The Stockholm School of Economics
Department of Accounting and Financial Management
Bachelor Thesis
May 2023

Predicting Nordic Takeover Targets

A Binary Logit Analysis

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Abstract

This thesis aims to investigate if certain firm characteristics increase the likelihood of a company being acquired and if these factors can successfully predict which firms become subjects to takeovers in the Nordic setting. We compare data on a sample of Nordic targets and non-targets between the years 2012 and 2021, and test hypotheses regarding firm and industry characteristics, as well as market sentiments through binary logit models. Finally, we test the predictive ability of the best model on a separate sample of targets and non-targets from 2022. Our study suggests that firms with undervalued assets, lower growth and increased trading volume have a higher likelihood of becoming Nordic targets. Our prediction model has an overall 55.14% accuracy in its classification and is able to predict targets with a 50% success-rate.

Tutor: Henrik Andersson

Key words: Binary logit model, prediction, Nordics, takeover, target

Acknowledgements: We would like to thank our supervisor Henrik Andersson for valuable guidance and input.

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1.0 Introduction

Mergers and Acquisitions (M&A) are often critical for growth and development. Over the past century there has been a boom in takeover activities which has led to a substantial body of literature exploring various aspects of M&A (Cho and Chung, 2022; Tunyi, 2021). One of the aspects that has attracted attention from scholars is predicting takeovers by using publicly available data. This focus stems from the fact that when acquisition bids are announced, takeover targets tend to encounter significant abnormal stock returns (Jensen and Ruback, 1983; Martynova and Renneboog, 2008). According to Jensen and Ruback (1983), target firms can obtain abnormal returns of between 20% and 30% in takeovers. Therefore, while there are several motivators behind the research on takeover prediction modeling, the predominant driver is the prospect of realizing abnormal returns by correctly identifying target firms (see e.g., Barnes, 1990; 1999; Brar et al., 2009; Cudd and Duggal, 2000; Palepu, 1986; Powell, 1997; 2001). Beyond the economic incentive, anticipating future takeover bids could also be important for the management teams of potential target firms, who are typically dismissed during the M&A integration phase (Ruback, 1987). Ruback (1987) argues that managers may want to employ defense strategies to deter potential bidders, thereby aiming to enhance the value of the firm, increase the offer price or maintain their current positions. Insights into the drivers of takeover activities can further assist policymakers in formulating regulations that prevent unwanted takeovers and safeguard public interest (Espahbodi and Espahbodi, 2003).

Most early studies focused on finding discriminant characteristics between targets and non-targets in the US setting (see e.g., Hasbrouck, 1985; Monroe and Simkowitz, 1971; Stevens, 1973, Palepu, 1986). With a systematic approach to identifying variables with theoretical underpinnings, Palepu’s (1986) study on US firms is still to this day considered an influential piece within the field of takeover prediction. With his six hypotheses laying the ground for much of the future literature most researchers have focused on developing different predictive models and employing new methodologies to improve the accuracy of the predictions. Most of these empirical studies have also been conducted in the US context (see e.g., Ambrose and Megginson, 1992; Bartley and Boardman, 1986, 1990; Cudd and Duggal, 2000; Espahbodi and Espahbodi, 2003), with a few exploring efforts of takeover modeling in the UK setting (see e.g., Barnes, 1990; 1999; Powell, 1997, 2001). The majority of these studies conclude that it is difficult to predict targets, and few have managed to construct portfolios that generate significant positive abnormal returns. Nonetheless, Europe remains a rather unexplored setting for takeover prediction. Brar et al. (2009) presented one of the few European studies that, in contrast to other studies, concluded that investing in predicted targets had the potential to generate positive abnormal returns.

1.1 Purpose

This study is motivated by the need to build a better understanding of takeover prediction in the ongoing seventh merger wave.[1] Despite being a subject of research since the late-1960s, takeover prediction has faced a steady decrease in attention and continues to be moderately overlooked in Europe. Thus, the first objective of this paper is to evaluate the effectiveness of a logit model for the accurate prediction of takeover targets in the Nordic region. Since previous studies have shown rather low prediction rates, our second objective is to examine if the Nordics can provide new insights regarding the factors driving takeovers. To reach these objectives, this thesis seeks to re-evaluate the Palepu (1986) hypotheses in the light of evidence from later studies to provide a comprehensive understanding of the factors that drive acquisitions. In addition, we aim to understand if measures of technical nature, introduced by Brar et al. (2009) in the European context, remain valid when solely looking at the Nordics. Our two main research questions are as follows:

1. *What are the common firm and market characteristics of Nordic publicly traded firms that have received a takeover bid in the period 2012 to 2021?*

2. *Is it possible to correctly predict Nordic targets in 2022 based on identified discriminating factors between target and non-target firms in the period 2012 to 2021?*

1.2 Scope

The scope of our study is limited to targets and non-targets that have been publicly listed in the Nordics during 2012 to 2022. These firms have been listed on either the Nasdaq Stock Exchanges in Copenhagen, Helsinki, Iceland, Stockholm, or the Oslo Stock Exchange. Unlisted firms are not of interest, as this thesis aims to investigate whether it is possible to predict targets

[1] Merger wave refers to a cyclical pattern of M&A activity, with each new wave displaying slightly different characteristics compared to previous ones (Martynova and Renneboog, 2008). The seventh M&A wave in the United States commenced in 2012 (Cho and Chung, 2022), while Europe is hypothesized to mirror this pattern.

based on publicly available information. Firms of all sizes and ages and deals irrespective of values and payment methods have been included to retain a sufficient sample size. The screening criteria of the samples are further described in section 4. The goal of the study is to identify discriminating factors and test the feasibility of takeover prediction in the Nordics. Our study does not attempt to explain how abnormal returns are calculated from a portfolio of predicted targets, neither do we investigate if this is possible to do on our predicted targets. We do not seek to expand current research by introducing self-developed hypotheses or variables. Although this study discusses various statistical techniques for prediction modeling, we only employ binary logit regression.

1.3 Disposition

This study is composed of eight sections. Section 2 provides an overview of the main theoretical perspectives and seminal studies in takeover prediction. Section 3 connects the theory to eight hypotheses regarding the motives for takeovers. Section 4 describes the sample construct and data collection, followed by our methodology. Section 5 initially presents descriptive statistics and Pearson correlations. This is followed by the results from our regression models, robustness tests, and the prediction tests. We proceed to analyze the findings in section 6. Potential areas for future research are presented in section 7. Finally, in section 8 we outline our concluding remarks.

2.0 Theory and Literature Review

Our understanding of the relevant theory and literature in the research area of takeover prediction has been significantly enhanced through the examination of literature presented in the paper “Fifty years of research on takeover target prediction: a historical perspective” (Tunyi, 2021). This extensive review has provided us with an overview of predominant studies in the field and played a significant role in guiding our research. In this section we first outline the primary theories that underpin takeover prediction. Subsequently, we provide an overview of some of the most important studies in takeover prediction modeling.

2.1 Theory

2.1.1 Positive accounting theory

Accounting and Finance literature commonly employs the feature of positive accounting theory to create concepts that can explain and predict future corporate events (Tunyi, 2021). Part of this theory's literature has assumed that accounting numbers supply information for market investment decisions (Watts and Zimmerman, 1990). Similarly, studies in the takeover prediction area suggest that the assessment of accounting information's worth can be derived from its ability to provide insights and foresight to investors. The reason for this is that it provides a basis for assessing a firm's past performance and predicting future business development. Much of the prior research in this field focuses on the prediction of bankrupt firms (see e.g., Altman, 1968, 1977; Ohlson, 1980; Zmijewski, 1984), with smaller portion of studies examining takeover prediction (see e.g., Barnes, 1990; 1999; Brar et al., 2009; Cudd and Duggal, 2000; Palepu, 1986; Powell, 1997; 2001)..

2.1.2 Market corporate control theory

Market for corporate control theory was initially introduced by Manne (1965) and has evolved into one of the key theoretical underpinnings of takeover prediction. This theory posits that takeovers have a disciplinary character, as they act as a mechanism by which managers of a firm who fail to maximize its market value are replaced by more efficient managers. The disciplinary effect on poorly performing managers, through a well-functioning market for corporate control, is further recognized by scholars, such as Jensen and Ruback (1983), and Morck et al. (1989). Manne (1965) believed that takeovers were an effective way to encourage managers to maximize shareholder wealth. He argued that corporate control is a valuable asset actively traded in a market, with the link between a firm's management performance and its share price. This theory also serves as the foundation for several hypotheses concerning the factors that influence acquisition likelihood (see e.g., Palepu, 1986; Powell, 1997). Palepu (1986) makes the argument that takeovers are primarily driven by competition in the market for corporate control, which is caused by a firm's accounting and market under-performance. Thus, he hypothesized that "management inefficiency" increases acquisition likelihood. Expanding on the market for corporate control theory, other studies have introduced alternative perspectives such as the agency cost of free cash flow, transaction costs, and information asymmetry (Tunyi, 2021).

2.1.3 Misvaluation theory

Misvaluation theory acts as the second theoretical underpinning of takeover prediction. Under the traditional neoclassical view, takeovers are productivity- and efficiency-improving measures adopted by firms as a response to economic events, such as structural or technological changes in the business environment. However, newer theories try to link takeover activity to stock valuation (Rhodes-Kropf et al., 2005). Shleifer and Vishny (2003) are among those who suggest that the stock market's inefficiency in the valuation of firms has important effects on takeover activity. They examine the differences in valuations between targets and non-targets and provide evidence that mergers occur when firms with high stock valuations use their stocks to purchase targets with relatively low valuations. Additionally, Dong et al. (2006) states that the misvaluation effects on takeover activities stem from intentional efforts of acquiring firms purchasing undervalued targets and capitalizing from the acquisition. They also propose the "Q" hypothesis, which suggests that market valuations are proxies for the believed growth opportunities of firms. Accordingly, a high valuation signifies that the firm has well-functioning managers or promising business opportunities ahead. Low valuation implies the opposite and may arise if managers are running the company poorly (Dong et al., 2006). Thus, there are similarities between the "Q" explanation and Palepu's (1986) management inefficiency hypothesis, where poor management causes firms to under-perform. Several studies have investigated the effect of misvaluation on takeover decisions. Hasbrouck (1985) found that American targets have lower valuations compared to acquirers. Lang et al. (1989) further support this finding and suggest that acquirers can create value in takeovers by leveraging synergies or utilizing the target's resources more efficiently. Acquiring firms may also exploit targets with high growth potential but limited resources (Powell, 1997).

2.1.4 Abnormal Returns

Research shows that when bids are made public, takeover targets experience an increase of between 20% and 30% in abnormal returns (Jensen and Ruback, 1983). Thus, investing in companies that have a predicted high probability of being acquired constitutes a plausible investment strategy. If investing in predicted targets can help investors outperform the market, it implies that the stock market fails to fully consider and incorporate all publicly available information when valuing stocks. This, in turn, would contradict the concept of assimilation in the semi-strong market efficiency hypothesis, which states that all public and private information is reflected in a securites market price (Keown and Pinkerton, 1981).

The potential of formulating an attractive investment strategy around takeover prediction, has prompted several authors to build statistical models that use publicly available information to predict targets (see e.g., Barnes, 1990; 1999; Brar et al., 2009; Cudd and Duggal, 2000; Palepu, 1986; Powell, 1997; 2001). As anticipated, many individuals attempt to exploit the benefits from this investment opportunity. Brar et al. (2009) find evidence that takeover targets show strong short-term price momentum characteristics, driven by a rise in their share price prior to the acquisition announcement, accompanied by increased trading activity. Several other takeover studies have shown that positive residual returns for targets start occurring months before the official announcement of the bid (see e.g., Halpern, 1976; Keown and Pinkerton, 1981; Mandelker, 1974). Keown and Pinkerton (1981) suggest that the dramatic increase in trading volume and target share price pre-announcement can be attributed to insider trading, and limited confidentiality regarding M&A deals, leading to poor kept secrets and insider information leakage. They emphasize that planning for a takeover requires several groups of people (e.g., investment bankers, lawyers, consultants, and public relations people), which increases the probability of insider trading. As only registered insiders can be directly detected, some insider trading is likely carried out by third parties (Keown and Pinkerton, 1981).

Alternatively, Jensen and Ruback (1983) argue that a well-functioning market for information, consistent with the efficient market's hypothesis, is responsible for the pre-announcement run-up. The authors have further indicated that when traders can uncover information before the announcement, there is typically significant anticipation. This market is primarily fueled by the research and speculation of arbitragers, who may observe economic, industry-specific, or firm-specific factors that a future takeover is likely (Jarrell and Poulsen, 1989). Jarell and Poulsen (1989) also finds that news media research also provides an explanation for the pre-bid run-up. Therefore, a significant portion of the pre-announcement surge in activity may be attributed to a well-functioning market rather than insider trading. This explanation is generally referred to as the market speculation hypothesis. However, the literature has primarily focused on testing the insider trading hypothesis because market anticipation is not directly observable. Consequently, prediction modeling has served as a useful tool for regulators to examine how much of the anticipation of takeover targets is based on publicly available information, and guide decisions on whether to investigate potential cases of market abuse (Espahbodi and Espahbodi, 2003; Tunyi, 2021).

2.2 Literature review

2.2.1 Palepu (1986)

Palepu's (1986) study on takeover prediction is widely recognized as the cornerstone of current research in the field. Notably, the paper makes a significant contribution by highlighting three methodological biases found in previous takeover prediction studies: (1) using non-random equal size target and non-target samples for estimation lead to biased or inconsistent estimates of the acquisition probabilities; (2) employing equal-size samples in prediction tests produced error rate estimates that did not reflect the model's predictive ability in the population; and (3) utilizing arbitrary cutoff probabilities in prediction tests made it challenging to interpret the computed error rates. He attempts to correct these biases by on a sample of 163 acquired firms and 256 non-acquired firms, belonging to the mining and manufacturing industries in the US. Palepu (1986) further estimates four different logit models with nine independent variables for the estimation of a firm's acquisition likelihood. The selection of independent variables is based on six hypotheses associated with takeovers, including inefficient management, a mismatch between growth and financial resources, industry disturbances, small firm size, low market-to-book values, and low price-earnings values. Palepu (1986) found evidence for four of his hypotheses, although the models' explanatory power were quite low. Using an estimated cutoff probability, the model correctly identified 80% of the actual targets. However, only 45% of the non-targets were correctly predicted. The author concludes that investing in the potential targets identified by his model does not yield substantial abnormal returns, implying that the model does not exhibit superiority over the stock market's ability in takover prediction.

2.2.2 Barnes (1990, 1999)

Similar to Palepu (1986), Barnes (1990) focus on methodological and statistical issues associated with takeover prediction modelling which had previously received attention in bankruptcy prediction, but long remained unexplored in takeover prediction. He argued that the stability of the model plays a significant role in sucessfully predicting takeovers. Barnes (1990) addresses this matter by conducting a multiple discriminant analysis (MDA) using industry relative rations on a sample of 92 targets and 92 non-targets from the UK, in the period between 1986 and 1987. Building upon this work, Barnes (1999) employs a logit model to further examine the use of industry-relative ratios and the issues of an estimated cutoff point. Ultimately, Barnes (1999) finds that industry adjustments did not improve the results of his model. He explains that the failure of employing industry adjustments is a consequence of variable sensitivity to unusual data and limited industry representation.

2.2.3 Powell (1997, 2001)

Powell (1997) employs Palepu’s (1986) six hypotheses to predict takeover targets and to assess the robustness of different takeover probability models over time. He finds that the prediction models developed based on the Palepu (1986) hypotheses have a very low explanatory power, and that the period under study seems to play a significant role in determining what characteristics are important in explaining takeovers. Similar to Ambrose and Megginson (1992) who suggest a temporal matching of firms, Powell (1997) distributes non-targets across the studied period. As an extension of the aforementioned study, Powell (2001) tests whether his model can “beat the market” and yield abnormal returns, by holding a portfolio of firms predicted to be targets. The author criticizes Palepu's (1986) method of constructing portfolios, stating that his estimated cutoff probability incorrectly identifies many non-targets as targets. Instead, Powell (2001) proposed a different procedure for constructing portfolios by examining the concentration of target firms within these sorted by probability of takeover. This led to smaller portfolios with higher average probabilities of takeover. The models predicted on average 84% of all firms correctly. However, the author states the true test is whether the models can clearly identify target firms, as this dictates whether it is possible to earn significant abnormal returns. He observes that the models fail to do so, as only two out of 96 firms predicted to be targets were actual targets. Although the author suggests that his methodology offers a more effective testing approach, he concludes that the development of statistical models for takeover prediction is unlikely to pose a profitable investment strategy.

2.2.4 Cudd and Duggal (2000)

Cudd and Duggal replicated the study of Palepu (1986) to investigate (1) the usefulness of his six acquisition hypotheses in takeover prediction and (2) the importance of industry-specific distributional characteristics in determining classification accuracies. They used a US sample of 108 targets and 235 non-targets between 1988 and 1991 and generated three models using the same variables as in Palepu (1986). Model 1 applied unadjusted financial variables, and Model 2 applied an adjustment factor to capture distributional effects unique to each firm’s industry. The third and final model was identical to Model 2 but with a redefinition of the industry disturbance variable. Without industry adjustments, Cudd and Duggal (2000) only found support for one of the six hypotheses, whilst the adjusted model (Model 2) was able to reject four of the six acquisition hypotheses. Additionally, the results showed that the adjusted model (Model 2) produced the highest classification accuracy. The authors therefore concluded that an industry adjusted model was more useful for takeover modeling.

2.2.5 Brar et al., (2009)

Brar et al. (2009) extended on the Palepu (1986) acquisition likelihood model in one of few European studies. By incorporating short-term technical factors, such as share price momentum and trading volume they could better capture the timing of the acquisition announcement and see the effect that market sentiment has on takeover likelihood. The inclusion of variables with a more technical nature has previously been neglected in the context of developing takeover likelihood models. The result of their empirical analysis suggests that share price momentum and trading volume appear to have a significant impact on acquisition likelihood. When further incorporating these factors in a prediction model, the authors show that the portfolio has the ability to earn abnormal returns. Additionally, they find that their results are robust across several dimensions. However, their prediction model is tested on the same dataset used to establish the model parameters, thus the results should be viewed with caution as they may be distorted by a look-ahead-bias (Tunyi, 2021).

2.3 Other related research in the Nordic setting

Although there are few studies on takeover prediction in the Nordic setting, they should not be disregarded. Berg and Riedel (2018) wrote a BSc thesis predicting takeover targets in Sweden. They employed a logit model to identify target characteristics of Swedish listed public firms between 2005 and 2014 and based their hypotheses on those examined by Palepu (1986) and Ambrose and Megginson (1992). Their estimated model was then used to predict takeover targets in 2015. However, they find their models to be insignificant, and therefore conclude that it is difficult to predict takeovers in a Swedish setting. Therefore, it would be interesting to examine if these findings hold true for a larger sample in the Nordic region.

3.0 Hypotheses

The literature review highlights significant levels of uncertainty surrounding the drivers of takeovers. However, we have identified three main sets of variables that influence acquisition probability: those related to the firm, the industry/market, and the country. With the Nordics providing a rather safe business environment and high accounting standards, we disregard country level factors. Thus, in this section we present our hypotheses related to firm and industry/market characteristics. First, we outline Palepu's (1986) six hypotheses for takeovers, and second, we specify two additional hypotheses supported by the findings of Brar et al. (2009).

3.1 Firm characteristics

H1: *Firms with inefficient management are more likely acquisition targets.*

This hypothesis presented by Palepu (1986) is built on the market for corporate control theory, which states that acquisitions are a mechanism by which managers who fail to maximize the firms' market value are replaced by more efficient managers. According to Manne (1965), corporate control is a valuable asset that is actively traded in the market. The functioning of this market depends on the relationship between a firm's share price and the performance of its management. Poor performance causes the share price to fall below its value under efficient management. This situation creates an opportunity for a transfer of control, as it encourages takeover bids from prospective new management teams. Therefore, this hypothesis has been tested in a number of studies in the area of takeover prediction (see e.g., Brar et al., 2009; Palepu, 1986; Powell, 1997).

H2: *Firms with a mismatch between their growth and financial resources are more likely acquisition targets.*

Acquisition likelihood is believed to be related to a mismatch between firms' growth opportunities and financial resources. Based on this premise, Palepu (1986) proposes two types of firms that are viewed as likely targets: (1) *low-growth, resource-rich firms* and (2) *high-growth, resource-poor firms*. The first type of company refers to one that possesses a significant pool of liquid resources, yet demonstrates low growth. These firms become appealing as the acquierer can leverage the excess cash flows of the target and enhance their own expansion efforts (Jensen, 1986; Powell, 1997). The second type of firm highlights situations where the target has growth potential, but lacks sufficient resources to stay on that trajectory. Consequently, firms of this kind are regarded as appealing because the bidder may possess the resources required to alleviate the financial constraint (Amborse and Megginson, 1993), and sustain the target's growth.This hypothesis has been integrated by several studies (see e.g., Palepu, 1986; Ambrose and Megginson, 1997), and appears to be an important discriminating factor in the likelihood of takeovers.

H3: *The likelihood of acquisition decreases with the size of the firm*

Palepu (1986) argues that the likelihood of takeover decreases with the size of the firm. The idea behind this is that there are several transaction costs related to the size of the acquired firm. Brar et al. (2009) explain that these costs are associated with the integration of the target into the acquirer's organizational framework, and the capacity of the firm to deploy costly takeover defenses. This underpinning suggests that the transaction costs should increase proportionate to firm size, making it more attractive and easier to acquire small firms compared to large firms (Palepu, 1986). It is, therefore, reasonable to assume that a larger firm would take longer time to become fully integrated in the acquiring firm’s organization and would have a greater ability to resist change. This hypothesis has been frequently used in takeover literature, and has received consistent support from the findings of other studies (see e.g., Ambrose and Megginson, 1992; Cudd and Duggal, 2000).

H4: *Firms whose market values are low compared to their book values are more likely acquisition targets.*

Palepu (1986) suggests that firms with low market-to-book ratios are often assumed to be “cheap” buys, and therefore likely takeover targets. This is due to the fact that a lower ratio signals undervalued or under-utilized assets, which may represent a bargain for the acquirer in that the price of the firm is lower than the replacement cost of purchasing its assets (Powell, 2004; Hasbrouck, 1985). The asset undervaluation hypothesis can also be explained on the grounds of the market for corporate control and misvaluation theory. Manne (1965) and Dong et al., (2006) agree that low valuations indicate that the market believes there exists a management team that could use the firm's assets more efficiently, and that revitalizing a poorly run company can yield enormous return for the acquirer. Morck et al., (1988) further consider the market-to-book ratio to reflect a measure of intangible assets, including the quality of management, but also monopoly power, goodwill, etc. Thus, lower values of this ratio are associated with higher odds of takeover. This hypothesis is supported by Hasbrouck (1985) and Walter (1994) who provides evidence that undervalued firms have a higher acquisition likelihood.

H5: *Firms with low PE ratios are more likely acquisition targets.*

Palepu (1986) suggests that bidders with high price-to-earnings (P/E) ratios seek to acquire firms with low P/E ratios to realize an instant capital gain. This is because the acquirer expects that earnings for the new combined firm will be valued at the higher ratio of the acquirer. Barnes (1999) and Powell (1997) presents an alternative explanation by proposing that a firm's P/E ratio connects to the inefficient management hypothesis and reflects the market's opinion on its future profitability potential. This explanation aligns with the rationale behind the market-to-book hypothesis (H5) and pertains to the concept of corporate control and misvaluation theory. Consequently, when a firm has a low P/E ratio, it suggests that the market has limited expectations on the management's ability to generate future earnings. Despite being two differing explanations, they both contend that a firm's appeal as an acquisition candidate increases with a lower P/E ratio. Beyond the studies already mentioned, there are additional studies that explore this hypothesis (Ambrose and Megginson, 1992 and Cudd and Duggal, 2000).

3.2 Industry characteristics and market sentiment

H6: *Firms within an industry subject to "economic disturbances" are more likely acquisition targets.*

This hypothesis builds on economic disturbance theory, which was initially proposed by Gort (1969) and further explored by Palepu (1986). It states that takeovers are caused by valuation differentials among market participants which arise from general economic and political shocks. These shocks include changes in technology, market structure and deregulation of specific industries, which may stimulate waves of M&A activity in certain industries (Brar et al., 2009). This implies that takeover targets cluster within specific industries, and a firm's probability of being acquired could be measured by the recent history of acquisition in its industry. Consequently, the likelihood of acquisition increases for firms in so-called "hot" industries. The already mentioned studies test this hypothesis and receive varying results.

3.2.2 Trading[2]

H7: *Firms exhibiting strong short-term price momentum are more likely acquisition targets.*
This hypothesis posits that takeover targets exhibit a rise in share price before the announcement of the deal. Consequently, targets demonstrate stronger momentum in their share price compared to non-targets, as discovered by Brar et al. (2009). To enhance the understanding of the acquisition timing, Brar et al. (2009) conducted tests analyzing both short-term (3-month) and long-term (12-month) momentum. Moreover, this hypothesis attempts to capture the sentiments of other market participants (such as option traders, technical traders and high-frequency traders) by examining the day-to-day movements in stock prices (Brar et al.,2009; Cahan et al., 2011).

H8: *Firms that are more actively traded are more likely acquisition targets.*
In accordance with Brar et al. (2009), this hypothesis suggests that takeover targets experience increased trading activity in the month preceding the bid announcement. Testing for trading volume was initially based on the premise that companies with a higher trading volume relative to their size tend to experience lower merger transaction costs (Dietrich and Sorensen, 1984; Kim and Arbel, 1998). Dietrich and Sorensen (1984) further suggest that a significant increase in trading volume during the year before the observation may be a signal that an acquisition is underway. Plausible explanations behind this phenomena include insider trading (Keown and Pinkerton, 1981) and market speculation (Jarell and Poulsen, 1989; Jensen and Ruback, 1983).

4.0 Methodology and data collection

In this section we first describe our data collection process, followed by a demonstration of how our samples are constructed. Next, we present how we conduct data adjustments. We further present the variables used to test our hypotheses, along with our logit models. Finally, we outline our method for the prediction tests.

[2] Brar et al. (2009) do not explicitly include “Trading” as hypotheses related to the industry/market. However, we feel that the premise these hypotheses are built on is very much related to rumors and market speculation.

4.1 Data collection

This study involves a comprehensive collection and preparation of the dataset. We have employed Thomson Reuters database (Refinitiv Eikon) to obtain information on listed firms between the period 2012 and 2022. In order to compare data across the Nordics, all financial information defined by currency is measured in millions EUR.[3] All observations (1) have financial data available in Eikon (2) are listed on Nasdaq Stock Exchanges in Copenhagen, Helsinki, Iceland, Stockholm, or the Oslo Stock Exchange, and (3) exclude financial companies based on the "Business Sector" definitions provided by The Refinitiv Business Classification (TRBC). Consistent with prior studies (see e.g., Barley and Boardman, 1990; Powell, 1997, 2001), it is preferable to exclude financial companies, due to the sector's unique legal constraints and accounting practices which have the potential to distort the results of our analysis. Additionally, while certain studies disregard companies below a certain size (see e.g., Brar et al., 2009), we have opted not to discriminate against small firms. Our decision is based on the absence of clear rationale for such exclusion and our aim to retain a sufficient number of observations.

4.2 Sample selection

Following Palepu's (1986) and Powell's (1997) method, building the prediction model calls for two separate samples, both of which include target and non-target firms. The first sample is used to estimate the coefficients of the selected variables in the binary models ("the estimation sample"). The second sample is used to test the predictive ability of the prediction model ("the prediction sample").

4.2.1 Estimation sample

A sample of 113 firms that were acquired during the time period 2012 to 2021, and a control group consisting of a random sample of 196 firms that were not acquired as of the end of 2021, are used for the estimation sample. When collecting the targets for the estimation sample, we started by gathering all publicly traded Nordic firms listed on the relevant stock exchanges that had been subject to a bid within the designated period. From these 1234 observations, we removed 415 incompleted deals. We also excluded financial companies, reducing the sample

[3] The observed data may exhibit small discrepancies due to the currency conversion performed by Refinitiv Eikon, which could potentially have a minor impact on our observations.

with 114 observations. Moreover, to classify as a target, the firm must be subject to a takeover where more than 50% of the shares have been acquired. This resulted in an additional reduction of the sample by 529 firms. Furthermore, we had to eliminate 63 observations from the final target sample due to missing data points. Ultimately, out of the 1234 announced bids during 2012 to 2021, the observations that met all of our criteria summed up to 113 targets. The observation year for the acquired firms is defined as the year in which the bid was announced, as indicated in previous studies (see e.g., Palepu, 1986; Powell, 1997). Table 1 provides an overview of hew the final sample was determined.

Table 1
Sample selection for the estimation sample.

Selection criteria	Number of firms
Targets	
Announced bids during 2012-2021 on the Nordic stock exchanges[4]	1234
Incompleted deals	-415
Financial companies	-114
Percentage of shares acquired ≤ 50%	-529
Missing data	-63
Total targets	113
Non-targets	
Firms not acquired during 2012-2021	196
Total sample	309

There were two considerations when collecting the non-targets for the estimation sample. First, we had to consider which firms to include, and second, which observation year these should have. Regarding which firms to choose, the most commonly employed methods are random sampling and state-based sampling. Random sampling is done by starting with a population of unacquired firms and then drawing a random sample of these. In this approach the number of targets and non-targets should not equal each other. Instead, the sample distribution should represent that of the population of companies from which the sample was obtained. In a state-based approach, the number of non-targets approximately equals the number of targets in the

[4] Stock exchanges include Nasdaq Copenhagen, Nasdaq Helsinki, Nasdaq Iceland, Nasdaq Stockholm, and Oslo Stock Exchange.

sample (Palepu, 1986). Palepu (1986) provides mathematical evidence that state-based sampling contains significant biases, which are based on the premise that an equal share is not representative of reality. Because of the limitations of the state-based method, we have derived the control sample following Palepu's (1986) random sampling approach. Firstly, we identified a group of 392 firms that were unacquired as of 2021, listed on one of the relevant stock exchanges and fulfilled the criteria for inclusion as outlined in section 4.1. Contrary to Palepu (1986), who chose every sixth firm from his population, we randomly selected every second firm from the group to be included in our sample. This decision is justified since opting for any alternative would result in a roughly equal, or potentially higher proportion of targets to non-targets. Finally, this yielded a control sample of 196 firms that were not acquired as of the end of 2021. The resulting estimation sample, including the targets and non-targets amounts to 309 firms.

Regarding the second consideration, there are two ways to specify the observation year for non-target firms. Palepu's (1986) sample consists of targets observed across the time period 1971 to 1979, and non-target firms observed in the year 1979. In other words, he assumes that the non-targets can be observed to have been not acquired in the last year of his estimation sample. In our case, this means that all targets are observed throughout the years 2012 to 2021, whereas all non-targets are observed in the year 2021. However, using data from such different time periods can introduce significant temporal effects and potential sources of bias. To address this issue, we decided to distribute targets across the examined period as proposed by Powell (1997), and temporally-match these in accordance with Ambrose and Megginson (1992). This implies that the proportion of non-target observations in a particular year is equivalent to the proportion of target observations in that same year. To clarify, if 5% of the total targets were acquired in 2015, we randomly assign 5% of the non-target companies to 2015. This method is particularly relevant given the time period being examined, which includes significant events like the COVID-19 pandemic. The composition of the estimation sample is further illustrated in Table 2.

Table 2
Composition of the estimation sample by year.

Year acquired	Targets: Number of firms	Targets: Percent	Non-targets: Number of firms	Non-targets: Percent
2012	15	13%	26	13%
2013	12	11%	22	11%
2014	18	16%	31	16%
2015	15	13%	26	13%
2016	10	10%	18	10%
2017	11	9%	19	9%
2018	7	7%	12	7%
2019	9	8%	15	8%
2020	9	8%	16	8%
2021	7	6%	11	6%
Total	113		196	
Unacquired firms 2021	392			
Random selection of firms	-196			
Total sample	309			

4.2.2 Prediction sample

The second sample referred to as the "prediction sample" is used to test the predictive ability of the estimated acquisition model in 2022. This sample consists of firms listed on the relevant stock exchanges in 2022, separate from those included in the estimation sample. Both targets and non-targets are screened based on the same criteria as in the estimation sample, and non-targets are once again chosen through a random sampling method, as specified by Palepu (1986). This results in a prediction sample of 18 targets and 196 non-targets.

4.3 Data adjustments

4.3.1 Industry adjustments

Some takeover prediction studies focus only on examining firms from a few industries (see e.g., Palepu, 1986). Due to the relatively limited sample size available from the Nordics, it is not feasible for us to confine our analysis to particular industries. However, by including firms from all industries, we run the risk of industry-specific parameters affecting the financial ratios of the firms, introducing a potential bias to the results.[5] Therefore, to account for industry effects we decide to adopt the industry-specific data adjustments proposed by Cudd and Duggal (2000). It should be noted that Cudd and Duggal (2000) do not explicitly mention the industry definition used in their calculations. We find that TRBC Industry Group definitions are quite narrow, which leads to several industries obtaining only one observation. This poses a problem as we are not able to adjust for industries with a single observation, something which not only creates outliers in the data, but also fails to accurately represent the reality. To address the issue, we choose to employ the TRBC Business Sector definitions, the same definition used in our data collection to exclude financial companies. This decision is further justified by Barnes (1999), who used sector definitions to compute industry adjustments. Ultimately, with a slight augmentation to Cudd and Duggal's (2000) industry adjustment formula, we adjust our variables by calculating each observation as below.[6]

$$A_i = (U_{ij} - M_j) / \sigma_j \qquad (1)$$

In the above equation, A_i represents the adjusted variable value of firm *i* in sector *j*. This value is determined by taking a firm's unadjusted variable (U_{ij}) less the average of that variable for all firms within the same sector (M_j). The resulting value is further divided by the standard deviation of that variable for all firms in sector *j*.[7] By repeating the empirical assessment with unadjusted variables in section 5.4.2, we can investigate whether industry distributional characteristics have an impact on identifying variables with potential discriminatory ability.

4.3.2 Outliers

We have identified the presence of a few outliers in our two samples. To address this issue, previous literature presents several approaches. The most commonly adopted method is the elimination of outliers due to its convenience. However, discarding observations may not be the most suitable solution if the sample size is limited (Powell, 1997). Given the relatively small size of our sample, we opted to use winsorization, a technique that replaces outlier values rather than discarding them. We employ Powell's (2004) method for winsorization and define outliers as the observations that lie outside of ±3 standard deviations from the mean of a given variable.

[5] One way of controlling for this unobserved heterogeneity is through industry fixed effects. Yet again, there are too few observations within each industry to allow for this approach.
[6] Excluding IDUMMY.
[7] Cudd and Duggal's (2000) definitions use the term "industry" instead of "sector".

When winsorizing, we reassign these deviating variables to ±3 standard deviations from the mean. Overall, we consider this approach to offer a viable solution to address outliers while retaining the sample size.

4.4 Binary logit model

There are several discrete choice models to choose from when applying quantitative methods to study takeover prediction. Binary and multinomial logit models are perhaps the most employed ones in the previous literature (see e.g., Ambrose and Megginson, 1992; Barnes, 1999; Brar et al., 2009; Cudd and Duggal, 2000; Palepu, 1986; Powell, 1997, 2001, 2004). The difference between these models' rests in the fact that the dependent variable in a binary model takes on only two values (0 or 1), whereas it can take on several values in a multinomial model. In this study, we employ a binary logit model in line with Palepu (1986), which is further described in section 4.4.2. Alternatives to logit regressions include, but are not limited to, different versions of discriminant analysis (DA). DA has been employed in a few studies (see e.g., Barnes, 1990; Espahbodi and Espahbodi, 2003). However, DA assumes that the predictor variables are normally distributed. With our independent variables being mainly accounting ratios, which are non-normally distributed, it disrupts the assumption of multivariate normality (Barnes, 1999; Espahbodi and Espahbodi, 2003). As noted by the authors, logit regression does not rely on such assumptions and is therefore a more suitable in takeover studies.

4.4.1 Independent variables

Table 3 presents the variables selected to test our eight hypotheses. Additional detail on the computation of these variables can be found in Appendix 6. Although there is a considerable amount of other financial discriminators proposed in prior research, there is an absence of theoretical support for a particular set of variables. The variables that are included in this study are based on a comprehensive examination of the literature and are further motivated by our hypotheses.

Table 3
Acquisition likelihood hypotheses and independent variables.

Hypothesis	Variable	Expected sign[8]
H1: Inefficient management hypothesis	Average excess return (AER)	-
H2: Growth-resource match hypothesis[9]	Growth-resources dummy (GDUMMY)	+
	GROWTH	
	LIQUIDITY	
	LEVERAGE	
H3: Firm size hypothesis	SIZE	-
H4: Asset undervaluation hypothesis	Market-to-book value (MTB)	-
H5: Price-earnings hypothesis	Price-earnings ratio (PE)	-
H6: Industry disturbance hypothesis	Industry dummy (IDUMMY)	+
H7: Short-term price momentum hypothesis	Short-term price momentum (SPM)	+
H8: Trading volume hypothesis	Trading volume (TV)	+

4.4.2 Main regression models

Following the procedure of Palepu (1986), our independent variables are estimated using logit models, accompanied by t-statistics to test their null hypotheses. The binary logit model estimates the log odds of the dependent variable being equal to one (i.e., being a target) based on the values of the independent variables. The log odds of a firm being a target are then transformed into probabilities through the logistic function. These probabilities range from 0 to 1 and represent the likelihood of a firm being a target. Moreover, the models are fitted in the statistical software package R (R-studio), which is considered a powerful tool for data analysis. Model 1 includes six independent variables which correspond to Palepu's (1986) six acquisition likelihood hypotheses. Model 2 is a re-estimate of Model 1 with the inclusion of three additional variables, GROWTH, LIQUIDITY and LEVERAGE, which are all used in defining the GDUMMY variable. These variables are tested in separate models to examine which component in the resource mismatch that is most predominant in the sample. Furthermore, Model 3 augments the set of variables in Model 2 with the inclusion of SPM and TV, as specified by Brar et al. (2009).

[8] A positive sign hypothesizes that the variables increase the likelihood of acquisition, and a negative sign indicates the opposite.
[9] The variables GROWTH, LIQUIDITY and LEVERAGE are also included in some versions of the model, but no expected signs have been hypothesized. These variables are used in constructing the GDUMMY.

Model 1: replication of Palepu[10]

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

$$= \beta_0 + \beta_1 AER_i + \beta_2 GDUMMY_i + \beta_3 IDUMMY_i + \beta_4 SIZE_i + \beta_5 MTB_i + \beta_6 PE_i + YFE + \varepsilon \qquad (2)$$

Model 2: replication of Palepu[11]

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

$$= \beta_0 + \beta_1 AER_i + \beta_2 GDUMMY_i + \beta_3 GROWTH_i + \beta_4 LIQUIDITY_i + \beta_5 LEVEREGE_i + \beta_6 IDUMMY_i + \beta_7 SIZE_i + \beta_8 MTB_i + \beta_9 PE_i + YFE + \varepsilon \qquad (3)$$

Model 3: thesis model[12]

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

$$= \beta_0 + \beta_1 AER_i + \beta_2 GDUMMY_i + \beta_3 GROWTH_i + \beta_4 LIQUIDITY_i + \beta_5 LEVEREGE_i + \beta_6 IDUMMY_i + \beta_7 SIZE_i + \beta_8 MTB_i + \beta_9 PE_i + \beta_{10} SPM_i + \beta_{11} TV_i + YFE + \varepsilon \qquad (4)$$

In the above models, $Logit(\rho)$ denotes the natural logarithm of the odds that the dependent variable (Y) will be assigned the classification of a target (Y=1). β_i represents the regression coefficients for the independent variables included in the models, which explain the impact respective variable has on the log-odds of being a target. β_0 represents the constant, i.e., the log-odds of a firm being a target when all independent variables have a value of zero. Year-fixed effects (YFE) are included to control for any time-invariant factors across the studied period.[13] Lastly, represents an error term which measures the variability in Y that is not explained by the independent variables.

[10] Replication of Palepu Model 1.
[11] Replication of Palepu Model 3.
[12] This is our own model, constructed based on our hypotheses in section 3.0.
[13] When estimating year fixed effects, the heterogeneity observed in the estimation sample is only applicable on the prediction sample if they are based on the same time period. Since our estimation sample and prediction sample are not from the same period, the inclusion does not serve any purpose with regard to the actual prediction test.

4.5 Prediction test

4.5.1 Prediction model

To specify the relationship between the firm characteristics and its acquisition likelihood, we employ the logistic probability model proposed by Palepu (1986). While alternative methodologies have been presented (see, e.g., Cudd and Duggal, 2000), Palepu's base probability model is seen as an established approach when employing logit regression (see e.g., Powell, 2001; Ambrose and Megginson, 1992; Brar et al., 2009).

$$\rho(i,t) = 1 / [1 + e^{-\beta x(i,t)}] \tag{5}$$

In the above equation, *p(i,t)* represents the probability that firm *i* will be the target of a takeover bid during the specific time period *t*. A vector of our chosen variables with potential discriminatory ability is denoted as *x(i,t)*. To estimate these probabilities, a vector of unknown parameters, denoted as *β* is used. The estimated regression model with the highest explanatory power will be used as the prediction model (Palepu, 1986).

4.5.2 Cutoff probability

When conducting the prediction test, the classification of an observation as being a target or non-target is done by comparing its predicted acquisition probability with a predefined cutoff probability. This cutoff probability serves as a threshold above which an event is likely to occur, and below which the event is unlikely to occur (Palepu, 1986). I.e., if the estimated probability is greater than the cutoff probability, the firm is classified as a target, if less than the cutoff, the firm is classified as a non-target (Cudd and Duggal, 2000). Previous literature presents two methods for determining the classification threshold.

The first method involves using an arbitrary cutoff probability, often set at 0.5 (Palepu, 1986). This approach is considered acceptable when the share of targets and non-targets is equal (state-based sampling), as the threshold will match the distribution of targets and non-targets. However, the method fails to account for the specific decision-context at hand, particularly when the sample is imbalanced between targets and non-targets (Palepu, 1986; Cudd and Duggal, 2000). Instead of using an arbitrary threshold, Palepu (1986) argues that a cutoff must be derived using standard decision theory. Therefore, he introduced a second method that determines the cutoff probability by the distributions of acquisition probability in the estimation model. To obtain the sample distributions, the range of target and non-target probabilities is divided into ten equal intervals. Firms are then distributed into these intervals, based on their estimated probabilities, creating one distribution table for targets and one for non-targets. When plotting the results for each distribution, the point of intersection determines the optimal cutoff probability (Palepu, 1986). Employing this method has typically led to cutoffs well below 0.5, and supposedly decreases the risk of committing Type I and Type II errors (Palepu, 1986; Cudd and Duggal, 2000; Barnes, 1999; Brar et al., 2009). Although there are advantages to this method, it also assumes that the cost of a Type I and Type II error are equal and constant (Powell, 2001). As targets exhibit gains far greater than those of unacquiered firms (Jensen and Ruback, 1983), the validity of this assumption could be questioned. Based on this, Powell (2001) argues that if the objective is to earn abnormal returns, the optimal cutoff probability should maximize the proportion of correctly classified targets, not minimize the total number of misclassifications. Since the second method typically generates lower cutoffs (<0.5), Powell (2001) instead suggests employing a higher cut-off probability. Based on this argument, we deem it necessary to validate the method choice by adopting both methodologies in section 5.5.2.[14]

5.0 Empirical results

In this section, we first present descriptive statistics for our variables. Second, we present Pearson correlations for the same variables. In section 5.3 we present the results from our main regression models, followed by robustness tests in section 5.4. Lastly, we present the results from our prediction model.

5.1 Descriptive statistics

Descriptive statistics for unadjusted variables can be found in Table 4. We investigate the potential discriminatory ability of the considered variables by looking at the differences in mean values between targets and non-targets. We further examine whether these differences are statistically significant through a two-sided Welch t-test in R. The rationale behind presenting descriptive statistics for only the unadjusted variables in this section is that these represent the actual values of the data. The adjusted dataset, on the other hand, provides information which

[14] This is further justified as our estimated cutoff is below 0.5.

is difficult to interpret given their modification. Nonetheless, t-tests on the adjusted sample are still included as it provides an indication of whether some of the independent variables are associated with being a target.

Table 4
Descriptive statistics.

	Target sample n=113		Non-target sample n=196			
Variable	Mean value	Median value	Mean value	Median value	T-test for difference in mean values[15]	T-test for difference in mean values[16]
AER	0.06	0.06	0.09	0.07	-0.88	-0.39
GDUMMY	0.18	0.00	0.23	0.00	-1.12	-1.12
GROWTH	0.20	0.02	0.36	0.05	-0.94	-2.24**
LIQUIDITY	-0.19	-0.19	-0.18	-0.19	-0.59	-1.91*
LEVERAGE	0.90	0.60	0.91	0.62	-0.03	-0.58
SIZE	1013.75	210.49	1428.35	315.72	-1.22	1.12
MTB	1.00	0.69	1.40	0.78	-2.32**	-2.92**
PE	9.53	10.09	9.33	8.96	-1.61	0.31
IDUMMY	0.34	0.00	0.37	0.00	-0.64	-0.64
SPM	101.75	97.10	105.36	103.01	-1.13	-1.27
TV	0.21	0.03	0.05	0.01	4.61***	3.47***

*** p<0.01, ** p<0.05, * p<0.1

The t-tests for unadjusted variables suggest that TV has the most significant difference in mean values at 1%. Additionally, MTB is significant at the 5% level. For adjusted variables, TV again appears to be the most significant in discriminating targets from non-targets at 1%, and the MTB ratio is still significant at the 5% level. However, the difference in mean values for GROWTH now appears significant at 5%, and LIQUIDITY at 10%. Accordingly, companies with undervalued assets, lower liquidity and growth, and whose shares that are more actively traded the month prior to the announcement appear to have a higher acquisition likelihood. Our findings mostly diverge from those of Palepu (1986). However, similar to us he finds lower growth to be a discriminant factor. Moreover, consistent with our findings, Brar et al. (2009) observed that targets experience higher trading volume.

[15] t-test for the difference in mean values for unadjusted variables at 95% confidence interval.
[16] t-test for the difference in mean values for industry adjusted variables at 95% confidence interval.

5.2 Pearson correlations

In Appendix 5, we present the Pearson correlations between the independent variables, as part of testing for the presence of multicollinearity. This will help us understand if changes in one variable are associated with shifts in another. Overall, we have quite low correlation coefficients, but several variables are significantly correlated with each other. LIQUIDITY has the highest correlation with GDUMMY significant at the 1% level. LIQUIDITY is further correlated with MTB at the 1%, as well as GROWTH and LEVERAGE the 10% level. MTB also has relatively high correlations with GROWTH, LEVERAGE and TV at the 1% level, and a low level of correlation with PE at the 10% level. Furthermore, AER is significantly correlated with SPM at the 1% level and with PE at the 5% level. It is also correlated with SIZE and MTB at the 5% level; however, these coefficients are quite small. LEVERAGE is significantly correlated with GDUMMY at the 5% level. Lastly, TV is significantly correlated with SIZE at the 1% level, yet again the magnitude is not that high. Quite a few of the independent variables are significantly correlated with each other and some of those with higher coefficients. As the detection of correlation must not imply that there exists multicollinearity, we will conduct a variance inflation (VIF) to ensure that these correlations do not affect our results. The result of the VIF test is presented in section 5.4.1.

5.3 Results from regression models[17]

Table 5 presents regression results for the three models constructed in section 4.4. A positive sign on a coefficient indicates that a rise in the corresponding variable increases the likelihood of takeover and a negative sign indicates the opposite. It is important to note that interpreting results from logit regression is different from linear OLS regression. While the coefficients accurately show the direction of the marginal effects of each significant independent variable on the dependent variable, their magnitude cannot be interpreted in the same way as coefficients in linear regressions (Wooldridge, 2012). Also presented in Table 5 are the likelihood ratio indexes for each model, which provide an indication of the overall explanatory power of the model, as well as the likelihood statistic which tests the models' statistical significance. When evaluating the explanatory power of the models, we cannot use a normal R2 value as the logit model has binary outcomes, and the relationship between the variables is not linear. To assess

[17] Intercept values are often of little interest in logit regressions with a mix of dichotomous and continuous independent variables (Hosmer and Lemeshow, 1989), therefore we do not comment upon these values.

how well the data the model, we therefore use McFadden's pseudo R2, presented as the likelihood index (McFadden, 1974). The pseudo R2 value is expected to be lower than the R2 value of a linear regression, with a pseudo R2 value of 0.2 or above indicating an excellent fit (Hensher and Stopher, 1979).

Table 5
Estimates of logit acquisition likelihood models with data adjustments.

Variable	Expected sign	Estimates		
		Model 1	Model 2	Model 3
AER	-	-0.0288	-0.0371	-0.0775
GDUMMY	+	-0.3196	-0.3482	-0.2634
GROWTH			-0.2779*	-0.3123**
LIQUIDITY			-0.1060	-0.1191
LEVERAGE			-0.1227	-0.1044
SIZE	-	-0.1753	-0.1882	-0.0932
MTB	-	-0.4894***	-0.3781*	-0.3615*
PE	-	0.0465	0.0409	0.0538
IDUMMY	+	-0.2185	-0.2129	-0.2629
SPM	+			-0.2348
TV	+			0.4724***
Constant		-0.7128*	-0.6754*	-0.7038*
Year fixed effect[18]		-	-	-
Likelihood ratio index[19]		0.0284	0.0400	0.0811
Likelihood ratio statistic[20]		11.54	16.21	32.92**

*** p<0.01, ** p<0.05, * p<0.1

In Model 1 the variable MTB is statistically significant at the 1% level and matches the expected sign. This implies that firms whose market values are low compared to their book values are more likely acquisition targets. This result is inconsistent with Palepu (1986), who did not find MTB a significant motive for takeovers. Contrary to our findings, he also identified AER, GDUMMY, IDUMMY and GROWTH to be significant in his model. When adding GROWTH,

[18] Year fixed effects are included in all the models. None of these are significant, hence their values are not represented in Table 5.
[19] The likelihood ratio index (pseudo R2) is defined as (1- log likelihood at convergence / log likelihood with constant term only). It provides an indication of the model's explanatory power and is similar to R2 in the case of a linear regression model (Powell, 1997).
[20] The likelihood ratio statistic is defined as 2*(log likelihood at convergence - log likelihood with constant term only). It is computed to test the null hypothesis that all parameters in the model are simultaneously equal to zero. The statistic follows a chi-square distribution with degrees of freedom equivalent to the number of parameters in the model (Powell, 1997).

LIQUIDITY and LEVERAGE in Model 2, GROWTH is significant at a 10% level with a negative coefficient, indicating that targets are characterized by lower growth. Furthermore, MTB remains significant in Model 2, but now at the 10% level. Regarding the variables LIQUIDITY and LEVERAGE, there is no observed statistically significant relationship with being a target. Palepu (1986), on the other hand, finds the coefficients of GROWTH and LEVERAGE negative and significant. Model 3, which augments Model 2 with the inclusion of SPM and TV, produces similar results as the previous models, except that GROWTH is now significant at the 5% level rather than at the 10% level. Regarding the two added variables, TV is significant at the 1% level and matches the expected sign, and SPM is insignificant with a negative sign. Our findings are partially consistent with Brar et al. (2009), who also finds TV to be significant with a positive coefficient, indicating that targets' shares are more actively traded in the month prior to the acquisition. However, contrary to Brar et al. (2009), our findings indicate that SPM does not have a significant impact on the dependent variable.

In terms of model significance, the likelihood ratio index for the three models ranges between 2.84% to 8.11%. This indicates that the models have a weak ability to explain the variation in the dependent variable, resulting in low explanatory power. In order to find the p-value from the likelihood ratio statistic, we compare the respective models with the null model.[21] This is done through an ANOVA test in R, and we can conclude from the test that Models 1 and 2 are insignificant at 0.7136 and 0.5776 p-values respectively. Model 3, on the other hand, is significant at the 5% level. However, the magnitude of this explanation is still very low since a maximum of only 8.11% of the variation in a firm's acquisition probability is explained by the model.

Of the three logit acquisition likelihood models, Model 3 has the greatest explanatory power of 8.11%. Therefore, Model 3 is employed to further analyze the variables' predictive ability of targets and non-targets.

5.4 Robustness tests

Prior to testing the predictive ability of Model 3, we conduct a series of robustness checks to investigate the potential impact of various decisions on our main regression analysis. We start

[21] The null model contains only the constant term, and all predictor variables are set to zero, assuming that the probability of being a target is constant across all levels of the independent variables.

with testing for multicollinearity conducted in relation to the observed correlations in section 5.2. We then test the binary regressions on a non-industry adjusted sample, as well as a sample using Palepu's (1986) observation year definition.

5.4.1 Multicollinearity test

Multicollinearity occurs when there is high correlation between two or more independent variables, making it difficult to interpret the results of the regression analysis since the contribution of each variable to the explained variance cannot be distinguished (Farrar and Glauber, 1967). To control for any multicollinearity, we run a Variance Inflation Test (VIF) test on Model 3. A VIF score of 10 is commonly regarded as too high, and a more conservative rule of thumb is a VIF of four (Wooldridge, 2012). However, the use of fixed VIF levels has been criticized for being arbitrary, since acceptable VIF values vary with the type of study and data used (O'Brien, 2007). Our VIF test presented in Appendix 1 displays values ranging between 1.028 and 1.258, indicating no reason for concern regarding multicollinearity.

5.4.2 Unadjusted variables

In Appendix 2, we present the regression results for variables that have not been adjusted for industry, as described in section 4.3. The table shows that the significance among the independent variables remains mostly unchanged. Although, we can note that MTB is now significant at the 5% level in all three models. Furthermore, GROWTH remains significant only in Model 3 at the 10% level and TV remains significant at the same level as in the main regression. The SPM variable becomes significant at the 10% level in the unadjusted model with a negative coefficient, contrary to the findings of Brar et al. (2009) who found SPM to be significant with a positive sign. All other variables remain insignificant, although a few of them have switched signs. The likelihood ratio index ranges between 0.0293 and 0.1096, which indicates a higher explanatory power compared to the industry-adjusted models. Based on the likelihood ratio statistics, Models 1 and 2 are still insignificant, and Model 3 is significant at the 1% level. This result is not consistent with the findings of Cudd and Duggal (2000), who observed that the effect of industry distributional characteristics on firm-specific variables would improve the models' explanatory power.

5.4.3 Observation year[22]

As discussed in section 4.2.1, Palepu (1986) specifies the observation year for non-targets in his estimation sample as the last year of the period studied. We thus repeat our analysis by employing Palepu's (1986) definition, specifying the observation year for non-targets as 2021. The results from using this method are presented in Appendix 3. The table shows that MTB has increased its significance in Model 2 and 3, while GROWTH has lost its significance in both models in which it is present. Both SIZE and SPM become significant in the models, although SIZE is not significant in Model 3. SIZE obtains the expected sign, whilst SPM obtains the reverse sign. Moreover, considering the likelihood ratio statistic, all our models are significant at the 1% level and the likelihood ratio index ranges between 0.0543 and 0.1791, which indicates a higher explanatory power compared to the main regression. This result is not consistent with the findings of Powell (1997) and Ambrose and Megginson (1992) who suggested that the effect of distributing non-targets should improve the models' explanatory power.

5.5 Prediction

5.5.1 Estimation of the optimal cutoff probability

In order to test the predictive usefulness of Model 3, we first estimate the optimal cutoff probability in line with Palepu (1986). As pointed out in section 4.5.2, the optimal cutoff probability is determined by the distributions of acquisition probability for targets and non-targets in the estimation sample. The estimated probability values of Model 3 range between 0 and 0.8733 for all observations except one. In line with Palepu (1986), we disregard the deviating observation. To obtain the sample distributions, we then divide the range of 0 to 0.8733 into ten equal intervals. The number of and percentage of the total targets and non-targets that fall into each range is illustrated in Table 6. By plotting the percentage of targets ($f1(p)$) and non-targets (f$2(p)$) that fall into each probability interval against the mid-value ((p)) of that interval, we obtain the discrete approximation of the acquisition probability. The optimal cutoff probability is derived from the point at which the two distribution functions are equal.

[22] Since all non-target observations are based in the same year, the year fixed effects are capturing the effect of the year 2021 where all y=0 observations are located rather than controlling for time-invariant effects. This leads to collinearity issues, thus, year fixed effects are not included in this version of the models. Although this is in line with Palepu (1986), we understand that this creates some limitations in the comparison of these models and the main regression models.

These plots are illustrated in Appendix 4 and intersect where the estimated acquisition likelihood is equal to 0.3647. This means that if a firm in the prediction sample is predicted to have more than an 0.3647 acquisition likelihood, it will be classified as a target. Conversely, if a firm has a likelihood predicted below 0.3647, it will be classified as a non-target. This number is significantly larger compared to Palepu (1986), who estimated a cutoff probability of 0.1120.

Table 6
Distribution of estimated acquisition probability for targets and non-targets in estimation sample.

Estimated acquisition probability		Target firms		Non-target firms		
Range	Mid-value *(p)*	Number	Percent f1*(p)*[23]	Number	Percent f2*(p)*[24]	f1*(p)*/f2*(p)*
0.0000 - 0.0873	0.04	0	0.0%	7	3.6%	0.00
0.0874 - 0.1747	0.13	4	3.5%	14	7.1%	0.50
0.1748 - 0.2620	0.22	10	8.8%	36	18.4%	0.48
0.2621 - 0.3494	0.31	18	15.9%	64	32.7%	0.49
0.3495 - 0.4367	0.39	35	31.0%	45	23.0%	1.35
0.4368 - 0.5240	0.48	20	17.7%	19	9.7%	1.83
0.5241 - 0.6114	0.57	11	9.7%	4	2.0%	4.77
0.6115 - 0.6987	0.66	5	4.4%	2	1.0%	4.34
0.6988 - 0.7860	0.74	4	3.5%	2	1.0%	3.47
0.7861 - 0.8733	0.83	6	5.3%	2	1.0%	5.20
> 0,8733		0	0.0%	1	0.5%	
Total		113		196		

*** p<0.01, ** p<0.05, * p<0.1

5.5.2 Prediction tests

As argued by Palepu (1986), a test of the model on the estimation sample would likely be biased as the model parameters and cutoff probability is obtained from that group of firms. Hence, we examine the ability of Model 3 to predict targets by testing it on the prediction sample outlined in section 4.2.2. The values for the independent variables are computed as described in Appendix 6, and the estimated parameters from Model 3 are then used to compute the probability of a firm being a target in 2022. Below, we present the results obtained from first

[23] The figures are calculated by dividing the number of targets in each probability interval by 113 and expressing the result as a percentage.
[24] The figures are calculated by dividing the number of non-targets in each probability interval by 196 and expressing the result as a percentage.

using the estimated cutoff probability (0.3647), and second the arbitrary cutoff probability (0.5). Note that a Type I error occurs when a non-target is mistakenly classified as a target, and a Type II error refers to when a target is mistakenly classified as a non-target. The results are further illustrated in Table 7.

Table 7
Prediction results.

	Estimated cutoff		Arbitrary cutoff	
	Targets	Non-targets	Targets	Non-targets
Actual	18	196	18	196
Prediction	96	118	42	172
Correctly predicted	9	109	3	157
Sensitivity[25]	50.00%		16.70%	
Specificity[26]	55.61%		80.10%	
Accuracy[27]	55.14%		74.80%	

Using the optimal cutoff probability estimated in line with Palepu (1986), our model predicts 96 of the firms as targets and 118 as non-targets. Of the 96 predicted to be targets, nine of them were actual targets. Of the 118 classified as non-targets, 109 are actual non-targets. In other words, the nine correctly classified targets give the model a sensitivity of 50.00%. Accordingly, the 109 correctly classified non-targets correspond to a specificity of 55.61%. Palepu (1986) is able to classify 80.00% of the targets in his prediction sample correctly, which indicates that our model permits more Type II errors. However, his results indicate a higher level of Type I errors, with 45.00% of the non-targets predicted correctly. Additionally, our findings suggest higher overall accuracy at 55.14% compared to Palepu's (1986) 45.66%. When instead employing the arbitrary cutoff probability of 0.5, our model predicts 42 firms as targets and 172 as non-targets. Of the 42 firms classified as targets, only 3 are actual targets. Of the 172 firms classified as non-targets, 157 are actual non-targets. Thus, we can conclude that a higher cutoff probability in our case achieves a greater overall accuracy of 74.80%, as well as fewer Type I errors with a specificity of 80.10%. However, more Type II errors are prevalent, generating a sensitivity of 16.70%.

[25] Sensitivity = TP / (TP + FN)
[26] Specificity = TN / (TN + FP)
[27] Accuracy = (TP + TN) / (TP + FN + TN + FP)

6.0 Analysis

6.1 Descriptive statistics and regression models

The t-tests for difference in mean values for the adjusted variables show that both GROWTH and LIQUIDITY are significant, whilst they are insignificant when carrying out the same test with unadjusted variables. This indicates that adjusting for industries has a significant effect on our models. We can further conclude that the influence of sales growth and liquidity varies among industries, which justifies our choice of using industry adjusted variables in our empirical models.[28] TV and MTB have significant differences in mean values for both adjusted and unadjusted variables, which indicates that trading volume and asset undervaluation are potentially discriminant across industries.

When examining our regression results, we make several interesting findings and find support for two of our hypotheses. In section 5.3 we present that the coefficient of MTB is statistically significant, with a negative sign in all three models. This is in line with our fifth hypothesis (H5) as well as with Hasbrouck's (1985) and Walter's (1994) findings. Thus, consistent with the misvaluation theory we reject our null hypothesis and find support for the fact that Nordic firms whose market values are low compared to their book values are more likely acquisition targets. However, what is interesting is that MTB has varying levels of significance in each model. Although the VIF test confirmed the absence of multicollinearity, the change in significance suggests that other factors are influencing the observed results. It is possible that GROWTH, LIQUIDITY, LEVERAGE, TV or SPM have stronger relationships with the dependent variable, explaining a larger portion of the explained variation. Therefore, it is not known which imbalance is more prevalent. Consequently, the significance of MTB diminishes when these variables are included. This showcases the complex and nonlinear relationships in logit regressions, which can lead to some variables being overshadowed by the effect of others.

Furthermore, consistent with Brar et al. (2009) we find TV statistically significant in Model 3. This finding supports our eighth hypothesis (H8). Therefore, we reject our null hypothesis, implying that stocks of targets are more actively traded during the month prior to the acquisition. This phenomena could be explained by Keown and Pinkerton (1981) who attribute

[28] Further discussion regarding the robustness of industry adjusted variables is done in section 6.2.

the increase in trading volume to information leakage and insider trading activity, or market speculation (Jarrell and Poulsen, 1989; Jensen and Ruback, 1983). Moreover, the coefficients of GROWTH are negative and statistically significant when added in Model 2 and 3. This implies that firms with lower historic sales growth are more likely to be acquired. This is in line with Palepu (1986), who also found growth to be significant at the 5% level. However, since GROWTH is used in constructing the variable GDUMMY, no hypothesis was constructed regarding its effect on acquisition likelihood. Interestingly, GROWTH is significant at the 10% level in Model 2 and at the 5% level in Model 3. This increase in significance can be attributed to the inclusion of SPM and TV, which provide additional information and improve the fit of the model, possibly through interaction effects or as mediators/moderators. This highlights the importance of considering a comprehensive set of variables and their interplay in understanding the complex dynamics of takeovers.

Due to the lack of significance in the other variables, we must accept their corresponding null hypotheses. Accepting implies that no conclusion can be drawn regarding the hypothesized characteristics and their association with being a target. Therefore, we find that neither management inefficiency, growth resource imbalance, firm size, P/E ratio, industry disturbance and short-term price momentum are discriminating factors in the Nordic setting. The fact that we find little support for our hypotheses is also reflected by the low explanatory power of our models, which range from 0.0284 to 0.0811, compared to Palepu's (1986) that range between 0.065 and 0.1245. Furthermore, Model 3 is the only significant model, compared to Palepu (1986) who finds all his models to be significant. Conclusively, our explanatory power is well below the 0.2 rule of thumb, which decreases the usefulness of the model, and therefore constitutes an important limitation to the study. We hypothesize that the use of distributed observation years partially contributes to why our models are generally weaker than those of Palepu (1986). However, since this study is from a different region, time period and covers several industries, we cannot deduce the exact cause.

6.2 Robustness tests

The results of the VIF test prove that we do not need to be concerned about multicollinearity. This implies that each variable's contribution to the explanatory value of the model is valid (Farrar and Glauber, 1967). Thus, we can rely on the results of the main regression models, reinforcing the retained specification as shown in Table 5 and our previous discussion remains unchanged.

Moreover, when employing variables that have not been industry adjusted, our estimated variables change slightly, and we find Model 1 and 3 to have higher explanatory power, with likelihood ratio indexes of 0.0299 and 0.1096 respectively. The significance of the models remains mostly unchanged. Notably, SPM becomes statistically significant at the 10% level with a negative sign, which does not support the associated hypothesis (H7). These results are not in line with what we had expected, and neither with the results presented by Cudd and Duggal (2000), who concluded that their adjusted model had higher explanatory power. This could be explained by Barnes (1999) who emphasizes that industry adjusted variables force similarities due to a common denominator for all firms in the sector. This leads to higher error rates, particularly in industries with unusual data and limited representation in the sample, where firms classified in the same industry may actually be dissimilar. Hence, we hypothesize that the relatively small size of our sample contributes to a poor representation of firms in each sector, and in turn generate unsatisfactory results.

We next check the stability of the estimates in our sample method by employing Palepu's (1986) specification for observation year. When including year fixed effects in the main regression models, we did not find issues with regards to time variations. However, given the results from this robustness test we can still conclude that changing the observation years does have an effect on the outcome of our models. The results indicate higher explanatory power and significant models. Additionally, both SIZE and SPM are significant, although SIZE is not significant in Model 3. Palepu's (1986) method, therefore, appears to be more useful in identifying motivators behind takeovers. However, we are cautious to draw such conclusions. We believe that these results stem from two things. Firstly, assigning a single observation year to non-targets in our estimation sample does not allow us to control for year fixed effects, which creates a major limitation. Secondly, since SPM is measured at the same point in time for all non-targets, it is probable that the parameter is affected by systematic market risk. We further hypothesize that the significance in SPM is also what is causing Model 3 to have a substantially higher likelihood ratio and likelihood statistic, compared to in the main regression.

In summary, our robustness tests reveal that MTB, TV and GROWTH are significant determinants of the takeover likelihood. This conclusion is independent of any multicollinearity, industry and year distribution in the sample. However, we find that SPM has an impact on Model 3 when changing the observation years for non-targets, although we have reason to believe that these results are biased because of systematic risk.

6.3 Prediction tests

By using Model 3 to derive the estimated cutoff probability, we receive a threshold of 0.3647 which is significantly higher than Palepu's (1986) cutoff of 0.1120. This discrepancy may be due to our model's lower significance level, along with the weaker explanatory power. When validating Model 3 on our prediction sample we utilize both the estimated and the arbitrary cutoff probability. This is because Powell (2001) suggests that a larger number of targets should be correctly classified when adopting a higher cutoff probability.

Comparing the results of the respective cutoff methods, we obtain a 50% sensitivity from the estimated one, and 16.7% sensitivity from the arbitrary one. Therefore, we conclude that Palepu's (1986) method for estimating a cutoff leads to more accurate target classifications. This was relatively expected, as employing a threshold at 0.5 does not consider the specific decision context at hand (Palepu, 1986; Cudd and Duggal, 2000). Our findings suggest that a higher cutoff probability leads to less Type I errors, yet more Type II errors. This is partially in line with Palepu (1986), who suggested that it should lead to more of both. Nonetheless, we can conclude that our model, despite the cutoff employed, performs worse in takeover prediction compared to Palepu (1986). We believe that these results, again, to some extent stem from having a less significant model with worse explanatory power. We further theorize that our higher estimated cutoff probability could contribute to inferior results, as we have already concluded that a lower threshold reduces the amount of Type II errors. One could further speculate that external economic shocks (such as the effects of COVID-19) have been most prevalent during the observation period used for our prediction sample (2022). Hence, the discriminating factors between targets and non-targets likely look different during this period compared to the years 2012 to 2021 which is studied in estimation sample, making the prediction test less reliable. Regardless, in line with much previous research, these findings suggest that it is not impossible to predict targets, but it is difficult to do so with high sensitivity.

7.0 Suggestions for future research

Our study has given rise to several interesting ideas for future research. Despite the extensive literature on takeover prediction, the factors driving takeovers remain largely unknown. Thus, it is important to interpret the conclusions of this study as indications that takeovers are complex and in many aspects intriguingly unpredictable. Our use of a limited set of variables and older hypotheses may not accurately capture the present reality. Therefore, reexamining and questioning the assumptions underlying takeover prediction could perhaps yield more valuable insights around the factors behind acquisitions, and constitutes an area of further investigation

An additional interesting venue for future research relates to industries and the changing nature of the business landscape. Many of the previous studies were undertaken in an industrial society dominated by large corporations. Since then, knowledge intensive firms have appeared in entirely new sectors such as high-tech and biotech. Here, we often see enormous numbers with regard to their market-to-book ratios, as compared to more traditional firms. If industries are becoming increasingly different, studies comparing takeovers across the entire industrial landscape could be extremely interesting. Of particular importance could be to study variations between industries subject to decreasing returns and those where increasing returns rule as discussed by Arthur (1994).

Lastly, the comparison with other studies conducted in the Nordics, rather than to previous studies in the US and UK (see e.g., Barnes, 1990, 1999; Cudd and Duggal, 2000; Palepu, 1986; Powell, 1997, 2001), is of particular interest as these countries exhibit high accounting value. This would help us understand if the differences in our findings are a result of high accounting standards and a contrasting business landscape. Therefore, we invite future research on takeover prediction in the Nordics and rest of Europe. Furthermore, it could be instructive to study the variations among countries, as national differences in financial reporting, and number of listed firms, may have an effect on the results.

8.0 Summary and conclusion

Takeover prediction is an important aspect of understanding what drives M&A over time. The possibility of predicting targets can create arbitrage opportunities for investors, help managers safeguard their company against takeovers and aid regulators in protecting public interest. Prior research mainly focused on takeover modeling in the US and UK setting and has seen a rapid decline in recent years. Through this study, our aim was to establish discriminant characteristics between Nordic targets and non-targets, and to test if we can accurately predict takeovers based on those. With no best practice in place, we further wanted to shed light on some of the different established methodologies in takeover prediction modeling and explore how they contribute to our findings.

To achieve this, we constructed an industry adjusted estimation sample consisting of 113 targets and 196 non-targets, observing data from 2012 to 2021, following a random sampling approach. We tested our hypotheses on the estimation sample through three binary logit models, consisting of 11 independent variables in total. Model 3 had the highest explanatory power with a likelihood ratio index of 0.0811 and was statistically significant at the 5% level. Our results are consistent with two of our hypotheses, suggesting that targets in the Nordics exhibit undervalued assets and higher trading volume compared to non-targets. This means that the market price targets' shares below their intrinsic values and trades their stocks more frequently prior to the announcement of the acquisition bid. Our findings further suggest that targets have lower sales growth, however, no hypothesis was formed regarding this. The robustness tests indicate no sign of multicollinearity; however, it reveals that our results are vulnerable to changes in methodology. When using Model 3 to conduct the prediction test on a separate group of firms from 2022, we find that an estimated cutoff probability (0.3647) compared to an arbitrary one (0.5) leads to less Type II errors. Overall, our model is able to predict targets with 50% sensitivity.

In conclusion, our findings suggest that the prediction of takeover targets, using publicly available information, is possible to a certain degree. However, our models, irrespective of methodology, have very low explanatory power. Additionally, we have not investigated whether the predicted portfolio could generate abnormal returns. Nevertheless, we hope that our findings can further the understanding of the motives behind takeovers in the Nordics.

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Appendix

Appendix 1

VIF-test.

Variable	VIF
AER	1.088
GDUMMY	1.245
GROWTH	1.069
LIQUIDITY	1.258
LEVERAGE	1.103
SIZE	1.057
MTB	1.116
PE	1.028
IDUMMY	1.024
SPM	1.063
TV	1.049

Appendix 2

Estimates of logit acquisition likelihood models with unadjusted variables.

Variable	Expected sign	Estimates		
		Model 1	Model 2	Model 3
AER	-	-0.1761	-0.2504	-0.2005
GDUMMY	+	-0.3126	-0.4173	-0.2935
GROWTH			-0.1060	-0.1882*
LIQUIDITY			0.4172	0.4378
LEVERAGE			0.0003	0.0166
SIZE	-	-0.0001	-0.0001	0.0000
MTB	-	-0.2077**	-0.2297**	-0.2079**
PE	-	-0.0559	-0.0559	0.0484
IDUMMY	+	-0.1928	-0.1924	-0.2852
SPM	+			-0.0100*
TV	+			3.0790***
Constant		-0.1888	-0.0378	0.5348
Year fixed effect		-	-	-
Likelihood ratio index		0.0293	0.0339	0.1096
Likelihood ratio statistic		11.88	13.78	44.48***

*** p<0.01, ** p<0.05, * p<0.1

Appendix 3

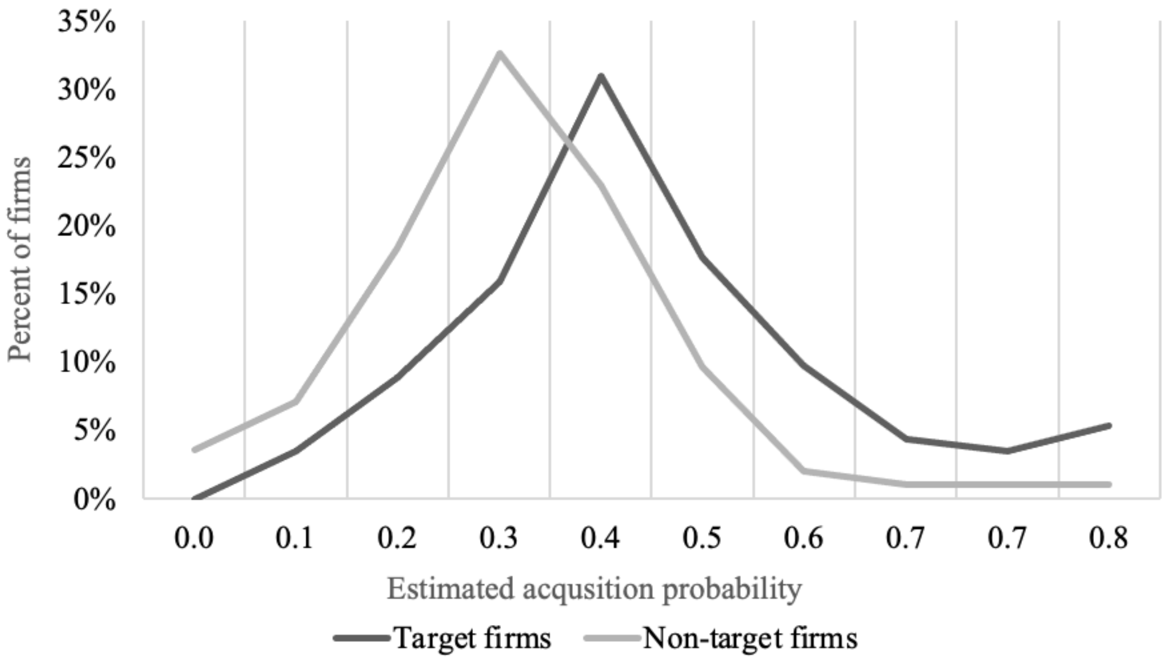
Estimates of logit acquisition likelihood models with a different observation year.

Variable	Expected sign	Estimates[1] Model 1	Model 2	Model 3
AER	-	-0.0706	-0.0418	-0.0685
GDUMMY	+	0.0983	0.0140	-0.1385
GROWTH			0.0345	-0.0413
LIQUIDITY			-0.1750	-0.1585
LEVERAGE			-0.1375	-0.0776
SIZE	-	-0.3069**	-0.2855*	-0.1701
MTB	-	-0.6072***	-0.6031***	-0.4695**
PE	-	-0.1393	-0.1468	-0.0997
IDUMMY	+	0.2503	0.2113	0.2285
SPM	+			-0.9576***
TV	+			0.6514***
Constant		-0.7607***	-0.7939***	-0.7789***
Likelihood ratio index		0.0543	0.0588	0.1791
Likelihood ratio statistic		22.04***	23.88***	72.66***

*** p<0.01, ** p<0.05, * p<0.1

Appendix 4

Cutoff probability graph.



Appendix 5

Pearson correlations.

Variable	AER	GDUMMY	GROWTH	LIQUIDITY	LEVERAGE	SIZE	MTB	PE	IDUMMY	SPM	TV
AER	1.00										
GDUMMY	0.01	1.00									
GROWTH	0.03	-0.07	1.00								
LIQUIDITY	0.05	0.35***	0.10*	1.00							
LEVERAGE	0.07	-0.23***	-0.07	-0.10*	1.00						
SIZE	-0.10*	-0.02	-0.10*	0.08	0.02	1.00					
MTB	0.11*	0.02	0.23***	0.31***	0.07	-0.02	1.00				
PE	0.14**	0.01	-0.04	0.02	0.02	-0.08	0.05*	1.00			
IDUMMY	0.09	-0.02	-0.05	-0.03	0.04	-0.03	-0.09	-0.04	1.00		
SPM	-0.22***	0.07	-0.05	-0.02	-0.14**	0.09	-0.09	-0.02	0.02	1.00	
TV	0.03	-0.03	0.03	-0.06	-0.08	-0.16***	-0.06	0.01	0.08	0.04	1.00

*** p<0.01, ** p<0.05, * p<0.1

Appendix 6

Definitions and computations of variables.[29, 30]

Average excess return (AER): Calculated by the average daily return of the stock during the four years prior to that of the observation less the average daily return of the stock market index for which the company is listed during the same period. Refinitiv Eikon data item “Daily Total Return” is used to determine the daily return of the stock, and “.OMXSPI”, “.OMXCPI”, “.OMXHPI”, “.OSEBX”, “.OMXIPI” determines the average daily return of the stock market index.

Growth-resource dummy (GDUMMY): Defined based on the three variables GROWTH, LIQUIDITY and LEVERAGE. The dummy variable is assigned a value if the firm has a combination of either (1) low growth, high liquidity, and low leverage or (2) high growth, low liquidity and high leverage. The dummy takes on the value zero for all other combinations. For each of the variables—growth, liquidity, and leverage—a firm's classification is determined as "high" if its value exceeds the population average; otherwise, it is classified as "low."

GROWTH: Defined as the average annual rate of change in a firm’s sales over the three years prior to the year of the observation. To clarify, for a target acquired in 2014, the sales data will range from the period January 1, 2011 to December 31, 2013, and is consequently used to calculate the sales growth (%) during the fiscal years 2011, 2012 and 2013. Refinitiv Eikon data item “Net Sales” is used in the computations.

LIQUIDITY: Computed by dividing the net liquid assets of a firm by its total assets and represents the three fiscal years prior to the observation. Net liquid assets are the sum of Refinitv Eikon’ items “Cash and Short Term Investments” less “Total Current Liabilities”. Total assets is referred to as “Total Assets, Reported”, in Refinitv Eikon’s database.

LEVERAGE: Calculated by using the ratio of the long-term debt of a firm to its total equity, averaged by the three fiscal years preceding the observation year. Refinitiv Eikon data items ”Total Debt” and ”Total Equity” are employed in the calculation.

[29] The observation year for targets is that in which it was acquired (Palepu, 1986) (for non-targets see Table 2).
[30] All financial information defined by currency is measured in millions EUR.

SIZE: Measured by the total net book value of a firm's asset. Refinitiv Eikon data item ”Total Assets Reported” to withdraw data. The variable is measured as of the fiscal year end immediately prior to the observation year.

Asset undervaluation (MTB): Estimated by the market-to-book ratio, defined as the ratio of the closing stock price of the firm multiplied by the number of common shares outstanding divided by the book value of equity. The product of the denominator represents the market value of equity. Refinitiv Eikon data items ”Price Close”, ”Total Common Shares Outstanding” and ”Total Equity” are employed in the calculation. Each component of the market value, and also the book value, are measured at the end of the fiscal year preceding the observation year.

Industry dummy (IDUMMY): Assigned a value of one if at least one acquisition has occurred in a firm's “The Refinitiv Business Classification" (TRBC) industry group during the 12 months prior to the year of the observation.[31]

Price-to-earnings ratio (PE): Defined as the closing stock price of the firm multiplied by the number of common shares outstanding divided by its net earnings for that same year. Refinitiv Eikon data items ”Price Close”, ”Total Common Shares Outstanding” and ”Net Income After Taxes” are employed in the calculation. The variable is computed as of the fiscal year end preceding the observation year.

Short-term price momentum (SPM): Calculated by subtracting the closing price the day of the observation to the closing price from three months prior to that of the observation, using daily data, multiplied by 100. Refinitiv Eikon data item ”Price Close” is used to calculate the variable.

Trading volume (TV): Defined as the average number of free float shares multiplied by the share price, divided by trading volume. The variable is computed as of the month prior to that of the observation. Refinitiv Eikon data items ”Price Close”, “Volume” and “Shares Free Float” are employed in the calculation.

[31] Palepu (1986) assigns the value based on a firm's four digit Standard Industrial Classification (SIC) code. Due to the fact that Refinitiv Eikon does not provide SIC codes, we have instead used the “Industry Group” definitions provided by The Refinitiv Business Classification (TRBC). With high similarities to SIC codes and the GICS codes used by Brar et al. (2009), this definition should not alternate insights gained.