whether the market reacts more positively to an asset-light business model compared to an asset-heavier one.

For the two sub-samples described in section 4.1, a similar regression model was specified. The main difference compared to the full sample regression model is that *Asset light* is included as a control variable instead of an explanatory variable. This adjustment is based on the assumption that investor reactions to the target's asset lightness are unlikely to vary meaningfully across different interest rate environments.

In addition to the two regression models, several robustness tests were conducted to see whether outliers have a disproportionate effect on the regression. As seen in Table 2 in section 4.2, all independent variables have outliers that are significantly different from the median. This is also the case for CAR. Therefore, two robustness tests were made per sample, one winsorizing the 95^{th} and 5^{th} percentile of CAR and one winsorizing the 95^{th}- and 5^{th} percentile of all the explanatory variables. Additionally, industry fixed effects were excluded to determine if there is any unobserved heterogeneity across industries that could help explain CAR, following Masulis et al's (2023) study.

5. Empirical Findings

5.1 Hypothesis Testing for the Full Sample

Table 5 presents the results for regressions using the full sample of 224 transactions. Columns (1) and (3) report estimates from the OLS regression model described in section 4.6, including industry fixed effects. Columns (2) and (4) report estimates with the corresponding model excluding industry fixed effects.

As outlined in Section 4.4, CAR is tested using both the parametric t-test as well as the non-parametric Wilcoxon signed-rank test. For the [-1, 1] event window in column (1), both the t-test and the Wilcoxon signed-rank test indicate that CAR is significantly different from zero at a 5% significance level, with a mean of 0.599%. Since both tests are significant at the same level, the findings suggest that the significance of CAR is not driven by outliers or deviations from normality. Moreover, the statistically significant CAR also supports H1, showing that M&A compounders earn statistically significant abnormal returns when announcing acquisitions. In contrast, no significant effect is observed for the [-2, 2] event window in column (3), suggesting that expanding the event window may introduce additional noise.

Furthermore, for *Asset light*, a statistically significant positive relationship with CAR is observed in columns (1) and (2) over the [-1, 1] event window, at a 5% significance level. Contrary to expectations, the result does not support H2. Consequently, the results presented in columns (1) and (2) show that each percentage point increase in *Asset light* is associated with a 0.039 and 0.040 percentage point increase in CAR, respectively. In contrast, no statistical significance is observed in columns (3) and (4) over the [-2, 2] event window, suggesting similar conclusions as for CAR.

Regarding *Growth*, a statistically significant but relatively weak positive relationship is observed in columns (1) and (3), with both columns showing significance at a 10% level. Since expanding the event window from [-1, 1] to [-2, 2] does not alter the significance of the relationship, this indicates that the relationship between *Growth* and CAR remains robust across both event windows. The result stands in contrast to H4. As observed in columns (1) and (3), a one percentage point increase in *Growth* is associated with a 0.032 and 0.044 percentage point increase in CAR, respectively. Therefore, the result suggests that M&A compounders earn a higher abnormal return when acquiring companies with higher growth. Furthermore, when excluding industry fixed effects, no statistical significance is observed in

columns (2) and (4), suggesting that unobserved heterogeneity across industries may mask the true relationship between CAR and *Growth*.

For *Profitability*, no statistically significant relationship is identified across any event window. Contrary to initial expectations stated in H3, *Profitability* does not appear to explain CAR. This suggests that investors do not react differently to acquisitions involving targets with lower versus higher profitability. Regarding the control variable *Relative size*, a statistically significant positive relationship is observed across all four columns, at a 0.1% significance level. The result shows that a one percentage point increase in *Relative size* leads to a 0.222, 0.221, 0.254 and 0.252 percentage point increase in CAR, respectively. This suggests that relative size helps explain the variation in CAR effectively.

To ensure that the results are robust, two additional tests are conducted to assess whether the findings hold when winsorizing outliers at the 5^{th} and 95^{th} percentile in both CAR as well as the explanatory variables (see Appendix 4). Both tests indicate that the results remain robust for all relationships, apart from *Growth*. The relationship becomes stronger when the dependent variable is winsorized and non-significant when the explanatory variables are winsorized. This suggests that outliers in CAR have a negative impact on the estimated relationship, while outliers in the explanatory variables appear to drive the significance.

Table 5. Regression Output for Full Sample

This table reports the regression results for the full sample of transactions conducted between 2000 and 2023. The dependent variable is cumulative abnormal return (CAR), and the explanatory variables are *Profitability*, *Growth*, and *Asset light*. All four regressions include *Relative size* as a control variable. Columns (1) and (3) include industry fixed effects, while columns (2) and (4) do not. All models include an intercept. In models without industry fixed effects, the intercept reflects the expected value of CAR when all independent variables are zero. In models with industry fixed effects, the intercept represents the baseline for the omitted industry category. Standard errors are reported in parentheses. Definitions of all independent variables are provided in Appendix 3.

	Announcement returns			
	[-1, 1]		[-2, 2]	
	(1)	(2)	(3)	(4)
Mean CAR (T-test)	0.599		0.440	
T-test (CAR ≠ 0)	p=0.014		p=0.169	
Wilcoxon (CAR ≠ 0)	p=0.038		p=0.318	
(Intercept)	-0.289	-1.025*	0.255	-1.152+
	(0.966)	(0.485)	(1.297)	(0.652)
Relative size	0.222***	0.221***	0.254***	0.252***
	(0.056)	(0.055)	(0.076)	(0.074)
Profitability	0.037	0.043	0.034	0.035
	(0.031)	(0.030)	(0.042)	(0.040)
Growth	0.032+	0.029	0.044+	0.039
	(0.019)	(0.018)	(0.025)	(0.024)
Asset light	0.039*	0.040*	0.029	0.032
	(0.017)	(0.016)	(0.023)	(0.022)
Num.Obs.	224	224	224	224
Industry FE	Yes	No	Yes	No
R2	0.115	0.109	0.078	0.071
R2 Adj.	0.083	0.092	0.044	0.054
F	3.507	6.673	2.276	4.198
RMSE	3.41	3.42	4.57	4.59

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

5.2 Hypothesis Testing for Sub-Samples

Tables 6 and 7 present regression results based on two sub-samples of the full sample, as described in Section 4.1. In contrast to the previous analysis, these sub-sample regressions exclusively examine the effects of *Growth* and *Profitability*. Table 6 reports the results for transactions conducted during periods of positive interest rates, while Table 7 covers transactions completed during periods of zero or negative interest rates. For both tables, columns (1) and (3) report estimates from the OLS regression model described in Section 4.6, which includes *Asset light* as a control variable and incorporates industry fixed effects. Columns (2) and (4) present results from the corresponding model excluding industry fixed effects.

For the event window [-1, 1] in column (1) of Table 6, both the t-test and the Wilcoxon signed-rank test indicate that CAR is significantly different from zero at a 5% significance level, with a mean of 0.999%. The observed result suggests that M&A compounders earn statistically significant abnormal returns during periods of positive interest rates. For event window [-2, 2] in column (3) of Table 6, no statistically significant effect is observed. Since both the t-test and the Wilcoxon signed-rank test present the same significance as for Table 5, same conclusions can be drawn as for the full sample.

For the explanatory variables of interest, *Growth* and *Profitability*, no statistically significant relationships are observed across any of the four columns, indicating that the results do not support H5 and H7. The results suggest that, during periods of positive interest rates, investors do not react differently to variations in the target firms' growth and profitability characteristics.

Regarding the control variables *Relative size* and *Asset light*, Table 6 presents mixed findings. For *Relative size*, no statistical significance is observed across any of the four columns, indicating that during periods of positive interest rates, the target's relative size does not appear to explain variations in CAR. In addition to *Relative size*, column (2) of Table 6 presents a statistically significant relationship between *Asset light* and CAR, at a 5% significance level. The result suggests that a one percentage point increase in *Asset light* is associated with a 0.052 percentage point increase in CAR. Since the relationship between *Asset light* and CAR is only observed when excluding industry fixed effects, the result suggests that the relationship is partially driven by industry-level differences.

Similarly to Table 5, two additional tests are conducted to assess the validity of the results presented in Table 6. In contrast to Table 5, all results are robust even when winsorizing CAR, as well as *Profitability*, *Asset light* and *Growth* (see Appendix 5).

As column (1) of Table 7 indicates, no significance is observed for either the t-test or the Wilcoxon signed-rank test across the two event windows. This suggests that M&A compounders do not earn significant abnormal returns when announcing acquisitions during periods of zero or negative interest rates. Furthermore, for *Growth*, a weak but significant positive relationship is observed across all four columns at a 10% significance level. This indicates that a one percentage point increase in *Growth* is associated with a 0.044 percentage point increase in CAR for columns (1) and (2), as well as a 0.060 percentage point increase for column (3), and a 0.059 percentage point increase in column (4). Consequently, H6 is supported, since *Growth* has a significant and positive relationship with CAR in zero or negative interest rate environments. Moreover, contrary to expectations, no support is found for H8 as no statistically significant relationship is observed for *Profitability* across any columns in Table 7.

Regarding *Asset light* and *Relative size*, mixed findings are presented in Table 7. For *Asset light*, no statistical significance is observed across any of the four columns, suggesting that investors are indifferent towards higher or lower asset lightness in targets. Furthermore, *Relative size* shows statistical significance across all four columns at a 0.1% significance level, suggesting that a one percentage point increase in *Relative size* is associated with an increase in CAR of 0.261, 0.256, 0.267 and 0.264 percentage points respectively. Moreover, in Appendix 6 it is shown that the relationship between *Growth* and CAR strengthens for both event windows when winsorizing CAR. This indicates that outliers in CAR have a disproportionate influence on the relationship.

Table 6. Regression Output for Positive Interest Rate Environment

This table reports the regression results for the sub-sample consisting of transactions made during periods of positive interest rates (January 1, 2000, to October 28, 2014, and May 4, 2022, to December 31, 2023). The dependent variable is cumulative abnormal return (CAR), and the explanatory variables are *Profitability* and *Growth*. All four regressions include *Relative size* and *Asset light* as control variables. Columns (1) and (3) include industry fixed effects, while columns (2) and (4) do not. All models include an intercept. In models without industry fixed effects, the intercept reflects the expected value of CAR when all independent variables are zero. In models with industry fixed effects, the intercept represents the baseline for the omitted industry category. Standard errors are reported in parentheses. Definitions of all independent variables are provided in Appendix 3.

	Announcement returns			
	[-1, 1]		[-2, 2]	
	(1)	(2)	(3)	(4)
Mean CAR (T-test)	0.999		0.725	
T-test (CAR ≠ 0)	p=0.013		p=0.170	
Wilcoxon (CAR ≠ 0)	p=0.013		p=0.084	
(Intercept)	0.537	-0.125	1.194	-0.751
	(1.347)	(0.925)	(1.828)	(1.251)
Relative size	-0.013	0.029	0.243	0.225
	(0.198)	(0.193)	(0.269)	(0.261)
Profitability	0.040	0.029	0.076	0.058
	(0.060)	(0.059)	(0.081)	(0.079)
Growth	0.015	0.014	0.031	0.017
	(0.031)	(0.029)	(0.042)	(0.040)
Asset light	0.044	0.052*	0.024	0.028
	(0.027)	(0.026)	(0.037)	(0.035)
Num.Obs.	85	85	85	85
Industry FE	Yes	No	Yes	No
R2	0.085	0.051	0.053	0.024
R2 Adj.	-0.011	0.004	-0.047	-0.024
F	0.882	1.079	0.528	0.501
RMSE	3.44	3.51	4.67	4.74

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 7. Regression Output for Zero or Negative Interest Rate Environment

This table reports the regression results for the sub-sample consisting of transactions made during periods of positive interest rates (October 29, 2014, to May 3, 2022). The dependent variable is cumulative abnormal return (CAR), and the explanatory variables are *Profitability* and *Growth*. All four regressions include *Relative size* and *Asset light* as control variables. Columns (1) and (3) include industry fixed effects, while columns (2) and (4) do not. All models include an intercept. In models without industry fixed effects, the intercept reflects the expected value of CAR when all independent variables are zero. In models with industry fixed effects, the intercept represents the baseline for the omitted industry category. Standard errors are reported in parentheses. Definitions of all independent variables are provided in Appendix 3.

	Announcement returns			
	[-1, 1]		[-2, 2]	
	(1)	(2)	(3)	(4)
Mean CAR (T-test)	0.354		0.265	
T-test (CAR ≠ 0)	p=0.252		p=0.511	
Wilcoxon (CAR ≠ 0)	p=0.495		p=0.941	
(Intercept)	-1.466	-1.409*	-1.646	-1.429+
	(1.520)	(0.574)	(2.059)	(0.777)
Relative size	0.261***	0.256***	0.267***	0.264***
	(0.058)	(0.057)	(0.079)	(0.077)
Profitability	0.038	0.044	0.014	0.022
	(0.038)	(0.035)	(0.051)	(0.047)
Growth	0.044+	0.044+	0.060+	0.059+
	(0.024)	(0.023)	(0.032)	(0.032)
Asset light	0.029	0.026	0.029	0.029
	(0.022)	(0.021)	(0.030)	(0.029)
Num.Obs.	139	139	139	139
Industry FE	Yes	No	Yes	No
R2	0.171	0.169	0.113	0.110
R2 Adj.	0.120	0.144	0.058	0.084
F	3.356	6.799	2.062	4.160
RMSE	3.29	3.29	4.45	4.46

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

6. Discussion

6.1 Implications

Do M&A Compounders Experience Abnormal Returns When Announcing Acquisitions?

Our results indicate that M&A compounders, on average, generate positive abnormal returns over the [-1, 1] event window, whereas no statistical significance is observed over the [-2, 2] event window. This is in line with Fama's (1970) theory about semi-strong market efficiency. Accordingly, the statistical insignificance over the event window [-2, 2] may suggest that irrelevant noise introduced by expanding the event window to [-2, 2] mask additional relevant information about the acquisition.

Furthermore, when comparing the result for the event window [-1, 1] to prior research on serial acquirers, our empirical results are consistent with the findings of Fuller et al (2002), and Kengelbach et al (2012). They observe positive abnormal returns for serial acquirers, especially when acquiring private targets, in line with the type of companies commonly targeted by M&A compounders (Hadziefendic et al, 2023).

On the other hand, our findings stand in contrast to those of Hossain et al (2021) and Billett and Qian (2008), who observed negative abnormal returns. Closer examination reveals that the contextual settings of these studies differ from our study and those reporting positive abnormal returns. All studies reporting positive abnormal returns focus on the U.S. market and both private and public targets. On the other hand, Hossain et al (2021) focuses exclusively on the Australian market. Similarly, Billet and Qian (2008) focus exclusively on public targets.

Moreover, as shown in Appendix 4, the significance of CAR increases from 5% level to 1% level when CAR is winsorized. This aligns with the general expectation that reducing the variance in CAR increases its statistical significance.

To What Extent Do a Target's Financial Characteristics Explain CAR?

As shown in Table 5, our analysis of target financial characteristics yields mixed results. Contrary to expectations, a statistically significant positive association between CAR and *Asset light* is identified, suggesting that acquirers earn higher abnormal returns when acquiring asset-heavier targets. As a result, our findings diverge from those of Lys and Yehuda (2015), Masulis et al (2023) and Lussi et al (2023), who all report that acquisitions of asset lighter targets yield higher abnormal returns for the acquirer. This may partially be explained by the distinct business model of M&A compounders. As described by both Hadziefendic et al (2023) and Kujala (2021), M&A compounders tend to acquire asset-light firms, which is also confirmed by this study (see Panel A of Table 2). As a result, the market should anticipate that targets acquired by M&A compounders typically are asset-light. In addition, M&A compounders tend to acquire firms in fragmented, low-growth industries (Scott Management LLC, 2020). Therefore, investors may perceive acquisitions of asset-heavier targets as positive, since such firms may possess additional competitive advantages linked to their physical assets.

Another possible explanation is that M&A compounders operate with a decentralized business model, limiting potential synergies between subsidiaries. According to Masulis et al (2023), one of the primary value drivers associated with intangible assets are synergies created between the acquirer and the target. Consequently, given the limited synergies between the acquirer and the target, the market may put less emphasis on asset lightness than previously anticipated.

For *Profitability*, no statistical significance is observed across any event window. This stands in contrast to the M&A compounder business model. As described in section 4.6, profitability was identified as a key investment criteria for most acquirers. With this in mind, one possible explanation is that the market already anticipates M&A compounders to only acquire profitable targets, in line with the semi-strong efficient market hypothesis (Fama, 1970). This interpretation is further supported by evidence in Panel A of Table 2, which demonstrates that targets are on average profitable, and that *Profitability* exhibits low variability across observations.

In contrast to our findings for *Profitability*, a weak but statistically significant positive relationship between CAR and *Growth* is observed when industry fixed effects are included. This suggests that the relationship may be masked by industry-level variation, which can

partially be explained by the substantially lower average growth rate in Consumer Discretionary compared to other industries (see Panel A of Table 3).

Nevertheless, this finding stands in contrast to our third hypothesis, predicting that *Growth* would have a negative impact on CAR. This may be attributed to the fact that prior studies, such as Hazelkorn et al (2004), have examined earnings growth as a driver of abnormal returns, whereas this study focuses on sales growth. Consequently, using an alternative growth metric could potentially yield different results. Another possible explanation is that M&A compounders depend on growing cash flows from their subsidiaries to acquire new companies (Hadziefendic et al, 2023). Therefore, investors may react more positively to faster-growing targets, as higher growth coupled with high profitability signals greater potential for future cash flows. Lastly, the idea that acquirers would overpay for growth (Hazelkorn et al, 2004) might not be as severe for M&A compounders as for other types of acquirers. This can be attributed to their disciplined investment strategy, which prioritizes the acquisition of companies with acquisition multiples below their own (Kujala, 2021). Accordingly, investors seem to adjust their expectations and favor fast-growing companies.

Moreover, our results also reveal a statistically significant positive relationship between CAR and the control variable *Relative size.* This finding supports the notion from prior studies, such as Moeller et al (2004), that size plays a critical role in explaining acquirer returns. While robustness tests generally confirm our findings, the relationship between *Growth* and CAR proved sensitive to outliers. One possible explanation is that certain outliers may have high growth and low CAR or high CAR and low growth. A similar explanation may apply to the explanatory variables, where one or more outliers exert substantial influence on the regression results.

Does the Interest Rate Environment Moderate the Relationship Between Target Firm Characteristics and CAR?

When examining transactions made during periods of positive interest rates, our findings indicate that M&A compounders generate statistically meaningful positive abnormal returns upon acquisition announcements. Moreover, our results regarding *Growth* and *Profitability* stand in contrast to our hypotheses H5 and H7, indicating that investors are indifferent to these target characteristics in a positive interest rate environment. Alternatively, the divergence from our initial predictions could be due to the small sample size of 85 transactions, which limits the regressions' explanatory power.

Nevertheless, the control variable *Asset light* demonstrates a statistically significant positive association for the [-1, 1] event window when excluding industry fixed effects. This finding aligns with general expectations that some industries by nature are more asset-heavy compared to others. This interpretation is further supported by evidence in Panel B of Table 3, indicating that there is great variability between industries regarding asset lightness.

However, during periods of zero or negative interest rates, a weak yet statistically significant positive association between *Growth* and CAR is identified. Notably, the magnitude is larger in this subsample than in the full sample, with the same significance level, supporting that investors place greater value on growth in a zero or negative interest rate environment. This aligns with the reasoning of Mauboussin et al (2023), who argue that the opportunity cost and the hurdle rate for investors decline when interest rates decrease, thereby potentially placing a premium on growth.

By contrast, no statistically significant relationship is observed for *Profitability*. This can be explained by the importance of profitability for M&A compounders. As seen in Panel B and C of Table 2, there is little variation in *Profitability*. Therefore, the link between interest rates and investor behavior outlined by Mauboussin et al (2023) might not be applicable for profitability to the same extent as for other types of companies.

A comparative analysis of the results across both interest rate environments reveal a notable difference in how investors respond to target firm characteristics. While neither *Growth* nor *Profitability* is significant during periods of positive interest rates, *Growth* exhibits a significant positive association with CAR during periods of zero or negative interest rates, with a larger magnitude than in the full sample for the same significance level. This finding suggests that investors value the target firm's growth differently depending on the prevailing interest rate environment, thereby supporting the expectation that interest rates moderate the relationship between the target’s *Growth* and the acquirer’s CAR.

6.2 Limitations and Future Research

Despite its relevance to the academic community, this study is subject to several limitations and challenges that should be acknowledged and kept in consideration when reading this paper. The primary limitation is the challenge of identifying a clear definition for serial acquirers. As described in the literature review, the academic community has long struggled to establish a common definition of what constitutes a serial acquirer. Therefore, by changing the definition of a serial acquirer, the sample size could either increase or decrease, potentially introducing a sample selection bias in the estimates. In addition to the absence of a universal definition for serial acquirers, the academic community lacks a clear definition of what constitutes a M&A compounder, adding on to the complexity of establishing a representative sample of transactions.

Moreover, the data obtained from Serrano only contains Swedish companies. M&A compounders are known for making cross-border acquisitions, which creates a limitation in terms of data availability. By excluding cross-border transactions, valuable information about M&A compounders is omitted, potentially introducing a bias about the perception of M&A compounders. Furthermore, as M&A compounders make multiple acquisitions per year, and often close to each other, many transactions were excluded from the final data sample to reduce noise, further amplifying the issue of data limitations.

Another important limitation concerns the broader economic environment. The sample period, spanning 2000 to 2023, covers a wide range of macroeconomic conditions, including the dotcom crash, the global financial crisis and COVID-19. Even though the analysis accounts for different interest rates periods, other macroeconomic factors may have influenced market reactions to M&A announcements.

Consequently, this study opens several avenues for future research that could deepen the understanding of M&A compounders and address some of the key limitations. A particularly important one would be to examine whether the results of this study hold across multiple different definitions of serial acquirer and M&A compounder. As discussed earlier, the lack of consensus regarding universal definitions for these concepts create challenges for comparability across studies. Repeating this analysis using different definitions could either reinforce concerns about definition dependent results or establish that variations in definitions do not significantly affect the results.

Furthermore, there are several additional factors that could be of interest to examine, one being cross-border transactions. This could be achieved by comparing a sample of cross-

border transactions with a sample of Swedish transactions and analyze whether the independent variables explain CAR differently across these contexts. In addition, it would be valuable to investigate whether the pattern of diminishing returns observed in prior literature of serial acquirers also applies to M&A compounders. Lastly, future research could extend the time horizon of the analysis by moving beyond short-term CAR to investigate long-term performance using methods such as Buy-and-Hold Abnormal Returns (BHAR). This would allow researchers to assess whether the effects identified in this study persist over longer time periods, offering a more comprehensive view of value creation by M&A compounders.

7. Conclusion

This paper investigates whether Swedish M&A compounders generate abnormal returns in response to acquisition announcements, with a focus on the role of target firm financial characteristics and the potential moderating effect of interest rate environments. The empirical results show positive abnormal returns across the full sample for the [-1, 1] event window, which supports the semi-strong form of market efficiency. Further analysis of target characteristics reveal, contrary to expectations, that more asset-heavy targets are associated with higher CAR for the acquirer. Furthermore, no significant relationship between *Profitability* and CAR is observed, indicating the market may already price in that M&A compounders acquire profitable firms. In contrast to *Profitability*, *Growth* shows a weak but positive relationship with CAR when industry fixed effects are included. Taken together, these findings highlight that while the market responds to certain target firm characteristics, it does not react uniformly across all variables, suggesting a selective approach to financial attributes.

Moreover, regressions across different interest rate environments reveal that during periods of positive interest rates, *Profitability* and *Growth* are not statistically significant, implying that investors do not respond differently to variations in these variables. In contrast, during periods of zero or negative interest rates, the target's *Growth* is positively associated with CAR, suggesting that investors reward high-growth acquisitions to a greater extent when capital is cheap. However, consistent with the findings from the positive interest rate environment, *Profitability* remains statistically insignificant. These results, in line with the findings from the full sample, indicate that capital markets respond selectively to target firm characteristics and suggest that monetary policy may influence how these characteristics are valued.

This study is constrained by its focus on Swedish transactions and by the absence of consistent definitions for the acquirer types across the literature. Nevertheless, it represents an early contribution toward building a structured empirical understanding of M&A compounders, offering novel insights into how target characteristics and the interest rate environment shape investor reactions. Ultimately, these findings may help inform both future academic research and the strategic decision-making of M&A compounders' leadership teams when evaluating potential acquisition opportunities.

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9. Appendix

Appendix 1. Acquirer-Level Summary Statistics

This table presents descriptive statistics for the acquirers in the sample, including IPO year, number of transactions, and firm-level averages for *Profitability*, *Relative size*, *Growth*, and *Asset light*. Definitions of all independent variables are provided in Appendix 3.

ACQ	IPO	Transactions	Profitability	Relative size	Growth	Asset light
OM:ADDT B	2001	27	12.21%	1.16%	5.16%	7.84%
OM:ALIF B	2016	2	-4.07%	4.51%	1.35%	7.17%
OM:ANOD B	1999	9	14.22%	1.85%	5.49%	8.53%
OM:AQ	2001	2	1.89%	0.18%	-16.80%	25.80%
OM:BEIA B	1987	6	16.79%	0.77%	9.14%	15.31%
OM:BEIJ B	1983	1	4.96%	1.37%	5.55%	39.63%
OM:BERG B	1982	11	8.01%	0.87%	5.33%	8.08%
OM:BERNER B	2014	4	10.21%	16.86%	3.94%	16.27%
OM:FG	2020	6	7.83%	0.72%	14.48%	5.05%
OM:GREEN	2018	5	12.59%	2.59%	21.07%	11.41%
OM:IDUN B	2021	2	18.74%	2.44%	8.75%	48.87%
OM:INDT	2005	37	11.83%	0.80%	8.06%	10.81%
OM:INFREA	2018	5	7.40%	6.69%	11.72%	42.77%
OM:INSTAL	2017	36	9.53%	0.84%	14.43%	9.51%
OM:LAGR B	2001	16	11.82%	2,00%	4.81%	9.59%
OM:LIFCO B	2014	7	19.44%	0.58%	9.15%	9.79%
OM:MMGR B	2022	4	12.37%	4.71%	7.99%	4.74%
OM:NORB B	2021	2	8.39%	0.72%	12,00%	31.84%
OM:OEM B	1983	7	10.72%	4.08%	6.63%	15.26%
OM:SDIP B	2017	3	21.77%	1.57%	19.56%	0.93%
OM:SEAF	2019	6	11.54%	11.53%	6.54%	9.71%
OM:STOR B	2021	1	13.60%	0.09%	4.43%	0.33%
OM:TEQ	2019	2	22.57%	5.53%	15.91%	4.69%
OM:VESTUM	2021	4	20.13%	0.54%	4.69%	3.20%
OM:VIT B	1998	7	15.83%	0.98%	9.8%	3.59%
OM:VOLO	2016	8	5.34%	1.14%	6.15%	4.77%
OM:XANO B	1988	4	7.31%	1.26%	15.46%	21.01%

Appendix 2. Impact of Zero Daily Returns

This table reports the regression results from a robustness test examining the effect of including and excluding days with zero returns in the estimation window. The analysis is based on the full sample of transactions between 2000 and 2023. Columns (1) and (3) include days with zero-return in the estimation window, while columns (2) and (4) exclude them. The dependent variable is cumulative abnormal return (CAR), and the explanatory variables are *Profitability*, *Growth*, and *Asset light*. All models control for *Relative size* as well as industry fixed effects. Standard errors are reported in parentheses. Definitions of all independent variables are provided in Appendix 3.

	Announcement returns			
	[-1, 1]		[-2, 2]	
	(1)	(2)	(3)	(4)
Mean CAR (T-test)	0.599	0.561	0.440	0.377
T-test (CAR ≠ 0)	p=0.014	p=0.021	p=0.169	p=0.239
Wilcoxon (CAR ≠ 0)	p=0.038	p=0.056	p=0.318	p=0.432
(Intercept)	-0.289	-0.287	0.255	0.241
	(0.966)	(0.965)	(1.297)	(1.298)
Relative size	0.222***	0.221***	0.254***	0.252**
	(0.056)	(0.056)	(0.076)	(0.076)
Profitability	0.037	3.690	0.034	3.377
	(0.031)	(3.089)	(0.042)	(4.155)
Growth	0.032+	0.032+	0.044+	0.044+
	(0.019)	(0.019)	(0.025)	(0.025)
Asset light	0.039*	0.038*	0.029	0.027
	(0.017)	(0.017)	(0.023)	(0.023)
Num.Obs.	224	224	224	224
Industry FE	Yes	Yes	Yes	Yes
R2	0.115	0.114	0.078	0.076
R2 Adj.	0.083	0.081	0.044	0.042
F	3.507	3.449	2.276	2.218
RMSE	3.41	3.40	4.57	4.58

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix 3. Explanation of Independent Variables

This table defines each independent variable used in the regression models and explains how they are measured.

Variable	Explanation
Industry fixed effects	Dummy variable based on GICS industry codes, covering Industrials, Healthcare, Information Technology, Materials and Consumer Discretionary
Relative size	Measured as the target's total assets divided by the acquirer's total assets.
Profitability	Measured as the average EBIT margin over five fiscal years prior to the acquisition.
Growth	Measured as the compound annual growth rate (CAGR) of the target's revenue over five fiscal years prior to the acquisition.
Asset light	Measured as the average ratio of Property, Plant, and Equipment (PPE) to total assets over five years prior to the acquisition.

Appendix 4. Robustness Tests for Full Sample

This table reports the results of the baseline OLS regression outlined in section 4.6 as well as two robustness tests made for the full sample between 2000-2023. The dependent variable is cumulative abnormal return (CAR), and the explanatory variables are *Profitability*, *Growth*, and *Asset light*. All four regressions include *Relative size* as a control variable as well as industry fixed effects. Columns (1) and (4) present the results of the baseline OLS regression shown in Table 5. Columns (2) and (5) present the regression results using winsorized CAR values, where the CAR is winsorized at the 5th and 95th percentile values. Columns (3) and (6) report regression results where the explanatory variables *Profitability*, *Growth* and *Asset light* are winsorized at the 5th and 95th percentile values. Standard errors are reported in parentheses. Definitions of all independent variables are provided in Appendix 3.

	Announcement returns					
	[-1, 1]			[-2, 2]		
	(1)	(2)	(3)	(4)	(5)	(6)
Mean CAR (T-test)	0.599	0.563	0.599	0.440	0.411	0.440
T-test (CAR ≠ 0)	p=0.014	p=0.007	p=0.014	p=0.169	p=0.123	p=0.169
Wilcoxon (CAR ≠ 0)	p=0.038	p=0.027	p=0.038	p=0.318	p=0.241	p=0.318
(Intercept)	-0.289	-0.089	-0.437	0.255	0.486	0.084
	(0.966)	(0.823)	(1.003)	(1.297)	(1.082)	(1.344)
Relative size	0.222***	0.164***	0.220***	0.254***	0.182**	0.253***
	(0.056)	(0.048)	(0.056)	(0.076)	(0.063)	(0.076)
Profitability	0.037	0.036	0.029	0.034	0.034	0.021
	(0.031)	(0.026)	(0.036)	(0.042)	(0.035)	(0.048)
Growth	0.032+	0.034*	0.036	0.044+	0.044*	0.056
	(0.019)	(0.016)	(0.027)	(0.025)	(0.021)	(0.036)
Asset light	0.039*	0.033*	0.044*	0.029	0.022	0.031
	(0.017)	(0.014)	(0.019)	(0.023)	(0.019)	(0.026)
Num.Obs.	224	224	224	224	224	224
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.115	0.108	0.107	0.078	0.072	0.072
R2 Adj.	0.083	0.074	0.074	0.044	0.037	0.037
F	3.507	3.241	3.218	2.276	2.075	2.086
RMSE	3.41	2.90	3.42	4.57	3.81	4.59

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix 5. Robustness Tests for Positive Interest Rate Environment

This table reports the results of the baseline OLS regression outlined in section 4.6 as well as two robustness tests for all transactions made during periods of positive interest rates (January 1, 2000, to October 28, 2014, and May 4, 2022, to December 31, 2023). The dependent variable is cumulative abnormal return (CAR), and the explanatory variables are *Profitability* and *Growth*. All four regressions include *Relative size* and *Asset light* as control variables as well as industry fixed effects. Columns (1) and (4) present the results of the baseline OLS regression shown in Table 6. Columns (2) and (5) present the regression results using winsorized CAR values, where the CAR is winsorized at the 5th and 95th percentile values. Columns (3) and (6) report regression results where the independent variables *Profitability*, *Growth* and *Asset light* are winsorized at the 5th and 95th percentile values. Standard errors are reported in parentheses. Definitions of all independent variables are provided in Appendix 3.

	Announcement returns					
	[-1, 1]			[-2, 2]		
	(1)	(2)	(3)	(4)	(5)	(6)
Mean CAR (T-test)	0.999	1.000	0.999	0.725	0.792	0.725
T-test (CAR ≠ 0)	p=0.013	p=0.006	p=0.013	p=0.170	p=0.074	p=0.170
Wilcoxon (CAR ≠ 0)	p=0.013	p=0.010	p=0.013	p=0.084	p=0.072	p=0.084
(Intercept)	0.537	0.469	0.739	1.194	1.280	1.238
	(1.347)	(1.207)	(1.422)	(1.828)	(1.510)	(1.934)
Relative size	-0.013	0.008	-0.020	0.243	0.272	0.230
	(0.198)	(0.177)	(0.199)	(0.269)	(0.222)	(0.270)
Profitability	0.040	0.052	0.028	0.076	0.083	0.061
	(0.060)	(0.054)	(0.070)	(0.081)	(0.067)	(0.095)
Growth	0.015	0.018	-0.015	0.031	0.032	0.017
	(0.031)	(0.028)	(0.052)	(0.042)	(0.035)	(0.070)
Asset light	0.044	0.041	0.041	0.024	0.013	0.020
	(0.027)	(0.024)	(0.028)	(0.037)	(0.031)	(0.038)
Num.Obs.	85	85	85	85	85	85
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.085	0.100	0.077	0.053	0.075	0.040
R2 Adj.	-0.011	0.006	-0.020	-0.047	-0.022	-0.061
F	0.882	1.059	0.791	0.528	0.770	0.394
RMSE	3.44	3.09	3.46	4.67	3.86	4.71

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix 6. Robustness Tests for Zero or Negative Interest Rate Environment

This table reports the results of the baseline OLS regression outlined in section 4.6 as well as two robustness tests for all transactions made during periods of zero or negative interest rates (October 29, 2014, to May 3, 2022). The dependent variable is cumulative abnormal return (CAR), and the explanatory variables are *Profitability* and *Growth*. All four regressions include *Relative size* and *Asset light* as control variables as well as industry fixed effects. Columns (1) and (4) present the results of the baseline OLS regression shown in Table 7. Columns (2) and (5) present the regression results using winsorized CAR values, where the CAR is winsorized at the 5th and 95th percentile values. Columns (3) and (6) report regression results where the independent variables *Profitability*, *Growth* and *Asset light* are winsorized at the 5th and 95th percentile values. Standard errors are reported in parentheses. Definitions of all independent variables are provided in Appendix 3.

	Announcement returns					
	[-1, 1]			[-2, 2]		
	(1)	(2)	(3)	(4)	(5)	(6)
Mean CAR (T-test)	0.354	0.303	0.354	0.265	0.146	0.265
T-test (CAR ≠ 0)	p=0.252	p=0.211	p=0.252	p=0.511	p=0.665	p=0.511
Wilcoxon (CAR ≠ 0)	p=0.495	p=0.415	p=0.495	p=0.941	p=0.979	p=0.941
(Intercept)	-1.466	-1.083	-1.630	-1.646	-1.368	-1.821
	(1.520)	(1.205)	(1.562)	(2.059)	(1.741)	(2.116)
Relative size	0.261***	0.172***	0.260***	0.267***	0.184**	0.267***
	(0.058)	(0.046)	(0.058)	(0.079)	(0.067)	(0.079)
Profitability	0.038	0.034	0.029	0.014	0.015	0.003
	(0.038)	(0.030)	(0.042)	(0.051)	(0.043)	(0.057)
Growth	0.044+	0.045*	0.057+	0.060+	0.057*	0.072+
	(0.024)	(0.019)	(0.029)	(0.032)	(0.027)	(0.040)
Asset light	0.029	0.020	0.043	0.029	0.024	0.046
	(0.022)	(0.018)	(0.028)	(0.030)	(0.025)	(0.037)
Num.Obs.	139	139	139	139	139	139
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.171	0.151	0.172	0.113	0.092	0.113
R2 Adj.	0.120	0.099	0.121	0.058	0.037	0.059
F	3.356	2.897	3.374	2.062	1.655	2.072
RMSE	3.29	2.61	3.29	4.45	3.77	4.45

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

AI Disclosure

For this paper, ChatGPT was utilized as a tool to increase the quality of the text as well as a support tool for coding. More specifically, ChatGPT was used to enhance the overall quality of the text by correcting grammar and increasing coherence. Furthermore, ChatGPT was also used as a support tool for coding. It primarily assisted us with correction of errors, optimizing formatting as well as provided suggestions on how to visualize the results of this paper. Consequently, ChatGPT has contributed to this thesis in several ways. Foremost, it has improved the quality of the paper by enhancing clarity, reducing redundancies, and refining wording. Secondly, it has also assisted with identifying errors and inconsistencies in the code, thereby increasing the reliability of the results.

Nevertheless, there are several risks associated with using AI that could affect the reliability of this thesis. One concern is that output from AI tools aimed at improving the text may lack coherence with the rest of the document and can be incorrect or unreliable. Therefore, all text generated by ChatGPT were thoroughly reviewed, corrected manually and adapted to fit the specific context of the text. Another potential issue is that AI-generated code may be incorrect or improperly specified, leading to inaccurate results or visualizations. Consequently, all lines of code were carefully vetted and for each chunk of code, a sample of the underlying data was reviewed to see that the output was correct.

The conclusion drawn from using ChatGPT in this thesis is that AI is a powerful tool for enhancing the clarity and coherence of the text, as well as for improving and correcting code. Even so, there were several instances where ChatGPT's output was incorrect or mis specified, reinforcing the conclusion that AI is best used as a carefully monitored assistant rather than an independent creator.