"Acquisition Rate and Financial Performance: An Absorptive Capacity Perspective"

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Abstract

This thesis investigates how the financial performance of publicly listed high-technology firms is affected by their rate of acquisitions, and whether this relationship is moderated by prior acquisition experience. Guided by Absorptive Capacity Theory (ACT), the study hypothesises that firms benefit most from a moderate acquisition rate, as both very low and very high levels of acquisition activity may hinder performance. Too few acquisitions may limit opportunities for external knowledge absorption, while excessive acquisition activity can exceed firms' capacity to process and integrate external knowledge. It is also expected that prior acquisition experience enhances a firm's ability to manage more intensive acquisition programs. A panel dataset covering multiple years of firm-level data is used to test these relationships through multiple linear regression analysis. The results do not support the hypothesised effects: neither acquisition rate nor its quadratic term shows a significant relationship with performance, and prior experience does not moderate this relationship. These null findings challenge earlier empirical results and suggest that acquisition outcomes are highly context dependent. The study contributes to the literature by extending ACT into the temporal dimension of acquisition strategy and highlights the importance of firm-specific integration capabilities over general pacing prescriptions.

INTRODUCTION

In high-tech industries, the ability to innovate rapidly and respond to technological shifts is essential for survival (Fontana & Nesta, 2009). Because internal development is often costly and time-intensive, firms increasingly turn to acquisitions as a strategic tool for accessing external knowledge and technology (Ahuja & Katila, 2001; Lee & Kim, 2016; Makri, Hitt, & Lane, 2010). Acquisitions enable firms to enhance market power, overcome entry barriers, expand into new markets, and acquire critical knowledge and resources (Vermeulen & Barkema, 2001). Through acquisitions, firms gain rapid access to new knowledge stocks, facilitating swift adaptation to technological changes, mitigating competitive threats, and fostering breakthrough innovations (Bhussar et al., 2022; Kapoor & Klueter, 2015).

Yet, acquisitions do not always lead to success. Their performance impact varies considerably between firms (King et al., 2004), raising questions about what drives post-acquisition outcomes. While acquisitions provide access to external knowledge (Kapoor & Klueter, 2015), firms vary in their ability to integrate and utilize this knowledge effectively (Cohen & Levinthal, 1990). Some firms leverage acquisitions successfully to enhance innovation and financial performance (Bhussar et al., 2022), while others struggle with integration challenges that diminish the expected benefits (Laamanen & Keil, 2008). To explain this variation, this study draws on Absorptive Capacity Theory (ACT) (Cohen & Levinthal, 1990). ACT explains how a firm's prior knowledge base and organizational routines shape its ability to assimilate and exploit new knowledge, a process highly relevant in the context of acquisitions.

One key factor that influences whether acquisitions contribute positively to firm performance is the acquisition rate, the frequency with which firms engage in acquisitions (Jiang et al., 2014). Defined as the number of acquisitions completed within a specific timeframe (Laamanen & Keil, 2008), acquisition rate can place significant demands on a firm's absorptive capacity. Firms that acquire at a rapid pace may struggle to process and integrate knowledge effectively, leading to inefficiencies and diminished returns (Jiang et al., 2014). In contrast, firms that acquire too slowly risk losing the relevance of earlier learning, making it harder to apply past insights and sustain a competitive advantage (Argote et al., 1990). These mixed findings suggest that the relationship between acquisition rate and performance is not linear. Rather, firms must find a balance—one that aligns their acquisition rate with their capacity to absorb and utilize external knowledge.

One factor that may influence a firm's ability to manage their acquisition rate effectively is prior acquisition experience. Firms that frequently engage in acquisitions develop structured routines, integration capabilities, and learning mechanisms that can enhance their ability to process and apply external knowledge (Zollo & Singh, 2004). This accumulated experience can strengthen a firm's absorptive capacity, which determines how well it can recognize, assimilate, and exploit new knowledge (Cohen & Levinthal, 1990). This study therefore examines acquisition experience as a potential moderator in the relationship between acquisition rate and performance.

Building on the previous discussion, this study applies Absorptive Capacity Theory (ACT) to examine how firms process and utilize external knowledge gained through acquisitions. Given that acquisition rate and experience affect how firms manage knowledge integration, ACT provides a suitable lens for understanding variation in post-acquisition performance. This leads to the following research question:

"What is the effect of acquisition rate on the financial performance of high-tech firms, and to what extent is this relationship influenced by prior acquisition experience?"

This study makes three key contributions. First, it advances acquisition research by applying Absorptive Capacity Theory (ACT) to explain how firms process and integrate external knowledge — an approach that is rarely used to examine the performance effects of acquisition rate. This theoretical framing sheds light on why some firms benefit more from acquisition activity than others. Second, it offers a new perspective on acquisition experience, which is often treated as a control variable, by exploring its role as a potential moderator that may strengthen firms' ability to manage acquisition rate. This adds a dynamic view to existing models by linking prior experience to firms' internal learning capabilities. Third, it provides practical guidance for high-tech firms by emphasizing the need to align acquisition strategies with organizational capacity to absorb and apply knowledge. This insight supports managers in designing acquisition approaches that avoid both underutilization and overload.

The structure of this study is divided into six chapters. Chapter 2 outlines the theoretical framework, introducing Absorptive Capacity Theory (ACT) as the central lens through which the relationship between acquisition rate, financial performance, and prior acquisition experience is examined. Chapter 3 details the research methodology, including data collection, variable measurement, and analytical techniques. Chapter 4 presents the results, analysing the effect of acquisition rate on financial performance and the moderating role of prior acquisition experience. Chapter 5 interprets the findings in relation to existing literature, highlighting theoretical contributions and managerial implications. Chapter 6 concludes the study, summarizing key insights and proposing avenues for future research.

THEORY AND HYPOTHESES

High-tech firms frequently use acquisitions to rapidly gain access to new technologies and knowledge, which are essential for maintaining competitiveness (Kapoor & Klueter, 2015). However, the outcomes of these acquisitions can vary widely and appear to be influenced by the rate at which firms acquire—i.e., the frequency of acquisitions within a given timeframe (Laamanen & Keil, 2008). This raises important questions about how acquisition rate influences post-acquisition performance, particularly in relation to firms' ability to process and utilize external knowledge. Prior acquisition experience (Laamanen & Keil, 2008) and absorptive capacity (Cohen & Levinthal, 1990; Zahra & George, 2002)—the ability to assimilate and apply external knowledge—are likely to play a key role in shaping these outcomes. This chapter introduces the theoretical concepts that underpin this relationship.

Absorptive Capacity Theory

Absorptive Capacity Theory (ACT), introduced by Cohen and Levinthal (1990), describes a firm's ability to recognize external knowledge, absorb it into internal operations, and apply it to drive innovation and improve performance. This capacity is not static but develops over time as firms accumulate relevant experience and build routines that facilitate organisational learning. (Cohen & Levinthal, 1990). It is rooted in prior related knowledge and shaped by structured processes that support the recognition, processing, and application of external information—factors that are particularly salient in firms that rely on acquisitions to access knowledge beyond their organisational boundaries.

Zahra and George (2002) build on this foundation by distinguishing four interrelated dimensions of absorptive capacity: acquisition, assimilation, transformation, and exploitation. These dimensions together describe the internal processes through which external knowledge is converted into organisational outcomes. Acquisition refers to the ability to identify and obtain valuable knowledge from the environment. Assimilation captures the firm's capacity to analyse, interpret, and understand this knowledge. Transformation reflects the ability to combine new knowledge with existing cognitive structures, and exploitation relates to the application of this integrated knowledge to create value.

Together, these four dimensions represent the core mechanisms through which absorptive capacity is exercised. They function as a cumulative and recursive system: each dimension builds on the previous, and the capacity as a whole strengthens as firms develop learning routines and deepen their knowledge base (Cohen & Levinthal, 1990; Zahra & George, 2002). This dynamic is especially important in high-technology industries, where knowledge flows rapidly and the ability to absorb and leverage external inputs is essential for maintaining competitiveness (Kapoor & Klueter, 2015). Within this study, ACT serves as the theoretical foundation for analysing how acquisition rate and prior acquisition experience shape a firm's ability to absorb and apply external knowledge in the context of post-acquisition performance. The next section elaborates on how acquisition rate, in particular, interacts with absorptive capacity mechanisms to affect financial outcomes.

Acquisition rate and financial performance

Firms seeking growth through acquisitions often face a strategic dilemma: should they expand aggressively to seize opportunities, or proceed cautiously to ensure stability and integration? Absorptive Capacity Theory (ACT) provides a theoretical lens for understanding how firms' ability to absorb and apply external knowledge interacts with acquisition strategy. According to ACT, firms vary in their ability to recognize, assimilate, and apply external knowledge (Cohen & Levinthal, 1990). Acquisition rate influences the flow of external knowledge (Choi & McNamara, 2017), but ACT suggests that firms must balance their ability to integrate this knowledge with their acquisition strategy to optimize financial performance.

At one extreme, acquiring firms too rapidly can create significant challenges due to knowledge overload. Laamanen and Keil (2008) found that firms with an overly aggressive acquisition strategy often experience declining financial performance, as the burden of managing multiple integrations becomes overwhelming. Jiang et al. (2014) further argue that high acquisition speed reduces the survival chances of newly acquired subsidiaries, as managerial attention and financial resources are stretched thin across multiple integration efforts. ACT helps explain these negative effects by suggesting that firms that acquire too quickly may overload their assimilation and transformation capacities, reducing their ability to process and integrate acquired knowledge effectively (Zahra & George, 2002). As a result, they may fail to fully exploit that knowledge, leading to inefficiencies and declining financial performance. Additionally, Li et al. (2024) highlight that an acquisition spree may divert management's focus away from internal research and development, limiting the firm's ability to generate organic innovation and sustain long-term competitiveness. This aligns with ACT's premise that firms must have the cognitive capacity and organizational mechanisms to absorb knowledge from external sources effectively (Cohen & Levinthal, 1990). When a firm is constantly in acquisition mode, its ability to learn from each deal diminishes because there is insufficient time for knowledge internalization (Li et al., 2024). As a result, frequent acquirers may fail to leverage potential synergies and innovation opportunities, ultimately weakening their financial performance.

While high acquisition rates may challenge a firm's absorptive capacity, overly cautious acquisition behaviour also carries risks. In dynamic high-tech industries, where innovation cycles are short and knowledge becomes obsolete quickly, a low acquisition rate may hinder a firm's ability to acquire timely access to emerging technologies. Bhussar et al. (2022) argue that firms which fail to engage in acquisitions at a sufficient pace risk falling behind competitors in innovation, as critical knowledge and capabilities become embedded elsewhere. From an ACT perspective, reduced acquisition activity limits exposure to external knowledge stimuli, which are essential for activating and strengthening absorptive processes (Zahra & George, 2002). In this sense, a slow acquisition rate can restrict learning opportunities, leaving firms less adaptable to technological shifts.

Given these contrasting perspectives, Yang et al. (2017) propose that the relationship between acquisition pace and firm performance follows an inverted U-shape. Firms that expand too quickly suffer from compression diseconomies, as they struggle to effectively absorb and integrate multiple acquisitions at once, leading to inefficiencies (Jiang et al., 2014). However, an overly cautious approach can also hinder performance (Bhussar et al., 2022). When firms take too long between acquisitions, they risk losing the relevance of past learning experiences, making it harder to apply insights from earlier deals (Argote et al., 1990). This aligns with findings from Hayward (2002) and Kusewitt (1985), who emphasize that firms achieve superior performance when they maintain a moderate acquisition pace, allowing them to integrate new knowledge efficiently while sustaining strategic momentum. These arguments imply an inverted U-shaped relationship between acquisition rate and financial performance, which is formally stated in the following hypothesis.

Hypothesis 1: The relationship between acquisition rate and financial performance follows an inverted U-shape, where a moderate acquisition rate maximizes financial performance, while high and low acquisition rates result in diminishing returns.

Moderating effect prior acquisition experience

According to Absorptive Capacity Theory (ACT), a firm's prior related knowledge plays a key role in its ability to recognize, assimilate, and apply external knowledge (Cohen & Levinthal, 1990). Firms that engage in acquisitions more frequently tend to accumulate such knowledge over time, developing cognitive frameworks and routines that facilitate more effective integration (Feldman, 2020; Keil et al., 2023). This cumulative acquisition experience, particularly in related industries, supports learning processes and strengthens the firm's capacity to absorb and leverage new knowledge in subsequent deals (Haleblian & Finkelstein, 1999; Villalonga & McGahan, 2005).

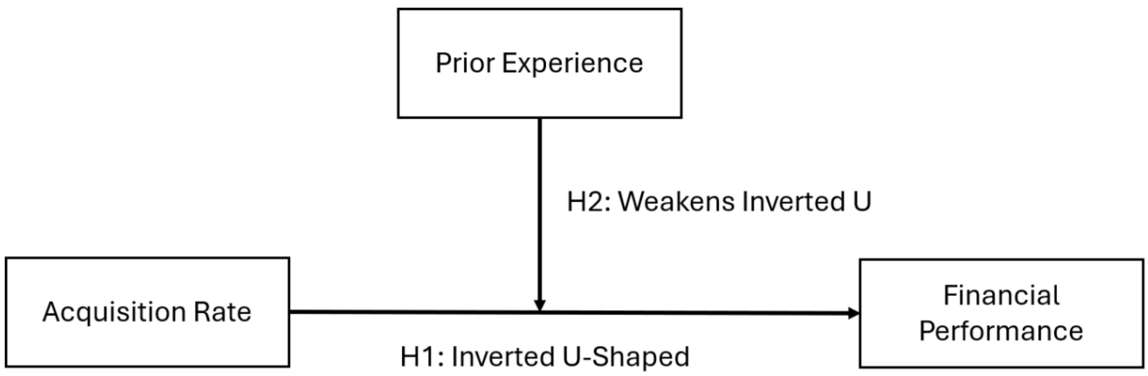
Building on this view, ACT suggests that firms with prior acquisition experience are better able to identify and assimilate valuable external knowledge, as they have developed schemas and routines from earlier deals (Cohen & Levinthal, 1990). These routines help streamline integration processes and improve a firm's ability to translate acquired knowledge into performance outcomes (Choi & McNamara, 2017). In line with this, Bhussar et al. (2022) find that ventures with established experience and structured routines are more likely to achieve positive integration and innovation results after acquisitions.

Conversely, ACT suggests that firms with limited prior related knowledge are more likely to face integration difficulties due to underdeveloped cognitive frameworks and routines (Lenox & King, 2004). These limitations can lead to ineffective assimilation of external knowledge or even negative knowledge transfer, where acquired practices conflict with existing systems or capabilities (Finkelstein & Haleblian, 2002; Shukla & Kumar, 2023). As a result, less experienced firms may struggle to extract value from acquisitions, particularly when acquisition rate is high and absorptive demands increase.

Prior acquisition experience shapes how firms respond to different levels of acquisition activity. According to Absorptive Capacity Theory, experienced firms have developed routines and cognitive structures that allow them to process external knowledge more efficiently (Cohen & Levinthal, 1990; Zollo & Singh, 2004). As acquisition rate increases, these routines help mitigate the risk of overload, enabling firms to integrate knowledge without suffering the performance decline that typically occurs beyond the optimal point in an inverted U-shaped relationship (Haleblian & Finkelstein, 1999). In contrast, firms with limited experience are more likely to reach their absorptive limits earlier, resulting in a steeper performance drop when acquisition activity is high (Shukla & Kumar, 2023). These dynamics suggest that prior acquisition experience moderates the shape of the relationship between acquisition rate and financial performance.

Hypothesis 2: Prior acquisition experience moderates the relationship between acquisition rate and financial performance such that the inverted U-shaped relationship is weaker for firms with high acquisition experience.

Conceptual Model



METHODOLOGY

Empirical Setting

This study examines publicly listed firms operating in high-technology industries, which are characterized by short innovation cycles, intensive knowledge flows, and high acquisition activity, making them particularly relevant for studying absorptive capacity and acquisition performance (Aalbers et al., 2021). To identify firms in high-tech sectors, this study adopts the SIC code classification recommended by Kile and Phillips (2009), who developed a benchmark-based methodology for selecting high-technology firms. Their approach outperforms prior ad hoc classifications by systematically comparing firm disclosures against a validated industry benchmark. Based on their findings, the high-tech sector in this study includes firms classified under the following SIC codes: 283 (Drugs), 357 (Computer and Office Equipment), 366 (Communication Equipment), 367 (Electronic Components and Accessories), 382 (Laboratory Instruments), 384 (Medical Instruments), 481 (Telephone Communications), 737 (Computer Programming and Data Processing), and 873 (Research and Testing Services). This combination yields high alignment with actual high-tech firm characteristics and minimizes classification error, making it a reliable foundation for empirical research in this domain. The sample spans the period from 2011 to 2024, allowing sufficient variation in acquisition activity and performance over time. This period is long enough to construct time-based variables, such as acquisition rate (measured over a three-year window) and prior acquisition experience (measured cumulatively before that window).

Data Sources

This study integrates firm-level financial and acquisition data from two primary sources: LSEG Workspace and Orbis.

Financial data were obtained from LSEG Workspace and cover the period from 2010 to 2024. This start date ensures that lagged variables—such as Prior ROA—can be calculated beginning in 2011, the first year of analysis. The dataset includes annual figures for total assets, net income, revenue, and R&D expenditures. Firms operating in the financial and utilities sectors were excluded due to their unique regulatory and accounting structures, which reduce comparability.

Acquisition data were collected from Orbis, which provides global coverage of mergers and acquisitions. The dataset includes all announced or completed transactions between 1997 and 2025 in which the acquiring firm obtained a full 100% ownership, and the deal value exceeded USD 1 million. This threshold excludes minor or administrative transactions and ensures strategic relevance. Deal types such as recapitalizations, joint ventures, share buybacks, and reverse mergers were excluded to avoid capturing internal restructuring events.

The choice to include transactions from as early as 1997 was made to enable the construction of the acquisition experience variable, which measures the cumulative number of acquisitions completed by each firm prior to a given year.

The two datasets were merged at the firm–year level using standardized ticker codes. Only observations with complete information across all relevant variables were retained. All data transformation, structuring, and merging procedures were conducted in Microsoft Excel, using Power Query and formula logic to ensure consistency and replicability.

Sample Selection and Data Cleaning

The merged dataset initially contained firm–year observations for high-tech companies between 2010 and 2024. A series of selection and cleaning steps were applied to ensure data quality and analytical validity.

First, all observations from 2010 were excluded, as key lagged variables such as Prior ROA could not be computed for that year. Observations with missing or invalid values in core variables—such as ROA, Prior ROA, Acquisition Rate, Acquisition Experience, R&D Intensity, Firm Age, and Firm Size—were also removed. Firm–year records with Firm Age < 0 were excluded, as these reflected erroneous combinations of founding year and observation year. Observations with Firm Age = 0 were retained, provided that other values were valid.

To ensure the analysis focused on firms actively engaged in acquisitions, the dataset was restricted to firm–year observations with Acquisition Rate > 0. This approach is consistent with prior studies on acquisition behaviour, which typically distinguish between acquirers and non-acquirers (e.g., Laamanen & Keil, 2008).

After applying these filters, the final sample comprised 1,088 firm–year observations from high-tech companies that completed at least one strategic acquisition in the focal year or the two preceding years, over the period 2011 to 2024.

Variable Construction

All variables were constructed at the firm–year level using a merged dataset from Orbis and LSEG Workspace. Only observations with complete and valid data were retained for analysis.

The dependent variable is Return on Assets (ROA), calculated as net income divided by total assets, and measured for the focal year (*t*). ROA serves as a standard proxy for operational performance in acquisition studies (King et al., 2021). The original distribution contained several extreme values, ranging from –36.48 to 0.99 (*Appendix A1*). To limit their influence, ROA was winsorized at the 1st and 99th percentiles, resulting in a value range from –3.38 to 0.27. A bounded version of ROA, capped between –1 and 1, was also constructed for robustness checks to prevent distortion from implausible financial ratios, such as those arising in distressed or highly leveraged firms.

The independent variable, acquisition rate, reflects the number of acquisitions completed within a three-year rolling window: the focal year and the two preceding years (*t*, *t–1*, *t–2*). This measure captures short-term acquisition behaviour, consistent with Laamanen and Keil (2008). Acquisitions were included based on the filtering criteria outlined before: a minimum deal value of USD 1 million, an ownership stake of 100%, and a deal status of completed or announced. Internal restructurings were excluded. A squared term was added to test for non-linear effects, based on the expectation of an inverted U-shaped relationship between acquisition rate and firm performance (Yang et al., 2017).

The moderating variable, acquisition experience, was defined as the cumulative number of qualifying acquisitions completed by each firm up to and including year *t–1*. This measure reflects a firm's historical acquisition and integration experience and was constructed using the same criteria as acquisition rate (Laamanen & Keil, 2008). An interaction term between acquisition rate and experience was included to test for moderation effects.

Several firm-level control variables were included to isolate the effects of acquisition activity on financial performance. Prior ROA, defined as return on assets in year t–1, was included to control for baseline profitability. It was calculated using the same formula as the dependent variable: net income divided by total assets. The original distribution showed several extreme values, ranging from -469.12 to 5.02 (*Appendix A2*). To limit their influence, Prior ROA was winsorized at the 1st and 99th percentiles, resulting in a value range between –2.14 and 0.27. Firm size was measured as the natural logarithm of total assets, capturing differences in scale and resource availability (Haleblian et al., 2009). Firm age, calculated as the number of years since incorporation, reflects organizational maturity and cumulative learning effects (Bhussar et al., 2022). Observations with negative age were removed, while firms with age equal to zero were retained if other values were valid. R&D intensity, defined as R&D expenditure divided by total revenue, was included as a proxy for innovation orientation—particularly relevant in high-tech sectors where acquisitions often serve exploratory purposes (Ahuja & Katila, 2001). The original distribution of this variable also exhibited extreme outliers, ranging from 0 to 1022.7 (*Appendix A3*). To reduce their impact, R&D intensity was winsorized at the 1st and 99th percentiles, resulting in a final range between 0 and 78.24. Missing R&D values were recoded as zero under the assumption that firms with no reported R&D spending did not engage in formal R&D investment. In contrast, observations with zero or missing revenue were excluded, as the absence of revenue was interpreted as either incomplete reporting or non-operational status.

All variables were constructed using Microsoft Excel, with the support of Power Query for data filtering, sorting, and structured transformation. Consistency and traceability were ensured through stepwise validation during the data preparation process.

Estimation Strategy

This study uses an ordinary least squares (OLS) regression model estimated on firm–year level data to examine the relationship between acquisition activity and financial performance. The main specification includes acquisition rate, its squared term to capture potential non-linearity, prior acquisition experience, and an interaction term between acquisition rate and experience. All continuous predictors were mean centered before constructing squared and interaction terms to reduce potential multicollinearity. Robust standard errors clustered at the firm level were applied to correct for heteroskedasticity and within-firm correlation.

Although the dataset contains repeated observations per firm across years, the primary goal is to explain variation between firms rather than dynamic within-firm change. Therefore, no panel-specific estimator was applied. Instead, the regression includes industry and year fixed effects to account for unobserved heterogeneity across sectors and macroeconomic cycles. Industry fixed effects were based on 3-digit SIC codes, aligned with the high-tech classification used in sample selection. Year dummies were included for all years between 2012 and 2024, with 2011 as the reference category.

The model was estimated using an unbalanced panel, as the number of observations per firm varies depending on data availability. Observations with missing values for any model variable were excluded listwise.

To assess the robustness of the findings, additional model specifications were tested using the bounded and original versions of ROA as the dependent variable. The results remained consistent across specifications, confirming the stability of the main effects.

The underlying assumptions of the OLS regression models were tested to ensure the validity of statistical inference. Linearity and homoskedasticity were assessed through scatterplots of standardized residuals against predicted values (*Appendix B1*). The plots showed a slight funnel shape at lower predicted values, indicating mild heteroskedasticity, though not severe enough to warrant corrective measures. Normality of residuals was evaluated using histograms and Q–Q plots, which revealed minor deviations at the tails (*Appendix B2*). Given the sample size (N = 1088), these deviations were not considered problematic. Autocorrelation was tested using the Durbin–Watson statistic (DW = 1.995), confirming independence of residuals (*Appendix B3)*. Multicollinearity was assessed via variance inflation factors (all VIFs < 3, *Appendix B4*), and influential observations were examined using Cook's Distance (*Appendix B5*). While 38 observations exceeded a value of 0.10, none surpassed the conventional threshold of 1.0. Overall, no serious violations of OLS assumptions were identified, supporting the robustness of the regression results.

Research Ethics

This research was conducted with due regard for the ethical principles as described by the APA (Smith, 2003). Since this thesis was of quantitative nature, making use of data from Refinitiv's SDC Platinum database, issues revolving around confidentiality and privacy were not of concern. To circumvent any form of deception derived from the handling of data, it was only transformed with caution and reference when necessary. No data was altered to adhere to expectations or to any theoretical outcome or deleted without demonstrably sound grounds. Additionally, no results were intentionally interpreted incorrectly. Furthermore, I ensured acknowledgement of the intellectual property rights of each author's contribution to the literature. Finally, an integrity form was signed to ensure ethical conduct. This code of conduct was monitored closely, as this study was part of ongoing PhD research.

RESULTS

Descriptive Statistics and Correlations

Table 1 presents the descriptive statistics for all variables included in the main regression model (N = 1,088). The statistics are based on the winsorized versions of ROA, Prior ROA, and R&D Intensity. The average firm performance, measured as ROA, was –1.20%, with a standard deviation of 0.49. Although the minimum and maximum values of ROA were adjusted through winsorization, the range (–3.38 to 0.27) still reflects considerable variation in firm outcomes.

The average acquisition rate, measured over a three-year window and centered around the mean, was close to zero, consistent with the centered transformation. The squared term, based on the centered acquisition rate, ranged from 0.21 to 29.84, indicating that some firms exhibit notably high levels of acquisition activity. Prior acquisition experience ranged from 0 to 95 acquisitions, also centered, with a standard deviation of 7.77. Control variables such as firm size (mean = 20.91) and firm age (mean = 23.50) showed substantial variation, as expected. R&D Intensity had a mean of 1.52 and a maximum of 78.24, justifying the earlier winsorization due to right-skewed outliers.

Table 1. Descriptive Statistics of Main Model Variables

	Mean	**Std. Dev.**	**Min**	**Max**
ROA (winsorized)	-0.12	0.49	-3.38	0.27
Acquisition Rate (centered)	0.00	0.94	-0.54	5.46
Acquisition Rate^2 (centered)	0.89	2.72	0.21	29.84
Experience (centered)	0.00	7.77	-4.99	95.01
Interaction term	1.55	6.18	-50.01	58.06
Prior ROA (winsorized)	-0.16	0.67	-4.72	0.29
Firm Size	20.91	2.67	8.91	26.72
Firm Age	23.50	20.30	0.00	121.00
R&D Intensity (winsorized)	1.52	8.86	0.00	78.24

Pearson correlations among the variables are shown in Table 2. As expected, the correlation between acquisition rate and its squared term was high (r = .79), due to their mathematical dependency. No other correlations approached problematic levels. Multicollinearity was further evaluated via variance inflation factors (all below 3; see Appendix B4), confirming that multicollinearity is not a concern in the regression analysis.

Table 2. Pearson Correlations Among Model Variables

	1	2	3	4	5	6	7	8	9
1. ROA (winsorized)	1.00								
2. Acquisition Rate (centered)	0.12**	1.00							
3. Acquisition Rate^2 (centered)	0.06*	0.79**	1.00						
4. Experience (centered)	0.18**	0.21**	0.10**	1.00					
5. Interaction term	0.01	0.35**	0.33**	0.30**	1.00				
6. Prior ROA (winsorized)	0.61**	0.11**	0.05	0.17**	0.01	1.00			
7. Firm Size	0.56**	0.20**	0.13**	0.35**	0.12**	0.50**	1.00		
8. Firm Age	0.25**	0.17**	0.10**	0.24**	0.12**	0.22**	0.35**	1.00	
9. R&D Intensity (winsorized)	-0.23**	-0.08*	-0.04	-0.08**	0.01	-0.17**	-0.18**	-0.13**	1.00

$^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Hypothesis Testing

Table 3 presents the results of three hierarchical OLS regression models predicting firm performance, measured by winsorized ROA. Model 0 uses only control variables to establish the baseline explained variance. Model 1 adds the linear and squared terms of acquisition rate to test Hypothesis 1, and Model 2 incorporates prior acquisition experience and the interaction between acquisition rate and experience to test Hypothesis 2.

Contrary to expectations, Hypothesis 1 receives no support. In Model 1, neither the acquisition rate ($B = –0.13$, $p > 0.10$) nor its squared term ($B = 0.003$, $p > 0.10$) is statistically significant, failing to provide evidence of an inverted U-shaped relationship between acquisition activity and ROA. The inclusion of these variables also does not meaningfully improve the model fit, as reflected in unchanged R^2 and Adjusted R^2 values (both remaining at approximately 0.49).

Hypothesis 2 is similarly unsupported. In Model 2, neither the main effect of experience ($B = –0.002$, $p > 0.10$) nor the interaction term ($B = –0.003$, $p > 0.10$) reaches statistical significance, indicating that prior acquisition experience does not moderate the relationship between acquisition rate and financial performance. Adding these terms yields no notable change in explanatory power.

By contrast, control variables show consistent relations across all models. Prior ROA remains a strong positive predictor (Model 2: $B = 0.277$, $p < 0.001$), suggesting persistence in firm performance. Firm size also exhibits a positive association ($B = 0.070$, $p < 0.001$), while R&D intensity shows a small but significant negative effect ($B = –0.004$, $p < 0.001$). Firm age remains non-significant. The full model successfully explains nearly half of the variance in ROA ($R^2 \approx 0.495$; Adjusted $R^2 \approx 0.481$), but acquisition-related variables do not enhance the model beyond this.

In sum, the hierarchical analyses confirm that Hypotheses 1 and 2 are not supported. Acquisition rate, its quadratic form, and prior acquisition experience contribute no additional explanatory value over control variables alone.

Table 3. OLS Regression Results Predicting ROA (Winsorized Sample)

	Model 0	Model 1	Model 2
Acquisition Rate (centered)		-0.13	-0.006
Acquisition Rate^2 (centered)		0.003	0.003
Experience (centered)			-0.002
Interaction term			-0.003
Prior ROA (winsorized)	0.280***	0.280***	0.277***
Firm Size	0.066***	0.067***	0.070***
Firm Age	0.001	0.001	0.001
R&D Intensity (winsorized)	-0.004***	-0.004***	-0.004***
Constant	-1.478***	-1.490***	-1.547***
R^2	0.493	0.493	0.495
Adjusted R^2	0.481	0.480	0.481
N	1088	1088	1088
Year Fixed Effects	Included	Included	Included
Industry Fixed Effects	Included	Included	Included

†p < 0.1; *p < 0.05; **p < 0.01; ***p < 0.001

Robustness Checks

Table 4 reports two robustness models that replicate the full specification of Model 2 but with alternative operationalisations of ROA. Model 3 uses the original ROA, and Model 4 uses bounded ROA, constrained between –1 and 1.

Although acquisition rate (both linear and squared terms) and the interaction with prior experience remain non-significant in both models, the model fit diverges notably between them. Specifically, the Adjusted R^2 drops to 0.170 in Model 3 when using the original ROA, suggesting that extreme outlier values introduce substantial noise and reduce the model's explanatory power. Conversely, Model 4 achieves a higher Adjusted R^2 of 0.531—surpassing that of the winsorized baseline model. This indicates that truncating ROA to a plausible range enhances overall explanatory strength.

Importantly, despite these differences in model fit, the substantive interpretation remains unchanged: the acquisition-related variables and their interaction with experience continue to lack statistical significance. Control variables consistently predict performance: prior ROA remains highly positive, firm size shows a significant positive association, and R&D intensity retains a small negative effect. Firm age shows a small, positive effect that becomes statistically significant in Model 4, indicating some sensitivity to the ROA operationalisation.

These results confirm that conclusions drawn in the main models are robust to different treatments of the dependent variable. However, the variation in explanatory power across models highlights how data preprocessing decisions can affect overall fit and reinforces the rationale for using a bounded or winsorized ROA in the main analysis.

Table 4. Robustness Check Regressions Using the Original and Bounded ROA

	Model 3 (Original ROA)	Model 4 (Bounded ROA)
Acquisition Rate (centered)	-0.073	0.003
Acquisition Rate^2 (centered)	0.010	0.001
Experience (centered)	-0.013†	0.000
Interaction term	-0.001	-0.002†
Prior ROA (winsorized)	0.541***	0.120***
Firm Size	0.181***	0.045***
Firm Age	-0.002	0.001**
R&D Intensity (winsorized)	-0.020***	-0.003***
Constant	-3.778***	-1.013***
R^2	0.192	0.543
Adjusted R^2	0.170	0.531
N	1088	1088
Year Fixed Effects	Included	Included
Industry Fixed Effects	Included	Included

$^{\dagger}p < 0.1$; $*p < 0.05$; $**p < 0.01$; $***p < 0.001$

All models include the same predictors as Model 2 in Table 3. ROA was defined as (a) the original value and (b) a bounded value between –1 and 1.

DISCUSSION

This study examined whether the financial performance of high-tech firms is affected by their acquisition rate, and whether this relationship is moderated by prior acquisition experience. Grounded in Absorptive Capacity Theory (Cohen & Levinthal, 1990; Zahra & George, 2002), the expectation was that firms may face cognitive and organisational limits in processing external knowledge when acquisition activity exceeds their absorptive thresholds. Based on this reasoning and prior empirical finding (Jiang et al., 2014; Laamanen & Keil, 2008), it was hypothesised that a moderate acquisition rate would yield superior performance outcomes, and that prior experience could enhance a firm’s ability to manage more intensive acquisition patterns.

The empirical results did not confirm these expectations. Neither acquisition rate nor its quadratic term was significantly related to firm performance, and prior acquisition experience did not moderate this relationship. These null findings call into question the applicability of absorptive capacity mechanisms as a universal explanation for performance variation in acquisition strategies, at least in the context of publicly listed high-tech firms. While control variables such as prior ROA and firm size behaved as expected, the absence of significant effects for the focal variables suggests that acquisition performance may be driven by other, unobserved factors that are not captured through the current model.

There are several possible interpretations for these results. First, while ACT offers a compelling conceptual foundation, its mechanisms may not operate uniformly across firms or contexts. Theoretical models often assume that experience enhances absorptive routines (Bhussar et al., 2022; Zollo & Singh, 2004), yet such learning effects are contingent and may not generalise across strategic configurations (Haleblian & Finkelstein, 1999). Firms may differ significantly in how they structure, codify, and apply knowledge from past acquisitions. For instance, some firms may invest heavily in formal integration routines and codified knowledge transfer tools, whereas others rely on informal, ad hoc processes that may not scale effectively.

Second, firms in high-technology industries may increasingly rely on decentralised or externalised integration mechanisms (Kerstens & Langley, 2025), which could reduce the relevance of internal absorptive strain. Examples include the use of third-party integration consultants, digital post-merger management platforms, or modular acquisition structures that limit the complexity of internal coordination. These practices could enable firms to process acquisitions at scale without exhausting their internal knowledge-processing capacities. This may explain why no evidence of diminishing returns was observed at higher acquisition rates, contrary to the inverted U-shape proposed in earlier studies.

Taken together, these findings suggest that while ACT remains a useful starting point, its explanatory reach in this context may be limited. The absence of significant effects may suggest that acquisition performance is more context-dependent than previously assumed, possibly shaped by firm-specific capabilities, integration strategies, and structural configurations that are not easily captured through secondary data.

This study contributes to the literature in several ways. First, it extends the application of Absorptive Capacity Theory to the temporal dynamics of acquisition strategy, an area that has received limited attention in the absorptive capacity literature. By applying the concept of absorptive limits to acquisition rate, this research offers a conceptual expansion of ACT into the timing and frequency dimensions of M&A activity. This lens helps to reframe acquisition behaviour not just as a function of strategic intent, but as a process constrained by firms' ability to absorb and integrate knowledge over time.

Second, it adds to the debate on acquisition rate and performance. While earlier studies have reported an inverted U-shaped relationship (Jiang et al., 2014; Laamanen & Keil, 2008), the current findings challenge the robustness of this pattern. This indicates that such effects may be more situational than generalisable, and that acquisition outcomes are likely shaped by interactions between internal capabilities and external integration environments. The findings highlight the need for more nuanced and context-sensitive frameworks that take into account organisational heterogeneity.

Third, it questions the assumed benefits of cumulative experience in managing acquisition sequences. Prior work has stressed the value of learning-by-doing (Zollo & Singh, 2004), but the lack of significant moderating effects in this study suggests that experiential learning alone may not be sufficient. More attention should be given to how firms structure their post-acquisition processes and whether experience is meaningfully internalised into replicable routines. Experience without reflective learning or process standardisation may provide limited strategic advantage.

From a managerial perspective, the findings suggest that acquisition pacing should be treated as a contingent decision, rather than a one-size-fits-all formula. Firms should assess whether their internal structures, knowledge management routines, and integration capabilities are equipped to handle multiple acquisitions within a short period. This includes formalising integration procedures, investing in IT systems that track knowledge flows, and embedding learning feedback loops into the post-merger process.

Additionally, acquisition experience alone does not guarantee better outcomes. Firms should evaluate how past lessons are captured and transferred across units. Prior research shows that codified integration routines and structured learning processes enhance acquisition performance through increased organisational memory and knowledge transfer (Vermeulen & Barkema, 2001; Zollo & Winter, 2002). For example, post-acquisition audits or internal playbooks can help ensure that experiential learning is transformed into actionable routines.

Finally, several limitations should be acknowledged, which also point toward fruitful directions for future research. First, the key constructs were operationalised using aggregate secondary data, which may obscure firm-level variation in absorptive mechanisms and learning structures. As a researcher, the decision to rely on secondary quantitative data offered the benefit of scale, but it also meant that deeper processual insights into learning mechanisms remained inaccessible. This limitation is consistent with prior critiques of quantitative M&A research, which highlight the difficulty of capturing micro-level integration dynamics without qualitative inquiry (Graebner et al., 2017; Haleblian et al., 2009). Future studies could benefit from incorporating qualitative or mixed method approaches to better capture the nuances of knowledge integration and learning processes.

Second, the distribution of the acquisition rate variable was highly skewed, with most firm-year observations reflecting low acquisition activity (Appendix C). This may have limited the ability to detect non-linear effects, particularly in the higher ranges of acquisition frequency, and constrains generalisability to firms with more aggressive acquisition strategies. Future research should aim to include more balanced samples across the full spectrum of acquisition intensities to provide a more robust test of curvilinear effects.

Third, the study focused exclusively on publicly listed high-tech firms, limiting generalisability to other sectors or privately held companies. Future studies could explore whether the absence of pacing effects holds in more traditional or capital-intensive industries, where acquisition motives and integration approaches may differ substantially.

Fourth, ROA was used as the sole performance measure, which may not capture longer-term or strategic benefits of acquisition activity, such as innovation output, strategic positioning, or capability development. Future research could adopt multi-dimensional or lagged performance indicators to offer a more holistic understanding of acquisition outcomes.

These limitations do not undermine the value of the findings but rather highlight the complexity of acquisition dynamics and the importance of organisational context in shaping absorptive outcomes. Addressing these issues in future work can deepen theoretical insight and enhance the practical relevance of research on acquisition strategy and absorptive capacity.

CONCLUSION

This study set out to examine how the financial performance of high-technology firms is affected by their acquisition rate, and whether this relationship is moderated by prior acquisition experience. Drawing on Absorptive Capacity Theory (ACT), the research aimed to understand whether firms face performance constraints when acquisition activity exceeds their ability to process and integrate external knowledge. It was hypothesised that a moderate acquisition rate would yield superior outcomes, and that prior acquisition experience would strengthen a firm's ability to manage more intensive acquisition programs.

The empirical analysis, based on a panel of publicly listed high-tech firms, did not provide support for these expectations. Neither acquisition rate nor its quadratic term showed a significant relationship with firm performance. Moreover, prior acquisition experience did not moderate the relationship. These findings challenge the generalisability of earlier results and suggest that the relationship between acquisition strategy and performance is more context-dependent and complex than commonly assumed.

Despite the absence of statistically significant effects, the study offers meaningful theoretical and practical insights. It contributes to the literature by applying ACT to the temporal dynamics of acquisition behaviour, and by questioning the robustness of experience-based learning mechanisms. Furthermore, it highlights the importance of firm-specific capabilities and integration strategies, which may be overlooked when relying solely on aggregate performance indicators.

Taken together, the results suggest that firms should not rely on standardised acquisition pacing strategies or assume that experience automatically translates into integration success. Instead, strategic decision-making in M&A should be adaptive and informed by firm-specific absorptive structures and post-acquisition processes.

This study thus reinforces the need for more nuanced theoretical frameworks and richer empirical approaches when evaluating the performance consequences of acquisition strategy—particularly in dynamic, innovation-intensive sectors where learning, integration, and organisational complexity play a decisive role.

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APPENDIXES

Appendix A – Boxplots of Key Variables

This appendix presents boxplots for the key variables ROA, Prior ROA, and R&D Intensity. These plots were used to identify extreme values and justify the winsorization procedure described in the methodology section. Outliers that fall far outside the interquartile range can distort regression results, particularly in small or skewed samples.

A1. Boxplot of ROA (Return on Assets)

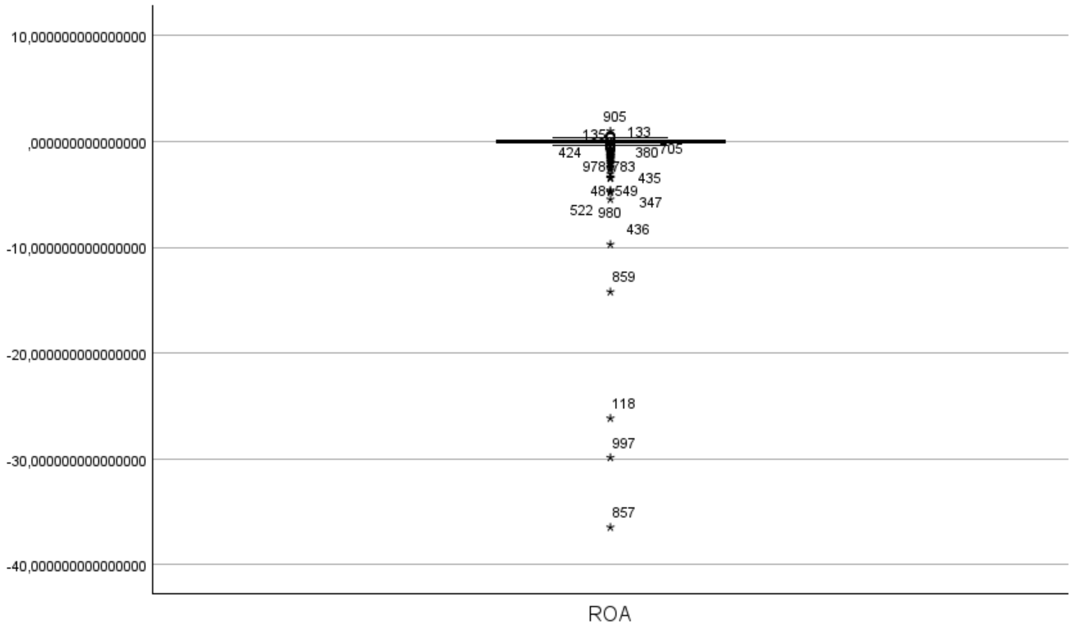

Figure 1: Boxplot of ROA

Interpretation: Multiple extreme negative outliers (e.g., below –30), justifying winsorization at the 1st and 99th percentiles.

A2. Boxplot of Prior ROA

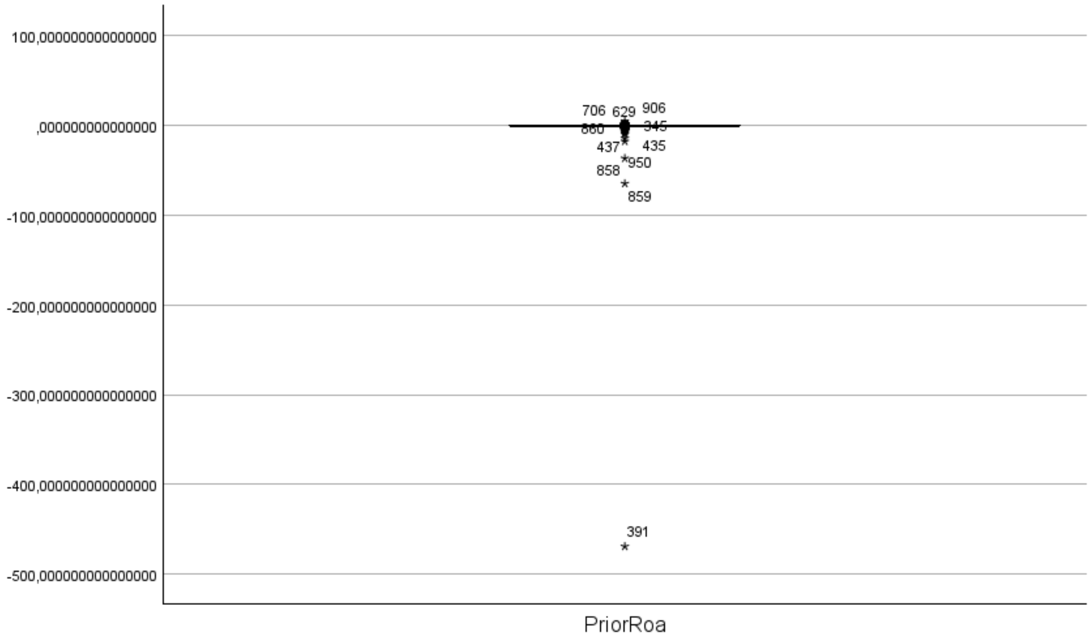

Figure 2: Boxplot of Prior ROA

Interpretation: Multiple extreme negative outlier (e.g., below –400), which could strongly bias estimates without adjustment.

A3. Boxplot of R&D Intensity

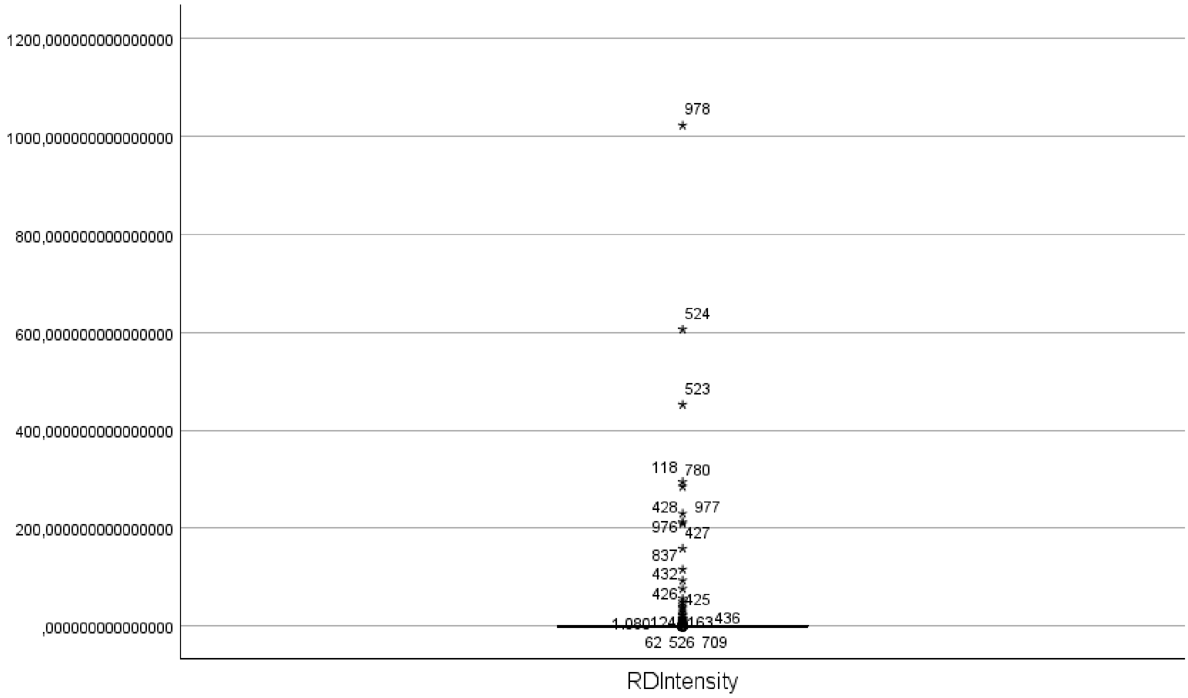

Figure 3: Boxplot of R&D Intensity

Interpretation: Heavy right skew due to several extreme values (e.g., above 600), confirming the need for winsorization.

Appendix B – Assumption Diagnostics

This appendix provides visual and statistical evidence supporting the assumption checks conducted for the OLS regression models described in the methodology section. Each assumption is tested individually.

B1. Linearity and Homoskedasticity

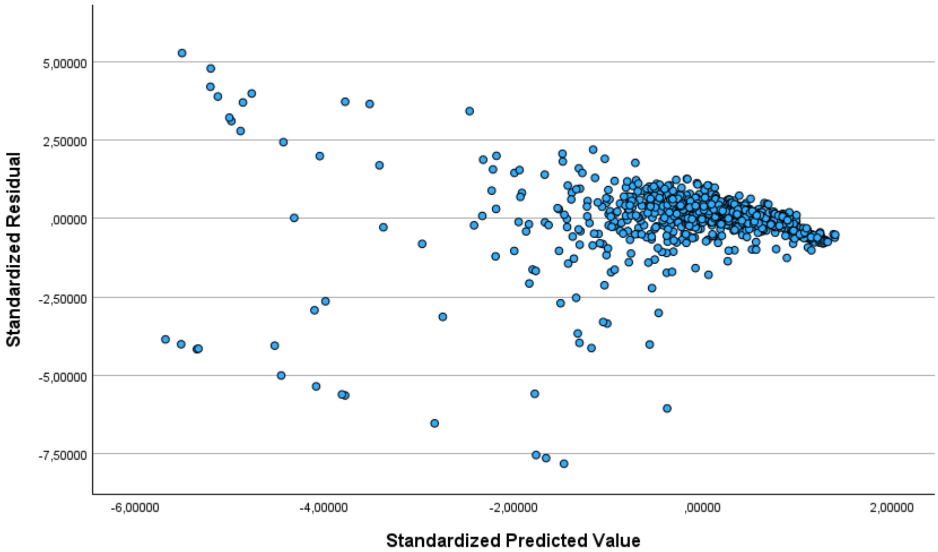

Figure 4: Scatterplot of standardized residuals vs. predicted values

Interpretation: No clear non-linearity detected. Mild funnel shape indicates slight heteroskedasticity, but not enough to affect the model validity.

B2. Normality of Residuals

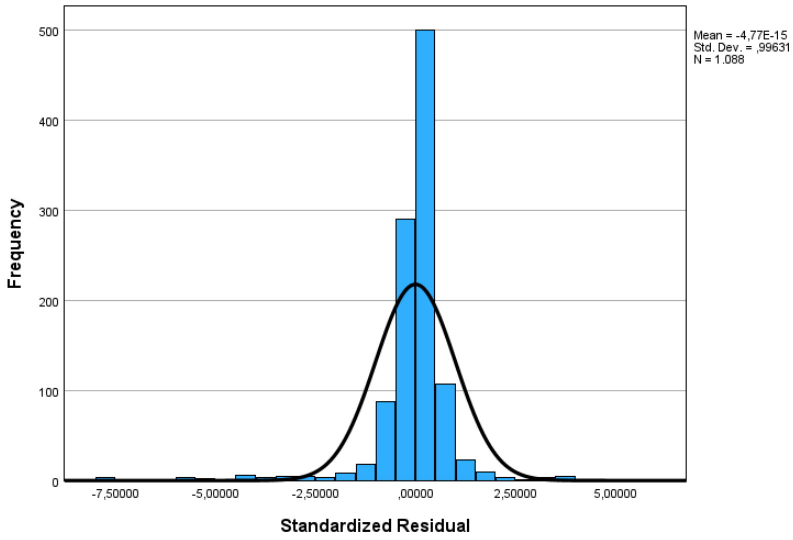

Figure 5: Histogram of standardized residuals

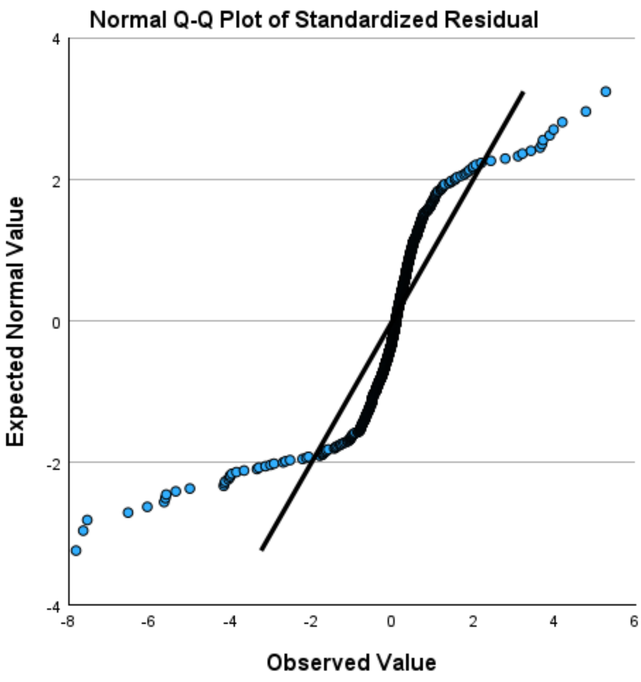

Figure 6: Q–Q plot of standardized residuals

Interpretation: Residuals show minor tail deviations but are approximately normally distributed given the sample size (N = 1088).

B3. Independence of Residuals

Durbin-Watson statistic: 1.995

Interpretation: Value close to 2 indicates no autocorrelation.

B4. Multicollinearity

Table 5: Variance Inflation Factors (VIFs) for all variables

Variable	VIF
Acquisition Rate (centered)	2.911
Acquisition Rate^2 (centered)	2.792
Experience (centered)	1.281
Acquisition Rate x Experience	1.241
Prior ROA (winsorized)	1.347
Firm Size	1.579
Firm Age	1.178
R&D Intensity (winsorized)	1.051

Interpretation: All VIFs < 3 → no multicollinearity concerns.

B5. Influential Observations

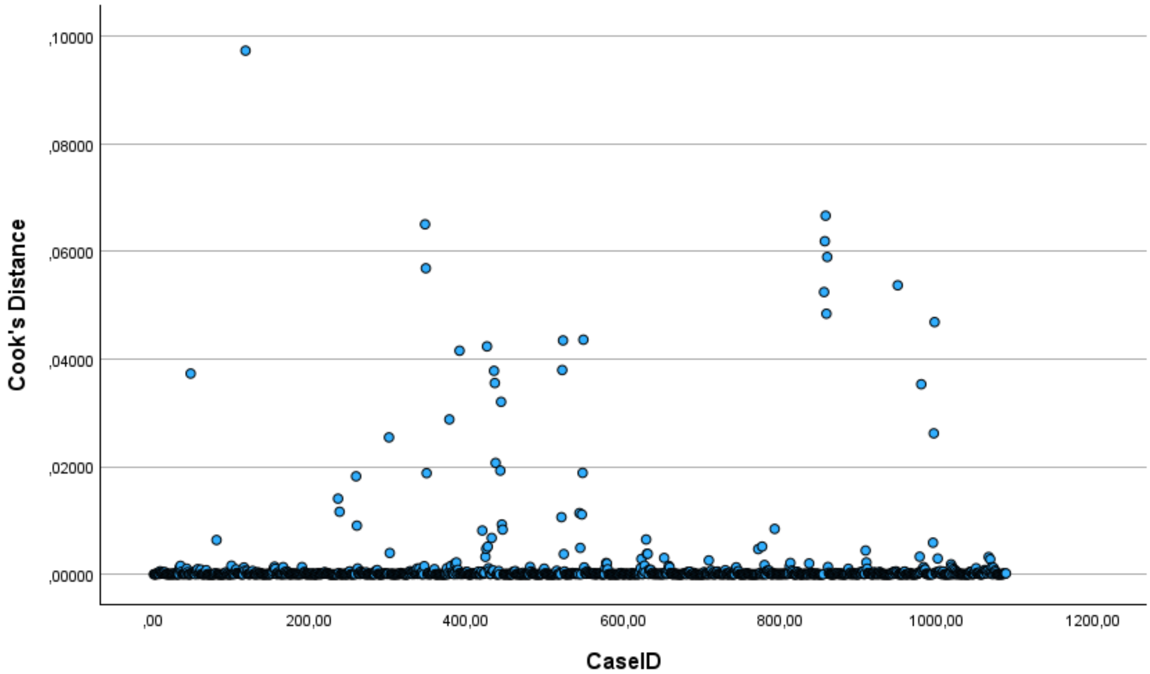

Figure 7: Cook’s Distance plot

Interpretation: 38 observations > 0.10, none > 1.0 → no influential outliers.

Appendix C – Acquisition Rate Distribution

This appendix presents a histogram of the acquisition rate variable, illustrating the distribution of firm-year observations used in the regression analysis. The plot reveals a strong right-skew, with the majority of firms completing only one or two acquisitions per year, and relatively few cases at higher acquisition intensities. This distribution is relevant for interpreting the non-significant results in the regression model, as it may constrain the ability to detect non-linear effects such as the hypothesised inverted U-shape.

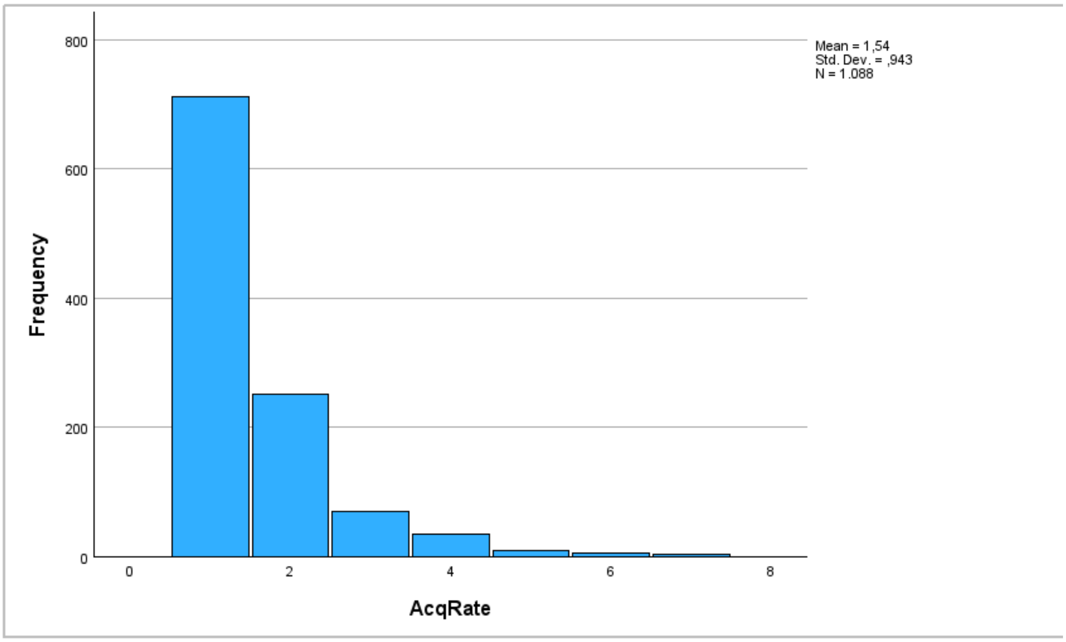

Figure 8: Histogram of Acquisition Rate variable

Appendix D – Use of Generative AI

This appendix describes how generative AI (ChatGPT) was used during the writing process of this thesis. ChatGPT was employed as a language refinement tool to enhance the academic tone and clarity of pre-written content. The process followed several clearly defined steps:

- Throughout the research process, relevant academic sources were collected, reviewed, and key insights were summarised manually.
- These summaries and insights were then compiled into draft paragraphs, which were often informal or unpolished in style.
- These rough drafts were entered into ChatGPT using prompts such as: *"Please edit this paragraph in an academic tone featuring a clear and succinct writing style."*
- The resulting output was reviewed for language quality, and any AI-generated claims or interpretations not grounded in the original sources were removed.
- All references included in the revised text were manually checked against the original literature to ensure that each claim was accurately supported.

ChatGPT was not used to generate original arguments, perform data analysis, or interpret results. Its role was strictly limited to language editing of content developed and structured by the author.

Appendix E – Research Integrity Form

This appendix includes the signed Research Integrity Form, which confirms compliance with Radboud University's academic integrity guidelines.

Research Integrity Form – Master thesis

Name: Richard Buurman	Student number: S1061785
RU e-mail address: richard.buurman@ru.nl	Master specialisation: Strategic Management

Thesis title: Acquisition Rate and Financial Performance: An Absorptive Capacity Perspective
Brief description of the study: This study examines how the rate at which high-tech firms acquire other companies affects their financial performance. Using Absorptive Capacity Theory, it argues that acquisition rate influences a firm's ability to process external knowledge, which in turn impacts performance. Additionally, the study considers whether prior acquisition experience moderates this relationship by enhancing firms' integration capabilities.

It is my responsibility to follow the university's code of academic integrity and any relevant academic or professional guidelines in the conduct of my study. This includes:

- ☐ providing original work or proper use of references;
- ☐ providing appropriate information to all involved in my study;
- ☐ requesting informed consent from participants;
- ☐ transparency in the way data is processed and represented;
- ☐ ensuring confidentiality in the storage and use of data;

If there is any significant change in the question, design or conduct over the course of the research, I will complete another Research Integrity Form.

Breaches of the code of conduct with respect to academic integrity (as described / referred to in the thesis handbook) should and will be forwarded to the examination board. Acting contrary to the code of conduct can result in declaring the thesis invalid

Student's Signature: ______________________ Date: 13.06.2025

To be signed by supervisor

I have instructed the student about ethical issues related to their specific study. I hereby declare that I will challenge him / her on ethical aspects through their investigation and to act on any violations that I may encounter.

Supervisor's Signature: ______________________ Date: 15.06.2025