INFORMATION UNCERTAINTY AND THE LIKELIHOOD OF CORPORATE TAKEOVERS

EVIDENCE FROM U.S. PUBLIC FIRMS

GUSTAV JAHN

OSKAR LANDIN

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Abstract:

This thesis investigates whether information uncertainty influences the likelihood of acquisition among publicly listed firms in the United States. Drawing on theories of asymmetric information and valuation frictions, we examine whether firms characterized by higher uncertainty, which is proxied by idiosyncratic return volatility, forecast dispersion, and R&D-based development stage status, are systematically less likely to become takeover targets. Using a panel dataset of over 29,000 firm-year observations, comprising acquisition data for deals completed between 2015–2024, and applying logistic regression models, we find that firms with higher idiosyncratic volatility and those classified as development-stage are significantly less likely to be acquired. In contrast, forecast dispersion does not predict acquisition likelihood, suggesting that not all proxies capture uncertainty in ways relevant to acquirer behavior. Follow-up analyses show that development-stage firms are more likely to be acquired by strategic and foreign buyers, indicating that certain acquirer types may be better equipped to evaluate or exploit uncertain targets. These findings contribute to the M&A literature by highlighting how information frictions shape not only deal outcomes, but also the ex ante selection of acquisition targets.

Keywords:

Mergers and Acquisitions, Information Uncertainty, Takeover Likelihood, Idiosyncratic Volatility, R&D Intensity, Forecast Dispersion, Acquirer Type, Logit Model

Authors:

Gustav Jahn (25633)
Oskar Landin (25683)

Tutor:

Michał Dzieliński, Assistant Professor, Department of Finance

Examiner:

Ramin Baghai, Associate Professor, Department of Finance

Bachelor Thesis
Bachelor Program in Business & Economics
Stockholm School of Economics

1. Introduction

Mergers and acquisitions (M&A) represent a fundamental mechanism for corporate restructuring and strategic growth. While traditional research has emphasized motives such as synergy realization and agency-related management replacement (Grossman and Hart, 1980; Jensen, 1988), more recent studies point to the role of information frictions in shaping acquisition behavior. In particular, the presence of information uncertainty can complicate not only deal pricing but also the selection of potential targets (Chatterjee, John and Yan, 2012; Officer, Poulsen and Stegemoller, 2009; Powell, 1997).

Firms characterized by high return volatility, divergent analyst forecasts, or heavy investments in intangibles such as R&D may be more difficult to value (Dierkens, 1991; Zhang, 2006). Such uncertainty can act as a deterrent to acquirers who fear overpaying (Shleifer and Vishny, 1992), or conversely, as an opportunity for informed buyers able to exploit valuation gaps (Cheng, Li and Tong, 2016). While prior research has explored how uncertainty affects takeover premiums and acquirer returns (Chatterjee et al., 2012), less attention has been given to whether it systematically influences the likelihood of being acquired.

This thesis addresses that gap by investigating whether proxies for information uncertainty, specifically idiosyncratic volatility, forecast dispersion, and a development-stage dummy based on R&D intensity, help predict takeover activity among U.S. public firms. In doing so, we extend a literature that has traditionally focused on firm size, profitability, and leverage as primary predictors of acquisition likelihood (Palepu, 1986; Powell, 1997), by introducing informational uncertainty as a potentially central but underexamined determinant. The study also contributes timely evidence from a modern setting increasingly defined by intangible assets, analyst coverage, and heightened informational complexity.

Our objective is to investigate whether information uncertainty influences the likelihood of public firms becoming acquisition targets, and whether it shapes the type of acquirer involved in M&A transactions. Using three commonly employed proxies, namely idiosyncratic volatility, forecast dispersion, and a development-stage dummy based on R&D intensity, we focus exclusively on publicly listed U.S. firms. The study is guided by the following research questions:

Does higher information uncertainty reduce the likelihood that a public firm will be acquired?

Which proxies for information uncertainty are most strongly associated with acquisition probability?

Does the relationship between information uncertainty and acquisition outcomes vary by acquirer type, specifically in terms of domestic versus foreign and strategic versus financial buyers?

Building on prior research, we hypothesize that firms characterized by higher uncertainty are less likely to be acquired. We further test whether this relationship depends on the identity of the acquirer, specifically distinguishing between foreign and domestic buyers, and between strategic and financial buyers. To investigate these relationships, we construct three matched datasets and estimate a series of logit regression models. Our findings show that certain proxies for information uncertainty significantly reduce the likelihood of acquisition, while also influencing the type of buyer among acquired firms.

The remainder of this thesis is organized as follows. Section 2 presents the theoretical background and reviews the relevant literature. It begins by introducing the concept of takeovers and the notion of information uncertainty, followed by a discussion of common proxies and a review of related empirical studies. Section 3 outlines the study's hypotheses, derived from the theoretical framework and prior findings. Section 4 describes the methodology, including the sample construction, variable definitions, and regression models used to test the hypotheses. Section 5 reports the empirical results, starting with descriptive statistics and progressing through three sets of regression models, concluding with robustness checks. Section 6 discusses the findings in light of the theoretical expectations and prior research. Section 7 summarizes the main conclusions, while Section 8 addresses the study's limitations and implications for future research. Section 9 provides references, and Section 10 includes the appendix with additional data and results.

2. Theoretical background and literature review

The literature review is divided into two main parts. It begins by introducing key theoretical concepts, including the definition of takeovers and the notion of information uncertainty, followed by a discussion of common proxies used to measure the latter. The second part reviews relevant literature, starting with studies that explicitly examine the relationship between information uncertainty and takeover outcomes. It then expands to include broader empirical work focused on predicting takeover likelihood. While we draw on the most closely related research available, we note that the intersection between information uncertainty and M&A activity remains relatively underexplored, making our study a valuable addition to the limited body of work connecting these two domains.

2.1 Theoretical background

2.1.1 Defining takeovers

Takeovers is an umbrella term, comprising mergers and acquisitions. While mergers and acquisitions are often used interchangeably, their theoretical definitions differ (Anuar, Khan, Khan and Malik, 2014). Horne and Wachowicz (2004) posit that in a merger, firms combine to form a single legal entity. In an acquisition, a larger firm generally purchases the controlling interest in a smaller firm. Unlike in a merger, the companies do not integrate into a single entity. Instead, the target generally continues to operate, but now as a subsidiary to or as a separate part of the acquirer (DePamphilis, 2010). When constructing our sample of takeover targets, we define takeovers as corporate actions where one firm acquires a majority share in another firm. While acquisitions more intuitively conform to this definition, mergers often also involve one company acquiring a controlling stake in the other. Thus, we recognize that our sample most likely contains both mergers and acquisitions, but like prior literature (e.g., Anuar et al., 2014), we will use the terms interchangeably, and synonymously with takeovers.

Commonly identified motives for takeovers include exploiting financial, operational and collusive synergies (Bradley, Desai and Kim, 1983; Chatterjee, 1986), managerial hubris, and the agency motive, which suggests that takeovers occur because they provide value to the acquirer's management, at the expense of the acquirer's shareholders (Berkovitch and Narayanan, 1993). In this study, we examine a possible deterrent for takeovers, namely information uncertainty.

2.1.2 Information uncertainty

Information uncertainty is a term closely related to difficult-to-value firms and information asymmetry, with similar methods being used to approximate all three (e.g., Chatterjee et al., 2012; Cheng et al., 2016; Officer et al., 2009). In accordance with related literature, we define information uncertainty as ambiguity pertaining to the implications of new information for a firm's value (Zhang, 2006). Given the intangible nature of this term, it is generally estimated using several, more tangible, proxies. These include idiosyncratic volatility, R&D intensity, the relative bid-ask spread, forecast dispersion, forecast error, the breadth of ownership etc.

(Chatterjee et al., 2012, Moeller, Schlingemann and Stulz 2007, Officer et al., 2009). This study uses idiosyncratic volatility, R&D intensity and forecast dispersion as proxies. Partially because these feature in the most closely related literature (Moeller et al., 2007; Officer et al., 2009), and partially because these proxies provide the most readily available data for the firms in our M&A dataset.

2.1.3 Proxies for information uncertainty

Idiosyncratic volatility: Dierkens (1991) argues that idiosyncratic volatility, as measured by the residual variance/standard deviation of stock returns, is a good measure of the total uncertainty of the firm. Officer et al. (2009) similarly posits that high idiosyncratic volatility is a characteristic of difficult-to-value firms. The intuition is rather straightforward. If the stock price fluctuates a lot, the market experiences uncertainty in trying to price the company.

R&D Intensity: Officer et al. (2009) propose that uncertainty is likely to exist around targets with high R&D intensity, because such targets are highly speculative. They define R&D intensive targets as companies where research and development expenses exceed sales, or where sales are less than $500 000. Francis, Lafond, Olsson and Schipper (2004) show that development expenditures negatively impact the quality of reported earnings, further highlighting the uncertainty inherent in this variable.

Forecast dispersion: Forecast dispersion, generally measured by the standard deviation of analysts' forecasts of earnings or EPS, captures divergence of opinion regarding the value of a firm, and thereby uncertainty (Diether, Malloy and Scherbina, 2002). Also, studies find that analyst dispersion decreases when firms provide more information, further justifying the inclusion of this proxy (e.g., Thomas, 2002; Abarbanell and Lehavy 2003).

2.2 Literature review

2.2.1 Relating information uncertainty to takeovers

In this section, studies relating information uncertainty to takeover outcomes are explored. Officer et al. (2009) examine how idiosyncratic volatility and a development stage dummy affect the acquirer's cumulative abnormal returns (CAR) in cash vs stock acquisitions. The CAR is measured as the firm's return minus CRSP value-weighted market return and calculated from the day before the announcement date to the day after the announcement date. Regardless of the payment method, Officer et al. (2009) finds that the CAR for the acquirer is lower than average when information uncertainty surrounds the target company.

Chatterjee et al. (2012), relate another takeover outcome to proxies for information uncertainty, namely takeover premiums. The takeover premium reflects the share of the consideration transferred that exceeds the targets pre-takeover market value (Simonyan, 2014). Chatterjee et al. (2012) use breadth of ownership, forecast disagreement and idiosyncratic volatility to explain the size of the takeover premium. They find that when forecast disagreement and idiosyncratic volatility for the target is higher, the acquirer pays a higher takeover premium.

To explain their results, the authors use stock-market theories to infer that greater divergence of opinion inflates acquisition premiums, due to the challenge of persuading at least 50% of shareholders to tender their shares amid heterogeneous beliefs.

While looking at different takeover outcomes, both Officer et al. (2009) and Chatterjee et al. (2012) find results that portray information uncertainty as a deterrent for takeovers. When information uncertainty surrounds the target firm, the acquirer realizes a lower cumulative abnormal return and is forced to pay a higher takeover premium, possibly dissuading acquirers from approaching such firms.

Furthermore, there are indications that the relationship between information uncertainty and takeover activity is contingent upon the identity of the buyer. Firstly, literature indicates that strategic and financial buyers may respond differently to information uncertainty. A strategic buyer is generally defined as a company in a related type of business, such as a supplier, a competitor or a customer, while financial buyers are typically private equity firms (Gorbenko and Malenko 2014). Gorbenko and Malenko (2014) establish that strategic buyers are willing to pay more for firms with higher investment opportunities. This variable includes the R&D expenditure of the firm; a metric closely related to the development stage dummy which is used to approximate information uncertainty. Similarly, Fidrmuc, Paap, Roosenboom and Teunissen (2012) find that companies acquired by strategic buyers have significantly higher R&D expenditure than companies acquired by financial buyers. Altogether, these studies indicate that strategic buyers are less sensitive to information uncertainty, particularly pertaining to R&D activities.

Secondly, the acquirer's nationality may serve as an indicator of their sensitivity to information uncertainty. Specifically, whether the acquirer is a domestic or a foreign buyer. Van Nieuwerburgh and Veldkamp (2009) show that investors are less likely to pursue information about foreign firms. If they pursue information about foreign firms, they will be as informed as the average investor. Nevertheless, if they specialize in what they already know, by learning more information about domestic firms, they can become more informed than the average investor. By amplifying information asymmetry, home investors can more accurately assess and thereby profit from, investing in domestic firms. Our study extends on Van Nieuwerburgh and Veldkamp's (2009) study, examining if higher initial information uncertainty poses even more of an advantage to home investors, evaluated by their willingness to acquire domestic targets relative to that of foreign acquirers.

2.2.2 Prominent predictive studies

Our study is not a predictive study, per say. In predictive studies, the primary goal is high model performance (e.g., accuracy and precision), and variable selection is based on predictive power. We are conducting an estimation study, where the objective is instead to isolate and understand the effects of our independent variables. Nevertheless, exploring prominent studies that predict takeovers provides valuable methodological insights, including which other factors we need to control for in order to estimate the independent effects of our variables of interest.

In his 1986 study, Palepu first criticizes earlier predictive studies, pointing out methodological flaws that inflate the predictive power of their models. Adjusting for these flaws, Palepu obtains a model with much lower accuracy. Nevertheless, Palepu finds, at the 5 % significance level, that targets are typically comparatively small in market size, exhibit lower abnormal returns, have lower leverage and lower revenue growth. Also, he finds that if an acquisition has occurred in a firm's four-digit SIC code industry, the firm is less likely to be an acquisition target in the subsequent year.

Palepu's (1986) methodological approach lay the foundation for several subsequent studies. Powell (1997, 2004) closely follow Palepu (1986) when defining hypotheses and independent variables, but the studies apply a few key differences that culminate in different results. While Palepu (1986) defines LIQUIDITY as net liquidity, Powell (2004) uses gross liquidity. In contrast to Palepu (1986), Powell (2004) then finds that targets have significantly lower liquidity. Powell (1997) highlights the time-variant nature of predictive models, for instance finding that tangible assets to total assets are significant to explain takeovers in one time-period, while insignificant in another. This elucidates the unstable nature of predictive ratios, and the importance of including year fixed effects.

In a more recent study, Cremers, John, and Nair (2009) replicate Palepu's (1986) framework and arrive at partially contrasting findings, further underscoring the time-varying nature of takeover predictors. Examining completed takeovers between 1981 and 2004, they find, in contrast to Palepu (1986), that firms are more likely to be acquired in the following year if an acquisition has occurred within their SIC code industry. Additionally, they report that market-to-book ratios are significantly lower for acquired firms, whereas Palepu found this variable to be insignificant across all models. Conversely, while leverage was a consistently significant predictor in Palepu's analysis, Cremers et al. (2009) find it to be insignificant. These findings inform our selection of control variables and highlight the importance of exercising caution when comparing predictor significance and model estimates across different time periods.

3. Hypotheses

Based on the literature review, we formulate three hypotheses. The first tests whether information uncertainty predicts the likelihood of a firm being acquired. The second and third explore whether it also predicts acquirer type.

3.1 Information uncertainty hypothesis

We hypothesize that firms subject to higher information uncertainty are less likely to be acquired. Information uncertainty captures the extent to which firm value is difficult to observe and assess to outside investors and potential acquirers. There are two primary theoretical rationales for expecting a negative relationship between information uncertainty and acquisition likelihood.

First, drawing on Akerlof's (1970) "lemon theory," we argue that information uncertainty intensifies problems of asymmetric information between buyers and sellers in the market for corporate control. Firms are generally better informed about their future prospects than potential acquirers. When information uncertainty is high—such as in firms with speculative business models (proxied by development-stage status) or highly firm-specific risk (proxied by idiosyncratic volatility)—the inability to credibly disclose this information may result in a market breakdown. High-quality firms may avoid seeking acquisition due to fear of undervaluation, while lower-quality firms may actively pursue buyers. Rational acquirers, anticipating this adverse selection problem, are likely to treat uncertain firms with suspicion. This limits acquisition interest and reduces the likelihood of takeover.

Second, information uncertainty may discourage acquisitions by inflating target valuations through divergence of investor beliefs. This logic builds on Miller's (1977) theory of heterogeneous beliefs and short-sale constraints. Miller argues that stock prices tend to reflect the expectations of the most optimistic investors, when there is substantial disagreement about a firm's fundamentals. For public firms, where the listed stock price typically serves as a lower bound for any takeover offer, this can substantially increase the effective acquisition cost. Forecast disagreement is a direct proxy for this divergence of opinion and has been shown to correlate with higher takeover premiums (Chatterjee et al., 2012). When shareholder beliefs about firm value are widely dispersed, acquirers often need to offer substantial premiums to persuade a sufficient proportion of investors to tender their shares. This added cost introduces another deterrent to acquiring firms characterized by high information uncertainty.

In sum, both the adverse selection risk associated with poor information disclosure and the inflated pricing pressures driven by valuation disagreement potentially contribute to a common mechanism: that firms which are harder to assess are less attractive acquisition targets. Our three proxies each represent distinct dimensions of this uncertainty.[1]

[1] Besides the primary theoretical rationales, we infer two additional rationales from related literature. Firstly, Powell (1997) and Ambrose and Megginson (1992) finds that the ratio tangible assets to total assets is significantly and positively related to takeover likelihood. This implicitly suggests that firms with comparatively high R&D intangibles would be less likely targets. Additionally, Officer et al. (2009) find that acquisitions of publicly traded

H1: Firms with higher information uncertainty are less likely to be acquired.

3.2 Domestic buyer hypothesis

The domestic buyer hypothesis suggests that domestic buyers are more likely than foreign buyers to purchase targets with high information uncertainty. This prediction is based on research by Van Nieuwerburgh and Veldkamp (2009). This research suggests that domestic buyers aim to amplify information-asymmetry in relation to the average investor, by pursuing more information about domestic firms. We believe that a rational extension of this argument is that domestic buyers are more interested in firms with high information uncertainty, because there are even larger opportunities to gain an information advantage in comparison to the average investor.

H2: Targets with higher information uncertainty are more likely to be acquired by domestic rather than foreign buyers.

3.3 Strategic buyer hypothesis

This hypothesis suggests that strategic buyers are less sensitive to information uncertainty, and thus more likely than financial buyers to acquire difficult-to-value firms. The rationale is that strategic buyers possess a superior ability to navigate information uncertainty, which stems from two key mechanisms. Firstly, Hansen (1987) proposes that acquirers gain from using stock as the currency, when the target is difficult to value. When stock is used as consideration, the risk of overvaluation is shared between the acquirer's and the target's shareholders, whereas in a cash transaction, the acquirer assumes the full risk of potential overvaluation. Stock is a more accessible acquisition currency for strategic buyers, giving them a comparative advantage over financial buyers when acquiring firms characterized by high information uncertainty. Secondly, it is important to recognize that strategic buyers typically exhibit greater organizational proximity to the target, potentially placing them in a stronger position to evaluate, for example, the future cash flows arising from the target's R&D initiatives. Also, Shleifer and Vishny (1992) find that financial buyers fear overpaying for firms that are more difficult to value. This further indicates that strategic buyers are more likely to purchase firms with high information uncertainty.

H3: Targets with higher information uncertainty are more likely to be acquired by strategic rather than financial buyers.

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firms with higher idiosyncratic volatility result in negative cumulative abnormal returns for the acquirer, indicating that acquirers would be less interested in such companies.

4. Methodology

The methodology section is organized into three main parts. We begin by outlining the sample selection process, detailing how our three datasets, namely the M&A sample, the main sample and the forecast disagreement subsample, were constructed. This is followed by a description of how our variables are defined and processed, including dependent, independent, and control variables, as well as fixed effects. Lastly, we present the regression models used to test our hypotheses, with each model corresponding to one of the datasets introduced earlier.

4.1 Sample selection

To investigate whether information uncertainty predicts takeover activity, we start by constructing a dataset of U.S. public M&A targets and matching them with firm-level data covering both acquired and non-acquired firms.[2] This allows us to test whether firm characteristics, specifically proxies for information uncertainty, help predict the likelihood of becoming a takeover target.

Our data was constructed by matching M&A transactions to three separate datasets: (1) return data from WRDS Beta Suite, used to calculate idiosyncratic volatility as one proxy for information uncertainty; (2) accounting data from Compustat, used for constructing firm-level control variables and the development stage dummy based on R&D intensity; and (3) long-term analyst forecast data from I/B/E/S, from which we compute forecast disagreement, our third proxy for information uncertainty. Ultimately, we work with three final samples:

A M&A sample, containing only the acquired firms with matched control and independent variables. This dataset is used in a separate set of regressions that explore follow-up hypotheses related to characteristics of the acquirer (e.g., domestic vs. foreign, strategic vs. financial). The sample features 892 observations.

A main analysis sample based on idiosyncratic volatility and the development stage dummy. This is the largest and most complete dataset, and serves as the primary basis for our empirical analysis. It features 28,683 firm-year observations, of which 892 exhibit a positive acquisition outcome, indicating that the firm was acquired in the following year.

A forecast disagreement sample, which also includes idiosyncratic volatility. This dataset is significantly smaller due to limited analyst coverage—only larger firms are typically covered by multiple analysts—meaning it cannot be matched broadly across the population. To preserve

[2] In examining acquisition likelihood, researchers adopt different sampling strategies. One approach is state-based sampling, which selects similar numbers of acquired and non-acquired firms (e.g., Palepu, 1986; Stevens, 1973). This method can enhance estimation precision by balancing rare outcomes, but can also lead to biased estimates if traditional estimators are used (Cosslett, 1981; Palepu, 1986). Manski and McFadden (1981) propose conditional maximum likelihood estimation (CMLE) as an appropriate correction. In contrast, population-based sampling begins with the full universe of firms, allowing for generalizable inference. While this strategy entails higher computational burden and potential data availability bias (Zmijewski, 1984), it avoids the selection issues inherent in state-based designs. Studies such as Morck, Shleifer, and Vishny (1988) argue for population-based samples when the goal is causal inference rather than prediction. Given that our study aims to test the relationship between firm-level uncertainty and acquisition outcomes, rather than predict takeovers, we adopt a population-based sampling strategy.

statistical power and avoid bias from excessive sample restriction, we opted to analyze forecast disagreement in a separate model, rather than limit our main analysis to firms for which all three proxies are available. This smaller sample comprises 5,160 firm-year observations, of which 148 observations correspond to firms that were acquired in the following year.

While constructing separate samples for different proxies is somewhat unconventional, we view this structure as justified. Using a single dataset that includes all three proxies would substantially reduce the size and representativeness of our sample, potentially limiting the generalizability and robustness of our findings. At the same time, forecast disagreement is a well-established proxy in the literature and merits inclusion. By splitting the analysis based on the two samples, we retain both statistical power and empirical relevance across proxies.

4.1.1 M&A sample

We extracted data on U.S. M&A transactions from the Refinitiv Eikon database for the period 2015–2024, filtering transactions based on effective date to ensure all included transactions were completed. The initial dataset included all completed acquisitions during the period involving publicly traded targets and featured 10,479 observations. Following standard procedures in the M&A literature, we restricted the sample to transactions where the target firm was publicly listed and domiciled in the United States (e.g., Moeller et al., 2007; Officer et al., 2009) and the acquirer obtained more than 50 percent of the target's shares. This resulted in a sample of 1,484 completed acquisitions.

Each acquisition observation was then matched to firm-level control variables extracted from *Compustat Daily Updates – Annual Fundamentals for North American Firms* via WRDS. While the M&A data is based on the effective date of the transaction, control variables were aligned using the announcement date, as this is when the market responds to the deal (e.g., Moeller et al., 2007 & Officer et al., 2009). To ensure consistent treatment across all observations, we extracted annual control variables for the period 2013–2023, lagging them one year relative to the announcement date of the deal. This means each firm-year observation contains financial data for year t, and an acquisition indicator (along with related deal variables) for year t+1, allowing us to test whether firm characteristics influence acquisition likelihood in the following year. Lagging the variables by one year follows standard practice in the M&A literature (Palepu, 1986) and addresses two key issues: it ensures financial data are available and unaffected by the acquisition, and it avoids potential bias from market reactions around the time of the acquisition announcement. This approach also ensures consistent timing across all firms, regardless of when during the year the deal was announced.

To construct the final M&A sample, we first matched the 1,484 acquisition observations to firm-level control variables from Compustat. This yielded 1,286 matched observations with available financial data for the year preceding the acquisition. We then matched these to the idiosyncratic volatility data extracted from *Beta Suite* by WRDS (detailed below), resulting in 1,179 matched M&A transactions. After that we applied a series of data cleaning steps to ensure consistency and reliability. First, we excluded all observations lacking a U.S. ISO code, ensuring alignment with our definition of U.S.-domiciled firms.[3] Next, we removed firm-year observations reporting zero total assets and/or zero net income, as these are typically inactive firms and lack the financial information needed to compute control variables. After these filters, our final M&A sample consisted of 892 acquired firms with complete and valid data across all relevant variables (see Table 1).

Table 1.
Sample screening (M&A sample)

Filtering step	No. of observations
No. of acquired public targets 2015-2024	
Resulting no. of observations	*10,479*
Percentage acquired ≤ 50%	**-6,597**
Resulting no. of observations	*= 3,882*
Target nation ≠ USA	**-2,398**
Resulting no. of observations	*= 1,484*
Could not be matched to Compustat dataset	**-216**
Resulting no. of observations	*= 1,268*
Could not be matched to WRDS Beta Suite dataset	**-89**
Resulting no. of observations	*= 1,179*
ISO Code ≠ USA	**-40**
Resulting no. of observations	*= 1,139*
Assets = 0	**-11**
Resulting no. of observations	*= 1,128*
Net income = 0	**-236**
Resulting no. of observations	*= 892*
Final sample	**892**

This table outlines the screening process used to construct the final M&A sample of acquired U.S. public firms from 2015 to 2024. Starting from 10,479 completed acquisitions, we sequentially applied exclusion criteria based on acquisition percentage, target nation, and data availability across Compustat and WRDS Beta Suite. Additional filters excluded observations with missing U.S. ISO codes, zero assets, or zero net income. The final sample consists of 892 firm-year observations with complete and reliable data for all relevant variables used in the regression analysis.

4.1.2 Main sample

For our main sample, we began by retrieving daily return data for all globally listed firms from WRDS Beta Suite for the period 2013–2023. This raw dataset included 82,579 firm-year observations across 14,521 unique tickers. We first matched this data to our original M&A dataset of 1,484 completed transactions, successfully linking 1,339 of these to corresponding return data.

Next, we merged the resulting dataset with our control variable data from Compustat. This step removed 12,703 observations lacking corresponding financial data, leaving 69,876 matched firm-year observations. We then restricted the sample to U.S.-incorporated firms by filtering on ISO code, which resulted in the exclusion of an additional 7,977 observations, yielding a sample of 61,899 U.S. firm-year observations with both return and accounting data.

[3] While all targets were originally classified as U.S. companies in the EIKON database, 40 observations were removed when filtering by ISO code due to inconsistencies across datasets. To maintain a consistent definition of U.S. firms throughout the analysis, we rely on the ISO code across all datasets.

Lastly, we cleaned the data by removing observations with zero total assets or zero net income. These filters resulted in a final main sample of 29,683 firm-year observations, of which 892 correspond to firms acquired in the following year. This sample served as the primary dataset for our empirical analysis using idiosyncratic volatility and the R&D-based development stage dummy as proxies for information uncertainty (see Table 2).

Table 2.
Sample screening (main sample)

Filtering step	No. of observations	whereof acquisitions
No. of idiosyncratic volatility observations 2013-2023		
Resulting no. of observations	*82,579*	*1,339*
Could not be matched to Compustat dataset	**-12,703**	**-160**
Resulting no. of observations	*= 69,876*	*= 1,179*
ISO Code ≠ USA	**-7,977**	**-40**
Resulting no. of observations	*= 61,899*	*= 1,139*
Assets = 0	**-24,788**	**-11**
Resulting no. of observations	*= 37,111*	*= 1,128*
Net income = 0	**-7,428**	**-236**
Resulting no. of observations	*= 29,683*	*= 892*
Final sample	**29,683**	**892**

This table details the screening process for constructing the main sample used in Model 1. Starting from 82,579 firm-year observations with available idiosyncratic volatility data between 2013 and 2023, we sequentially excluded observations lacking Compustat financials, non-U.S. firms, and firms reporting zero assets or zero net income. The final sample includes 29,683 observations, of which 892 were acquired in the following year, and forms the basis for our primary regression analysis on acquisition likelihood.

4.1.3 Subsample

For our second analysis sample, we extracted long-term earnings per share (EPS) growth forecasts from the I/B/E/S Summary Statistics database for the period 2013–2023. The raw dataset contained 263,132 observations, each representing aggregated statistics for analyst estimates issued on a specific date, along with the number of contributing analysts. As I/B/E/S reports at a monthly frequency, no firm had more than one such observation per month.

We first matched this data to our M&A sample and identified 686 acquisition targets with at least one forecast observation in the year prior to acquisition. Following Moeller et al. (2007), we excluded all observations based on fewer than three analyst estimates, as limited coverage makes forecast disagreement measures unreliable. This filtering step reduced the sample to 61,949 observations, covering 208 acquired firms.

To align with the annual structure of our other datasets, we annualized the forecast disagreement by averaging the standard deviation of long-term forecast estimates across each calendar year. This resulted in 8,286 firm-year observations, which were then matched to our Compustat control variable dataset. The merge yielded 6,804 matched observations, after which we applied the same cleaning procedures as with the other datasets. We removed firms without a U.S. ISO code, and excluded those with zero total assets or zero net income. The cleaned sample consisted of 5,217 firm-year observations.

Lastly, we matched this dataset with our return data from WRDS Beta Suite to incorporate idiosyncratic volatility. This final step yielded a sample of 5,160 firm-year observations, of which 148 correspond to firms that were acquired in the following year (see Table 3).

Table 3.
Sample screening (subsample)

Filtering step	No. of observations	whereof acquisitions
No. of analyst I/B/E/S forecast observations 2013-2023		
Resulting no. of observations	*263,132*	*686*
Forecast estimates per observation ≤ 2	**-201,183**	**-478**
Resulting no. of observations	*= 61,949*	*= 208*
Annualizing observations	**-53,663**	**-0**
Resulting no. of observations	*= 8,286*	*= 208*
Could not be matched to Compustat dataset	**-1,482**	**-32**
Resulting no. of observations	*= 6,804*	*= 176*
ISO Code ≠ USA	**-875**	**-13**
Resulting no. of observations	*= 5,929*	*= 163*
Assets = 0	**-12**	**-2**
Resulting no. of observations	*= 5,917*	*= 161*
Net income = 0	**-700**	**-11**
Resulting no. of observations	*= 5,217*	*= 150*
Could not be matched to WRDS Beta Suite dataset	**-57**	**-2**
Resulting no. of observations	*= 5,160*	*= 148*
Final sample	**5,160**	**148**

This table outlines the sample construction process for the subsample used in Model 2, based on I/B/E/S analyst forecast data from 2013 to 2023. Starting from 263,132 analyst-year observations, we applied several filters, including a minimum threshold of three analyst estimates, annualization of observations, and matching to Compustat and WRDS Beta Suite datasets. Observations for non-U.S. firms and those with zero assets or net income were also removed. The resulting subsample comprises 5,160 observations, of which 148 were followed by an acquisition, and is used to assess the predictive power of forecast disagreement.

4.2 Variable construction

This section outlines how the key variables used in our empirical analysis are defined and constructed. Each variable is assigned a unique variable code, which is used to represent the variable in all subsequent regression outputs and tables. A complete list of these codes is provided in Appendix 1.

4.2.1 Dependent variables

Our empirical models rely on three binary dependent variables, each designed to capture a distinct outcome relevant to our hypotheses. The primary objective of the thesis is to examine whether proxies for information uncertainty influence acquisition activity among U.S. publicly listed firms. Accordingly, the main dependent variable captures whether a firm is acquired in the following year. In addition, we conduct follow-up regressions among acquired firms only, examining whether information uncertainty proxies predict the type of acquirer, distinguishing between foreign and domestic acquirers as well as strategic and financial buyers.

Acquisition dummy (ADUMMY): Our main dependent variable is a binary indicator capturing whether a firm is acquired in the subsequent year. It equals 1 if the firm is the target of a completed acquisition in year t+1, and 0 otherwise. The variable is constructed based on the announcement date of the transaction as reported in the Refinitiv Eikon M&A database and is matched to firm-level observations from year t. The acquisition dummy serves as the dependent variable in both our main regression models.

Foreign acquirer dummy (FDUMMY): The second dependent variable is a binary indicator capturing whether the acquirer is foreign. It is equal to 1 if the acquirer is domiciled outside the United States, and 0 if the acquirer is U.S.-based. The variable is constructed using acquiror nationality data from the Refinitiv Eikon M&A database, and is used exclusively in the subset of acquired firms.

Strategic acquirer dummy (SDUMMY): The third dependent variable is a binary indicator reflecting the type of the acquiring firm. It equals 1 if the acquirer is a strategic buyer and 0 if the acquirer is classified as a financial buyer. This classification is based on acquirer type information from the Refinitiv Eikon M&A database, and is used exclusively in the subset of acquired firms.

4.2.2 Independent variables

Our independent variables serve as proxies for information uncertainty, which is central to the hypotheses tested in this thesis. We employ three distinct proxies: idiosyncratic volatility, forecast disagreement, and a development stage dummy based on R&D intensity. Each is constructed from different data sources, and all are lagged by one year relative to the acquisition event, ensuring a consistent temporal ordering and avoiding endogeneity concerns.

Idiosyncratic volatility (IVOL): Idiosyncratic volatility is used as a proxy for firm-specific uncertainty and is included as a continuous variable. The variable is defined as the standard deviation of residuals from a market model regression of daily stock returns over a 252-trading-day estimation window ending on the last trading day of each calendar year. The data is retrieved from *WRDS Beta Suite*, which applies the market model using CRSP return data. The standard deviation is then annualized by multiplying with the square root of 252.[4]

Forecast disagreement (FDSTD and FDDUMMY): Forecast disagreement is measured as the standard deviation of long-term earnings growth forecasts, retrieved from the *Summary History – Summary Statistics* module in the I/B/E/S database. The forecast represents the expected annual growth in operating earnings over a 3-to-5-year period. Only observations with at least three analyst estimates are retained, following Moeller et al. (2007), to ensure meaningful

[4] Previous studies (e.g., Cheng et al., 2016; Officer et al., 2009) define idiosyncratic volatility relative to the acquisition announcement date. Since our analysis includes both acquired and non-acquired firms, this approach would introduce inconsistencies for non-targets, which lack a reference event. Instead, we define volatility on a yearly basis for all firms, ensuring comparability across observations. To avoid issues of data availability in the acquisition year, the measure is lagged by one year.

dispersion measures. The variable is included both as a continuous measure (FDSTD) and as a dummy variable (FDDUMMY). The dummy equals one if the firm's annualized forecast standard deviation falls within the top decile of its analyst coverage bucket, and zero otherwise. Buckets are defined by rounding the average number of analyst estimates per forecast period (observation) throughout the year, with firms receiving 3–8 estimates placed in separate buckets, and firms with 9 or more pooled due to limited frequency and stable dispersion patterns.[5]

Development stage dummy (RDDUMMY): The development stage dummy is included as a binary proxy for firms in a R&D-intensive phase. The variable equals one if a firm's R&D expenditure exceeds its sales, or if annual sales are below $500,000, and zero otherwise. The definition follows Officer et al. (2009), who use the measure to identify early-stage or high-uncertainty firms. Although originally applied to private targets, we extend the definition to public firms, as approximately 13% of the firms in our main sample meet these criteria. The binary variable is calculated based on R&D expenditure and annual sales data retrieved from *Compustat Daily Updates – Annual Fundamentals for North American Firms* via WRDS.

4.2.3 Control variables

To isolate the effect of our independent variables, we include a set of firm-level control variables commonly used in the M&A literature. These controls are primarily based on Palepu (1986), with some modifications supported by later studies such as Powell (1997, 2004) and Cremers et al. (2009). All variables are lagged one year relative to the acquisition year and are retrieved from *Compustat Daily Updates – Annual Fundamentals for North American Firms* via WRDS.

Firm size (SIZE): To control for the effect of size on acquisition likelihood, we include the log of total assets as a proxy for firm size. Palepu (1986) finds a significant negative relationship between firm size and takeover probability, as larger firms are associated with higher transaction costs. The variable is defined as total assets (item "Assets – Total") and is measured in billion USD.

Leverage (LEVERAGE): Leverage is included to control for the firm's capital structure. It is defined as the book value of total debt divided by shareholder equity, following Palepu (1986). The relevant items are "Total Debt Including Current" and "Shareholders' Equity – Total". While Palepu reports a significant negative effect, the expected sign is theoretically ambiguous.

Liquidity (LIQUIDITY): Liquidity is measured as cash and short-term investments divided by total assets, consistent with the definition used in Powell (2004) who finds the variable significant. The numerator is the item "Cash and Short-Term Investments" and the denominator is "Assets – Total". This variable captures the firm's short-term financial flexibility, which may influence acquisition vulnerability. Palepu (1986), in contrast, defines liquidity as net liquid

[5] Long-term earnings forecasts are preferred over short-term estimates as they are less influenced by fiscal timing and earnings guidance practices, and they use percentage values rather than absolute figures, improving comparability across firms (Moeller et al., 2007). To address bias from lower analyst coverage inflating dispersion, Moeller et al. (2007) divide firms into buckets based on the number of analyst estimates and classify those in the top decile of dispersion within each bucket as having high forecast disagreement.

assets over total assets and reports no significant effect. We adopt Powell's specification to motivate its inclusion as a control variable.

Market-to-book ratio (MTB): The market-to-book ratio is included as a control variable due to its frequent use in takeover prediction models. Palepu (1986), however, questions its theoretical grounding and finds it statistically insignificant. Despite this, we include MTB following Powell (1997), who argues that the predictive relevance of such valuation measures may vary over time due to changing market dynamics, and Cremers et al. (2009), who finds MTB significant. Including MTB allows for both a robustness check and a meaningful comparison to prior literature. The variable is calculated as "Common Shares Outstanding" multiplied by "Price – Close – Annual – Fiscal", divided by "Shareholders' Equity – Total".

Price-to-earnings ratio (PE): The price-to-earnings ratio is similarly incorporated as a standard valuation control. Palepu (1986) finds it to be statistically insignificant and questions its economic justification. However, as Powell (1997) notes, the performance of such predictors can fluctuate over time, and excluding them entirely may overlook relevant variation in certain periods. The PE ratio is calculated as "Common Shares Outstanding" multiplied by "Price – Close – Annual – Fiscal", divided by "Net Income (Loss)".

4.2.4 Fixed effects

To account for unobserved heterogeneity across industries and time, we include industry and year fixed effects in our main regression models. For the regressions on our M&A sample, we only use year fixed effects to preserve degrees of freedom, given its more limited sample size.

Industry fixed effects (INDUSTRY): Industry fixed effects are included to capture differences in acquisition activity and financial characteristics across sectors. Following Mitchell and Mulherin (1996), we construct industry categories using the first two digits of the SIC code, balancing granularity with degrees of freedom. This approach is consistent with Officer et al. (2009) and Moeller et al. (2007).[6]

Year fixed effects (YEAR): Year fixed effects are included to control for time-varying macroeconomic and market conditions that affect acquisition activity. This accounts for shocks or trends common to all firms in a given year, as supported by D'Antonio, Ledolter and Melicher (1983) and Barnes (1990).

[6] Mitchell and Mulherin (1996) show that takeover rates vary substantially across industries. Gort (1969) introduces the "economic disturbance hypothesis," suggesting that mergers are driven by shocks to industry structure. Cudd and Duggal (2000) emphasize that financial ratios are not evenly distributed across industries, justifying the inclusion of industry-level controls. While Palepu (1986) avoids this issue by restricting his study to two industries (mining and manufacturing), Cudd and Duggal (2000) construct industry-adjusted variables to address cross-sector variation.

4.3 Regression models

To test our hypotheses, we estimate three sets of logit regression models, each tested with various specifications, all using binary dependent variables.[7] The regressions are designed to evaluate whether proxies for information uncertainty, specifically idiosyncratic volatility, forecast disagreement, and an R&D-based development stage dummy, predict acquisition likelihood and, in follow-up analyses, the type of acquirer. The models are built progressively, beginning with base specifications and subsequently incorporating control variables and fixed effects to assess robustness and isolate effects. Only the final versions of each model are written out as equations below.

In our two primary regression settings, we cluster standard errors at the firm level to account for within-firm correlation over time. This adjustment is necessary due to the panel structure of the data, where individual firms may appear across multiple years, violating the assumption of independent observations. In all regressions where control variables are included, they are first winsorized at the 1st and 99th percentiles to reduce the influence of extreme outliers, and then standardized to facilitate interpretability and comparison of coefficient magnitudes. The only exception is firm size (total assets), which is instead log-transformed due to its skewed distribution and economic interpretation. For continuous independent variables, we apply winsorization but do not standardize them, as doing so would complicate the interpretability of the original units of analysis.

The models are interpreted as expressing the log-odds of the binary dependent variable being classified as positive (Y=1). Each coefficient reflects the expected change in the log-odds of acquisition associated with a one-unit increase in the corresponding independent variable, holding all else constant. The intercept captures the baseline log-odds when all predictors are zero, and the error term accounts for unexplained variation.

4.3.1 Model 1 – Estimating acquisition likelihood using the main sample

Our main model is estimated using the full dataset of 28,683 firm-year observations. The dependent variable is a binary indicator equal to 1 if the firm is acquired in the following year, and 0 otherwise. The primary explanatory variables are idiosyncratic volatility (IVOL) and the R&D-based development stage dummy (RDDUMMY).

To ensure the individual validity of each proxy for information uncertainty, the two explanatory variables are first tested separately in a stepwise sequence. In the first step, each variable is estimated on its own, without control variables. In the second step, control variables are added to each specification individually. In the third step, year and industry fixed effects are included alongside the controls. Finally, both IVOL and RDDUMMY are included simultaneously in a fully specified model with all control variables and fixed effects, allowing us to test their joint effect while accounting for confounding factors.

[7] While Moeller et al. (2007) and Officer et al. (2009) use OLS regressions due to their continuous return-based dependent variables, our models use binary outcomes, for which logit regressions are more appropriate. This is consistent with the approach taken by Palepu (1986).

$$Logit(\rho) = \ln\left(\frac{\rho}{(1-\rho)}\right)$$

$$= \beta_0 + \beta_1 \text{ IVOL}_{it} + \beta_2 \text{ RDDUMMY}_{it} + \beta_3 \text{ SIZE}_{it} + \beta_4 \text{ LEVERAGE}_{it} + \beta_5 \text{ LIQUIDITY}_{it} + \beta_6 \text{ MTB}_{it} + \beta_7 \text{ PE}_{it} + \text{INDUSTRY}_j + \text{YEAR}_t + \varepsilon_{it}$$

Model 1 (main sample)

4.3.2 Model 2 – Estimating acquisition likelihood using forecast disagreement

Our secondary model is estimated on the forecast disagreement subsample consisting of 5,160 firm-year observations. The dependent variable remains a binary indicator for acquisition in the following year. The main explanatory variable is forecast disagreement, tested both as a standardized continuous variable (FDSTD) and a top-decile dummy (FDDUMMY), with FDSTD being the primary measure.

Due to analyst coverage bias, the subsample includes larger, more visible firms, making it structurally different from the main sample. The development stage dummy is therefore excluded, as too few firms meet its criteria to yield meaningful results. Following the same stepwise structure as Model 1, each forecast disagreement proxy is first tested individually without controls, then with controls, and finally with year and industry fixed effects. In the final step, FDSTD is included alongside idiosyncratic volatility (IVOL) to test robustness.

$$Logit(\rho) = \ln\left(\frac{\rho}{(1-\rho)}\right)$$

$$= \beta_0 + \beta_1 \text{ FDSTD}_{it} + \beta_2 \text{ IVOL}_{it} + \beta_3 \text{ SIZE}_{it} + \beta_4 \text{ LEVERAGE}_{it} + \beta_5 \text{ LIQUIDITY}_{it} + \beta_6 \text{ MTB}_{it} + \beta_7 \text{ PE}_{it} + \text{INDUSTRY}_j + \text{YEAR}_t + \varepsilon_{it}$$

Model 2 (subsample)

4.3.3 Model 3 – Information uncertainty as a predictor of acquirer type

The third set of models is restricted to the subset of firms that were acquired, aiming to examine whether information uncertainty predicts the type of acquirer. Two binary dependent variables are analyzed in separate regressions: Model 3a tests the likelihood of the acquirer being foreign (1 if domiciled outside the U.S.), while Model 3b tests the likelihood of the acquirer being strategic (1 if classified as a corporate buyer). In both regressions, the key explanatory variables are idiosyncratic volatility (IVOL) and the development stage dummy (RDDUMMY). All control variables are initially considered, but only those found to be statistically significant are retained in the final specifications to reduce model noise. Year fixed effects are included, while industry fixed effects are excluded to preserve degrees of freedom and avoid overfitting due to the smaller sample size.

$$Logit(\rho) \;=\; \ln\left(\frac{\rho}{(1-\rho)}\right)$$

$$= \beta_0 + \beta_1\ IVOL_{it} + \beta_2\ RDDUMMY_{it} + \beta_3\ SIZE_{it} + \beta_4\ LEVERAGE_{it} + \beta_5\ LIQUIDITY_{it} + \beta_6\ MTB_{it} + \beta_7\ PE_{it} + INDUSTRY_j + YEAR_t + \varepsilon_{it}$$

Model 3a; 3b (M&A sample)

5. Results

The results section is divided into five parts. It begins with descriptive statistics comparing firm characteristics across groups defined by the dependent variable in each sample. This includes mean values of control and independent variables, with p-values from t-tests indicating whether differences are statistically significant. These comparisons help identify relevant predictors, guide control variable selection, and relate findings to existing literature. We then present results from three regression models: Model 1 uses the full sample, Model 2 focuses on the forecast disagreement subsample, and Model 3 examines acquirer type. Model 3a compares domestic and foreign acquirers, while Model 3b contrasts strategic and financial acquirers. The section concludes with robustness checks assessing the stability of results and the validity of model assumptions.

5.1 Descriptive statistics

Before presenting the regression results, we begin by comparing descriptive statistics for acquired and non-acquired firms in the main sample to identify initial patterns. Acquired firms appear to be smaller on average and exhibit higher gross liquidity, while also displaying significantly lower idiosyncratic volatility and a lower incidence of being classified as development-stage firms. These descriptive differences suggest that lower information uncertainty may be associated with a higher likelihood of acquisition, a relationship further examined in the regression analysis. Full summary statistics are reported in Table 4 below.[8]
Turning to the descriptive statistics for acquired and non-acquired firms in the subsample with available forecast disagreement data, Table 5 presents the relevant summary statistics. In contrast to the main sample, no significant differences are observed for the forecast disagreement variables or idiosyncratic volatility. The only variable that remains significantly different is total assets, which are lower among acquired firms.[9]

[8] The difference in average firm size is significant at the 1% level and aligns with prior findings that smaller firms are more likely to be acquired (Palepu, 1986; Stevens, 1973). Higher gross liquidity among acquired firms is significant at the 5% level and may indicate greater financial flexibility, although Powell (2004) finds the opposite pattern.
[9] In this restricted subsample, gross liquidity also declines in significance, from the 5% level in the main sample to 10%. This attenuation, together with the loss of significance for idiosyncratic volatility, reflects the altered composition of the narrowed sample.

Table 4.
Descriptive statistics main sample

Variable	Target Sample Mean	Non-target Sample Mean	Difference	Std. Error	p-Value	Significance
IVOL	0.505	0.636	-0.131	0.017	0.000	***
LEVERAGE	0.720	0.472	0.248	0.514	0.630	
LIQUIDITY	0.286	0.262	0.025	0.012	0.042	**
MTB	-1.261	5.076	-6.338	7.017	0.367	
PE	26.930	22.441	4.489	40.196	0.911	
SIZE	2.017	6.668	-4.651	0.456	0.000	***
RDDUMMY	0.125	0.199	-0.075	0.014	0.000	***

This table presents descriptive statistics for the main sample used in Model 1, comprising 29,683 firm-year observations from 2013 to 2023, of which 892 are acquisition targets. The table compares mean values of key variables across the target and non-target groups, along with their differences, standard errors, p-values, and significance levels. No transformations have been applied to the variables. IVOL represents the annualized standard deviation of residuals from a market model regression of daily stock returns, serving as a proxy for firm-specific uncertainty. LEVERAGE is measured as total debt divided by total shareholder equity. LIQUIDITY is calculated as cash and short-term investments divided by total assets. MTB is the market-to-book ratio, computed as the market value of equity divided by total shareholder equity. PE is the price-to-earnings ratio, defined as market value of equity divided by net income. SIZE is total assets in billion USD. RDDUMMY is a binary indicator equal to 1 if a firm's R&D expenditure exceeds its sales or if annual sales fall below $500,000, capturing early-stage or high-uncertainty firms. All variables are lagged by one year relative to the acquisition event. Significance levels are denoted as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table 5.
Descriptive statistics subsample

Variable	Target Sample Mean	Non-target Sample Mean	Difference	Std. Error	p-Value	Significance
IVOL	0.327	0.323	0.004	0.013	0.758	
LEVERAGE	0.267	0.347	-0.080	0.569	0.889	
LIQUIDITY	0.173	0.133	0.039	0.020	0.053	*
MTB	1.942	1.961	-0.019	2.676	0.994	
PE	14.137	24.046	-9.909	23.758	0.677	
SIZE	6.004	20.431	-14.427	1.752	0.000	***
FDSTD	0.072	0.073	-0.001	0.011	0.938	
FDDUMMY	0.188	0.136	0.051	0.041	0.218	

This table presents descriptive statistics for the subsample used in Model 2. The sample consists of 5,160 firm-year observations from 2013–2023, of which 148 correspond to acquired firms. The data combines analyst forecast observations from I/B/E/S with firm fundamentals from Compustat and volatility measures from WRDS Beta Suite. The table shows group means for targets and non-targets, the difference in means, standard errors, p-values, and significance levels. No transformations were applied to the variables. FDSTD measures the standard deviation of long-term earnings growth forecasts over a 3–5-year horizon, based on at least three analyst estimates per observation. FDDUMMY is a binary indicator equal to 1 if a firm-year observation falls into the top decile of forecast dispersion within its analyst coverage bucket, and 0 otherwise. All other variables are defined in previous tables. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

When comparing asset levels across these two samples, we find that the mean total assets for both acquired and non-acquired firms in the forecast disagreement sample are roughly three times higher than in the main sample. This indicates that the forecast disagreement subsample does not represent a random reduction of the original sample size, but rather reflects a systematic selection based on firm characteristics. Specifically, the availability of analyst forecast data tends to be concentrated among larger, more mature firms with greater market visibility and lower volatility. As a result, the subsample disproportionately excludes smaller firms and those in earlier stages of development, segments that are more prevalent in the broader population of U.S. public companies. Furthermore, the requirement of sufficient analyst coverage introduces an additional layer of selection bias, skewing the sample toward firms with heavier analyst following and greater institutional interest. Taken together, this suggests that the forecast disagreement sample represents a narrower, more specialized subset of public firms, and its external validity in capturing general patterns of acquisition likelihood across the entire U.S. public firm landscape is therefore limited.

We now shift focus to the subset of firms that were acquired, examining whether their characteristics differ based on the type of acquirer. Specifically, using the M&A sample, we compare firms acquired by foreign versus domestic buyers. As shown in Table 6, the only variable exhibiting a statistically significant difference between these groups is the development stage dummy, which has a higher mean among foreign acquirers. This indicates that foreign buyers are more likely to target firms engaged in R&D activities. This finding is further explored in the regression analysis of Model 3a.

Table 7 also presents descriptive statistics where we compare strategic and financial acquirers. The results indicate that strategic acquirers have significantly higher mean gross liquidity and total assets among the firms they acquire, as well as a higher incidence of development-stage targets.[10] No other variables display statistically significant differences between the two acquirer types.

Table 6.
Descriptive statistics M&A sample (foreign vs. domestic acquirers)

Variable	Foreign acquirer Mean	Domestic acquirer Mean	Difference	Std. Error	p-Value	Significance
RDDUMMY	0.178	0.083	0.095	0.030	0.002	***
IVOL	0.497	0.468	0.028	0.022	0.192	
LIQUIDITY	0.291	0.250	0.041	0.024	0.081	*
MTB	-13.273	3.505	-16.778	23.329	0.473	
PE	-8.932	34.276	-43.208	37.689	0.252	
LEVERAGE	0.461	-0.011	0.472	0.955	0.621	
SIZE	2.163	2.966	-0.803	0.459	0.081	*

This table presents descriptive statistics for the M&A sample used in Model 3a, comparing acquired public firms based on the nationality of the acquirer (foreign vs. domestic). The table includes 892 firm-year observations. All variables are lagged by one year and retrieved from Compustat and WRDS Beta Suite, covering the period 2013–2023. No transformations have been applied to the variables. All variable definitions are provided in previous tables. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

[10] Strategic acquirers target firms with significantly higher gross liquidity (1% level), total assets (1% level), and development stage dummy values (1% level) compared to financial acquirers, indicating less aversion to R&D-related uncertainty. This contrasts with Fidrmuc el al. (2012), who find no significant difference in average target size between strategic and private equity buyers.

Table 7.
Descriptive statistics M&A sample (strategic vs. financial acquirers)

Variable	Foreign acquirer Mean	Domestic acquirer Mean	Difference	Std. Error	p-Value	Significance
RDDUMMY	0.133	0.036	0.097	0.018	0.000	***
IVOL	0.483	0.455	0.028	0.018	0.120	
LIQUIDITY	0.287	0.194	0.092	0.018	0.000	***
MTB	-1.218	2.816	-4.034	7.065	0.568	
PE	40.297	-8.298	48.595	59.563	0.415	
LEVERAGE	-0.198	0.725	-0.923	1.070	0.389	
SIZE	3.167	1.975	1.191	0.382	0.002	***

This table presents descriptive statistics for the M&A sample used in Model 3b, comparing acquired public firms based on the type of acquirer (strategic vs. financial). The table includes 892 firm-year observations. All variables are lagged by one year and retrieved from Compustat and WRDS Beta Suite, covering the period 2013–2023. No transformations have been applied to the variables. All variable definitions are provided in previous tables. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

5.2 Model 1 – Regression results on the main sample

Our main regression model finds strong evidence that information uncertainty reduces the likelihood of acquisition. In the fully specified model, including both proxies for uncertainty, all control variables, and year and industry fixed effects, both idiosyncratic volatility and the development stage dummy exhibit negative and statistically significant coefficients at the 1% and 5% level respectively. This indicates that they explain unique variance in the dependent variable, and that their effects are not redundant. Specifically, a 100-percentage-point increase in idiosyncratic volatility is associated with approximately 48% lower odds of being acquired, while firms classified as being in a development stage face 28% lower odds.[11] These findings support the hypothesis that firms with higher information uncertainty are less attractive acquisition targets.

To ensure robustness, each proxy was first tested in isolation across stepwise specifications. These include regressions without controls, with controls, and with fixed effects.[12] Results from these intermediate models consistently show negative and significant coefficients for both proxies, confirming that their effects are not driven by omitted variable bias or specific model

[11] To make interpretation easier, we convert logit coefficients into odds ratios by raising *e* to the power of the coefficient.
[12] Including year and industry fixed effects excludes 472 observations due to no within-group variation in the dependent variable. Supplementary regressions excluding fixed effects produce nearly identical coefficients and significance levels, indicating that the exclusion of these observations does not materially affect the results.

choices.[13] Detailed results from all specifications are provided in Appendix 2 and Appendix 3. The final model specification's regression output is presented in Table 8 below.[14]

Table 8.
Regression output Model 1 (final model specification)

Variable	Expected sign	Model 1 Coef.	Std. Error
RDDUMMY	-	-0.323**	(0.163)
IVOL	-	-0.654***	(0.139)
LIQUIDITY		0.019	(0.051)
MTB		-0.169***	(0.051)
PE		-0.073**	(0.036)
LEVERAGE		0.136***	(0.045)
SIZE	-	-0.277***	(0.040)
No. of observations		29,211	
No. of targets		892	

This table presents the final specification of Model 1, a logistic regression estimating the likelihood of acquisition among U.S. publicly listed firms from 2013 to 2023. The dependent variable is a binary indicator equal to 1 if the firm was acquired in a given year and 0 otherwise. The model includes 29,211 firm-year observations, of which 892 were acquisitions. All variable definitions are provided in previous tables. All control variables are winsorized at the 1st and 99th percentiles and subsequently standardized, with the exception of SIZE, which is only log-transformed. IVOL is also winsorized at the 1st and 99th percentiles. Year and industry fixed effects are included but not reported. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

5.3 Model 2 – Regression results on the subsample

Our second regression model, based on the substantially smaller forecast disagreement subsample, finds no evidence that analyst disagreement influences acquisition likelihood. In the fully specified model, including forecast disagreement (FDSTD), all control variables, idiosyncratic volatility (IVOL), and fixed effects[15], the coefficient on FDSTD is statistically insignificant and directionally unstable (see Table 9). As shown in Table 9 below, IVOL also loses significance compared to our main regression model (Model 1).[16] These results are

[13] For idiosyncratic volatility, the coefficient remains negative and statistically significant across all model specifications. In the baseline regression without controls nor winsorization, the estimate is significant at the 1% level (unpresented results); after applying winsorization at the 1st and 99th percentiles to mitigate the influence of outliers, significance decreases slightly to the 5% level. Nevertheless, once control variables and fixed effects are introduced, the coefficient regains both magnitude and significance, strengthening the inference of a negative relationship (Appendix 2). Similarly, the development stage dummy exhibits a negative and significant coefficient at the 5% level when estimated in isolation, which becomes more pronounced, both in magnitude and statistical significance (1%), when additional covariates are included (Appendix 3). These consistent results across specifications underscore the robustness of the main findings.

[14] The results show that market-to-book and P/E ratios are both negatively associated with acquisition likelihood, significant at the 1% and 5% levels, respectively; leverage is positively associated, significant at the 1% level; and firm size is strongly negatively associated, significant at the 1% level. These patterns are consistent with the theoretical expectations proposed by Palepu (1986).

[15] Including year and industry fixed effects excludes 527 observations due to no within-group variation in the dependent variable. Supplementary regressions excluding fixed effects produce nearly identical coefficients and significance levels, indicating that the exclusion of these observations does not materially affect the results.

[16] The lack of significance for IVOL in this model highlights the variables insignificant effect in this new population. It becomes evident when comparing descriptive statistics (Table 4 and Table 5), that this subsample differs materially from the full sample used in Model 1, particularly with respect to size and volatility. Since

consistent across all stepwise specifications, where both FDSTD and its dummy variant FDDUMMY are tested independently. At no stage do either of the forecast disagreement proxies yield statistically significant results, raising doubts about their explanatory power in this context. Full regression results for each model step are presented in Appendix 4 and Appendix 5.[17]

Table 9.
Regression output Model 2 (final model specification)

Variable	Expected sign	Model 1 Coef.	Model 1 Std. Error
FDSTD	-	-1.367	(1.658)
IVOL	-	0.785	(0.789)
LIQUIDITY		-0.050	(0.092)
MTB		-0.258**	(0.125)
PE		-0.127*	(0.074)
LEVERAGE		0.087	(0.113)
SIZE	-	-0.500***	(0.099)
No. of observations		4,633	
No. of targets		148	

This table presents the final specification of Model 2, a logistic regression estimating the likelihood of acquisition using the subsample for which I/B/E/S forecast data is available. The regression is based on 4,633 U.S. publicly listed firm-year observations from 2013 to 2023, of which 148 were acquisition targets. The dependent variable is a binary indicator equal to 1 if the firm was acquired in a given year and 0 otherwise. All variable definitions are provided in earlier tables. All control variables are winsorized at the 1st and 99th percentiles and standardized, except for SIZE, which is only log-transformed. IVOL is also winsorized at the 1st and 99th percentiles. Year and industry fixed effects are included in the model but are not reported in the table. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

5.4 Model 3 – Acquirer type regression results (M&A sample)

In the third model, we explore whether information uncertainty predicts the type of acquirer among acquired firms, using two separate dependent variables. Model 3a tests the likelihood of the acquirer being foreign, while Model 3b tests the likelihood of the acquirer being strategic. Both models include the same two explanatory variables: idiosyncratic volatility (IVOL) and the development stage dummy (RDDUMMY). Year fixed effects are applied in all regressions, while industry fixed effects are excluded to preserve degrees of freedom. In line with earlier models, variables are winsorized, but here only the statistically significant controls are retained in the final specifications shown in Table 10 below[18]. Complete versions of both regressions including all control variables are presented in Appendix 6.

inclusion in the subsample is conditional on sufficient analyst coverage, the sample is not randomly drawn and instead reflects systematic differences in firm characteristics. Consequently, the lack of significance for IVOL here should not be interpreted as contradicting earlier findings, but instead as reflecting characteristics of this narrower population.

[17] The significance levels of the control variables remain stable across all model specifications, including those testing both the forecast disagreement dummy and the continuous measure. Specifically, firm size (log of total assets) is significant at the 1% level, market-to-book at the 5% level, and P/E ratio at the 10% level. Gross liquidity and leverage remain statistically insignificant in all specifications.

[18] In descriptive statistics, and in other specifications of the models, very few control variables are found to statically impact the models. To prevent them from introducing noise in the final specifications, insignificant control variables are thus excluded.

5.4.1 Model 3a (foreign acquirer dummy)

The development stage dummy is positively associated with the likelihood of foreign acquisition. As shown in Table 10, it has a statistically significant coefficient of 0.926, significant at the 1% level, corresponding to approximately 152% higher odds of being acquired by a foreign buyer for firms classified as being in a development stage. This finding contrasts with our initial hypothesis that domestic acquirers would dominate among high-uncertainty targets. Idiosyncratic volatility, by contrast, does not significantly influence the likelihood of foreign acquisition, with a small positive coefficient and a large standard error. No control variables are included in the final specification, as none demonstrated statistical significance in preliminary analyses. The full regression output including all controls is provided in Appendix 6.

5.4.2 Model 3b (strategic acquirer dummy)

Model 3b finds that development stage status significantly influences the likelihood of being acquired by a strategic buyer. In the fully specified model, including both uncertainty proxies and selected control variables, the development stage dummy is positive and statistically significant at the 5% level, corresponding to a 168% increase in the odds of strategic acquisition. Idiosyncratic volatility remains statistically insignificant, mirroring results from Model 3a. Among the control variables, gross liquidity and firm size are both positively associated with strategic acquisition likelihood, significant at the 1% level. The full regression results with all tested controls are reported in Appendix 6.

Table 10.

Regression output Model 3 (final model specifications)

		Model 3a		Model 3b	
Variable	Expected sign	Coef.	Std. Error	Coef.	Std. Error
RDDUMMY	-	0.926***	(0.202)	0.985**	(0.387)
IVOL	-	0.227	(0.649)	0.713	(0.472)
LIQUIDITY				0.334***	(0.066)
SIZE				0.435***	(0.140)
No. of observations		892		892	
No. of targets		892		892	

This table reports the final specifications of Model 3a and Model 3b, logistic regressions examining whether information uncertainty predicts the type of acquirer for M&A targets. Model 3a uses a binary dependent variable equal to 1 if the acquirer is foreign and 0 if domestic, while Model 3b uses a binary dependent variable equal to 1 if the acquirer is strategic and 0 if financial. Both models are estimated on 892 U.S. publicly listed targets. The control variables are drawn from the year prior to the announcement date of each acquisition and span the period 2013–2023. All variables are defined in earlier tables. All control variables are winsorized at the 1st and 99th percentiles and standardized, except for SIZE, which is only log-transformed. IVOL is also winsorized at the 1st and 99th percentiles. Year fixed effects are included in the regressions but are not reported. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

5.5 Robustness test

To ensure the reliability of our results, we implement a range of robustness checks across all models. Each key explanatory variable is tested independently before being included jointly in the fully specified regressions, and all models are estimated using multiple specifications—with and without control variables, and with and without fixed effects. This layered approach allows us to assess whether results are stable across alternative model constructions and not driven by omitted variable bias. The consistency of coefficient signs and significance levels across these steps reinforces the credibility of our findings.

We also cluster standard errors at the firm level to account for intra-firm correlation over time, which is inherent in panel data and could otherwise lead to underestimated standard errors. To mitigate endogeneity concerns, all explanatory variables are lagged by one year relative to the acquisition outcome, ensuring they reflect firm characteristics prior to any deal activity. Additionally, continuous variables are winsorized at the 1st and 99th percentiles to reduce the influence of extreme outliers. Finally, we conduct separate tests of multicollinearity using Pearson correlation matrices and Variance Inflation Factors (VIF) for both the main sample and the M&A sample.

For the main sample, many of the independent variables are significantly correlated at the 1% level, as shown in the correlation matrix in Appendix 7.[19] To assess potential multicollinearity, we conduct a VIF analysis (Appendix 8), which reveals that all VIF values are below 2, indicating that multicollinearity is not a concern in the main regression model.[20] A similar analysis is performed for Model 3b (Strategic acquirer dummy) using the M&A dataset. The corresponding Pearson correlation matrix (Appendix 9) shows that all variables included in the final model specification are also significantly correlated at the 1% level. VIF diagnostics for this model likewise show no values exceeding 2, suggesting that multicollinearity is not an issue in Model 3b either (Appendix 10). No such diagnostics are conducted for Model 3a (Foreign acquirer dummy), as they would be redundant given our tests on model 3b.[21] Finally, we do not replicate these tests for the forecast disagreement subsample, given that none of the tested variables in that model yield statistically significant results.

[19] In the main model, all independent and control variables are significantly correlated at the 1% level (5% for MTB with SIZE and RDDUMMY), except for the P/E ratio, which shows no significant correlation with the market-to-book ratio and leverage.

[20] VIF quantifies how much the variance of an estimated regression coefficient is increased due to multicollinearity. A VIF value of 1 indicates no correlation between the variable and other regressors, while values above 5 are typically seen as indicative of problematic multicollinearity (Menard, 2001).

[21] We do not present a separate correlation matrix or VIF table for the foreign acquirer model, as it includes only two explanatory variables, both of which are also included in the strategic acquirer model. Since the models are estimated on the same underlying dataset, the multicollinearity diagnostics for these variables are identical in structure, and their bivariate relationship is already fully captured in the correlation matrix and VIF results reported for the strategic model. Moreover, in a two-variable specification, the VIF for each variable is a direct mathematical transformation of their squared correlation and thus offers no additional insight beyond what the correlation coefficient already reveals. Presenting a second set of diagnostics would therefore be redundant.

6. Discussion

This study investigates whether information uncertainty reduces the likelihood of a firm being acquired and whether it influences the type of acquirer. We examine this using three main regression models: Model 1 analyzes acquisition likelihood in the full sample, Model 2 focuses on a forecast disagreement subsample, and Model 3 explores differences by acquirer type. The findings are discussed below.

6.1 Main findings

We tested three hypotheses. The main hypothesis (H1) proposed that firms facing higher information uncertainty are less likely to be acquired. This was evaluated using three proxies: idiosyncratic volatility (IVOL), an R&D-based development stage dummy (RDDUMMY), and analyst forecast disagreement (FDSTD). In the final regression on the main sample (n = 29,211), both IVOL and RDDUMMY were negatively and significantly associated with acquisition likelihood at the 1% and 5% levels, respectively. However, in the final regression on the smaller forecast disagreement subsample (n = 4,633), neither FDSTD nor IVOL were statistically significant. We return to the implications of this later.[22]

The two follow-up hypotheses addressed whether information uncertainty predicts the type of acquirer. For H2, we expected that more uncertain firms would be more likely to be acquired by domestic rather than foreign buyers. For H3, we expected that more uncertain firms would be more likely to be acquired by strategic rather than financial buyers. RDDUMMY was positively and significantly associated with foreign and strategic acquisitions in Model 3a (1% level) and 3b (5% level), respectively, while IVOL was not significant in either case.

6.2 Interpretation of the results

The results from Model 1 provide strong support for the hypothesis that firms facing higher information uncertainty are less likely to be acquired. In the full sample, both proxies tested—idiosyncratic volatility (IVOL) and the development stage dummy (RDDUMMY)—were significantly and negatively associated with acquisition likelihood, at the 1% and 5% levels, respectively. Economically, the results imply that a 100-percentage-point increase in IVOL corresponds to approximately 48% lower odds of acquisition, while firms classified as development stage face roughly 28% lower odds of being acquired. These findings support the notion that information uncertainty acts as a deterrent in the M&A process.[23]

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[22] The reported sample sizes (n = 29,211 and n = 4,633) are slightly smaller than the original sample sizes (n = 29,683 and n = 5,160, respectively) due to the inclusion of year and industry fixed effects, which exclude observations with no within-group variation in the dependent variable. As explained in the results sections 5.1 and 5.2, supplementary regressions excluding fixed effects yield nearly identical coefficients and significance levels, suggesting that the exclusion of these observations does not materially affect the results.

[23] While our hypotheses are framed from the acquirer's perspective, it is also relevant to consider that firms with high information uncertainty may be reluctant to sell. Akerlof's (1970) theory of adverse selection suggests that when acquirers cannot accurately assess firm quality, high-quality targets may withhold from the market to avoid being undervalued. Similarly, Myers' (1984) pecking order theory implies that information-asymmetric firms

In contrast, Model 2 finds no significant association between acquisition likelihood and either forecast disagreement (FDSTD) or IVOL in the forecast disagreement subsample. Several potential explanations may account for this. First, the lack of significance for IVOL in this model highlights the variable's reduced predictive value in this new population. As is evident when comparing the descriptive statistic tables of the main and subsample (Table 4 and Table 5 in Section 5.1), the forecast disagreement sample differs materially from the full sample used in Model 1, particularly with respect to size and volatility. The broader U.S. population, as represented by the main sample, exhibits a mean IVOL that is roughly 100% higher and mean total assets that are approximately 70% smaller than in the forecast disagreement subsample. Since inclusion in the subsample is conditional on sufficient analyst coverage, the sample is not randomly drawn and instead reflects systematic differences in firm characteristics. Consequently, the lack of significance for IVOL here should not be interpreted as contradicting earlier findings, but instead as reflecting characteristics of this narrower population.

Second, the results offer insight into how our proxies perform in a more stable segment of the market. The forecast disagreement sample disproportionately includes larger, more established firms that are less volatile and generally operate in more transparent informational environments. Asquith, Mikhail, and Au (2005) demonstrate that smaller firms are more likely to operate in uncertain informational environments, whereas larger firms benefit from greater institutional coverage and disclosure requirements. In such a setting, the baseline level of information uncertainty is likely lower, and the explanatory power of our uncertainty proxies diminishes accordingly.

Finally, it is also possible that forecast disagreement itself is an inherently noisy proxy, poorly suited for detecting the kinds of valuation frictions relevant to M&A decisions. Unlike IVOL and RDDUMMY, which directly capture uncertainty in performance or development stage, forecast disagreement reflects analyst opinion dispersion. In our sample, over 80% of the estimates (4,244 out of 5,160 observations) are based on forecasts from only three or four analysts. This limited base raises questions about the extent to which the proxy can meaningfully capture true variation in information uncertainty across firms.[24]

The follow-up analysis explored whether information uncertainty influences the type of acquirer. Here, the two proxies display contrasting roles. Idiosyncratic volatility is insignificant in both Model 3a (foreign vs. domestic buyers) and Model 3b (strategic vs. financial buyers), while the development stage dummy is positively and significantly associated with both foreign and strategic acquisitions. Specifically, the likelihood of being acquired by a foreign buyer is approximately 152% higher for development-stage firms, while the likelihood of strategic acquisition is approximately 168% higher.

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prefer to avoid issuing equity, especially when they believe the market undervalues them. Together, these theories suggest a two-sided mechanism in which both acquirers and targets may act cautiously in the presence of information uncertainty.

[24] To avoid placing excessive weight on observations based on a low number of analysts, which tend to have higher standard deviations due to the smaller number of estimates, we also tested a forecast disagreement dummy (FDDUMMY) that adjusts for the analyst count behind each observation. This method grouped observations into buckets based on the number of forecasts available and then classified the highest decile within each bucket as high disagreement using a dummy variable. As noted in the results section, this dummy was also statistically insignificant.

These results offer partial support for H3; that firms with high information uncertainty are more likely to be acquired by strategic rather than financial buyers. While IVOL is not significant in Model 3b, development-stage firms are significantly more likely to be acquired by strategic acquirers. This supports the idea that strategic buyers are better equipped to evaluate and absorb uncertainty associated with innovation-intensive targets.

This also aligns with the proposition that strategic acquirers are better positioned to capitalize on future benefits of R&D and intangible assets (Gorbenko and Malenko, 2014). Strategic buyers typically have greater organizational proximity and integration capacity, enabling them to evaluate and realize synergies from the target's innovation potential. As outlined in our original hypothesis, strategic buyers also benefit from using stock as an acquisition currency when targets are difficult to value (Hansen, 1987), which allows them to share valuation risk. Financial buyers, by contrast, are typically more sensitive to overvaluation concerns (Shleifer and Vishny, 1992), and therefore more reluctant to acquire firms with high information uncertainty.

In contrast, H2 is not supported. Instead of being more likely to acquire uncertain firms, domestic buyers are significantly less likely to acquire development-stage targets. This contradicts our initial rationale, which drew from Van Nieuwerburgh and Veldkamp (2009), who suggest that domestic buyers have a comparative advantage in reducing information asymmetry through informational proximity. We hypothesized that this would make them more willing to acquire targets with high uncertainty. However, the opposite pattern emerges.

One plausible explanation is provided by internalization theory. According to Caves (1982) and Morck and Yeung (1990), the presence of intangible assets such as R&D increases the multinational value of a firm because such assets are difficult to trade at arm's length. To realize their value across borders, these intangibles often need to be transferred and managed within the acquirer's organizational structure. This makes foreign acquisition an effective way to internalize and extract value from innovative U.S. firms. While the theory originally describes R&D-intensive firms expanding abroad, the logic can be extended to explain why foreign buyers may be drawn to acquire domestic firms with substantial intangible assets.

These findings suggest that the type of uncertainty, and the strategic context of the acquirer, play a crucial role in shaping acquisition outcomes. While volatility appears to be broadly unattractive across the board, uncertainty stemming from innovation and intangibles may be viewed more favorably by certain acquirer types. Foreign and strategic buyers, in particular, may not merely tolerate but actively seek out targets with R&D-related information uncertainty.

6.3 Theoretical contributions and practical implications

This study contributes to the M&A literature by reinforcing and extending prior findings on the role of information uncertainty in acquisition outcomes. Consistent with the hypothesis that acquirers are deterred by uncertain targets, we find that both idiosyncratic volatility and development-stage status significantly reduce the likelihood of being acquired. These results align with and complement existing research in adjacent areas. For instance, Powell (1997) finds that firms with high tangibility are more likely to be acquired, suggesting an implicit aversion to intangible-heavy, R&D-driven firms. Officer et al. (2009) report that acquiring high-volatility targets leads to negative cumulative abnormal returns, further indicating that uncertainty is unfavorable to acquirers.

A further contribution lies in our distinction between different types of uncertainty. While both proxies are negatively associated with acquisition likelihood in the main sample, only development-stage status is positively associated with certain acquirer types. This highlights an important nuance in how uncertainty is perceived across different acquirer profiles. While higher uncertainty generally reduces acquisition likelihood, our findings indicate that strategic and foreign buyers are more likely to acquire firms characterized by development-stage status. This may reflect a differential evaluation of innovation-related uncertainty, where certain acquirers are better positioned or more inclined to internalize intangible assets. These findings contribute by illustrating that the effect of uncertainty on acquisition outcomes may vary depending on both its source and the characteristics of the acquirer.

Additionally, our results show that forecast disagreement, despite being a commonly used proxy for information uncertainty, does not significantly predict acquisition likelihood, regardless of how it is measured. We test both the continuous variable and an adjusted dummy version, and neither shows statistical significance. The finding is relevant as a reference point for understanding how the use of this proxy imposes sample restrictions, which is an important consideration for future empirical studies examining the effects of uncertainty in M&A contexts.

From a practical perspective, the results suggest that development-stage status, as a proxy for innovation-related uncertainty, does not deter all types of acquirers. In particular, strategic and foreign buyers appear more likely to acquire such firms, which may reflect differing capacities to evaluate or integrate intangible assets. These patterns point to the potential relevance of distinguishing between sources of uncertainty when assessing acquisition dynamics in practice. While the practical implications are limited in scope, they nonetheless reinforce the rationale for tailoring acquisition strategies to different firm profiles.

Finally, a relevant question for future research is how different forms of information uncertainty, including but not limited to volatility, forecast disagreement, and innovation intensity, relate to acquisition behavior and acquirer preferences. Developing or testing additional proxies may further illuminate the mechanisms through which uncertainty shapes M&A dynamics.

7. Conclusion

This thesis investigates whether information uncertainty affects the likelihood of acquisition and whether it influences the type of acquirer in M&A transactions. Using three established proxies, namely idiosyncratic volatility, forecast disagreement, and a development-stage dummy, we find strong evidence that firms with higher information uncertainty are less likely to be acquired. This relationship is particularly robust in our main sample, where both idiosyncratic volatility and development-stage status significantly and negatively predict acquisition likelihood. These findings reinforce and extend prior literature suggesting that uncertainty serves as a deterrent in the M&A process.

In contrast, forecast disagreement, despite its widespread use in related research, does not significantly predict acquisition likelihood. This result, obtained across multiple specifications and alternative definitions of the proxy, highlights important limitations in its empirical application. Our findings thus contribute not only by supporting the predictive relevance of certain uncertainty proxies but also by offering guidance for future research on proxy selection and sample construction.

In our follow-up analyses, we find that the relationship between information uncertainty and acquisition outcomes is not uniform across all acquirer types. Development-stage firms, while generally less likely to be acquired, are more likely to be acquired by foreign and strategic (relative to domestic and financial) buyers. This suggests that certain acquirers may possess capabilities or incentives, such as greater integration capacity or a strategic interest in intangible assets that enable them to pursue targets others might avoid. These findings challenge the assumption that information uncertainty is universally unattractive and instead point to the importance of distinguishing between its sources and contexts.

Taken together, our results underscore the value of a nuanced view of information uncertainty in M&A research. While higher uncertainty may reduce acquisition likelihood in general, its impact varies depending on the proxy used and the characteristics of the acquirer. Future research may benefit from developing additional, more refined measures of uncertainty and further examining how different acquirer profiles moderate its effect on M&A activity.

8. Limitations

Several limitations should be acknowledged when interpreting the results of this study. First, a number of observations were excluded due to data requirements necessary for calculating key financial ratios. Firms with zero values for total assets or net income were dropped, as these are essential for constructing commonly used variables such as the price-to-earnings ratio and size-adjusted financial metrics. While such exclusions were necessary for technical consistency, they likely introduce bias by disproportionately removing smaller or distressed firms, which may differ systematically from the retained sample.

Second, the use of different proxies for information uncertainty presents interpretive challenges. These proxies may not only reflect informational frictions but also correlate with other firm characteristics or strategic factors that are difficult to disentangle. For example, the development stage dummy, which is intended to capture R&D intensity, may also signal the presence of valuable intangible assets or patents that are strategically attractive to certain acquirers (Officer et al., 2009). Such features could influence acquisition decisions for reasons unrelated to uncertainty. While this is most apparent in the case of R&D-related proxies, similar concerns may apply, albeit less visibly, to the other two measures.

In addition, the three proxies used in this study likely capture different dimensions of information uncertainty. The development dummy reflects uncertainty associated with early-stage innovation and intangible asset valuation. Idiosyncratic volatility may capture unpredictability in firm-specific performance or managerial behavior. Forecast disagreement represents divergence in external analyst expectations, which may be driven by limited information availability or differing interpretations of firm prospects. These variations suggest that each proxy taps into a distinct aspect of uncertainty, with only partial overlap.

Taken together, these limitations highlight the conceptual ambiguity involved in measuring information uncertainty. No single proxy can fully capture the underlying construct, and any attempt to quantify it inevitably involves trade-offs. This complicates the interpretation of empirical findings and underscores the need for caution when drawing conclusions about the isolated effects of information uncertainty in this study.

Lastly, the external validity of the results should be considered. The analysis is limited to publicly traded U.S. firms during the sample period, and the findings may not generalize to private companies, firms in other jurisdictions, or different time periods (Barnes, 1990). Contextual factors could therefore lead to different relationships between uncertainty and acquisition outcomes elsewhere.

9. References

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10. Appendix

Appendix 1.
List of variable abbreviations

Variable name	Variable Code
Acquisition dummy	ADUMMY
Foreign acquirer dummy	FDUMMY
Strategic acquirer dummy	SDUMMY
Development stage dummy	RDDUMMY
Idiosyncratic volatility	IVOL
Forecast disagreement standard deviation	FDSTD
Forecast disagreement dummy	FDDUMMY
Liquidity	LIQUIDITY
Market-to-book ratio	MTB
Price-to-earnings ratio	PE
Leverage	LEVERAGE
Firm size	SIZE
Industry fixed effects	INDUSTRY
Year fixed effects	YEAR

This table lists the variable abbreviations used throughout the thesis. Full definitions and detailed descriptions of each variable are provided in Section 4.2.

Appendix 2.
Sequential regression outputs for idiosyncratic volatility (Model 1)

		No controls		Controls		Controls + FE	
Variable	Expected sign	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
IVOL	-	-0.190**	(0.091)	-0.626***	(0.135)	-0.718***	(0.136)
LIQUIDITY				0.022	(0.040)	-0.027	(0.046)
MTB				-0.108**	(0.048)	-0.163***	(0.050)
PE				-0.081**	(0.034)	-0.074**	(0.037)
LEVERAGE				0.090**	(0.044)	0.133***	(0.045)
SIZE	-			-0.254***	(0.041)	-0.280***	(0.040)
Constant		-3.383***	(0.055)	-2.943***	(0.089)	-	
No. of observations		29,683		29,683		29,211	
No. of targets		892		892		892	

This table presents the sequential regression outputs for Model 1, in which the dependent variable is a binary indicator equal to 1 if the firm is acquired in a given year and 0 otherwise. The table reports three different model specifications: one including no control variables, one including control variables only, and one including both control variables and fixed effects for year and industry. All specifications are estimated on a U.S. sample of publicly listed firms between 2013 and 2023. The full sample used for these regressions includes 29,683 firm-year observations, of which 892 were acquired. The main independent variable of interest is idiosyncratic volatility (IVOL), which proxies for firm-specific information uncertainty. IVOL is defined as the standard deviation of residuals from a market model regression on daily returns over a 252-day window, obtained from WRDS Beta Suite. LEVERAGE is defined as total debt divided by total shareholder equity. LIQUIDITY is measured as cash and short-term investments divided by total assets. MTB (market-to-book ratio) is calculated as the market value of equity divided by total shareholder equity. PE (price-to-earnings ratio) is defined as market value of equity divided by net income. SIZE is measured as total assets in billion USD. All control variables are winsorized at the 1st and 99th percentiles and standardized, except for SIZE, which is only log-transformed. IVOL is also winsorized at the 1st and 99th percentiles. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix 3.

Sequential regression outputs for development stage dummy (Model 1)

		No controls		Controls		Controls + FE	
Variable	Expected sign	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
RDDUMMY	-	-0.266**	(0.111)	-0.594***	(0.140)	-0.473***	(0.154)
LIQUIDITY				0.086*	(0.047)	0.007	(0.050)
MTB				-0.103**	(0.047)	-0.145***	(0.049)
PE				-0.070**	(0.034)	-0.063*	(0.037)
LEVERAGE				0.082*	(0.043)	0.118***	(0.043)
SIZE	-			-0.193***	(0.038)	-0.201***	(0.035)
Constant		-3.443***	(0.036)	-3.232***	(0.050)	-	
No. of observations		29,683		29,683		29,211	
No. of targets		892		892		892	

This table presents the sequential regression outputs for Model 1, where the dependent variable is a binary indicator equal to 1 if the firm was acquired in a given year and 0 otherwise. The table shows three model specifications: one with no control variables, one with controls only, and one with both controls and fixed effects for year and industry. All regressions are based on a U.S. sample of publicly listed firms between 2013 and 2023. The sample comprises 29,683 firm-year observations, of which 892 are acquisition targets. The main independent variable of interest is the development stage dummy (RDDUMMY), a binary variable equal to 1 if a firm's R&D expenditure exceeds its sales or if annual sales fall below $500,000, following the definition in Officer et al. (2009). It serves as a proxy for early-stage or high-uncertainty firms. All other variables are defined in previous tables. All control variables are winsorized at the 1st and 99th percentiles and standardized, except for SIZE, which is only log-transformed. RDDUMMY is untransformed. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Appendix 4.

Sequential regression outputs for forecast disagreement standard deviation (Model 2)

		No controls		Controls		Controls + FE	
Variable	Expected sign	Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
FDSTD	-	1.096	(1.199)	-0.150	(1.324)	-0.962	(1.518)
LIQUIDITY				0.027	(0.081)	-0.036	(0.090)
MTB				-0.230*	(0.138)	-0.282**	(0.121)
PE				-0.149*	(0.078)	-0.133*	(0.074)
LEVERAGE				0.077	(0.131)	0.109	(0.112)
SIZE	-			-0.498***	(0.084)	-0.538***	(0.091)
Constant		-3.582***	(0.108)	-2.570***	(0.186)	-	
No. of observations		5,160		5,160		4,633	
No. of targets		148		148		148	

This table presents sequential regression outputs for Model 2, where the dependent variable is a binary indicator equal to 1 if the firm was acquired in a given year and 0 otherwise. Three model specifications are reported: one without control variables, one including controls, and one including both controls and fixed effects for year and industry. The regressions are based on a subsample of 5,160 firm-year observations from 2013 to 2023, of which 148 are acquisition targets. The sample combines analyst forecast data from I/B/E/S with accounting data from Compustat and idiosyncratic volatility data from WRDS Beta Suite. The key independent variable, FDSTD, measures the standard deviation of long-term earnings growth forecasts over a 3–5-year horizon and is constructed using at least three analyst estimates per observation, following Moeller et al. (2007). FDSTD serves as a proxy for forecast disagreement and information uncertainty. All other variables are defined in previous tables. All control variables are winsorized at the 1st and 99th percentiles and standardized, except for SIZE, which is only log-transformed. FDSTD is also winsorized at the 1st and 99th percentiles. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Appendix 5.

Sequential regression outputs for forecast disagreement dummy (Model 2)

Variable	Expected sign	No controls		Controls		Controls + FE	
		Coef.	Std. Error	Coef.	Std. Error	Coef.	Std. Error
FDDUMMY	-	0.225	(0.256)	0.080	(0.261)	-0.081	(0.304)
LIQUIDITY				0.022	(0.081)	-0.042	(0.090)
MTB				-0.228*	(0.138)	-0.281**	(0.121)
PE				-0.146*	(0.078)	-0.131*	(0.074)
LEVERAGE				0.075	(0.130)	0.105	(0.111)
SIZE	-			-0.497***	(0.084)	-0.528***	(0.090)
Constant		-3.547***	(0.089)	-2.589***	(0.169)	-	
No. of observations		5,160		5,160		4,633	
No. of targets		148		148		148	

This table presents sequential regression outputs for Model 2, where the dependent variable is a binary indicator equal to 1 if the firm was acquired in a given year and 0 otherwise. Three model specifications are reported: one without control variables, one including controls, and one including both controls and fixed effects for year and industry. The regressions are based on a subsample of 5,160 firm-year observations from 2013 to 2023, of which 148 are acquisition targets. The sample combines analyst forecast data from I/B/E/S with accounting data from Compustat and idiosyncratic volatility data from WRDS Beta Suite. The independent variable of interest, FDDUMMY, is a binary indicator equal to 1 if a firm-year observation falls into the top decile of forecast dispersion within its analyst coverage bucket, and 0 otherwise. It serves as a proxy for forecast disagreement and information uncertainty, based on long-term earnings forecasts from the I/B/E/S database. All control variables are winsorized at the 1st and 99th percentiles and standardized, except for SIZE, which is log-transformed only. FDDUMMY is untransformed. All other variables are defined in previous tables. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Appendix 6.

Regression outputs for Model 3 including all control variables

Variable	Expected sign	Model 3a		Model 3b	
		Coef.	Std. Error	Coef.	Std. Error
RDDUMMY	-	1.174***	(0.227)	0.988**	(0.400)
IVOL	-	0.042	(0.721)	0.745	(0.506)
LIQUIDITY		-0.129	(0.094)	0.299***	(0.098)
MTB		-0.046	(0.103)	0.105	(0.148)
PE		-0.169	(0.133)	-0.023	(0.084)
LEVERAGE		0.065	(0.099)	-0.128	(0.160)
SIZE		-0.164	(0.127)	0.448***	(0.144)
No. of observations		892		892	
No. of targets		892		892	

This table presents regression outputs for Model 3a and Model 3b, each including the full set of control variables. Model 3a uses a binary dependent variable equal to 1 if the acquirer is foreign and 0 if domestic, while Model 3b uses a binary dependent variable equal to 1 if the acquirer is strategic and 0 if financial. Both models are estimated on 892 U.S. publicly listed targets. The control variables are drawn from the year prior to the announcement date of each acquisition and span the period 2013–2023. All variables are defined in earlier tables. All control variables are winsorized at the 1st and 99th percentiles and standardized, except for SIZE, which is only log-transformed. IVOL is also winsorized. Year fixed effects are included in the regressions but are not reported. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Appendix 7.

Pearson's correlation matrix for Model 1 (main sample)

	PE	MTB	LEVERAGE	LIQUIDITY	SIZE	RDDUMMY	IVOL
PE	-1.000						
MTB	-0.001	-1.000					
LEVERAGE	-0.001	-0.583***	-1.000				
LIQUIDITY	-0.098***	-0.133***	-0.109***	-1.000			
SIZE	-0.086***	-0.015**	-0.120***	-0.390***	-1.000		
RDDUMMY	-0.085***	-0.012**	-0.071***	-0.649***	-0.292***	-1.000	
IVOL	-0.131***	-0.036***	-0.055***	-0.403***	-0.445***	-0.440***	-1.000

This table presents the Pearson correlation matrix for the main sample used in Model 1, covering 29,683 U.S. publicly listed firm-year observations from 2013 to 2023. The table shows pairwise correlations between all control and independent variables included in the regression model. The variables are not transformed prior to calculation. All variable definitions are provided in earlier tables. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Appendix 8.

VIF-analysis on Model 1

Variable	VIF
RDDUMMY	1.670
IVOL	1.410
LIQUIDITY	1.880
MTB	1.633
PE	1.016
LEVERAGE	1.623
SIZE	1.313

This table reports the results of a VIF analysis conducted on the independent variables included in Model 1. The VIF values assess the degree of multicollinearity among the predictors, with values below 2 generally indicating no serious multicollinearity concerns. The analysis is based on the main sample comprising 29,683 U.S. publicly listed firm-year observations from 2013 to 2023. All variable definitions are provided in earlier tables.

Appendix 9.

Pearson's correlation for Model 3b on the M&A sample

	RDDUMMY	IVOL	LIQUIDITY	SIZE
RDDUMMY	1.000			
IVOL	0.410***	1.000		
LIQUIDITY	0.649***	0.461***	1.000	
SIZE	-0.240***	-0.434***	-0.418***	1.000

This table presents the Pearson correlation matrix for the variables included in Model 3b, estimated on the M&A sample of 892 U.S. publicly listed acquisition targets. The table shows pairwise correlations between all control and independent variables included in the regression model. The variables are not transformed prior to calculation. All variable definitions are provided in earlier tables.

Appendix 10.

VIF-analysis on Model 3b

Variable	VIF
RDDUMMY	1.377
IVOL	1.310
LIQUIDITY	1.574
SIZE	1.311

This table reports the results of a VIF analysis conducted on the independent variables included in Model 3b. The VIF values assess the degree of multicollinearity among the predictors, with values below 2 generally indicating no serious multicollinearity concerns. The analysis is based on the M&A sample consisting of 892 U.S. publicly listed acquisition targets.. All variable definitions are provided in earlier tables.

Appendix 11.

AI Disclosure:
Generative AI (ChatGPT by OpenAI) was used to support the development of this thesis. Specifically, we used ChatGPT for:

1. Writing code used in the data analysis and;
2. In refining the clarity, structure, and flow of the written text.

At no point were analyses or interpretations based solely on AI-generated reasoning. All conclusions, arguments, and analytical decisions reflect the authors' own understanding and judgment.